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Validating Operational Food Insecurity Indicators against a Dynamic Benchmark

Evidence from Mali

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Indicators of household food insecurity are typically static and thus ignore a key dimension of food insecurity.

An explicitly forward-looking food insecurity indicator is developed that takes into account both current dietary inadequacy and vulnerability to dietary inadequacy in the future. Relative to this dynamic benchmark, three readily available indicators are evaluated.

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Summary findings

Christiaensen, Boisvert, and Hoddinott develop an explicitly forward-looking indicator of food insecurity that takes into account both current dietary inadequacy and vulnerability to dietary inadequacy in the future.

Application of this measure to data from northern Mali shows that neglecting the future dimension of food insecurity causes serious underestimation of food insecurity in this area.

The authors evaluate the performance, relative to their dynamic benchmark, of three readily available alternative indicators:

- An agricultural production index.
- A dietary diversity index.
- A coping strategy index.

Despite the uneven performance of these indexes relative to the individual components of the dynamic food insecurity indicator developed in the paper, they all demonstrate strong associations with that indicator. This is a promising result, given the urgent demand for reliable indicators of food insecurity.

This paper—a product of the Poverty Reduction and Social Development Unit, Africa Region—is part of a larger effort in the region to understand the evolution of poverty and inequality in Africa in the 1990s. Copies of the paper are available free from the World Bank, 1818 H Street NW, Washington, DC 20433. Please contact Luc Christiaensen, room J8-080, telephone 202-458-1463, fax 202-473-7913, email address lchristiaensen@worldbank.org. Policy Research Working Papers are also posted on the Web at www.worldbank.org/research/workingpapers. November 2000. (30 pages)

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Validating Operational Food Insecurity Indicators against a Dynamic Benchmark: Evidence from Mali

Introduction

It is well understood that poor people in developing countries live in environments characterized by substantial idiosyncratic and common shocks, leading to wide variability in incomes (Baulch and Hoddinott, 2000; World Bank, 2000). When households are unable to smooth consumption in the face of variable incomes, these shocks generate a welfare loss. As underscored in the literature on famines (Sen, 1981; Drèze and Sen, 1989), when existing assets are limited or insurance is absent, these shocks can literally be a matter of life and death. With this understanding comes the necessity to broaden our view of poverty to incorporate not only an assessment of current living standards relative to some norm, but also one's vulnerability: the probability of living standards falling below some reference level in the future. Yet, existing measures of poverty, or dimensions of poverty such as food security, are typically static and non-probabilistic in nature (Maxwell and Frankenberger, 1992; Riely and Moock, 1995; Ravallion, 1996). In the case of food security, this is ironic as the commonly accepted definition "access for all persons to an adequate diet now *and in the future* to live an active and healthy life" (World Bank, 1986; Maxwell and Frankenberger, 1992; Barrett, 1998; emphasis is ours) is inherently forward-looking.

To operationalize this holistic view of poverty, one needs measures that simultaneously capture a person's current living standard and his vulnerability to future shortfalls. Given renewed international commitments to address worldwide problems of undernutrition and vulnerability, as emphasized by FAO's Food Security Conference in

1996 and the World Bank's forthcoming World Development Report on Poverty 2000/1, the demand for such comprehensive measures is more urgent than ever. They are needed to identify those who are currently poor and at risk to shocks, as well as to monitor their situation over time. They aid in testing hypotheses on the causes of current poverty and vulnerability, and are essential for evaluating the efficacy of interventions to reduce current poverty and vulnerability to future shocks.

In this paper, we develop a comprehensive indicator that takes into account both current living standards and vulnerability to future shocks. Given that joint consideration of these two dimensions lies at the core of food security and further motivated by the renewed international efforts to reduce hunger, we do so in the context of household food security. Our methods draw on the emerging literature on multi-dimensional poverty (Bourguignon and Chakravarty, 1998) and on earlier work measuring the ex ante probability distributions of future outcomes (Just and Pope, 1979; Mullahy and Sindelar, 1995; Christiaensen and Boisvert, 2000). We begin by outlining a general approach, then applying it to data from a household survey in northern Mali. In this application, we find that neglecting the future dimension of food insecurity causes us to seriously underestimate this population's food insecurity status. Although our specific application is to food security, we stress that the method can be applied more generally.

A drawback to our method is its rather demanding data requirements. These limit the operational usefulness of our approach, which, as noted above, provides a motivation for developing these measures in the first place. For this reason, we go beyond the development of the dynamic food security indicator to evaluate how well more readily available and easier-to-collect measures of food security associate with our dynamic benchmark. Staatz, D'Agostino and Sundberg (1990) note that policy makers typically focus on food production or supply; an alternative that we consider is an index of household agricultural production. Mindful of their admonition to decouple household food security from local food production, we also draw on anthropological studies of coping with shocks (Corbett, 1988; de Waal, 1989; Amare, 1998) and examine the performance of two promising, but rarely used alternative indicators: an index of dietary diversity (Hatloy *et al.*, 1998), and a coping strategy index (Radimer, Olson and Campbell, 1992; Maxwell, 1996). We find that the dietary diversity and coping strategy indices are reliable indicators of current dietary inadequacy but agricultural production is not. Agricultural production and the weighted coping strategy index predict food vulnerability well, but indices of dietary diversity perform less well. Despite the uneven performance with respect to the individual components of the benchmark, they all perform well in identifying the food insecure as defined by our dynamic benchmark.

A Dynamic Food Insecurity Indicator

A food insecurity indicator that incorporates both current food shortfalls and vulnerability to food shortfalls in the future is, by definition, multidimensional. This indicator should possess characteristics associated with an acceptable indicator of poverty, namely that should be monotonic, symmetric, continuous, subgroup decomposable, meet the transfer principle as well as the focus axiom (Zheng, 1997).

A Multidimensional Food Insecurity Indicator

Following Chakravarty, Mukherjee and Ranade (1998) and Bourguignon and Chakravarty (1998), who have extended the axiomatic approach to poverty measurement to include its multiple facets, we combine the different dimensions of food security into one index. We define a threshold for every dimension; a person is food insecure once one of the dimensions falls below its threshold. Specifically, let there be m dimensions to food security (e.g. current caloric intake, or the ex ante probability of future caloric shortfall), with x_{ij} the value of dimension j, for person i, and z_j the minimal requirement for dimension j. Person i is deprived with respect to dimension j, if x_{ij} is less than or equal to the threshold (z_j). The level of deprivation associated with each dimension j is $P_j(x_{ij}/z_j)$ with P_j: $(0,\infty) \rightarrow [0,1]$, a continuous, non-increasing, convex function of x_{ij}/z_j; $P_j(x_{ij}/z_j)=1$ if $x_{ij}=0$ and $P_j(x_{ij}/z_j)=0$ if $x_{ij} \geq z_j$.

If $x_{ij}=0$: $P_j(0)=1$; deprivation is at its maximum, e.g. nothing to eat now or certain of not enough to eat in the future. At the other extreme, $P_j(x_{ij}/z_j)=0$ if $x_{ij} \geq z_j$, a person is not deprived if the quantity is at least as high as the threshhold. Thus, a person's food insecurity is not affected by being overfed. The interpretation of intermediate values of P_j depends on the functional form.

The continuity of P_j ensures that small changes (or measurement errors) in dimension j cannot lead to large changes in deprivation status regarding j. The transition is also smooth when crossing the poverty line, or for changes in the deprivation threshold. Convexity of P_j implies that deprivation decreases at a non-increasing rate if a person's attribute j increases. In other words, a person is considered to be more deprived for a particular dimension, the larger its (relative) shortfall. This relates to the main criticism of the head count index, which does not meet this criterion (Sen, 1976).[1] In normalizing by thresholds, deprivation is scale invariant. Since only the relative distance of an attribute from its threshold matters, food insecurity can then be measured as:

$$fis_i = \sum_j a_j P_j(x_{ij}/z_j), \qquad (1)$$

where $a_j > 0$ ($\sum_j a_j=1$) is the weight or value attached to the shortfall with regard to dimension j. For a dynamic food insecurity index, a_j reflects the relative importance attached to the future. For the near future, current undernutrition and food vulnerability might be regarded as equally important. For the more remote future, one might discount vulnerability relative to current food shortage.

As in the case of multidimensional poverty indices (Chakravarty, *et al.*, 1998; Bourguignon and Chakravarty, 1998), this measure of individual food insecurity can also be aggregated across n individuals into a food insecurity index for the population:

$$FIS = (1/n)\sum_i\sum_j a_j P_j(x_{ij}/z_j). \qquad (2)$$

When FIS=1, everyone has maximal food insecurity; everyone is food secure if FIS=0. Our food insecurity index (2) also meets important axioms necessary for good poverty measures mentioned above. According to the focus axiom, for example, giving a person more of an attribute that is already above the threshold will not alter his/her food insecurity status. Consequently, the food insecurity index is also independent of the attribute levels of the food secure.

As shown by Christiaensen (2000), the index can be decomposed by socio-economic subgroup and by attribute. The population's food insecurity can be expressed as the population's share weighted average of subgroup food insecurity levels. By enabling one to calculate the percentage contribution of subgroups to total food insecurity, this property facilitates targeting of food security enhancing policies. Because the measure of food insecurity can also be written as a weighted (a_j) average of food insecurity levels for the dimensions (FIS_j), we can identify the contribution of each dimension to overall food insecurity (Christiaensen, 2000). This information is crucial for the appropriate design of food security policies.

A Convenient Functional Form for the Food Insecurity Indicator

To calculate the population's food insecurity empirically, we define P_j as:

$$P_j(x_{ij}/z_j) = (1-x_{ij}/z_j)^{\alpha j} \quad \text{for } 0\leq x_{ij} \leq z_j \text{ with } \alpha_j \geq 1 \qquad (3)$$
$$= 0 \quad \text{for } x_{ij}>z_j .$$

By substituting (3) into (2), we see that our food insecurity index is a multidimensional generalization of the P_α poverty index developed by Foster, *et al.* (1984):

$$FIS = (1/n)\sum_j a_j \sum_{i\in Dj}(1-x_{ij}/z_j)^{\alpha j} \qquad (4)$$

with $D_j=\{1\leq i \leq n{:}x_{ij}\leq z_j\}$, the set of subjects, d_j, deprived with respect to attribute j.

The index's properties differ depending on α. To avoid double counting and to meet the transfer axioms, we ignore α=0. For $\alpha_j=1$ $\forall$j, equation (4) is:

$$FIS_1=\sum_j a_j H_j I_j \qquad (5)$$

where $H_j = d_j/n$ is the head count ratio for those deprived with respect to attribute j and $I_j = \sum_{i\in Dj}(1-x_{ij}/z_j)(1/d_j)$ is the (conditional) average deprivation gap ratio for attribute j. Thus, assuming j represents current food intake, our food insecurity measure accounts for the proportion of undernourished people (H_j), and for the degree of their undernourishment (I_j). The greater is the population's average undernourishment ratio (holding H_j constant), the greater is the population's food insecurity.

For $\alpha_j=2$ $\forall$j, equation (4) can be written as (Foster, *et al.*):

$$FIS_2=\sum_j a_j H_j [I_j^2 +(1-I_j)^2 C_j^2] \qquad (6)$$

where $\mu_j= \sum_{i\in Dj} x_{ij}/d_j$ and $C_j^2 = \sum_{i\in Dj} [(x_{ij}-\mu_j)/\mu_j]^2/d_j$, the squared coefficient of variation for dimension j which measures the inequality of attribute j among those "j" deprived.

Thus, food insecurity increases with the proportion of deprived for each attribute (H_j), the average degree of deprivation (I_j), and the inequality for each attribute (C_j).

Estimating a Dynamic Food Insecurity Indicator

In this section, we show how this multidimensional index of food insecurity can be estimated, drawing on data collected in the Zone Lacustre region of northern Mali. Daily life in this remote, extremely poor area is dominated by concerns of food and vulnerability. Most households depend on rain fed agriculture and livestock, supplemented with migrant remittances, especially when harvests fail. As rainfall is scarce and erratic, droughts are common, often resulting in widespread hunger. Timely identification of the food insecure and the degree of their food insecurity is crucial to facilitate the frequent mobilization and targeting of emergency (food) aid in the area.

From 1997-98, 274 households, randomly selected from 10 purposively sampled villages,[2] were surveyed in each of four periods, including the 1997 post-harvest and the subsequent 1998 hunger season. Data were collected on agricultural production, income, food and non-food consumption, and households' strategies for coping with food shortages. Even though poverty is widespread, households differ widely in their caloric per capita consumption, even during the hunger season.[3] This variation, together with the panel nature of the data allows us to estimate a dynamic food security indicator.

Indicators of Current Undernutrition and Food Vulnerability

We focus on two aspects of food insecurity: current dietary inadequacy and vulnerability to future dietary inadequacy. We measure dietary adequacy by caloric availability. Women in these households were asked to recollect the quantities of different foods consumed in the previous seven days. These data were converted into daily per capita caloric availability using household size and locally adapted tables that convert physical units of food into calories. Were data available, however, the measure could be readily extended to explicitly account for deprivation with respect to micronutrients such as vitamin A, iron and zinc. We take the November 1997 survey round (which coincides with the immediate post harvest period) as the 'current period' and the August 1998 survey round (which coincides with the height of the subsequent hungry season) as the 'future'.

The incidence and depth of current caloric shortfall can be directly calculated from the survey data collected in November 1997. We take 2,345 kcal/person/day as caloric threshold which corresponds to the needs of a 60 kg male, aged 30-59, undertaking 'light' activities, or the needs of a 55 kg female between 30-59 undertaking seated work (Ministry of Agriculture, Fisheries and Food, 1996; Shetty *et al.*, 1996). The real challenge empirically is in determining a measure of vulnerability with respect to future dietary inadequacy. In a related paper, Christiaensen and Boisvert (2000), express a household's food vulnerability as:

$$V_{t,\gamma} = F(z) \int_{\underline{c}_{t+1}}^{z} (z - c_{t+1})^{\gamma} \frac{f(c_{t+1})}{F(z)} dc_{t+1} \qquad (7)$$

with $\underline{c}_{t+1}$ the lower bound of future caloric consumption c_{t+1}, z the caloric threshold, $f(c_{t+1})$ the household's ex ante probability distribution function of caloric consumption at t+1 and F(.) the corresponding cumulative distribution function. A household's food vulnerability is thus measured as the current probability of falling below the caloric threshold z in the future, multiplied by a conditional probability weighted function of the shortfall below this caloric threshold. Depending on γ, different aspects of shortfall are emphasized. If $\gamma=0$, vulnerability is measured as the probability of future caloric shortfall. If $\gamma=1$, vulnerability is measured as the product of probability of shortfall and the conditional expected gap, accounting for the depth of shortfall. By setting $\gamma>1$, we translate larger shortfalls into greater vulnerability, given the same conditional probability of occurrence, and account for the spread of the distribution of shortfalls.

To measure a household's food vulnerability empirically, we must estimate its ex ante probability distribution of future caloric consumption and select a caloric threshold (z), and a value for γ. To classify the food vulnerable, one must specify a vulnerability threshold (θ); a household is vulnerable if the probability of a caloric shortfall exceeds θ.

To estimate each household's ex ante probability distribution of future caloric per capita consumption, $C_{i,t+1}$, we exploit the insights contained in Just and Pope (1979) who examined how inputs could independently affect both the mean and variability of farm production. Applying their technique here, we specify a flexible heteroskedastic regression specification of the following form:

$$C_{i,t+1} = f(X_{i,t};\alpha) + h^{1/2}(X_{i,t};\beta)^{*}\, e_{i,t+1} = f(X_{i,t};\alpha) + u_{i,t+1} \qquad (8)$$

with $E(e_{i,t+1})=0$, $E(e_{i,t+1},e_{k,t+1})=0$ with $i\neq k$ and $V(e_{i,t+1})=\sigma^2_e$. Further, the conditional mean and variance of (8) are:

$$E(C_{t+1} \mid X_t)=f(X_t;\alpha) \quad \text{and} \quad \partial E(C_{t+1} \mid X_t)/\partial X_{j,t}=\partial f(X_t;\alpha)/\partial X_{j,t} \qquad (9)$$

$$V(C_{t+1} \mid X_t)=h(X_t;\beta)^{*}\, \sigma^2_e \quad \text{and} \quad \partial V(C_{t+1} \mid X_t)/\partial X_{j,t}=(\partial h(X_t;\beta)/\partial X_{j,t})^{*}\sigma^2_e \qquad (10)$$

This specification permits us to estimate the mean and variance of future consumption as functions of ex ante household and locality characteristics (X_t), with α and β the regression parameters of respectively the mean and variance equations. A second attractive feature of this approach, in contrast to traditional demand specifications which append the error term in an additive or multiplicative manner, is that it allows the marginal effects of the regressors on the ex ante mean and variance of future consumption to differ in sign. This property is crucial to reflect, for example, how the possession of assets facilitates consumption smoothing. Having more assets today decreases a household's ex ante variance of future consumption, while it increases its ex ante mean (Christiaensen and Boisvert, 2000). As Mullahy and Sindelar (1995) in a related application on the effect of alcoholism on the mean and variance of income, we assume that $f(X_{i,t};\alpha)$ is linear and that $h(X_{i,t};\beta)$ is exponential:

$$C_{i,t+1} = X'_{i,t}\alpha + u_{i,t+1} \qquad (11)$$

with $E(u_{i,t+1} | X_{i,t}) = 0$; $E(u_{i,t+1}, u_{k,t+1} | X_{i,t}) = 0$, $i \neq k$ and $V(u_{i,t+1} | X_{i,t}) = \sigma^2_i = \sigma^2_e * \exp(X_{i,t}'\beta)$. The model reflects multiplicative heteroskedasticity; α and β are estimated by a three-step heteroskedastic correction procedure (Judge *et al.*, 1988).

Through these regressions, we predict each household's ex ante mean and variance of (logarithmic) consumption during the hunger season, based on its socio-economic characteristics and those of its environment at the preceding post harvest time. In the appendix, we briefly describe the variables used in these regressions, and present the values of the coefficients; a fuller description, including a theoretical derivation of our specification from a household model of intertemporal consumption under uncertainty and imperfect capital markets is found in Christiaensen and Boisvert (2000).

By substituting household characteristics at post-harvest time into these estimated equations, we predict the ex ante mean and variance of hunger season (logarithmic) consumption for each household. With these predictions, and the assumption of lognormally distributed consumption, which is not rejected by the data, we estimate each household's ex ante distribution of future caloric per capita availability, and calculate for a given caloric threshold, its probability of caloric shortfall ($V_{\gamma=0}$).[4]

As with the estimate of current undernutrition, we take 2,345 kcal/person/day as the caloric threshold.[5] Note however that the vulnerability threshold – the probability level of caloric shortfall above which a household is considered food vulnerable – cannot be set objectively. We assume a 50% threshold and examine the sensitivity of our results to this assumption.

We find that only 24% of the households have less than a 50% chance that daily caloric consumption during the hunger season will fall below 2,345 kilocalories per capita. That is, in the post harvest period, just over three quarters of the households in this sample have at least a 50% chance that caloric availability in the next hungry season will fall below the minimum caloric threshold. If household and locality socio-economic characteristics were to remain constant, this implies that for at least five out of ten years, about three quarters of the population would not obtain sufficient calories during the hungry season. The marginal effect of an increase in the vulnerability threshold on the proportion of households who are not vulnerable is especially large once we exceed a threshold of 50%. With correlation coefficients, contingency tables, and out of sample predictions, Christiaensen and Boisvert (2000) further show the high predictive ability of this vulnerability measure of future undernourishment.

Food Insecurity in Zone Lacustre

Based on the estimates for the two dimensions of our food insecurity indicator - current undernutrition and food vulnerability - table 1 provides a food insecurity profile for our sample population in the Zone Lacustre. The threshold for kilocalories/person/day

(z_1) is 2345. V_0 is our food vulnerability measure; its threshold (z_2) is 0.5.[6] P_j is defined by equation (3), with α=1. As we look only one period ahead, we attach equal weight to both dimensions. Recall that the dynamic food security indicator is sub-group decomposable; we illustrate this property here by disaggregating by sex of household head, given the frequently voiced concern regarding the vulnerability of female headed households.

The food insecurity measure FIS_1 (α=1) for the sample is 0.18. On average, each household is 18 % short of the minimal caloric requirement and 18 % below the minimal probability to be secure with respect to future caloric sufficiency. Our population is very food insecure. Female headed households are less food insecure than male headed households if one compares either current shortfalls (0.07 compared to 0.11) or vulnerability to future shortfalls (0.13 for female headed households; 0.28 for male headed households). But perhaps the most striking result is that the food insecurity indicator for current undernourishment is 0.10, while it is 0.26 for food vulnerability. Almost three quarters (73%) of the population's food insecurity is related to vulnerability regarding future food availability, and only about one quarter (27%) of their food insecurity is related to their current undernourishment. This remarkable result is perhaps not so surprising given that our forward looking measure looks at the hungry season. However, note that this result is robust to placing disproportionate weight on current shortfalls. Setting a_1=0.66 and a_2=0.34, we find that 57% of food insecurity is still related to future caloric insufficiency. Clearly, by neglecting vulnerability, we substantially underestimate the population's food insecurity.

Performance of Operational Food Insecurity Indicators

We now turn to the second objective of this paper; evaluating more readily available operational indicators of food security - an index of agricultural production, a dietary diversity index, and a coping strategy index - against this dynamic benchmark. Given that a wide range of alternative food security indicators exists,[7] it is helpful to begin by explaining why we focus on these three alternatives.

Alternative Indicators of Food Insecurity

We consider food production as one alternative indicator because both the Government of Mali and the USAID sponsored Famine Early Warning System for Mali use it as a leading indicator of food insecurity. Since the availability of food is necessary for being food secure, and many rural households produce much of their own food, agricultural production is presumed to be a natural indicator of food security. However, there is increasing evidence that agricultural households derive a substantial portion of their income from off-farm activities (Reardon, *et al.*, 1992; Ellis, 1998) and buy a substantial share of their food (Weber *et al.*, 1988). Both features tend to weaken the association between household food production and household food security. Hence, it is of interest to compare food production to our dynamic food insecurity indicator. We use cereal production (in kilograms) per residential household member reported by the household head in the immediate post harvest period as the measure of agricultural production. As a production figure of 200 kg of cereals per capita is often taken as food self-sufficiency threshold (Carter, 1997), an agricultural production index potentially provides direct information on food shortfall. For example, only 10 % of the sample households attained this threshold in 1997, a drought year.

Our second alternative food insecurity indicator pertains to dietary diversity, the number of different foods or food groups that an individual consumes over a given period. It is inspired by the empirical observation, reported as early as 1930 (Bennett, 1954), that people consume a wider variety of foods, as they become better off. At the early stages such an increase in food diversity is also accompanied by an increase in caloric intake. Several studies further indicate that dietary diversity increases the extent to which the minimal requirements for all the different nutrients are met (e.g. Hatloy, *et al.*, 1998). Finally, our field experience suggests that it is relatively straightforward to obtain these data. However, dietary diversity indices do not record quantities and this complicates the assessment of caloric inadequacy solely based on the dietary diversity index.[8] Here, we construct a food variety score (FVS) to combine the diversity of a person's diet into a single index (Hatloy, *et al.*, 1998). The FVS is based on the number of different food items eaten over a registration period. We evaluate two versions: 1) a simple sum of the number of different food items eaten by the main female adult over the past month, and 2) a frequency-of-consumption weighted sum of food items.

Building on Corbett (1988) and de Waal (1989)'s observations that people display particular behavioral patterns to cope with food stress, and Radimer *et al.* (1992) on measuring hunger in the United States, Maxwell (1996) combines consumption behaviors associated with food shortages into a numerical index. Our third alternative indicator is an index of these 'coping strategies'. We asked the most knowledgeable woman within the household questions regarding the frequencies over the past seven days of: going without eating all day; skipping meals during the day; serving smaller portions to different household members, and serving less preferred foods. In the simple sum index, we summarize this information by counting the number of the different coping strategies used by the household. In the weighted index, we weigh each strategy by the frequency with which it is used and the severity of the strategy. Following Maxwell (1996), we assign a weight of 1 to strategies related to the consumption of less preferred foods and smaller portions, a weight of 2 to skipping meals, and a weight of 3 to not eating all day.[9] To weigh frequency of the application of strategies, we adopted a scale of 1 to 4, with "often" = 4, "from time to time" = 3, "rarely" = "2" and "never" = 1. Although theoretically promising and inexpensive to implement, as the dietary diversity index, the coping strategy index does not record quantities.

Methods for Assessing Alternative Indicators

We now assess the performance of these indicators in predicting the food insecure, as measured by our multi-attribute benchmark. We begin by evaluating how well they predict the currently undernourished and the food vulnerable - the two components of our multi-dimensional benchmark - separately. Based on our dynamic benchmark, 79% of households fail to meet their current caloric needs and/or have a 50% or less chance, of meeting future caloric needs. The remaining 21% are classified as food secure.

To make these comparisons, we must also define threshold values for the alternative indicators below which a household is food insecure. To see if these indicators classify households consistently with the benchmark, we assume the same proportion are food insecure and define the threshold for the alternative indicators as their respective values for which 79% of the households, when ranked from low to high, would be food insecure. Similarly, we define the threshold of the alternative indicators with respect to each of the two dimensions of our dynamic benchmark, as their respective values below which 37% are undernourished and 76% are food vulnerable. These are the proportions of households who were found to be undernourished and food vulnerable, respectively, based on our benchmark indicators.

Following Chung, *et al.* (1997), Wodon (1997) and Maxwell, *et al.* (1999), we quantify the association between the alternative indicators and the benchmark by Spearman correlation coefficients, contingency tables, ROC (Receiver Operator Curves) analysis and multivariate regressions. Contingency tables are commonly used in the nutrition literature. Observations are classified according to a benchmark and an alternative indicator, both defined categorically. If there is a statistically significant association, the performance of the alternative indicator can be rated further by: 1) the agreement percentage, the percentage of observations correctly classified by the alternative; 2) its sensitivity or the proportion of predicted positive outcomes also positive according to the benchmark; and 3) its specificity or the proportion of predicted negative outcomes also truly negative according to the benchmark.[10] For good performance, the agreement percentage should be high, as well as both the sensitivity and the specificity.

A limitation of contingency tables is that estimates of sensitivity and specificity depend on the choice of the cut-off by which the different observations are classified, with sensitivity and specificity moving in opposite directions. This limitation can be addressed by looking at receiver-operator curves (ROC). The ROC curve graphs an indicator's sensitivity against one minus its specificity across the range of cut-offs.[11]. The curve starts at (0,0), corresponding to the maximum cut-off, and continues in a monotone, non-decreasing fashion to (1,1) which corresponds to the minimum cut-off.

The more bowed the curve, the greater the indicator's predictive power. Hence, the area below the curve is often used as an indication of the predictive power of the alternative indicator with an area 0.5 (corresponding to the 45° line) reflecting no predictive power, and an area 1 indicating perfect prediction (Wodon, 1997).

A limitation of both contingency tables and ROC analysis is that the dependent variable is chosen with some degree of arbitrariness. Further, by restricting ourselves to a zero-one dependent variable, we throw away information on the variation in household food security which would seem informationally inefficient. Consequently, we also use OLS regressions[12], adding in controls for location and household size, to see what association exists between these indicators and our measures of food insecurity.

Associations with Current Caloric Shortfalls

Panel 2a in Table 2 reports associations between these alternative indicators and current shortfalls in caloric availability. Irrespective of the method used, cereal production per capita emerges as a poor predictor of current caloric intake at the immediate post harvest time.

The dietary and coping strategy indices, on the other hand, both appear as good indicators of current caloric intake. They correctly classify about 70% of the households as either undernourished or sufficiently nourished and the relatively large area under the ROC curve indicates that the good predictive power holds irrespective of the cut-off. These results are better than those by Maxwell *et al.* (1999), who find agreement between coping strategy indices and current caloric intake in 55 to 60% of the cases. Our results further validate the use of coping strategy indices to identify current dietary shortfalls.

The specificities for the dietary diversity and coping strategy indices are also high, but their sensitivities are somewhat lower, between 54 and 57%. This is, of course, related to the particular choice of our cut-off point (i.e. the 37th percentile). An increase in this cut-off point (to e.g. the 50th percentile) increases their sensitivity, but also decreases their specificity. For comparison, note that when specificity and sensitivity are summed together, they range between 130 and 135%, which is at least 10 percentage points higher than the best results reported by Maxwell *et al.* (1999).

Associations with Future Food Vulnerability

Panel 2b of table 2 indicates that cereal production emerges as a good predictor of food vulnerability. It correlates well with our benchmark vulnerability measure, correctly classifies 70% of the households and displays the largest area under its ROC curve. Yet, the results with respect to the dietary diversity indices are ambiguous. We find a significant relationship from the OLS regression and, in the case of the simple sum of dietary diversity, the area under the ROC is higher than for either coping strategy indicator. However, neither the Spearman correlation coefficient nor the contingency tables indicate a strong association between current dietary diversity and future food vulnerability.

By contrast, the coping strategy indices exhibit a statistically significant association using either the Spearman correlation coefficient or a chi squared statistic derived from the contingency table. The weighted sum correctly classifies 71% of households and displays high sensitivity (and a lower specificity). It accurately identifies the food vulnerable, but is less accurate in identifying those not vulnerable.

Associations with the food insecurity indicator

Despite the uneven performance of the alternative indicators in identifying the undernourished or vulnerable separately, they all perform well in identifying the food insecure, as shown in panel 2c of Table 2. The rank correlation coefficients between the alternatives and the benchmark index are statistically significant and lie between 0.21 and 0.27. They correctly identify between 70 and 76% of the households as either food secure or food insecure. The weighted coping strategy index has slightly more predictive power than the other indicators. It displays high correlation, higher sensitivity and the highest sensitivity-specificity combination. The weighted sum dietary diversity index has slightly less predictive power. As indicated by the respective areas under the ROC curves, these conclusions are robust to the choice of our cut-off.

Conclusions

In this paper, we develop an explicitly forward-looking food insecurity indicator that simultaneously considers current dietary inadequacy and vulnerability to dietary inadequacy in the future. Application of this measure to data from northern Mali shows that neglecting the future dimension of food insecurity causes us to seriously underestimate this population's food insecurity status. Almost three quarters of its food insecurity was related to its food vulnerability. Had our benchmark indicator not been decomposable, it would have been impossible to isolate the contribution of vulnerability.

We further compare this explicitly forward-looking food insecurity indicator to three alternative indicators, which are easy to collect. Our comparative analysis of the alternative indicators suggests that the dietary diversity and coping strategy indices are reliable indicators of current caloric intake, although agricultural production is not.

Agricultural production and the weighted coping strategy index predict food vulnerability well, but the dietary diversity index performs less well. Despite the uneven performance with respect to the individual components of the benchmark, they all perform well in identifying the food insecure.

We conclude by noting that there is need for similar comparative analyses in different geographic regions, for benchmarks with different attributes, and for consideration of vulnerability into a more distant future. That said, the results of these initial tests are encouraging and have immediate practical relevance. They demonstrate that relatively inexpensive and operational indicators, needed to monitor and evaluate food security programs and to target food security policies, can capture the complex concept of food insecurity with considerable accuracy.

Table 1: Two-way Breakdown of the Food Insecurity Measure FIS_1 (α=1)

Subgroup → Dimension ↓	Female Headed Household (n=24)	Male Headed Household (n=230)	Average Food Insecurity (n=254)	% contri-bution
Current caloric deprivation	0.07	0.11	0.10	27
Security deprivation w.r.t. future caloric sufficiency	0.13	0.28	0.26	73
Average Food Insecurity	0.10	0.19	0.18	
% contribution	5	95		

Table 2: Performance of Alternative Indicators

	Spear-man cor-relation	Contingency table analysis % agree	Se[a]	Spe[(2)]	χ^2	Area under ROC	OLS-regression coeff. a_1 (t-stat.)[c]
Panel 2a: Current Caloric Intake							
Cereal prod. (kg/cap)	0.09	56	64	44	2.1	0.57	0.0003 (1.67)
Dietary Diversity							
- simple sum	0.19**	69	54	77	25.6**	0.68	0.0305 (5.47)**
- weighted sum	0.29**	67	57	73	23.9**	0.72	0.0014 (3.77)**
Coping Strategy							
- simple sum	-0.36**	71	55	80	34.7**	0.72	-0.057 (-3.27)**
- weighted sum	-0.34**	68	57	73	25.4**	0.70	-0.029 (-5.34)**
Panel 2b: Food Vulnerability (V_0)							
Cereal prod. (kg/cap)	-0.23*	70	80	38	9.04**	0.65	-0.00024(-2.99)**
Dietary Diversity							
- simple sum	-0.13	65	77	30	1.33	0.61	-0.0077(-2.95)**
- weighted sum	-0.09	67	78	32	2.85	0.57	-0.00049(-2.88)**
Coping Strategy							
- simple sum	0.19**	55	56	52	1.46	0.57	0.0157 (1.94)
- weighted sum	0.20**	71	82	38	10.54**	0.59	0.0048 (1.84)
Panel 2c: Food Insecure (fis)							
Cereal prod. (kg/cap)	-0.24**	70	80	32	3.8*	0.64	-0.00034 (-3.67)**
Dietary Diversity							
- simple sum	-0.22**	72	82	33	4.8*	0.63	-0.0104 (-4.74)**
- weighted sum	-0.21**	70	81	28	2.3	0.58	-0.00061 (-4.30)**
Coping Strategy							
- simple sum	0.27**	74	87	23	3.75*	0.61	0.0179 (2.62)**
- weighted sum	0.27**	76	86	33	11.4**	0.63	0.0083 (3.70)**

* significant at 5% level ** significant at 1% level

[a] Se=sensitivity=percentage of truly undernourished (food vulnerable) or (food insecure) households detected by alternative indicator.

[b] Spe=specificity=percentage of truly sufficiently nourished (not food vulnerable) or (food secure) households detected by alternative indicator.

[c] fis_1 at t = $a_0 + a_1$* (alternative indicator at t) + a_2*(household size at t) + a_3*Vil_1 + a_4*Vil_2 + ... + a_{11}*Vil_9 with Vil_i = 1 if household belongs to village i and 0 otherwise, i=1..9 and t = post harvest time.

Appendix: Specifications of Equations for the Mean and Variance of Future Food Consumption and Estimated Results

We group the determinants of the mean and variance of future food consumption into three categories: income, savings and insurance. To measure human capital, we include four age/sex groups. Work experience is captured by the household head's age. Assuming positive intra household externalities (Basu and Foster, 1998), household's skills are represented by a dichotomous variable, which is one if at least one member has a primary education and zero otherwise.

For productive capital, we include draft animals, the value of agricultural, fishing and transport equipment, and access to a perimeter. Household income diversification is important in protecting consumption from income shocks (Ellis, 1998; Reardon *et al.*, 1992). To gauge income susceptibility to drought, we include the share of income from agriculture and remittances from the previous year.

Households facing imperfect credit markets smooth consumption by borrowing against assets or by asset liquidation. We include grain stocks, goats/sheep and cattle, and the value of consumer durables. Especially the former two are attractive as buffer stocks.

Insurance is provided through food and non-food gifts among family and community members, government food aid, the temporary placement of children with family or temporary out migration. Good indicators of this insurance potential are hard to obtain. Past gifts and food aid may not reflect access to these resources in the future. Those who received none may not have been in need. Actual gifts and food aid are endogenous. Despite these potential problems, we did control for food aid, and the interaction between food aid and actual temporary migration. We also included a variable reflecting the actual placement of children with family out of necessity during the current or previous hunger season. While the inclusion of present child placement potentially also introduces some endogeneity bias, this was traded off against the advantages of having an accurate proxy.

Table 1A: Estimates (3-step OLS) of Conditional Mean and Conditional Variance of Log Calorie Intake Per Capita During the Hunger Season

	$E(lnc_{t+1}/X_t)=X'_t\alpha$		$\ln Var(lnc_{t+1}/X_t)= X'_t\beta$	
Variable Names	Coeff.	t-stat.	Coeff.	t-stat.
Human Capital				
# adult male (16-65 yrs) (residential & migrant) at t	-0.01648	-0.94	-0.0812	-0.65
# adult female (16-65 yrs) (residential & migrant) at t	0.00822	0.36	-0.2106	-1.35
# children (≤15 yrs) (residential & migrant) at t	-0.08373	-6.40	0.2205	2.54
Interaction # children * potential to send children away	0.02890	1.87	-0.0380	-0.40
# elderly (> 65 yrs) (residential & migrant) at t	0.01259	0.25	0.1122	0.34
Age household head	0.00808	0.81	-0.0987	-1.60
Age household head squared	-0.00007	-0.67	0.0008	1.39
Female headed household(i.e. no adult men in hh)	0.08230	1.17	-0.8055	-1.55
Productive Capital				
# draft animals at t	0.06482	1.53	0.0856	0.31
Value (1000 cfa francs) agric., fishing & transport equipment at t	0.00045	1.60	-0.0061	-2.34
Access to perimeter	0.05773	0.91	-0.7403	-1.69
Income Diversification				
% income from migrant remittances at t-1	-0.07131	-0.77	-1.6820	-2.22
Savings/Credit				
Value (1000 cfa francs) food stock carried over at t	0.00283	2.89	0.0112	1.63
Interaction food stock value * % inc. from agric. at t-1	-0.00307	-2.45	-0.0077	-0.82
# goat/sheep at t	0.00285	1.15	0.0072	0.49
# cattle (bullocks, cows, calves) at t	-0.00022	-0.04	-0.0193	-0.65
Value (1000 cfa francs) consumer durables at t	0.00082	3.58	0.0005	0.38
Insurance				
Official food aid between t and t+1 (yes =1)	0.02476	0.44	-0.8956	-1.86
Interaction official food aid × migration hh or main adults between t and t+1			1.5425	2.05
Intercept	7.48391	29.05	-0.4132	-0.26
R^2,F	25.9	4.498	14.1	2.001
N[a]	251		251	

[a] Three outliers were removed from the regression based on regression diagnostics.

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Footnotes

1 If P_j is strictly convex, the transfer principle, where there is an increase in the poverty measure when there is a pure transfer from a poor person to a richer one, can be immediately generalized to the multidimensional case.

2 While not statistically representative, comparisons with other studies, indicates our sample is quite representative of households in Zone Lacustre (Christiaensen, 2000).

3 Median calorie consumption per capita during the 1997 post harvest season and the subsequent 1998 hunger season amounts to 2776 and 2161 kilocalories respectively; caloric per capita consumption for the 25^{th} percentile is respectively 1918 and 1615.

4 Christiaensen (2000) also reports results for vulnerability based on expected caloric shortfall ($V_{\gamma=1}$), or its expected shortfall squared ($V_{\gamma=2}$).

5 See Kakwani (1989), and Shetty *et al.* (1996) for possible problems using a single threshold.

6 To be consistent, we examine the probability of having more than the caloric threshold, $V^*_0=1-V_0$. A household is vulnerable when the probability of having more than 2345 kilocalories is under 50%.

7 Maxwell and Frankenberger (1992) list 25 broad indicators from an exhaustive review of the 1980s literature on food security. Riely and Moock (1995) propose 73 disaggregate indicators, while Chung *et al.* (1997) list 450 such indicators, based on permutations of simple indicators such as a dependency ratio.

[8] This can be overcome by regression analysis similar to the food energy intake method (Greer and Thorbecke, 1986) or by ROC (Receiver Operator Curves) analysis as illustrated by Wodon (1997).

[9] Weights are derived from a ranking of the severity of the different coping strategies by focus groups.

[10] The probability of type I error is one minus the specificity; the type II error is one minus the sensitivity.

[11] In ROC analysis, one predicts the probability of being food insecure based on the alternative indicator(s) through a logit or probit regression of the dichotomized benchmark variable on the alternative indicator. Depending on the choice of the probability threshold z, the indicator displays a different sensitivity-specificity combination. At z=1, i.e. when the probability threshold above which households are classified food insecure equals 1, nobody is ever classified as food insecure; the indicator's sensitivity equals zero and its specificity is one. When the probability threshold is reduced, more households are predicted food insecure; the indicator's sensitivity increases, but so does the error of erroneously classifying truly food secure households as food insecure, which in turn decreases the indicator's specificity. At z=0, all households are classified as food insecure, resulting in maximal sensitivity (=1) and minimal specificity (=0).

[12] When the dependent variable is truncated, we also estimate tobit regressions. The estimated results are very similar, and available upon request.

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