Validating Operational Food Security Indicators Against a Dynamic Benchmark

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Abstract:

Food security indicators used in practice are static in nature, thereby foregoing the key dimension of food security. This study develops an explicitly forward-looking food insecurity indicator and relative to this dynamic benchmark, we evaluate the performance of three readily available indicators: an agricultural production, a dietary diversity, and a coping strategy index. Calculation of our "gold standard" indicator, using panel data of 274 households from Mali, shows that neglecting the future may lead to substantial underestimation of a population's food insecurity. However, when compared to our "gold standard", the alternative indicators all identify most of the food insecure, with the coping strategy index displaying the most predictive power. This is an important result, given the great demand for operational, inexpensive and reliable food insecurity indicators.

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Introduction

In response to renewed commitments to address worldwide problems of undernutrition and vulnerability (FAO Food Security Conference in 1996, World Bank World Development Report on Poverty 2000/1), there is a pressing need for effective and operational food security indicators. They are needed to initiate, monitor and evaluate emergency and structural food security interventions. Without them, it is also impossible to investigate the causes of food insecurity or target scarce resources.

A wide range of food security indicators already exists today.[1] Some are directly related to current food intake, such as current total expenditures or dietary diversity indices. Others are based on the underlying causes of food insecurity, such as current food production or income, or the ex post outcome of consumption, such as current health and nutritional status measures. Despite this diversity, all have one thing in common: they are static in nature. None is consistent with the commonly accepted conceptualization of food security as: "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). According to this definition, having either an inadequate diet today or a high probability today of having an inadequate diet in the future, renders a person food insecure. Both dimensions are clearly not the same and there is growing empirical evidence, particularly in developing countries with hunger seasons (Dercon and Krishnan, 2000; Baulch and Hoddinott, 2000), that those with adequate food today may not have adequate food tomorrow, and vice versa.

[1] 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. Maxwell et al. (1999) suggest a measure based on households' strategies to cope with food stress.

Because comprehensive, dynamic food security indicators must account for both the current and future dimensions of food security, they require a great deal of data and skill to construct, and they may be difficult to implement in a timely manner. However, to help avoid significant errors in identifying the food insecure, thereby instigating ill-conceived interventions and serious misallocation of scarce resources, it is imperative that we evaluate the performance of operational indicators relative to a measure that explicitly incorporates the vulnerability aspect of food security.

In this paper, we develop such an explicitly forward-looking food security indicator, and, relative to this 'gold standard', we evaluate the performance of three readily available indicators: an index of agricultural production, a dietary diversity index, and a coping strategy index. The latter two are promising, but rarely used. The empirical analysis is based on panel data of 274 households in northern Mali.

We proceed by developing a multi-dimensional food insecurity indicator, and illustrate its use, focusing particularly on the construction of a vulnerability index necessary to capture the future dimension of food insecurity. We evaluate the performance of alternative indicators relative to our 'gold standard', and conclude with our major findings.

Development of a Family of 'Gold Standard' Food Insecurity Indicators

Following Chakravarty, et al. (1998) and Bourguignon and Chakravarty (1998) who have extended the axiomatic approach to poverty measurement to include multiple facets of poverty, we combine different dimensions of food security into one index. Within this framework, we define a threshold for every dimension; a person is food insecure once one of the dimensions falls below its threshold.

A Multidimensional Food Insecurity Indicator

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).[2] 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:

[2] 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. Here, such a transfer of an attribute from a person poor in that attribute to a person richer in that attribute does increase the multidimensional poverty index.

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

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) meets important axioms necessary for good poverty measures[3]. According to the focus axiom, 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.

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 (shown by rearranging terms in equation (2)).[4] By enabling one to calculate the percentage contribution of subgroups to total food insecurity, this property facilitates targeting of food security enhancing policies.

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[3] These include symmetry, monotonicity, continuity, subgroup decomposability and some transfer axioms. For a discussion, see Chakravarty et al. (1998) and Bourguignon and Chakravarty (1998).

[4] $FIS = (1/n)\sum_i\sum_j a_j P_j(x_{ij}/z_j)=\sum_k(n_k/n)FIS_k$ with k=1,…,s and $FIS_k=(1/n_k)\sum_{i\in Sk}\sum_j a_j P_j(x_{ij}/z_j)$ the food insecurity index for subgroup k with S_k = the set of subjects in subgroup k and n_k=number of subjects in S_k.

Because the measure of food insecurity is also a weighted (a_j) average of food insecurity levels for the dimensions (FIS_j)[5], we can identify the contribution of each dimension to overall food insecurity. This information is crucial for the appropriate design of food security policies. For example, if food insecurity stems mainly from current undernourishment, the appropriate answer might be to invest in general income generating activities. If food insecurity is mainly due to vulnerability to future dietary inadequacy, insurance mechanisms might be the appropriate intervention.

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 α_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

[5] $FIS = (1/n)\sum_i\sum_j a_j P_j(x_{ij}/z_j)=\sum_j a_j[(1/n)\sum_i P_j(x_{ij}/z_j)]=\sum_j a_j FIS_j$ with FIS_j the share of the population's food

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., 1984):

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

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).

A'Gold Standard' Food Insecurity Indicator in Practice

To make comparisons with the more readily available indicators, we estimate our multidimensional index of food insecurity for a sample of households in Zone Lacustre, in 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,[6] were surveyed in each of four periods, including a post-harvest and a subsequent hunger season. Data were collected on agricultural production, income, food and non-food consumption, and households' strategies for coping with food shortages.

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insecurity caused by attribute j.

[6] While not statistically representative, a comparison with other recent studies of the area, indicates that our sample is a reasonable representation of households in Zone Lacustre (Christiaensen, 1999). This study also provides a detailed discussion of the data.

Empirically, we focus on two aspects of food insecurity: current dietary inadequacy and vulnerability to future dietary inadequacy (j=1,2). We measure dietary adequacy by caloric intake, but, were data available, the measure could be readily extended to explicitly account for deprivation with respect to other nutrients (e.g. proteins, vitamin A, iron).[7] However, calories are often a reasonable indicator for the intake of the other necessary macro- and micro nutrients (Dasgupta, 1993).

Indicators of Current Undernutrition and Food Vulnerability

We take the 1997 post harvest period as the present and the subsequent hunger period as the future. Information on immediate post harvest caloric intake is directly available from the survey. Food intake from the different food groups over the past seven days preceding the interview was reported. This information was converted into daily caloric intake per residential household member using locally adapted conversion tables.

The real challenge empirically is in determining a measure of vulnerability with respect to future dietary inadequacy. Following Christiaensen and Boisvert (2000), we 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 current 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 (F(z)), multiplied by a conditional probability weighted function

[7] See Hatloy, et al. (1998) for a related application with respect to the nutritional adequacy of the diet for children in an urban area in southern Mali.

of the shortfall below this caloric threshold. Depending on the choice of 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; the depth of shortfall is accounted for. By setting $\gamma>1$, larger caloric shortfalls translate in greater vulnerability, given the same conditional probability of occurrence. One accounts 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 probability threshold (θ); a household is vulnerable if the probability of a caloric shortfall exceeds θ.

We estimate each household's ex ante probability distribution of future caloric per capita consumption, $C_{i,t+1}$, using a flexible heteroskedastic regression specification (Just and Pope, 1979; Mullahy and Sindelar, 1995):

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

with $E(e_{i,t+1})=0$, $E(e_{i,t+1},e_{k,t+1})=0$ with $i\neq k$ and $V(e_{i,t+1})=\sigma^2_{e.}$ This specification allows for the marginal effects of the regressors on the ex ante mean and variance of future consumption to differ in sign. The conditional mean and variance of (8) are:

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

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

Empirically, 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. The specification of the regression equations is derived from a theoretical household model of intertemporal consumption under uncertainty and imperfect capital markets. Variables are described in the appendix; estimated equations are in Table 1A.[8]

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 that consumption is lognormally distributed, which is not rejected by the data, we estimate each household's ex ante distribution of future caloric per capita consumption. For a given caloric threshold, we calculate each household's probability of caloric shortfall ($V_{\gamma=0}$), its expected shortfall ($V_{\gamma=1}$), or its expected shortfall squared ($V_{\gamma=2}$)[9].

We take 2,345 kcal/person/day as caloric threshold,[10] 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). Unlike the caloric threshold, there is no objective way to set a vulnerability threshold; we assume a 50% threshold and examine its sensitivity.

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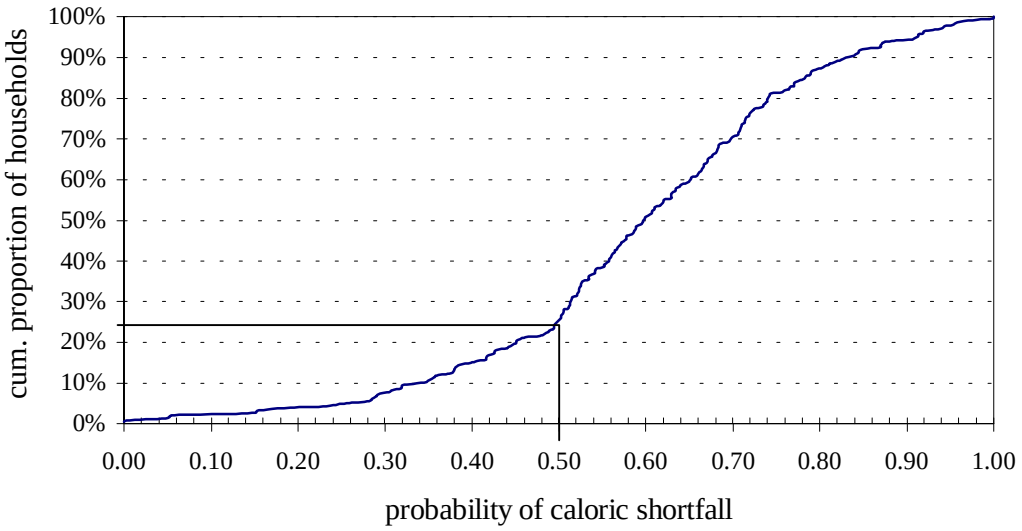
[8] See Christiaensen and Boisvert (2000) for more details on the theory and estimation.
[9] Here, we focus only on V_0. Results for V_1 and V_2 are similar and are in Christiaensen (2000).
[10] See Kakwani (1989), Ravallion (1990), and Shetty et al. (1996) for possible problems using a single threshold.

Based on these calculations, 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 (Figure 1). Put differently, at the post harvest time, 76% of households have at least a 50% chance of their caloric consumption during the hunger season falling below the caloric benchmark Holding socio-economic characteristics constant, this implies that for at least five out of ten years, about three quarters of the population would be undernourished during the hunger season. Judged by this 50% threshold, our population is extremely food vulnerable. For thresholds above 50%, the marginal effect of an increase in the vulnerability threshold on the proportion of households which are not vulnerable is especially large. [11]

Figure 1: Cumulative Probability Function of Households' Caloric Shortfall (V_0)



Source: Christiaensen and Boisvert (2000): p. 31.

[11] With correlation coefficients, contingency tables, and out of sample predictions, Christiaensen and Boisvert (2000) show the high predictive ability of this vulnerability measure of future undernourishment.

Food Insecurity in Zone Lacustre

Given estimates for the two dimensions of our food insecurity indicator, current undernutrition based directly on survey data and food vulnerability based on ex ante probabilities of caloric shortfalls from above, we calculate Zone Lacustre's food insecurity profile. The threshold for kilocalories/person/day is z_1=2345. V_0 is our food vulnerability measure; its threshold is z_2=0.5.[12] P_j is defined by equation (3), with α=1. Because we look only one period ahead, we attach equal weight to both dimensions.

The food insecurity measure FIS_1 (α=1)[13] for the entire sample is 0.18 (Table 1). Each household is, on average, 18% short of the minimal caloric requirement and, on average, 18% below the minimal probability to be secure with respect to future caloric sufficiency. Put differently (equation 5), 50% falls, on average, 36% short of minimal caloric intake and security requirements. From either perspective, our population is very food insecure.

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		

We also find from Table 1 that female headed households are less food insecure (average food insecurity=0.10) at the post harvest time than male headed households

[12] 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%.
[13] $FIS_1 = (1/2n)\sum_i[(2345-c_i)/2345 + (0.5-V^*_{0,i})/0.5]$ with c_i= current daily per capita caloric intake.

(average food insecurity=0.19). Therefore, it is not surprising that female headed households contribute less than their share in the population to total food insecurity.

Perhaps the most striking results in Table 1 stem from the fact that the food insecurity indicator for current undernourishment is 0.10, while it is 0.26 for food vulnerability. Almost three quarters (73 percent) of the population's food insecurity is related to vulnerability regarding future food availability, and only about one quarter (27 percent) of their food insecurity is related to their current undernourishment. One reason for this striking result is that our forward looking measure looks at the hunger season. In that sense, the results are not so surprising. However, even by weighting current undernourishment disproportionately (a_1=0.66; a_2=0.34), our results are still robust; 57% of food insecurity is still related to future caloric sufficiency. Clearly, by neglecting the vulnerability dimension, we substantially underestimate the population's food insecurity.

Performance of Operational Food Insecurity Indicators

We now turn to our final objective, that of evaluating three more readily available, operational indicators of food security against this dynamic benchmark. We examine: 1) an index of agricultural production; 2) a dietary diversity index; and 3) a coping strategy index. We analyze their performance in identifying the food insecure and discuss their reliability, i.e. their susceptibility to misreporting. As will become clear from the description below, the data for all these indicators are easy and inexpensive to collect, and they can be analyzed and interpreted after only limited manipulations.

Description of alternative indicators

Given its widespread use, we take a closer look at the performance of household agricultural production in identifying the food insecure. Since availability of food is a

necessary condition for being food secure, and many rural households produce much of their own food, agricultural production is a natural candidate as indicator of food security. However, with growing evidence that agricultural households derive a substantial portion of their income from off-farm activities (Reardon, et al., 1992; Reardon, 1997; Ellis, 1998) and buy a substantial share of their food (Weber et al., 1988), continued evaluation of food production as a measure of food security is essential.

We take the cereal production (in kilograms) per residential household member reported by the household head at the immediate post harvest time as the measure of agricultural production. A production of 200 kg per capita is often taken as food self-sufficiency threshold in West Africa (Carter, 1997). Only 10 percent of our sample households attained this threshold in 1997, a drought year. An agricultural production index thus potentially provides direct information on food shortfall, but the measure is susceptible to intentional misreporting, especially when used in an early warning context.[14]

Our second alternative food insecurity indicator pertains to dietary diversity, and 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. Along with these changes in dietary composition goes an increase in total energy availability (Poleman, 1995). Several studies indicate that dietary diversity increases the extent to which the minimal requirements for all the different nutrients are met (Guthrie and Scheer, 1981; Randall et al., 1985; Hatloy, et al., 1998). Despite these observations, dietary diversity indices have rarely been used in practice in developing countries. Their potential as a

food security indicator deserves further investigation. The index provides an indication of overall dietary adequacy, but it does not record quantities, which complicates the assessment of caloric inadequacy solely based on the dietary diversity index.[15]

Here, we construct a food variety score (FVS) (Hatloy, et al., 1998) to combine the diversity of a person's diet into a single index. 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.

Inspired by Corbett (1988) and de Waal (1989)'s observations that people display particular behavioral patterns to cope with food stress, Maxwell (1996) and Maxwell et al. (1999) propose a method for combining consumption related coping strategies into a numerical index. As those households, who use more coping strategies, or more severe strategies, are more likely to be currently undernourished, and more vulnerable in the future, this is a promising indicator. However, Maxwell, et al (1999) mention only four African applications. Also, the index has only been validated once, and only against caloric intake, where the correlation was statistically significant. The extent to which it captures vulnerability has not been tested.

Consistent with Maxwell et al. (1999), our coping strategy index focuses on the household's dietary change and its rationing strategies. We asked the most knowledgeable woman questions regarding the frequencies over the past seven days of: going without eating all day; skipping meals during the day; serving smaller portions to

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[14] A more objective measure of the absolute production level in the area could be obtained by comparison of the results to production figures gathered by other – non-beneficiary - authorities (e.g. Ministry of Agriculture). This more objective figure could be used to benchmark the distribution of the data.

different household members, and serving less preferred foods. In the simple sum index, we summarize this information by simply 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.[16] 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 easy and inexpensive to implement, the coping strategy index is also prone to misreporting. As with the dietary diversity index, it does not record quantities.

Performance of Alternative Food Insecurity Indicators Relative to the 'Gold Standard'

We now assess the performance of these indicators in predicting the food insecure, as measured by our multi-attribute benchmark. To obtain a better understanding of their performance, we also evaluate 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.[17] The remaining 21% are classified as food secure.

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[15] This can be overcome by regression analysis similar to the food energy intake method (Greer and Thorbecke, 1986).

[16] Weights are derived from a ranking of the severity of the different coping strategies by focus groups, which creates some additional work for the construction of this index.

[17] The food insecurity index for a person i is: $fis_1 = (1/2)[(2345-c_i)/2345 + (0.5-V^*_{0,i})/0.5]$ with c_i= daily current per capita caloric intake and $V^*_{0,i} = 1-V_{0,i,}$ the measure of security deprivation.

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 others (Habicht, et al., 1982; Chung, et al.,1997; and Maxwell, et al., 1999), we quantify the association between other indicators and the benchmark by calculating correlation coefficients, constructing contingency tables and doing some regressions. Correlation coefficients provide a quick notion of the linear relationship between two variables. Yet, when the statistically significant correlation follows from the strong correlation of the variables over a small range, they may be misleading.

In a contingency table, observations are classified according to the benchmark and the alternative both defined in dichotomous terms. If, by a χ^2test (Conover, 1980), there is a statistically significant association, the performance of the alternative indicator is 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 are also truly negative according to the

benchmark.[18] For good performance, the agreement percentage should be high, as well as both the sensitivity and the specificity. Given the detrimental effects of undernutrition (Cornia and Stewart, 1995) and vulnerability (Morduch, 1995), it is further essential that food insecurity indicators display high sensitivity, to minimize the number of erroneously excluded households.[19] Note however, that the indicator's sensitivity and specificity also depend on the choice of the cut-off by which the different observations are classified, with sensitivity and specificity moving in opposite direction.[20] We thus look at the relative sensitivity-specificity combinations of the different indicators, thereby paying particular attention to their sensitivity.

Finally, by estimating some regression equations, we see if the alternative indicators can explain the variation in the benchmark, after controlling for location and household size.

Identifying the Food Insecure. From Table 2, all alternative indicators appear to perform well in identifying the food insecure. 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

[18] The probability of type I error is one minus the specificity; the type II error is one minus the sensitivity.
[19] However, if program resources are the major constraint, one should maximize specificity, to minimize the number of erroneously included observations.
[20] For example, a low cut-off, whereby most observations are ranked as food insecure, tends to produce high sensitivity, but it also increases the erroneous classification of truly food secure households as food insecure, which in turns decreases the specificity. Alternatively, a high cut-off leads to high specificity, but it also increases the probability of being classified as food secure, while one is not, which in turns decreases the indicator's sensitivity. To compare jointly the sensitivity and specificity of an alternative indicator across a range of thresholds, response operator curves (ROC) are used in psychology, medicine and epidemiology. ROCs are especially helpful to control for the choice of the cut-off when comparing the performance of different indicators. Wodon (1997) illustrates the technique in a poverty study.

highest sensitivity-specificity combination. The weighted sum dietary diversity index has slightly less predictive power.

Table 2: Performance of alternative indicators in predicting the food insecure (fis_1).

	Spearman correlation	Contingency table analysis				OLS-regression coeff. a_1 (t-stat.)(3)
		%agree	Se(1)	Spe(2)	χ^2	
Cereal prod. (kg/cap)	-0.24**	70	80	32	3.8*	-0.00034 (-3.67)**
Dietary Diversity						
- simple sum	-0.22**	72	82	33	4.8*	-0.0104 (-4.74)**
- weighted sum	-0.21**	70	81	28	2.3	-0.00061 (-4.30)**
Coping Strategy						
- simple sum	0.27**	74	87	23	3.75*	0.0179 (2.62)**
- weighted sum	0.27**	76	86	33	11.4**	0.0083 (3.70)**

* significant at 5% confidence level ** significant at 1% confidence level
(1) Se=sensitivity=percentage of truly food insecure households detected by alternative indicator.
(2) Spe=specificity=percentage of truly food secure households detected by alternative indicator.
(3) 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.

Identifying Current Caloric Shortfall. From Table 3, we see that cereal production per capita emerges as a poor predictor of current caloric intake at the immediate post harvest time. For none of the three measures do we find a statistically significant relationship.

Table 3: Performance of alternative indicators in predicting current caloric intake

	Spearman correlation	Contingency table analysis				Regression coeff.a_1(t-stat.)(3)
		%agree	Se(1)	Spe(2)	χ^2	
Cereal prod. (kg/cap)	0.09	56	64	44	2.1	0.0003 (1.67)
Dietary Diversity						
- simple sum	0.19**	69	54	77	25.6**	0.0305 (5.47)**
- weighted sum	0.29**	67	57	73	23.9**	0.0014 (3.77)**
Coping Strategy						
- simple sum	-0.36**	71	55	80	34.7**	-0.057 (-3.27)**
- weighted sum	-0.34**	68	57	73	25.4**	-0.029 (-5.34)**

* significant at 5% level ** significant at 1% level
(1) Se=sensitivity=percentage of undernourished households detected by alternative indicator
(2) Spe=specificity=percentage of sufficiently nourished households detected by alternative indicator.
(3) ln (caloric intake/capita 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=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. These results are markedly 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. On this basis, the 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) will increase the indicators' sensitivity, but it will also decrease 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).

Identifying Future Food Vulnerability. From table 4, cereal production emerges as a good predictor of food vulnerability. It correlates well with our benchmark vulnerability measure and correctly classifies 70% of the households. The results with respect to the dietary diversity indices on the other hand are ambiguous. We find a significant relationship from the OLS regression. However, the correlation coefficient and the results in the contingency tables are more suspect from a statistical point of view. The fact that diets are less diversified during the hunger season (Christiaensen and Hoddinott, 1999) may explain the lack of a correlation between dietary diversity at post harvest time and food vulnerability in the coming hunger season.

The results are better for the coping strategy indices, especially the weighted index. This index correlates well with our benchmark vulnerability measure and correctly classifies 71% of households. This index also displays a high sensitivity (and a lower specificity); it accurately identifies the food vulnerable, but is less accurate in identifying those not vulnerable. As mentioned before, this is partly determined by the choice of our cut-off.

Table 4: Performance of alternative indicators in predicting food vulnerability (V_0)

	Spearman correlation	Contingency table analysis				OLS-regression coeff. a_1 (t-stat.)(3)
		%agree	Se(1)	Spe(2)	χ^2	
Cereal prod. (kg/cap)	-0.23*	70	80	38	9.04**	-0.00024(-2.99)**
Dietary Diversity						
- simple sum	-0.13	65	77	30	1.33	-0.0077(-2.95)**
- weighted sum	-0.09	67	78	32	2.85	-0.00049(-2.88)**
Coping Strategy						
- simple sum	0.19**	55	56	52	1.46	0.0157 (1.94)
- weighted sum	0.20**	71	82	38	10.54**	0.0048 (1.84)

* significant at 5% level ** significant at 1% level
(1) Se=sensitivity=percentage of truly food vulnerable households detected by alternative indicator
(2) Spe=specificity=percentage of truly not food vulnerable households detected by alternative indicator.
(3) V_0 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=immediate post harvest time.

Summary and Conclusions

In this paper, we develop an explicitly forward-looking food insecurity indicator and compare the performance of alternative indicators, which are inexpensive and readily available, with respect to this benchmark. Empirical application to northern Mali shows that neglecting the future dimension of food security may lead to serious underestimation of a population's food insecurity status. Almost three quarters of its food insecurity was related to its vulnerability regarding future food availability. It would have been

impossible to isolate the contribution of future vulnerability had our benchmark indicator not been decomposable.

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 does not. Despite the uneven performance with respect to the individual components of the benchmark, they all perform well in identifying the food insecure; the weighted coping strategy index appears to have a slight edge in overall predictive power.

Although 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, the results of these initial tests are very 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.

Appendix: Regression specifications and estimated results

We group the determinants of the mean and variance of future consumption into three categories: income, savings and insurance. To measure human capital, we include four age/sex groups. Temporary out migrants at the post harvest time are included because they contribute to household income through remittances. They may also affect the number of people to be fed during the hunger season. Work experience is captured by the household head's age. Household's skills are represented by a dichotomous variable, which is one if at least one member has a primary education and zero otherwise. We assume positive intra household externalities from education (Basu and Foster, 1998).

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, 1997; 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 (Adams, 1993). 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

	$E(\ln c_{t+1}/X_t)=X'_t\alpha$		$\ln Var(\ln c_{t+1}/X_t)=X'_t\beta$	
	Coeff.	t-stat.	Coeff.	t-stat.
Intercept	7.48391	29.05	-0.4132	-0.26
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 fcfa) 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
R^2 ,F	25.9	4.498	14.1	2.001
N*	251		251	

* Three outliers were removed from the regression based on regression diagnostics.

REFERENCES

Adams, A. 1993. Food Insecurity in Mali: Exploring the Role of the Moral Economy. *IDS Bulletin* 24 (1):41-50.

Barrett, C. 1998. Food Security and Food Assistance Programs. In *Handbook of Agricultural Economics*, edited by B. Gardner and G. Rausser. Amsterdam: Elsevier Science.

Basu, K., and J. Foster. 1998. On Measuring Literacy. *Economic Journal* 108 (November):1733-1749.

Baulch, B., and J. Hoddinott. 2000. Economic Mobility and Poverty Dynamics in Developing Countries. *Journal of Development Studies* forthcoming.

Bennett, M.K. 1954. *The World's Food*. New York: Harper & Brothers.

Bourguignon, F., and S. Chakravarty. 1998. *The Measurement of Multidimensional Poverty*. Paris: Ecole des Hautes Etudes en Sciences Sociales and DELTA Paris.

Carter, M.R. 1997. Environment, Technology, and the Social Articulation of Risk in West African Agriculture. *Economic Development and Cultural Change* 45 (3):557-90.

Chakravarty, S., D.. Mukherjee, and R. Ranade. 1998. On the Family of Subgroup and Factor Decomposable Measures of Multidimensional Poverty. *Research on Economic Inequality* 8:175-194.

Christiaensen, L. 1999. *Mali Case Study: Methodology and Descriptives*. Washington D.C.: International Food Policy Research Institute.

Christiaensen, L.. 2000. *Measuring Vulnerability and Food Security: Case Evidence From Mali*. unpublished Ph. D. Dissertation. Cornell University.

Christiaensen, L. and Richard, N. Boisvert. 2000. On Measuring Household Food Vulnerability: Case Evidence From Northern Mali. *Working Paper 2000-5*. Department of Agricultural, Resource and Managerial Economics. Cornell University. Ithaca. New York.

Christiaensen, L., and J. Hoddinott. 1999. *Food Security Indicators in the Zone Lacustre*. Washington D.C.: International Food Policy Research Institute.

Chung, K.L., L. Haddad, J. Ramakrishna, and F. Riely. 1997. *Identifying the Food Insecure. The Application of Mixed Method Approaches in India*. Washington D.C.: International Food Policy Research Institute.

Conover, W.J. 1980. *Practical Nonparametric Statistics*. 2nd ed. New York: John Wiley & Sons.

Corbett, J. 1988. Famine and Household Coping Strategies. *World Development* 16 (9):1099-1112.

Cornia, G. and F. Stewart. 1995. Two Erros of Targeting. in van de Walle, D., and K., Nead, eds., *Public Spending and The Poor: Theory and Evidence*. Johns Hopkins University Press: Baltimore.

Dasgupta, P. 1993. *An Inquiry Into Well-Being and Destitution*. Oxford: Clarendon Press.

de Waal, A. 1989. *Famine that Kills: Darfur, Sudan, 1984-85*. Oxford: Clarendon Press.

Dercon, S., and P. Krishnan. 2000. Vulnerability, Seasonality and Poverty in Ethiopia. *Journal of Development Studies* forthcoming.

Ellis, F. 1998. Household Strategies and Rural Livelihood Diversification. *Journal of Development Studies* 35 (1):1-38.

Foster, J., J. Greer, and E. Thorbecke. 1984. Notes and Comments: A Class of Decomposable Poverty Measures. *Econometrica* 52 (3):761-766.

Greer, J., and E. Thorbecke. 1986. A Methodology for Measuring Food Poverty Applied to Kenya. *Journal of Development Economics* 24 (1):59-74.

Guthrie, H.A., and J.C. Scheer. 1981. Validity of a Dietary Score for Assessing Nutrient Adequacy. *Journal of the American Dietetic Association* 78 (March):240-244.

Habicht, J.-P., L. Meyers, and C. Brownie. 1982. Indicators for Identifying and Counting the Improperly Nourished. *American Journal of Clinical Nutrition* 35 (May):1241-1254.

Hatloy, A., L.E. Torheim, and A. Oshaug. 1998. Food Variety - A Good Indicator of Nutritional Adequacy of the Diet? A Case Study From an Urban Area in Mali, West Africa. *European Journal of Clinical Nutrition* 52 (12):891-898.

Judge, G., R. Hill, W. Griffiths, H. Lutkepohl, and T. Lee. 1988. *Introduction to the Theory and Practice of Econometrics*. Second Edition ed. New York: John Wiley & Sons.

Just, R.E., and R.D. Pope. 1979. Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics* 61 (May):276-284.

Kakwani, N. 1989. On Measuring Undernutrition. *Oxford Economic Papers* 41 (3):525-552.

Maxwell, D. 1996. Measuring Food Insecurity: the Frequency and Severity of 'Coping Strategies'. *Food Policy* 21 (3):291-303.

Maxwell, D., C. Ahiadeke, C. Levin, M. Armar-Klemesu, S. Zakariah, and G. Lamptey. 1999. Alternative Food Security Indicators: Revisiting the Frequency and Severity of Coping Strategies. *Food Policy* 24:411-429.

Maxwell, S., and T.R. Frankenberger. 1992. *Household Food Security: Concepts, Indicators, Measurements: A Technical Overview.* New York/Rome: UNICEF/FAO.

Ministry of Agriculture Fisheries and Food. 1996. *Manual of Nutrition*. London: HMSO.

Morduch, J. 1995. Income Smoothing and Consumption Smoothing. *Journal of Economic Perspectives* 9 (3):103-114.

Mullahy, J., and J.L. Sindelar. 1995. Health, Income, and Risk Aversion: Assessing Some Welfare Costs of Alcoholism and Poor Health. *Journal of Human Resources* 30 (3):439-458.

Poleman, T. 1995. *Recent Trends in Food Availability and Nutritional Well-Being*. Ithaca: Department of Agricultural, Resource and Managerial Economics, Cornell University.

Randall, E., M. Nichaman, and C. Contant. 1985. Diet Diversity and Nutrient Intake. *Journal of the American Dietetic Association* 85 (7):830-836.

Ravallion, M. 1990. Income Effects on Undernutrition. *Economic Development and Cultural Change* 38 (3):489-515.

Reardon, T. 1997. Using Evidence of Household Income Diversification to Inform Study of the Rural Nonfarm Labor Market in Africa. *World Development* 25:735-748.

Reardon, T., C. Delgado, and P. Matlon. 1992. Determinants and Effects of Income Diversification Amongst Farm Households in Burkina Faso. *Journal of Development Studies* 28 (2):264-96.

Riely, F., and N. Moock. 1995. Inventory of Food Security Impact Indicators. In *Food Security Indicators and Framework: A Handbook for Monitoring and Evaluation of Food Aid Programs*, edited by Impact. Arlington, VA, USA.

Sen, A. 1976. Poverty: An Ordinal Approach to Measurement. *Econometrica* 44 (2):216-231.

Shetty, P., C. Henry, A. Black, and A. Prentice. 1996. Energy Requirements of Adults: An Update on Basal Metabolic Rates (BMRs) and Physical Activity Levels (PALs). *European Journal of Clinical Nutrition* 50 (Supplement 1):S11-S23.

Weber, T.W., et al. 1988. Informing Food Security Decisions in Africa: Empirical Analysis and Policy Dialogue. *American Journal of Agricultural Economics* 70(5).

Wodon, Q. 1997. Targeting the Poor Using ROC Curves. *World Development* 25 (12):2083-2092.

World Bank. 1986. *Poverty and Hunger: Issues and Options for Food Security in Developing Countries*. Washington D.C.: World Bank.

World Bank, 2000, World Development Report 2000/1: Attacking Poverty (Internet, WWW). 2000 (cited May, 2000). Available from http://www.worldbank.org/poverty/wdrpoverty/draft100.htm