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On Measuring Household Food Vulnerability: Case Evidence from Northern Mali

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Abstract

This study illustrates a methodology to measure empirically household food vulnerability. Food vulnerability is defined in terms of the probability now of being undernourished in the future. The empirical analysis is based on panel data from northern Mali, collected in 1997-98. Our empirical results clearly show that even though the groups of currently undernourished and food vulnerable households overlap, they are far from identical. Female-headed households appear less vulnerable to drought shocks, partly due to community solidarity. Households with good harvests are also less vulnerable, though greater dependence on agriculture attenuates this effect. Official food aid and family food gifts are important insurance mechanisms. Simulations indicate that food vulnerability can be significantly reduced through off-farm employment generation in the area and greater access to irrigation infrastructure.

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Introduction

Both theoretically and at the policy level, there is increased recognition that current poverty and vulnerability are inextricably linked (Banerjee and Newman, 1994; Morduch, 1994). Because people move in and out of poverty (Baulch and Hoddinott, 2000), a focus on current poverty partly misses the point; the non-poor today, may be the poor tomorrow. In participatory poverty assessments, the poor regularly identify vulnerability as a crucial dimension of poverty (Kanbur and Squire, 1999).

To develop a forward-looking approach to the evaluation of people's well being, we must construct consistent measures of vulnerability and understand the socio-economic factors contributing to it. As Kanbur and Squire (1999) point out, explicit vulnerability measures are currently non-existent. Past efforts reflect only indirect attempts to measure vulnerability. For example, Ravallion, et al. (1995), Grootaert, et al. (1997), and Glewwe and Hall (1998) examine empirically the determinants of *change* in consumption given an overhaul of national social policies or a macro-economic shock. The studies provide an indication of vulnerability, but do not develop actual measures. Within the context of poverty dynamics, one speaks of chronic and temporary poverty (Chaudhuri and Ravallion, 1994). In terms of vulnerability, one might consider the chronically poor as very vulnerable, the temporarily poor as vulnerable, and the non-poor as non-vulnerable. Such measures require longitudinal data, and are of limited practical use, particularly in developing countries. Also, measures of chronic and temporary poverty are descriptive and offer little foundation for policy analysis.

In this paper, we develop an explicit measure of household vulnerability that is forward-looking and derived from underlying socio-economic processes. We define food vulnerability by the probability now of being undernourished in the future. Although our methodology is easily adapted to study vulnerability with respect to other variables, our empirical analysis, based on household data from northern Mali, focuses on measuring food vulnerability. Using our vulnerability measure, we also assess the effectiveness of policies in reducing food vulnerability.

To proceed, we clarify the concept of vulnerability and its measurement. We construct a theoretical model to reflect the socio-economic processes leading to vulnerability, and to motivate the heteroskedastic regression specification needed to estimate households' ex ante distributions of future food consumption. Next, data are described, and the econometric results are presented. Policy evaluations are followed by a discussion of major conclusions.

The Concept of Vulnerability and Its Measurement

Vulnerability surrounding an individual's or a household's human condition concerns the potential now of a negative outcome in the future. The concept is forward-looking and implicitly also accounts for uncertainty surrounding future events. Poverty, on the other hand, is usually treated in static, non-probabilistic terms (Ravallion, 1996). It generally concerns not *having* enough *now,* whereas vulnerability is about having a high *probability now* of suffering a future shortfall. In practice, the poor are often also vulnerable, but both groups are typically not identical (Baulch and Hoddinott, 2000).

The notion of vulnerability as risk of shortfall can be expressed as a probability statement regarding the failure to attain a certain threshold of well-being in the future. To construct such a vulnerability indicator, we must identify a focal variable (x) e.g. food consumption, income, etc.; estimate the ex ante probability distribution ($f_t(.)$) of ex post outcomes with respect to this focal variable x_{t+1}; define a threshold (z) with respect to this focal variable (i.e. a poverty line); and determine a probability related threshold (θ) (i.e. a vulnerability line) such that a person will be considered vulnerable if the probability that his/her focal variable falls below the threshold z, exceeds θ. Vulnerability of a person now (at t) with respect to the situation in the future (at t+1) can then be measured as:

$$V_t = \int_a^z \varphi(x_{t+1}, z) f_t(x_{t+1}) dx_{t+1} \tag{1}$$

with $x_{t+1} \in [a,b]$, the range of values x_{t+1} can take, a, b $\in \Re$ and $\varphi(x_{t+1}, z)$ non-increasing in x_{t+1} and non-decreasing in z if $x_{t+1}<z$, and zero if $x_{t+1} \geq z$. Following Fishburn (1977) and Foster, et al. (1984), we adopt a functional form for $\varphi(x_{t+1}, z)$:

$$\varphi(x_{t+1}, z) = (z - x_{t+1})^{\alpha} \quad \text{for } x_{t+1} < z \ (\alpha \geq 0) \tag{2}$$

$$= 0 \quad \text{otherwise}$$

Substituting (2) in (1) and multiplying by F(z)/F(z), we obtain vulnerability measures:[1]

$$V_{t,\alpha} = F(z) \int_a^z (z - x_{t+1})^{\alpha} \frac{f(x_{t+1})}{F(z)} dx_{t+1} . \tag{3}$$

Vulnerability is measured as the probability of falling below the poverty line z (F(z)), multiplied by a conditional probability-weighted function of the shortfall below this poverty line. Different aspects of shortfall are emphasized depending on the choice of α.[2] If α=0, vulnerability is measured as the probability of shortfall ($V_{t,0}$=F(z)); the

[1] This measure of vulnerability is akin to safety-first risk criteria (Atwood, 1985; Fishburn, 1977).

[2] Foster, et al. (1984) discuss the same issues within the context of poverty measurement. If φ represents a utility function, α reflects risk preferences (Bigman, 1996; Fishburn, 1977).

depth of shortfall is not reflected. If $\alpha=1$, vulnerability ($V_{t,1}$) is measured as the product of the probability of shortfall and the conditional expected gap. $V_{t,1}$ accounts for the average size of shortfall, and given equal probabilities of shortfall ($F(z)$), people with higher conditional expected shortfall will be taken to be more vulnerable. By setting $\alpha>1$, we can also reflect the spread of the distribution of the shortfalls such that those with a higher probability of large shortfalls are more vulnerable. This may be important, as large shortfalls might lead to disastrous and irreversible consequences.

To measure vulnerability, we must choose a focal variable and estimate its ex ante probability distribution. Poverty and vulnerability lines (z and θ) must be selected, along with a value for α. The focal variable in this study is food intake as an indicator for nutritional well being. We look at household caloric consumption per capita.[3]

Since there is some consensus in the nutritional literature on minimal caloric needs to live an active and healthy life (Shetty et al., 1996; World Health Organization, 1985), we specify the caloric threshold in absolute terms. The literature on vulnerability thresholds (θ), on the other hand, is limited, even within the safety-first literature (Bigman, 1996). We consider different values of θ and examine the sensitivity of the results. To understand the effects of emphasizing different aspects of shortfall, we calculate V_α for different values of α.

The major challenge is to estimate the ex ante probability distribution of future caloric consumption. Using a limited panel data set, we assume that food consumption is lognormally distributed and characterize the distribution by estimating the ex ante

[3] While people need many different nutrients to be well-nourished, caloric intake is often a reasonable indicator for the intake of other necessary macro- and micro-nutrients (Dasgupta, 1993).

(conditional) mean and variance of the household's caloric consumption within a heteroskedastic regression specification.

Determinants of Food Vulnerability

The host of physical, economic, and institutional circumstances which households face determine their exposure to risks (e.g. droughts, sickness, price shocks). These risks affect the level and variability of the household's endowments and income. To protect their consumption from related income shocks, households engage in consumption and income smoothing behavior (Morduch, 1995). Consumption smoothing is directed at insulating consumption from variability in income through saving and borrowing (Fafchamps et al., 1998; Udry, 1995) or through insurance (Townsend, 1994). They happen ex post, after income has been realized. Income smoothing focuses on reducing income shocks directly through income diversification (Ellis, 1998) or less risky labor activities such as agricultural production with drought resistant varieties and cultivation techniques (Carter, 1997). They happen ex ante, before income is realized. The household's income and consumption smoothing strategies depend on its endowments and the character of the credit and insurance markets (Morduch, 1994; Rosenzweig and Binswanger, 1993). To understand how the interaction between the household's behavior and its risky environment determines the ex ante distribution of the household's future consumption, we consider a two-period model and proceed by backward induction.[4]

Optimal Household Consumption Under Imperfect Capital Markets

Consider a subsistence agricultural household, living over two periods, which could be thought of as the planting/hunger and the subsequent harvest season. Suppose

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[4] Generalizing the model to more than two periods will change none of the key insights.

the household maximizes intertemporal expected utility U, with instantaneous utility u(.) defined over consumption at time t, c_t. The household is risk averse, i.e. it has concave instantaneous utility ($u_c > 0$, $u_{cc} < 0$), and it neither leaves, nor receives bequests.

In each period, real income from labor, y_1 and y_2, is random. As agricultural subsistence households typically derive their income from different sources during the hunger (e.g. off-farm work) and harvest season (e.g. agricultural production), y_1 and y_2 are drawn from different probability distributions, respectively $f_1(y_1)$ and $f_2(y_2)$. These distributions reflect the risk characteristics of the environment, and depend on the resource allocation across the different income generating activities.[5]

In period one, the household has a bundle of assets with real value $A_1 \geq 0$, and chooses its consumption and assets s_1 to be transferred to period two. Before period two begins, assets yield a stochastic return. To abstract from portfolio choice, we assume homogeneous assets. Assuming imperfect credit markets, consistent with empirical evidence (Besley, 1995; Hazell et al., 1987), and a rate of time preference, δ, households maximize:

$$\max_{c_1, c_2} u(c_1) + (1/1+\delta)Eu(c_2) \quad (4)$$

$$\text{s.t.} \quad c_1 = y_1 + A_1 - s_1 \quad (5)$$

$$c_2 = y_2 + (1+r)s_1 \quad (6)$$

$$s_1 \geq 0 \quad (7)$$

[5] Abstracting from labor supply facilitates a focus on household consumption, income uncertainty, and imperfect capital markets, and their effects on the ex ante distribution of future consumption.

Credit market imperfections, reflected in a borrowing or liquidity constraint (equation (7)), imply that people cannot borrow against future income.[6] To smooth consumption, people borrow against current assets or liquidate them. The absence of insurance markets is captured by assuming that all income is from labor.[7]

First-order conditions for maximizing constrained expected utility (4)-(7) are:[8]

$$-u'(y_1 + A_1 - s_1) + E\left((1+r)/(1+\delta)\, u'(y_2 + (1+r)s_1)\right) + \lambda = 0 \qquad (8)$$

$$\lambda s_1 = 0$$

where λ is the Lagrange multiplier on the borrowing constraint. If credit markets are perfect, the optimal value of λ, λ^*, is always zero, irrespective of y_1, and marginal utility today is equated to discounted expected marginal utility tomorrow. When only income is uncertain, utility quadratic, and $r = \delta$, we can derive from (8) that consumption follows a martingale process. That is $c_2=c_1+e_2$ with e_2 a martingale difference. Anticipated changes in future income are offset by appropriate asset transactions, and to the extent that income changes can be anticipated, consumption will be constant over time. If insurance markets are also perfect, consumption can be protected from all income changes, including unanticipated ones (Deaton, 1992; Jacoby and Skoufias, 1998). The variance of consumption is zero in each period, and consumption in each period is determined by lifetime resources, which depend on current and future incomes.

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[6] Assuming that savings be larger than a constant different from zero does not affect the core conclusions.

[7] If people were insured, shocks in income from labor activities would be offset by insurance payments and in the extreme case of perfect insurance, total income (i.e. labor income + insurance payments) would be constant over time (see our discussion of insurance below).

[8] When households decide on consumption and savings at the end of period 1, period 1 income is known.

If capital markets are imperfect, $\lambda^* \geq 0$. If a household's period one income is such that $\lambda^* > 0$ - the household wants to borrow (or liquidate) more than the current value of its assets – period one consumption depends on period one income; and is stochastic. The ex ante variance of period one consumption is no longer zero.

To examine how this ex ante distribution of future consumption depends on the distributions of y_1 and y_2, the household's assets and other parameters, we derive a closed form expression of period one consumption, by assuming that the instantaneous utility function $u(c_t)$ exhibits constant absolute risk aversion (CARA), e.g. $u(c_t)=-\exp(-Rc_t)$ with R the coefficient of absolute risk aversion; that the interest rate, r, is fixed; that $y_2 \sim N(\mu_{y2}, \sigma^2_{y2})$; and that $y_1 \in [\underline{y}_1, \overline{y}_1]$, with $\underline{y}_1$ as the lower and $\overline{y}_1$ as the upper bound.

We begin with savings behavior. The optimal savings function $s^*_1(y_1)$ can be derived by substituting the CARA utility function into equation (8) (Christiaensen, 2000):

$$\begin{aligned} s^*_1 &= \phi\,(y_1 - y^*) && \text{if } y_1 > y^* && (\lambda^*=0) \\ &= 0 && \text{if } y_1 \leq y^* && (\lambda^* \geq 0)^9 \end{aligned} \qquad (9)$$

where $\phi = 1/(1+(1+r))$ and $y^* = (\mu_{y2} - R\sigma^2_{y2}/2) - A_1 - (1/R)\ln((1+r)/(1+\delta))$. The household saves only if income in period one is larger than y^*. Here, the household saves a fraction ϕ (<1) of its income above y^*. If y_1 falls below y^*, the borrowing constraint is binding ($\lambda^*>0$), the household consumes all period one income and depletes all assets A_1, either through borrowing against them or through liquidation. The household cannot protect itself from income shocks in period two. The parameter y^* determines the extent to which the household wants to insulate current consumption from current income through

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[9] Note, $\lambda^*=0$ if $y_1=y^*$, i.e. when the optimal amount of savings is zero. In that case, the household borrows as much as it can (i.e. it does not save anything) and does not want to borrow more. If $y_1<y^*$, then $\lambda^*>0$.

saving and borrowing. We must understand its determinants and the mechanism by which they affect savings and consumption.

Since the last term of y^* is negligible for reasonable values of r and δ, y^* is determined by the mean and variance of future income, current wealth, and the degree of risk aversion. As mean income in period two rises, ceteris paribus, there is a desire to borrow against future income for current consumption. If period one income is generally below period two income, households are more likely to face a borrowing constraint in period one.[10] In contrast, if the variance of period two income increases, households transfer more assets for future protection. This precautionary savings motive (Deaton, 1992; Kimball, 1990) is exacerbated by the degree of risk aversion; the more risk averse the household, the larger is its incentive to save. Finally, savings depend directly on the asset position in period one. The higher the initial asset position, the more, ceteris paribus, the household can transfer to the next period, providing greater protection for period one consumption from income shocks (Rosenzweig and Binswanger, 1993).

Given the household's savings function (9), we derive its period one consumption by substituting the optimal savings function $s^*_1(y_1)$ into budget constraint (5):

$$c_1^* = y_1 + A_1 - s_1^*(y_1) \qquad (10)$$

We use equation (10) to derive the factors affecting the mean and variance of the ex ante distribution of future consumption through backward induction.

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[10] As households in subsistence agriculture depend largely on agriculture for their income, income from off-farm activities during the planting/hunger period (y_1) will typically be much lower than income from agricultural production (y_2) which is realized during the harvest period.

Determinants of Household Food Vulnerability

At the beginning of period one, y_1 is unknown; the household faces ex ante a distribution of ex post consumption (consumption at the end of period one) with mean $E(c_1^*)$ and variance $V(c_1^*)$. From equation (10), the mean and variance of c_1^* are:

$$E(c_1^*) = E(y_1) + A_1 - E(s_1^*(y_1)) \quad (11)$$

$$V(c_1^*) = V(y_1) + V(s_1^*(y_1)) - 2\,Cov(y_1, s_1^*)$$

$$= V(y_1) + V(s_1^*(y_1))) - 2\,\rho_{y1,s1}\sigma_{y1}\sigma_{s1} \quad (12)$$

To clarify the effect of the borrowing constraint on the mean and the variance of c^*_1, we look at two extreme cases: ($\forall y_1 \in [\underline{y}_1, \bar{y}_1]$: $y_1 \leq y^*$) - the borrowing constraint always binds and the borrowing constraint never binds ($\forall y_1 \in [\underline{y}_1, \bar{y}_1]$: $y_1 \geq y^*$)[11]. By substituting (9) into (12), the variance of period one consumption is[12]:

$$V(c_1^*) = V(y_1) \qquad \text{if } \forall y_1: y_1 \leq y^* \quad (13)$$

$$V(c_1^*) = (1-\phi)^2 V(y_1) \qquad \text{if } \forall y_1: y_1 \geq y^* \quad (14)$$

Equation (13) shows that the ex ante variance of period one consumption equals the variance of period one income, when borrowing or saving is impossible. Consumption cannot be insulated from income. As seen in equation (14), the ex ante variance of period one consumption is less than the variance of period one income (recall $0 \leq \phi < 1$), when a household never meets the borrowing constraint (e.g. credit markets perfect).[13] When the

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[11] Strictly speaking the borrowing constraint does not bind when $y_1 = y^*$ (see footnote 9). However, in the special case when $y_1 \in [\underline{y}_1, \bar{y}_1 = y^*]$, the variance of period one consumption is also given by equation (13). Similarly, when $y_1 \in [\underline{y}_1 = y^*, \bar{y}_1]$, the variance of period one consumption is also given by equation (14).

[12] If $\forall y_1 \in [\underline{y}_1, \bar{y}_1]$: $y_1 \geq y^*$, $\rho = 1$ and $\sigma_{s1} = \phi\sigma_{y1}$. Substitution of these results into (12) yields (14).

[13] If r=0, $V(c^*_1) = V(y_1)/4$. While unlimited access to credit allows households in a two-period world to reduce the ex ante variance of their consumption, they cannot eliminate it altogether. In a two-period world, households can only pool risks from two independent gambles. If the time horizon is extended, households with access to credit can pool risks across a larger number of gambles, allowing them to further reduce the variance in their consumption (Eswaran and Kotwal, 1989) as seen in the martingale view of consumption.

borrowing constraint is binding over a range of y_1, the ex ante variance of period one consumption lies between $(1-\phi)^2V(y_1)$ and $V(y_1)$, and the larger the income range over which the borrowing constraint binds, the closer the ex ante variance of consumption is to $V(y_1)$ $(\partial V(c_1)/\partial y^* > 0$ if $y^* \in]\underline{y}_1, \bar{y}_1[)$.[14] Imperfect credit markets increase the ex ante variance of period one consumption.

Cast within the context of our agricultural subsistence society, this implies that the variance of consumption during the hunger period $(V(c^*_1))$ becomes a larger fraction of the variance of hunger period income $(V(y_1))$, the less the household can insulate its hunger period consumption from its hunger period income (i.e. the higher is y^*).

Analogously, Christiaensen (2000) derives that average period one income is a more important factor in the determination of average period one consumption, the larger the range of period one income for which the borrowing constraint binds. This implies that the more likely the household is to face a borrowing constraint (i.e. the larger y^*), the more its average consumption depends on its average income during the hunger period. As average income for agricultural subsistence households is generally lower during the hunger season than during the harvest period, households, who are more likely to face a borrowing constraint, have lower average consumption during the hunger period, and are more prone to consumption shortfall.

We conclude that the imperfection of credit markets increases the household's vulnerability with respect to its period one (hunger period) consumption; imperfect credit markets decrease the mean and increase the variance.[15]

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[14] See Christiaensen (2000) for proof.

[15] Within this context, the variance of period one income is exogenous. It can be shown that people who anticipate not being able to smooth consumption through borrowing, asset liquidation or insurance, engage

The Role of Insurance

Although we have assumed no insurance, households in developing countries are partly insured against income shocks by food aid and gifts in times of need through informal social networks (Adams, 1993; Fafchamps, 1992; Platteau, 1997). Other forms of informal insurance include ex post migration of family members (Lambert, 1994) and temporary placement of children with family and friends (Ellis, 1998).

To illustrate the effects of these community arrangements, assume that households have two simultaneous streams of random income: labor (y_t) and gifts (g_t), which can be correlated, and whose probability distributions are respectively represented by $f_t(y_t)$ and $g_t(g_t)$. By respectively adding g_1 and g_2 to the budget constraints in (5) and (6), and assuming that $y_2+g_2 \sim N(\mu_{y2+g2}, \sigma^2_{y2+g2})$, the optimal savings function becomes:

$$s_1^* = \phi\,(y_1 + g_1 - h^*) \qquad \text{if } y_1 + g_1 > h^* \tag{15}$$

$$= 0 \qquad \text{if } y_1 + g_1 \leq h^*$$

with $\phi = 1/(1+(1+r))$ and $h^* = (\mu_{y2+g2} - R\sigma^2_{y2+g2}/2) - A_1 - (1/R)\ln((1+r)/(1+\delta))$.

Using (15) and assuming that $h(y_1+g_1)$ represents the probability distribution of $h_1=y_1+g_1$, ($h_1 \in [\underline{y}_1+\underline{g}_1, \bar{y}_1+\bar{g}_1]$), one can derive that the availability of gifts/insurance (g_1, g_2) affects the mean and variance of period one consumption as follows:

$$E\,(c_1^*) = E(y_1) + A_1 + E(g_1) - \int_{h^*}^{\overline{y_1+g_1}} \phi(y_1 + g_1 - h^*)\,dH(y_1 + g_1) \tag{16}$$

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in less risky activities, resulting in a lower variance of income. However, strategies focused at reducing the variance of income typically also lead to a reduction in average income, shifting the probability distribution of consumption to the left, and thereby increasing the probability of consumption shortfall.

$$V(c_1^*) = V(y_1+g_1) + V(s_1^*(y_1+g_1)) - 2\,Cov(y_1+g_1, s_1^*)$$

$$= V(y_1) + V(g_1)+2\rho_{y1,g1}\sigma_{y1}\sigma_{g1} + V(s_1^*(y_1+g_1)) - 2\,\rho_{y1+g1,s1}\sigma_{s1}\sigma_{y1+g1} \qquad (17)$$

The effect of the availability of insurance depends on $E(g_1)$, $V(g_1)$, $\rho_{y1+g1,s1}$ and $h(y_1+g_1)$, whose values in turn depend on the underlying mechanism of gift giving.

Assume, for example, that $g_1=\gamma\,(E(y_1)-y_1)$; gifts are only given in case of income shocks ($\rho_{y1,g1}= -1$), and that they are based on balanced reciprocity ($E(g_1)=0$) (Coate and Ravallion, 1993).[16] If in addition $\gamma=1$, households are perfectly insured; negative and positive income shocks are completely offset by gifts and gift giving ($V(g_1)=V(y_1)$). Total period one income (y_1+g_1) is constant at $E(y_1+g_1) = E(y_1)$. Such gifts eliminate the variance of period one consumption and increase period one average consumption.[17]

Effects of the determinants of vulnerability: some hypotheses

This theoretical discussion helps specify regression equations to quantify the effect of the socio-economic characteristics of the household (and its environment) on the mean and variance of consumption one period ahead. The estimated regression coefficients are used to construct food vulnerability measures for each household and to evaluate the effects of alternative policy scenarios on the population's food vulnerability.

By substituting $\phi = 1/(1+(1+r))$ and $h^* = (\mu_{y2+g2} - R\sigma^2_{y2+g2}/2) - A_1 - (1/R)\ln((1+r)/(1+\delta))$ from equation (15) into equations (16) and (17), we obtain the

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[16] This contrasts with theories of altruistic informal insurance (Scott, 1976; Thompson, 1971).

[17] In case of perfect insurance, y_1+g_1 is constant at $E(y_1)$. From (15) it follows that in case of perfect insurance $E(s^*_1)=\phi(E(y_1)-h^*)$ if $E(y_1)>h^*$ and 0 otherwise. $E(s^*_1)$ in case of perfect insurance is always smaller than $E(s^*_1) = \int_{h^*}^{\overline{y}_1} \phi(y_1 - h^*)dF(y_1)$ in case of no insurance/gifts (in period one). Consequently, $E(c^*_1)$ with perfect insurance is larger than $E(c^*_1)$ without insurance/gifts.

reduced forms of the mean and variance of consumption one period ahead:

$$E\,(c_1^*)= k_1\,(E(y_1),E(g_1),\,A_1,\,\mu_{y2+g2},\,\sigma^2_{y\,2+g2},\,R,\,\delta,\,r,\,h(y_1+g_1)) \tag{18}$$

$$V(c_1^*)= k_2\,(V(y_1),\,V(g_1),\,\rho_{y1,g1},\,A_1,\,\mu_{y2+g2},\,\sigma^2_{y\,2+g2},\,R,\,\delta,\,r,\,h(y_1+g_1)) \tag{19}$$

The determinants of the mean and variance of future consumption fall into three groups: 1) income related variables (($E(y_1)$, $V(y_1)$ and $h(y_1+g_1)$); 2) savings/credit related variables (A_1, μ_{y2+g2}, $\sigma^2_{y\,2+g2}$, R, δ, r); and 3) insurance related variables ($E(g_1)$, $V(g_1)$ and $\rho_{y1,g1}$). Prior to discussing the data and the empirical strategy used to obtain empirical estimates of the effects of these determinants on the ex ante mean and variance of consumption, we derive insight with respect to the direction of their marginal effects from our theoretical model. The marginal effects in table 1 can be unambiguously derived. See Christiaensen (2000) for derivations and detailed discussion.

From table 1, we see that: 1) initial assets have a positive effect on average consumption one period ahead, and a negative one on its variance; 2) an increase in future income uncertainty reduces the mean as well as the variance of consumption one period ahead; and 3) an increase in average income in the remote future has a positive effect on both the mean and the variance of consumption one period ahead.

To examine the effect of the ex ante distribution of income and gifts one period ahead on the ex ante distribution of consumption one period ahead, we focus on the marginal effects of total income h_1 ($h_1 = y_1 + g_1$). Inspection of equation (16) suggests that average period one consumption becomes larger as total average period one income increases. This can be shown analytically if average income (h_1) increases such that the new total income distribution dominates by second-order stochastic dominance (SSD) the

Table 1: Hypotheses Regarding the Effect of Some Determinants of Food Vulnerability on the Ex Ante Mean and Variance of Consumption One Period Ahead

Marginal Effect of X on Average Future Consumption	$\partial E(c^*_1)/\partial X=$ [(1)]
Assets (A_1)	$1-[\partial E(s^*_1)/\partial h^*_1]*[\partial h^*_1/\partial A_1] > 0$ $1-[(-)*(-)] > 0$
Future income uncertainty (σ^2_{y2+g2})	$-[\partial E(s^*_1)/\partial h^*_1]*[\partial h^*_1/\partial \sigma^2_{y2+g2}] < 0$ $-[(-)*(-)] < 0$
Average future income (μ_{y2+g2})	$-[\partial E(s^*_1)/\partial h^*_1]*[\partial h^*_1/\partial \mu_{y2+g2}] > 0$ $-[(-)*(+)]>0$
Marginal Effect of X on the Variance of Future Consumption	$\partial V(c^*_1)/\partial X=$ [(1)]
Assets (A_1)	$[\partial(V(s^*_1)-2Cov(h_1,s^*_1))/\partial h^*_1]*[\partial h^*_1/\partial A_1] < 0$ $[(+)*(-)] < 0$
Future income uncertainty (σ^2_{y2+g2})	$[\partial(V(s^*_1)-2Cov(h_1,s^*_1))/\partial h^*_1]*[\partial h^*_1/\partial \sigma^2_{y2+g2}] < 0$ $[(+)*(-)] < 0$
Average future income (μ_{y2+g2})	$[\partial(V(s^*_1)-2Cov(h_1,s^*_1))/\partial h^*_1]*[\partial h^*_1/\partial \mu_{y2+g2}] > 0$ $[(+)*(+)] > 0$

(1) The signs depend on $h^* \in]\underline{h}_1, \bar{h}_1[$. Otherwise they might be zero (see Christiaensen (2000)).

old one (for proof, see appendix A.3 in Christiaensen (2000)).[18] This is a fairly general analytical result, which tends to break down only if the increase in average income is related to a shift in the probability mass from the middle of the distribution to the tails.

The marginal effect of the variance of total period one income on period one consumption is conjectured to be positive. This hypothesis is motivated by equations (13) and (14) (replace y_1 by h_1), which shows that an increase in the variance of income translates directly into an increase in the variance of consumption, when credit markets

[18] Explicit analytical results can only be established with respect to total income h_1 (= $y_1 + g_1$), as y_1 and g_1 follow different distributions and the relationship between these distributions is unknown.

are perfect and when saving/borrowing is impossible. There is no reason to assume that it would be different in case of imperfect credit markets. This is an empirical matter.

Rural Households in Zone Lacustre, Northern Mali

We begin a discussion of the empirical model with a description of the data. The empirical analysis is based on a panel data set of 274 households collected in Zone Lacustre, northern Mali over the period 1997-98. This remote and extremely poor area is characterized by scant and erratic rainfall (on average, 234 mm/year from 1992-97). Economic activity in the area is largely confined to agricultural cultivation and livestock breeding, supplemented with some fishing. The study area also has a longstanding tradition of temporary male out migration to bridge the dead post harvest season, with people returning when the agricultural campaign takes off. The ethnic composition of the region is diverse and one distinguishes a wide mix of different livelihood systems.

There are three agricultural systems: 1) rain fed millet; 2) water recession agriculture around ponds and lakes based on the yearly rise and decline of the Niger; and 3) irrigated agriculture in perimeters on the Niger banks. Only with the latter system are there two crops a year, one of which is harvested in the hunger season.

Households were selected in the sample using a two-step procedure. First, ten villages, covering the different agricultural and livelihood systems, were purposely selected around Niafunké. Within each village, one third of the households was sampled by systematic selection, resulting in a sample of 274 households. The survey work was begun in August 1997 (peak of hunger period), and each household was subsequently surveyed three more times: the immediate post-harvest period, the post harvest period, and the subsequent hunger period in August 1998.

Here, we only highlight some key points (see Christiaensen, 1999, for details). While agricultural income is important, we see from table 2 that 1996-97 was a mediocre agricultural year; only one third of all income was derived from agriculture. Self-employment income, such as petty trading, services and artisanal activities was about as important as that derived from agriculture. This is consistent with other studies of poor rural areas in developing countries (Ellis, 1998; Reardon, 1997; Reardon et al., 1992). Income from livestock was negative; many households lost animals.

During the second study year, a drought year with a complete failure of the millet and sorghum harvest, the joint average share of income from agricultural production and self-employment declined from two-thirds to one-third. Gifts and migrant remittances provided the lion's share of income in 1997-98.

Most gifts stemmed from friends and family. Three of the 10 sample villages also received government food aid during the hunger period, which constituted between 30 and 50 percent of their fourth round income. Gifts are important for female-headed households (37 percent of their income in 1996-97), particularly during the drought year in 1997-98, when their gifts were 61 percent of income.

Table 2: Household Income and Income Sources from 1996-98.

Average Nominal Income[1]/Capita (FCFA) and Average Share (%)	Average Nominal Inc./Cap.	Net Agri-cultural Income (%)	Net Livestock Income (%)[2]	Self-Employ-ment (%)	Gifts (%)	Migrant Remit-tances (%)
1996-97 (n=269)	50,207	32	-12	36	25	11
1997-98 (n=243)	52,412	12	-44	25	51	27

(1) Income includes cash as well as imputed values for in kind income and auto consumption of crops, livestock products, fish and wild fruits.

(2) Livestock sales or purchases are not included in net livestock income as they merely represent an asset transformation (from a physical into a financial asset and vice versa). Livestock loss through theft or death is deducted from gross livestock income, as it constitutes a cost of holding livestock.

Source: Christiaensen (1999, p. 42).

Median caloric intake per household member was 2,403 kilo calories during the 1997 hunger period.[19] It increased to 2,776 kilo calories per capita at the immediate post harvest time, and dropped again to 2,161 kilo calories per capita during the 1998 hunger season, indicating that food consumption is seasonal. As median per capita food intake dropped by 242 kilo calories from the 1997 to the 1998 hunger season, it is evident that the effects of the dismal harvest were heavily felt.

Christiaensen (2000) examined the seasonal pattern of caloric consumption further by means of a food poverty transition matrix over the 1997 post-harvest and the subsequent 1998 hunger period. He found that the proportion of undernourished[20] households increased from 37 percent during the post harvest season to 59 percent during the subsequent hunger period. On the other hand, almost one third (11%/37%) of the households who were undernourished during the post harvest period, acquired sufficient food during the hunger period. Furthermore, only 18 percent of all households remained in the same caloric ratio group and, more strikingly, 54 percent of the households moved two or more caloric ratio groups between the two seasons. Shorrock's mobility index[21] was 0.99, which suggests quasi-perfect mobility[22].

Thus, even if one looks only one season ahead, there seems to be little support for the theoretical martingale proposition that consumption today is the best predictor of consumption tomorrow. Households do not manage to smooth food consumption across

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[19] A discussion of our methodology to measure caloric intake is provided below.
[20] The caloric threshold (z) was set at 2,345 kcal/person/day. For further explanation, see below.
[21] Shorrocks' Mobility Index =(c-tr(P))/(c-1) with c = categories and tr(P) = trace of the conditional transition probability matrix (Shorrocks, 1978). The closer the index is to 1, the higher the mobility.
[22] Dercon and Krishnan (2000) report similar seasonal movements in and out of (total consumption) poverty in rural Ethiopia in 1994-95 with Shorrocks' mobility indices of seasonal consumption mobility of 0.80.

seasons[23]. This descriptive analysis of our data underscores the practical need of vulnerability measures, such that resources can be mobilized in time to undertake targeted and appropriate interventions to prevent hunger during the hunger season.

Econometric Strategy and Empirical Specification

From our theoretical discussion, it is clear that the ex ante mean and the ex ante variance of future consumption (C_{t+1}) are both functions of the ex ante characteristics (X_t) of the household and its environment. These characteristics include the real income, savings/credit and insurance related variables discussed in equations (18) and (19).

Empirical estimation of consumption functions is traditionally based on a functional specification with the disturbance term appended in an additive manner: $C_{i,t+1}=f(X_{i,t}) + e_{i,t+1}$ with $E(e_{i,t+1})=0$ and $V(e_{i,t+1})=\sigma^2$ and i=1…N, the number of observations. Such a specification assumes that the conditional variance of consumption is the same for all households ($V(C_{i,t+1} \mid X_{i,t})=\sigma^2$) and independent of the explanatory variables. Yet, our theoretical model suggests that the conditional variance of consumption is heteroskedastic. Assuming heteroskedasticity of the form $V(e_{i,t+1})=\sigma_i^2$ is also insufficient, as it does not allow us to estimate the variance of future consumption as a function of the ex ante household characteristics either. This property is crucial because several hypotheses from the theory developed above suggest that regressors do indeed have a differential effect on the conditional mean and variance of future consumption.

[23] While in any empirical study of this kind, some of the observed movements may be due to measurement error (Atkinson et al., 1988), our results seem sufficiently dramatic to conclude that household caloric intake varies substantially from season to season.

To accommodate these concerns, we specify a stochastic consumption function similar to the stochastic production function proposed by Just and Pope (1978; 1979).[24]

$$C_{i,t+1} = f(X_{i,t};\alpha) + h^{1/2}(X_{i,t};\beta)^{*} e_{i,t+1} = f(X_{i,t};\alpha) + u_{i,} \qquad (20)$$

with $E(e_{i,t+1})=0$, $E(e_{i,t+1},e_{k,t+1})=0$ with $i\neq k$ and $V(e_{i,t+1})=\sigma^2_{.}$ This specification allows household characteristics to affect the ex ante mean and variance of future consumption in opposite directions. This follows from (20), by deriving the conditional mean and variance and taking derivatives (dropping observational subscripts):

$$E(C_{t+1} \mid X_t)=f(X_t;\, \alpha) \quad \text{and} \quad \partial E(C_{t+1} \mid X_t)/\partial X_{j,t}=\partial f(X_t;\alpha)/\partial X_{j,t} \qquad (21)$$

$$V(C_{t+1} \mid X_t)=h(X_t;\, \beta)^{*}\, \sigma^2_e \quad \text{and} \quad \partial V(C_{t+1} \mid X_t)/\partial X_{j,t}=(\partial h(X_t;\beta)/\partial X_{j,t})^{*}\sigma^2_e \qquad (22)$$

For empirical purposes, we assume that $f(X_{i,t};\alpha)$ is linear and that $h(X_{i,t};\beta)$ is an exponential:

$$C_{i,t+1} = X'_{i,t}\alpha + u_{i,t+1} \qquad (23)$$

with $E(u_{i,t+1} \mid X_{i,t}) = 0$; $E(u_{i,t+1},\ u_{k,t+1} \mid X_{i,t}) = 0$, $i\neq k$ and $V(u_{i,t+1} \mid X_{i,t}) = \sigma^2_i = \sigma^2_e{}^{*}\exp(X_{i,t}'\beta)$. The econometric model reflects multiplicative heteroskedasticity, whose α and β coefficients can be estimated by a three-step heteroskedastic correction procedure described in Just and Pope (1978;1979) and Judge et al. (1988, p. 365-369).

In any empirical analysis, survey data often serve only as proxies for the theoretical concepts of our specification. Therefore, before we present the actual estimated results, we need to discuss in detail the actual data and proxy variables used.

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[24] These authors develop this flexible specification to address concerns regarding the differential effects of inputs on the mean and variance of output. They show that traditional specifications of stochastic production require that inputs affect the mean and variance of production in the same direction. A similar flexible specification is used by Mullahy and Sindelar (1995) to study the effect of alcoholism on the ex ante distribution of earnings and the resulting welfare.

In the empirical implementation, we estimate the coefficients of the determinants of the mean and variance of consumption in the hunger season (i.e. t+1), based on the information we have available during the preceding post harvest season (i.e. t). We focus on these two periods, because of the immediate practical relevance of the empirical results within the context of early warning in drought prone areas. Timely and targeted emergency interventions during the hunger season require accurate identification of the vulnerable at the immediate post harvest time. Also, insight into the relative importance of the different determinants of hunger season vulnerability could guide policymakers in their choice of structural interventions. The empirical analysis is thus based on the data from the immediate 1997 post harvest season, and the 1998 hunger season.

Table 3 presents descriptive statistics of the dependent and independent variables used in the regression analysis. The logarithm of daily caloric intake per residential household member during the hunger season is the dependent variable. It was obtained by converting total reported household food consumption over the seven days prior to the interview[25] into kilo calories per residential household member. Total food consumption was based on a list of 25 regularly consumed local foods from the different food groups (cereals, roots and tubers, vegetables and fruits, meat and fish, fats). By assuming that consumption is distributed lognormally, we can characterize the entire distribution by predicting the ex ante mean and variance of consumption from our estimated equations. The log-normality hypothesis is subjected to empirical testing.

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[25] There is no consensus on the optimal recall period. In our experience, a 7-day recall period seemed appropriate. By using a shorter recall period, one can miss infrequently served foods and one is more prone to idiosyncracies in consumption (marriage, birth). Longer recall periods may lead to understatement of consumption due to recall-error (Deaton and Grosh, 1998).

Table 3: Descriptive Statistics of Dependent and Independent Variables

	Mean	Standard Deviation	25 per-centile	75 per-centile
Dependent Variable				
Calorie per resid. Household member per day at t+1	2304	913	1615	2750
Human Capital				
# adult male (16-65 yrs) (residential & migrant) at t	2.0	1.4	1.0	3.0
# adult female (16-65 yrs) (residential & migrant) at t	1.8	1.2	1.0	2.0
# children (≤15 yrs) (residential & migrant) at t	2.6	2.4	1.0	4.0
# elderly (> 65 yrs) (residential & migrant) at t	0.4	0.6	0.0	1.0
Age household head	53	14	42	63
Age household head squared	3046	1518	1764	3969
At least 1 household member completed primary school at t (yes=1)	0.20	0.40	0	0
Female headed household (i.e. no adult men in hh)	0.09	0.29	0	0
Productive Capital				
#draft animals at t	0.2	0.7	0	0
Value (1000 cfa francs) agricultural, fishing & transport equipment at t	27	68	3	14
Access to perimeter (yes=1)	0.15	0.36	0	0
Income Diversification				
% income from agricultural production at t-1	0.35	0.37	0.09	0.52
% income from migrant remittances at t-1	0.11	0.20	0.00	0.14
Savings/Credit				
Value (1000 cfa francs) food stock carried over at t	15	41	0	13
# goat/sheep at t	7.1	10.7	1.0	9.0
# cattle (bullocks, cows, calves) at t	2.1	6.0	0	2.0
Value (1000 cfa francs) consumer durables at t	99	113	28	122
Insurance				
Non-food gifts (1000 cfa francs) between t and t+1	36	58	7	41
Family food gifts (1000 cfa francs) between t and t+1	22	50	1	19
Official food aid between t and t+1 (yes=1)	0.18	0.38	0.00	0.00
Child sent away over last 2 yrs (yes=1)	0.15	0.36	0.00	0.00
Main adults or household absent bw t and t+1 (yes=1)	0.17	0.37	0.00	0.00
# observations[1] = 254				

[1] Over the course of the survey, twenty observations were lost due to out migration. These observations do not, on average, differ in a statistically significant manner from the rest of the sample, neither in terms of their food intake, as observed during the first and second round, nor in terms of their socio-economic characteristics. Potential attrition bias is minimal.

We group the determinants of the mean and variance of future consumption into three categories: income, savings and insurance. Ideally, we would use the ex ante mean and variance of income as regressors, but these variables are unavailable. Since in agricultural households, income is conditioned by human capital, productive assets and income diversification (Singh et al., 1986), these variables are directly in the model.

A household's human capital is embodied in its members, their sexes, ages, experiences and skills. To accommodate comparisons with other studies (Glewwe and Hall, 1998; Grootaert et al., 1997), we include all four age/sex groups. As members who have temporarily migrated or are not in residence at post-harvest time may still contribute to household income through remittances or affect the number of people to be fed during the hunger season, they are also counted as household members. The household's work experience and stage in the life cycle are captured by the household head's age. Household skills are represented by a dichotomous variable, which is one, if at least one member completed primary education. By doing so, we account for potential intra-household externalities from the one educated member (Basu and Foster, 1998). Finally, we control for the gender of the household head.

As proxies for productive capital, we include: the number of draft animals at the immediate post harvest time, the value of agricultural, fishing and transport equipment, and access to a perimeter. For those with fishing equipment, income from fishing is an important source of income during the post harvest season. About 15 percent of the sample households, concentrated in three villages, have access to a perimeter.

Household income diversification has been important in protecting consumption from income shocks (Ellis, 1998; Reardon, 1997; Reardon et al., 1992). To gauge a household's income susceptibility to drought, we include the share of income from agricultural production and migrant remittances from the previous year.

Household's facing imperfect credit markets smooth consumption by borrowing against assets or by asset liquidation. As in other studies (Fafchamps et al., 1998; Udry, 1995), we include as saving/credit variables: grain stocks, goats/sheep and cattle owned, and the value of consumer durables.[26] Grain and livestock are attractive as buffer stocks as they provide insurance against price risk and a current return. As in most of semi-arid West Africa, land is not used as collateral (Fafchamps et al., 1998; Kergna, 1996). We have no information on cash holding.

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. In spite of these potential problems, we did control for food aid in the models, and the interaction between food aid and actual temporary migration, as some households obtained a large portion of their food consumption from food aid. By omitting food aid, our results might suffer substantially from omitted variable bias. 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 in our proxy potentially also introduces some endogeneity bias, this was traded off against the advantages of having an accurate proxy.

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[26] Consumption smoothing can also be achieved by liquidation of productive assets, but this may permanently reduce future income. Their sale is often avoided if possible, or postponed (Corbett, 1988).

From looking at the mean value of the different assets and animals in table 3, it is clear that our sample population is poor. Closer inspection of the distribution parameters shows that households differ widely in their assets and animals, as well as their harvests, which yields the variation necessary for our econometric analysis. Finally, because food prices in the two markets important to our villages are about the same, they were omitted.

Determinants of Food Vulnerability: Empirical Results

Table 4 presents the coefficient estimates of the determinants of the conditional mean and variance of log caloric intake per capita during the hunger season. The overall explanatory power of the regressions is encouraging and consistent with other empirical studies based on cross-sectional data. The signs of the coefficients are generally in line with theory, and several coefficients are large relative to their standard errors. Our results are also robust with respect to several alternative specifications.[27]

We believe that the model in table 4 performs the "best" based on several important performance criteria, and that it is also the most appropriate for our research purposes. We begin by noting that households with more children, consume, on average, less and face ex ante a higher variance. This suggests that households with more children are (ceteris paribus) more vulnerable, a result potentially related to the fact that children

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[27] For example, we estimated a model using actual gifts and actual temporary out migrations as instruments, as well as a model including village dummy variables to control for socio-economic and geographical differences between villages (Christiaensen, 2000). In both models, the sign, size and significance of the estimates for most coefficients are consistent with those in table 4. In the latter model however, the significance and size of the coefficient estimates for the perimeter and food aid variables are somewhat counterintuitive. As access to a perimeter and reception of food aid are largely village based, these changes are undoubtedly due to multicollinearity. By including the location variables in the model, we trade-off identifying specific village effects with precision on the effects of perimeters and food aid. The latter variables are more directly related to policy concerns. Also, to use the estimated results for out of sample predictions, it is most convenient to have a model without village dummies.

Table 4: 3-step OLS Estimates 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 $(lnc_{t+1}/X_t)= X'_t\beta$	
	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.

contribute less to household food availability than they consume. Further, households with more children may be less able to adjust or compensate for income shocks ex post.

If this interpretation of our results were valid, one would expect the food consumption of households who can temporarily place their children with family or friends when times are precarious to be less dependent on the number of children. The signs on the coefficients of the interaction term between the potential to send children away in times of need (measured as a zero-one dummy variable) and the number of children, are the negative of those on the coefficients for the number of children, both in the mean and variance equations. These results support our hypothesis.

A striking result is that female-headed households have on average a substantially larger (log) per capita caloric consumption and a substantially smaller variance, suggesting that female-headed households tend to be relatively less vulnerable with respect to food in case of a drought shock than do other households in the community. This phenomenon might be explained by the existence of basic community solidarity actions to help those in greatest need meet their basic requirements during periods of high stress. Christiaensen (2000) tests this hypothesis by including an interaction term between female-headed households and family food gifts received. The signs on the coefficient for the interaction term are the opposite of the signs on the coefficient for the female-headed household variable. This indicates that female-headed households are indeed better protected against general shocks because of basic community solidarity. The coefficients for the female-headed household term and the interaction term are jointly "statistically significant" at the 5 percent level in the equation for mean consumption. They are not jointly statistically significant in the variance equation.[28]

Our estimated results do not show an effect of formal education on the distribution of future consumption, as suggested by Schultz (1975).[29] It may be that

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[28] Another interpretation is that female-headed households care more about food than male headed households (Greer and Thorbecke, 1986). If this were the case, one would expect the food share of total household expenditures to be higher for female-headed households. This hypothesis is not confirmed by the data, even after controlling for income and household size (Christiaensen, 2000).

[29] Schultz's hypothesis suggests that educated individuals are less vulnerable; they adapt more easily to changing circumstances. To gain efficiency, the education variable was subsequently excluded.

because of the generally low level of education, there is not enough variation in the variable to measure its effect with any confidence. This result is common for other studies of rural areas, but contrary to what is often found in urban areas (Grootaert et al., 1997, Kyereme and Thorbecke, 1991).[30] This could suggest that there are few opportunities for formally educated persons to put their knowledge to work in rural areas. Alternatively, school curricula may not be sufficiently adapted to rural circumstances.

Agricultural, fishing and transport equipment leads to a rightward shift and a contraction of the ex ante distribution of hunger period consumption. Fishing and transport equipment provides income during the planting/hunger period, thereby increasing average consumption.. This equipment also provides a relative secure source of income during the planting/hunger season, explaining the reduction in variance.

Access to a perimeter has a substantial variance decreasing effect on hunger period consumption. It also leads to a relatively high (though not "statistically significant") increase in average future consumption by providing the potential for cultivating an additional crop during the hunger season. However, this production technique has only recently been introduced, and irrigated cultivation is not yet common. Further, the timely supply of inputs and spare parts remains problematic.

There is evidence that greater dependence on migration remittances substantially decreases the variance of consumption, without affecting its mean. This suggests that households, who diversify their income generating activities through seasonal urban migration, are better protected from income shocks.

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[30] Glewwe and Hall (1998) find that well-educated persons are less prone to macro-economic shocks, though rural and urban areas are not split up in their sample.

There is also strong statistical evidence that food stocks available at the end of the harvest season have a substantial positive effect on the mean of hunger season consumption. This positive effect is attenuated by the household's degrees of dependence on agriculture, as indicated by the negative sign on the coefficient for the interaction term between food stock and the typical household's income share from agriculture.

In contrast to South Asia (Kurosaki, 1995; Rosenzweig and Wolpin, 1993), we find no evidence that cattle or small ruminants are a buffer against income shocks. Our result is consistent with those in neighboring Burkina Faso (Fafchamps et al., 1998).

Food aid substantially reduces the variance of (log) consumption, without affecting the mean. This confirms our intuition that food aid acts as an effective insurance mechanism. It is difficult to find appropriate proxies for the other insurance variables such as the household's potential to receive gifts and the household's potential to migrate in response to income shocks. Christiaensen (2000) reports a model, which includes actual gifts and actual temporary out migration as instruments. The strong positive relationship between non-food gifts and average consumption during the hunger period, but no relationship with the variance, suggests that households receive non-food gifts irrespective of income. The negative relationship between the variance of hunger period consumption and family food gifts indicates that family transfers in response to income shocks happen mainly through food gifts. No clear pattern appears with respect to the effects of temporary out migration.

Food Vulnerability in Zone Lacustre

From equation (3), the calculation of the food vulnerability measures (V_α) requires knowledge of the ex ante probability distribution of the household's future consumption. One needs a caloric threshold, and to classify a household as food vulnerable, one must also specify a probability threshold. To obtain the ex ante probability distribution of each household's future food consumption from our estimated results, it is necessary to assume that consumption follows a parametric distribution. Based on both the Kolmogorov-Smirnov and the Bera-Jarque test for normality (Judge et al., 1988), we failed to reject the hypothesis that daily per capita calorie consumption during the hunger period is lognormally distributed.

Assuming lognormality, predictions of each household's ex ante mean and variance of logarithmic caloric consumption per capita during the hunger season are sufficient to characterize a household's ex ante probability distribution of future consumption. They are obtained by substituting the values of the regressors for that household into the equations in table 4. Knowledge of each household's probability distribution, combined with a caloric threshold, allows us to calculate each household's probability of shortfall ($V_{\alpha=0}$), its expected caloric shortfall ($V_{\alpha=1}$), or its expected caloric shortfall squared ($V_{\alpha=2}$).

We set the caloric threshold at 2,345 kcal/person/day,[31] corresponding to the needs of a 60 kg male, aged 30-59 undertaking 'light' activity, 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 vulnerability threshold of 50 percent.[32]

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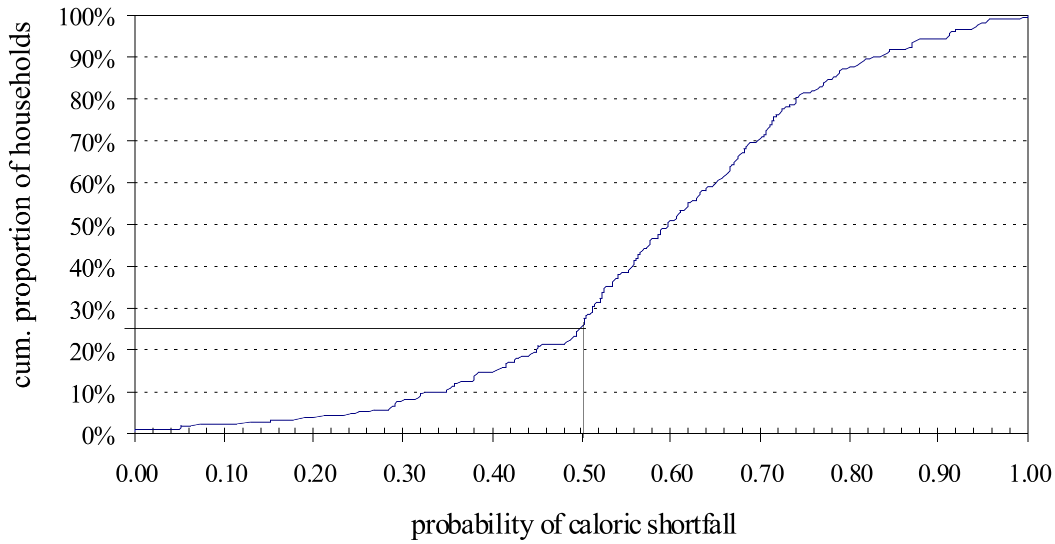
[31] Problems with using one caloric threshold and related issues are discussed in Kakwani (1989), Ravallion (1990), Shetty et al. (1996).

[32] Poverty thresholds are typically determined in absolute and objective terms (Ravallion, 1998). However, poverty could also be calculated based on a relative (Sen, 1983; Townsend, 1979) or subjective (Pradhan

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



From figure 1, we see that only 24 percent of the households have less than a 50 percent chance that their daily caloric consumption during the hunger season will fall below 2,345 kilocalories per capita. Or, at the post harvest time, 76 percent of the households have at least a 50 per cent chance that their caloric consumption during the hunger season will fall below the caloric threshold. Put differently, holding socio-economic characteristics constant, three quarters of the population would be undernourished during the hunger season in at least five out of ten years. Based on this threshold, which is used throughout the study, our population is extremely food vulnerable. By examining the sensitivity of the results, Christiaensen (2000) finds that the marginal effect of an increase in the vulnerability threshold on the proportion of

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and Ravallion, 1998) poverty threshold. Similarly one could define relative or subjective vulnerability thresholds. We do not have the necessary data to calculate subjective vulnerability thresholds.

households which will not be considered vulnerable, is especially large beyond a vulnerability threshold of 50 percent.

To understand the depth of the caloric shortfall, we also calculate the household's expected caloric shortfall (V_1); 78 percent of the households is classified as food vulnerable if we set the vulnerability threshold at 234 kilocalories per person, which corresponds to an expected shortfall of 10 percent of the caloric threshold. Our population is not only likely to be undernourished during the hunger season, they also stand to suffer from severe undernourishment.

Knowledge of a population's food vulnerability profile at the post harvest time is important not only for cognitive purposes, but also to forecast the need for emergency interventions. This presupposes that our vulnerability measures are accurate indicators of future undernourishment. The (Spearman) correlation coefficients between V_0, V_1 and actual caloric consumption per capita during the hunger period are respectively -0.45 and –0.43. The average probability of shortfall (59 percent) is nearly identical to the percentage of people who actually fell below the caloric threshold (58 percent). Similarly, average expected shortfall is estimated at 385 kilocalories/capita, which is very close to the actual caloric shortfall in 1998 of 373 kilocalories/capita. The predictive power of our food vulnerability measures is very good.

Further evidence of the predictive power can be obtained from a contingency table classifying observations according to two criteria, a benchmark and an alternative indicator. The performance of the alternative indicator can be rated by two criteria: 1) its sensitivity, defined as the proportion of predicted positive outcomes which are truly positive according to the benchmark and 2) its specificity, defined as the proportion of predicted negative outcomes which are also truly negative according to the benchmark. Both its sensitivity and its specificity should be high (Table 5). We rank our population into food vulnerable and food secure groups, based on a vulnerability threshold of 50 percent and a caloric threshold of 2,345.

There is clearly a statistically significant relationship between the vulnerability indicator and future undernourishment. By examining the diagonal cells, we see that 67.7 percent of all households are correctly classified. A sensitivity of 87 percent means that almost all households who suffered from undernourishment were found to be food vulnerable. The specificity of our vulnerability measure is 40 percent; under half of those who were sufficiently nourished were identified as not vulnerable. This analysis confirms that our vulnerability measure has very good predictive power. It correctly predicted the nutritional status of two-thirds of all households. It is especially accurate in identifying those who will be undernourished. This is the more important indicator given the detrimental effects of undernourishment.

Table 5: Contingency Table of Food Vulnerability at the Post Harvest Time (V_0) and Actual Caloric Intake During the Hunger Season

# households (cell %)	Actual caloric intake during hunger season		Total
	Not undernourished (>2345 kcal/cap)	Undernourished (≤ 2345 kcal/cap)	
Not vulnerable (V_0<0.5)	42 (16.5)	19 (7.5)	66 (24.0)
Vulnerable (V_0≥0.5)	63 (24.8)	130 (51.2)	188 (76.0)
Total	105 (41.3)	149 (58.7)	254 (100)
$\chi^2=25.06^{**}$	Specificity:42/105=0.40	Sensitivity:130/149=0.87	

** significant at 1 % level

As a final litmus test of the accuracy of our vulnerability measure, we analyze its predictive power out of sample. From our first survey round, we have data on caloric consumption in the 1997 hunger period and recall data on some socio-economic characteristics (asset and animal possession, reception of food aid, agricultural production) at the 1996 post harvest time. Using these latter data and the estimated coefficients of table 4, we estimate each household's vulnerability at the 1996 post harvest time, with respect to caloric consumption during the 1997 hunger season.

At the 1996 post harvest, the average probability of caloric shortfall during the subsequent hunger period is 50 percent, compared to 59 percent at the 1997 post harvest. As most socio-economic household characteristics remained about constant over this period, this result is largely due to the substantially higher agricultural production in 1996 compared with 1997.[33] About 62 percent of households are correctly classified by our vulnerability measure as either sufficiently nourished during the hunger season or undernourished. With respect to the vulnerability indicator's sensitivity, it identifies 62 percent of the sample's undernourished households. Its specificity is also 62 percent. We conclude that our methodology to measure household vulnerability is quite accurate.

Food Vulnerability and Food Poverty

By using our explicit vulnerability measure, we can examine if, in practice, vulnerability and poverty constitute different dimensions of a person's/household's well being. As Kanbur and Squire (1999) point out, such a direct comparison has so far not been possible, given the current lack of explicit vulnerability measures.

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[33] Average cereal production for each household drops from 128 kg/capita in 1996 to 74.5 kg/capita in 1997, a drought year.

Table 6: Classification of Households According to Their Undernourishment and Food Vulnerability at the Post Harvest Time

# households (cell %)	Actual caloric intake at post harvest time		Total
	Not undernourished (>2345 kcal/cap)	Undernourished (≤ 2345 kcal/cap)	
Not vulnerable ($V_0<0.5$)	48 (20.0)	12 (5.0)	60 (25.0)
Vulnerable ($V_0\geq0.5$)	103 (42.9)	77 (32.1)	180 (75.0)
Total	151 (62.9)	89 (37.1)	240 (100)

χ^2=10.09, significant at 1 percent level

In table 6, we find that 42.9 percent of all households are vulnerable with respect to their food access during the hunger season, even though they are not undernourished at the post harvest season. A small group of households (5 percent), who are currently undernourished, are not vulnerable with respect to their food access in the future even though they are currently undernourished. These figures convincingly show that being food vulnerable does not necessarily imply being currently undernourished, and vice versa, even though there exists some correlation as indicated by the chi-square statistic.

Policies to Reduce Food Vulnerability in Northern Mali

In high risk areas with low economic potential, two broad policy strategies to reduce food vulnerability are generally discussed: 1) those directed at promoting migration out of the area; and 2) those focused on reducing the population's exposure to risk (e.g. income diversification, irrigation) and the reinforcement of ex post capacity to cope with shocks (e.g. consumption credit, public work programs) in the area.

Temporary (and to a lesser extent permanent) out migration is a strategy that lies at the core of the livelihood system for several households in Zone Lacustre

(Christiaensen, 1999; Sidibe, 1993). To examine the potential of policies which facilitate temporary out migration for reducing food vulnerability for household members who remain in the area, we simulate the effect on food vulnerability of an increase by 10 percentage points in the share of income derived from migrant remittances for all households. Because only 11 percent of households' incomes were from migrant remittances in 1996-97, a 10 percentage point increase is substantial.

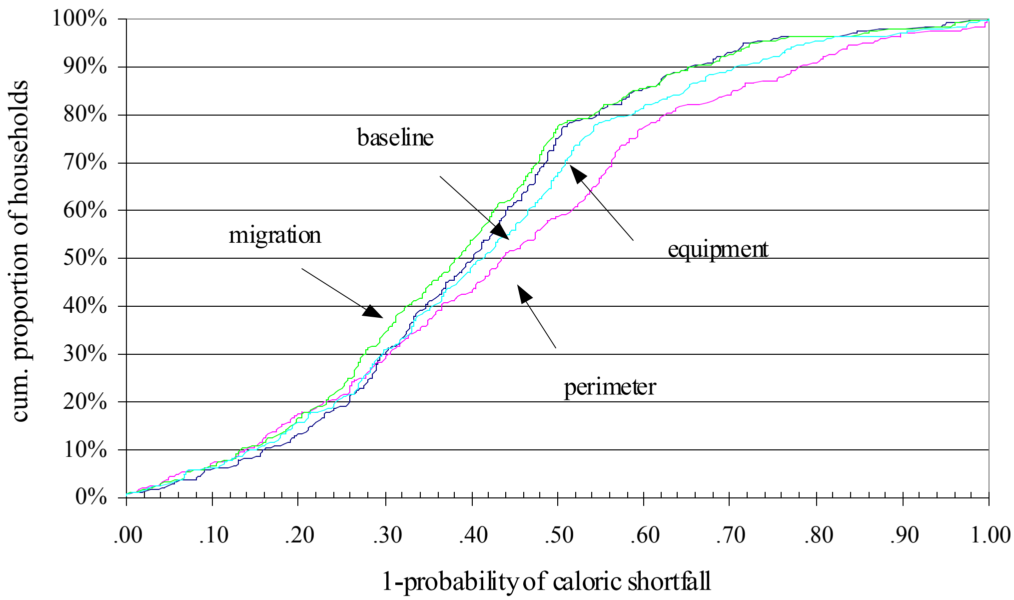
To reduce food vulnerability by direct interventions within high-risk areas, we look in particular at the effect of generalizing access to a perimeter to all households. Development specialists in the study area have focused on irrigated agriculture, and the population has also identified irrigation infrastructure as the most desired intervention. At the time of the survey, only 15 percent of households reported access to a perimeter. We simulate the effect on the food vulnerability profile of providing all households with access to a perimeter.

We also evaluate the effect of off-farm self-employment within the study area during the hunger season. We simulate the effect of a 50,000 CFA francs increase in the value of the household's agricultural, fishing and transport equipment, nearly doubling the current average value.

The different interventions are evaluated based on stochastic dominance criteria. To do so, we rank the households from the most vulnerable to the least vulnerable (i.e. based on $V^*_\alpha = V_{\alpha max} - V_\alpha$). This allows us to evaluate how successful the different interventions are in improving the situation of the most vulnerable.

Figure 2 depicts the effect of the different interventions on the cumulative density function of the probability of having more than the caloric threshold (V^*_0=1-probability

Figure 2: Effect of Policy Interventions on Cumulative Density Function of Probability of Having More than 2345 kcal/capita/day.



of shortfall =1-V_0). The baseline, as well as the perimeter and equipment interventions, dominate policies directed at simulating migration by second order stochastic dominance (SSD). Policies directed at encouraging temporary migration in case of shocks are ineffective at reducing food vulnerability.

The baseline and the irrigation and equipment interventions cannot be ranked further according to stochastic dominance criteria because none dominates in the lower tail – a necessary condition for SSD. Significantly, but unfortunately, this result suggests that these interventions do little to reduce the vulnerability of the most vulnerable.

This result seems counterintuitive as both interventions increase the ex ante mean and decrease the ex ante variance of a household's ex ante distribution of future consumption (see table 4), but it follows from the way in which vulnerability is measured. If a household faces a very high probability of shortfall (i.e. if the caloric threshold lies far to the right of the mode[34] of the household's distribution of future consumption), a decrease in the variance can, ceteris paribus, also lead to an increase in the probability of shortfall. If this decrease is not offset by the increase in the mean, a household's probability of shortfall, and thus its V_0 vulnerability, will actually increase. This results from the fact that the probability of shortfall measure does not account for a reduction in the degree of shortfall, which accompanies a reduction in the variance.

If we base our conclusions on vulnerability measures (such as V_1 and V_2), which account for the degree of shortfall, we attach greater weight to a reduction of the variance, and the stochastic dominance rankings are consistent with our intuition. For example, based on the V_1 measure, both the baseline and the policy of generalizing access to irrigated agriculture for all households dominate all other interventions by first order stochastic dominance (FSD). Improving access to equipment first order stochastically dominates the base line and the migration intervention by FSD. Therefore, they dominate by SSD as well. The base line and the migration intervention cannot be distinguished. Stochastic dominance analysis based on the V_2 measure yields similar conclusions (Christiaensen, 2000).

These rankings suggest that we can achieve reductions in food vulnerability more effectively by directly providing the population with secured employment opportunities during the hunger season in the area itself (either through irrigation agriculture or off-farm activities) than from promoting (temporary) out migration.[35] This finding lends

[34] The mode and the mean are equal in our case as we assumed a lognormal distribution.

[35] The vulnerability reducing effect of promotion of out migration might be underestimated, because the negative effect of a higher reliance on migrant remittances on the mean of the distribution of future consumption is statistically insignificant (see table 4). To examine this issue, we reestimated our model from

some empirical support to the proposition by Lipton and Ravallion (1995) that policies to encourage migration away from high risk areas to low risk environments are less desirable than policies focused on the provision of risk reducing inputs such as irrigation and the introduction of relief works schemes.

Interventions which facilitate access to irrigated agriculture and off-farm employment have both the potential to reduce substantially the number of food vulnerable households, and the *average* food vulnerability of the population. For example, generalized access to irrigated agriculture reduced average expected shortfall for the entire population by about 90 kilocalories/capita.

These findings provide some support for the development route taken in Zone Lacustre, which is largely focused on the promotion and construction of local irrigation infrastructure.[36] To realize the vulnerability reducing potential of irrigated agriculture, however, substantial investment must be made in extension and the development of a reliable input supply system. According to our results, the promotion of off-farm employment opportunities to diversify the household's income generating activities also has high potential to reduce vulnerability. This strategy has so far been largely neglected by the development community in our study area and deserves much more attention as a complementary development strategy. It might also be a cheaper strategy, as the start-up cost for perimeters is often substantial.

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table 4 excluding the income share from migrant remittance as a determinant of mean (log) consumption. The simulations based on this model confirm the earlier result

[36] Careful examination of the robustness of these results confirms the vulnerability reducing potential of irrigated agriculture (Christiaensen, 2000).

Summary and Conclusions

In this study, we develop a methodology to analyze and measure household food vulnerability, defined as the probability now of caloric shortfall in the future. Each household's ex ante distribution of future consumption necessary to calculate this probability is obtained from a flexible heteroskedastic regression specification, which allows us to predict the ex ante mean and variance of future consumption for each household, based on its current socio-economic characteristics.

Our methodology to measure vulnerability has several strengths. First, it proves to be an accurate tool to address issues of vulnerability, even with limited panel data. Second, the approach is related to the underlying causes of vulnerability, which facilitates policy analysis. Third, it could be easily adapted to study the vulnerability regarding a wide array of other variables such as income, total consumption, nutrition, etc.

In terms of the empirical results, we clearly show that current poverty and vulnerability constitute separate dimensions of well being and failure to account for food vulnerability might lead to substantial underestimation of a people's nutritional well-being. Even though "only" 37 percent of the households are undernourished at the post harvest time in our study area, 76 percent of the population had more than 50 percent chance of suffering from undernourishment during the subsequent hunger season.

There are several important results concerning the main socio-economic factors determining a household's food vulnerability. First, probably because children place larger food demands on the household than they contribute, food vulnerability increases unambiguously with the number of children in the household. They further reduce a household's flexibility to deal with income shocks. The fact that food vulnerability is lower in households that can temporarily place their children with relatives during times of food shortages, supports these conclusions.

Second, ours is also a third contemporary study – the other two are by Grootaert, et al. (1997) and Glewwe and Hall (1998) - which contradicts the conventional belief that female-headed households are more vulnerable. Due largely to the existence of basic community solidarity actions, female-headed households in our study are less vulnerable to widespread shocks.

Third, we find no evidence that formal education reduces a household's vulnerability, as suggested by Schultz's education hypothesis. This conclusion is not uncommon in other studies of rural areas.

Finally, average food consumption during the hunger season increases with the size of the household's harvest. Yet, the vulnerability reducing effect of good harvests decreases, the larger the income share derived from agriculture.

The policy implications of our simulation analysis are significant as well. We find that even though households relying more on migrant remittances face a smaller variance in their future consumption, there is little to be gained from policies which facilitate temporary out migration. There is more promise in public activities to enhance the diversity of income sources in the immediate area. By increasing the value of current agricultural, transport and fishing equipment, by twice the current population's average value, the proportion of vulnerable households can be decreased by about 10 percentage points. Such equipment, especially the fishing equipment, provides households with access to off-farm employment during the hunger season. However, recent development efforts in our study area have focused mostly on the expansion of irrigated agriculture, also a promising tool to reduce food vulnerability. Generalizing access to perimeters to all households could potentially reduce the number of vulnerable households by about 20 percentage points, but farmers have only just begun to experiment with this complex agricultural production technique. Thus, substantial extension efforts are needed to realize its full potential, as are efforts to effect timely provision and application of other inputs such as fertilizer, pesticides and water. Sufficient attention needs to be paid to the institutional organization of the supply - and also marketing - systems when complex agricultural production systems are introduced in societies characterized by low input agriculture and deficient transport and communication infrastructure. Otherwise, these efforts are bound to fail, despite their substantial potential for reducing vulnerability.

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