Toward an Understanding of Household Vulnerability in Rural Kenya

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Abstract:

Considerations of risk and vulnerability are key to understanding the dynamics of poverty. This study conceives vulnerability as expected poverty and illustrates a methodology to empirically assess household vulnerability using pseudo panel data derived from repeated cross sections augmented with historical information on shocks. Application of the methodology to data from rural Kenya shows that in 1994 rural households faced on average a 40 percent chance of becoming poor in the future. Households in arid areas that experience large rainfall volatility appear more vulnerable than those in non-arid areas, where malaria emerges as a key risk factor. Idiosyncratic shocks also cause non-negligible consumption volatility. Possession of cattle and sheep/goats appears ineffective in protecting consumption against covariant shocks, though sheep/goat help reduce the effect of idiosyncratic shocks, especially in arid zones. Of the policy instruments simulated, interventions directed at reducing the incidence of malaria, promoting adult literacy, and improving market accessibility hold most promise to reduce vulnerability.

1   Introduction

Worldwide consultations with the poor have revealed that they are preoccupied with dealing with risks and uncertainty, and their inability to effectively deal with shocks often lies at the core of their poverty (World Bank, 2001). This has renewed interest in examining the role of risk in the dynamics and causes of poverty (Dercon, 2004a). Policy makers are now increasingly aware that social risk management strategies should be an integral part of poverty-reducing strategies (Holzmann and Jorgensen, 2001).

Along with the renewed focus on risk and vulnerability in developing poverty-reducing policies, there is increased demand for empirical methodologies to measure and assess household vulnerability. As a result, a series of studies and empirical approaches toward measuring vulnerability[1] have been attempted, which differ essentially in their conceptualization of vulnerability (vulnerability as expected poverty (Christiaensen, 2000; Chaudhuri, 2003) versus vulnerability as expected utility (Ligon and Schechter, 2002)), their consideration of states of the world yielding non-poverty outcomes (included versus excluded) and the information base for their empirical application (cross-section versus panel data).

Given the complex nature of the risk environment and the dynamic nature of the consumption generating process, vulnerability assessments are prone to be data intensive, requiring multiple observations on the same households over time. Yet such information is mostly not available in developing countries, and when it is available, it is usually only for a small sub-sample of the population. This has motivated researchers to explore what can be learned about household vulnerability from analyzing cross-sections (Chaudhuri,

2003) and the effect of shocks on consumption (Glewwe and Hall, 1998; Dercon and Krishnan, 2000). This study extends these approaches in three ways. First, by applying pseudo-panel econometric techniques to repeated cross-sectional household consumption surveys, which are usually nationally representative and increasingly available in Sub-Saharan Africa, the study circumvents the usual absence of true panel data, while still exploiting some of the attractive features of panel data analysis, such as the ability to control for unobserved heterogeneity (Deaton, 1985; Verbeek and Nijman, 1993).

Second, even when panel data are available, they typically do not cover sufficiently long time periods to properly identify the stochastic nature of consumption, which is often related to locally covariant weather shocks such as droughts and floods. The study addresses this challenge by including information on the shocks themselves in the regression analysis and by combining the estimated effects of the shocks with historical information on their frequency and severity. Such information can be readily obtained from secondary sources (e.g. meteorological agencies), and the approach could be applied even when the time series are short. Third, the study goes beyond the construction of vulnerability measures and seeks to shed some light on the determinants of vulnerability, the relative contribution of idiosyncratic and covariant shocks, and the implications for policy. The empirical application is to rural Kenya.

The paper begins with a discussion of the concept of vulnerability and proceeds by laying out the empirical strategy to measure and analyze it. Next, it presents a descriptive overview of rural households in Kenya and the risks they face. This is followed by a discussion of the emerging vulnerability profile and the implications for

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[1] Christiaensen and Boisvert, 2000; Pritchett, Suryahadi, and Sumarto, 2000; Chaudhuri, Jalan and Suryahadi, 2002; Ligon and Schechter, 2003; Kamanou and Morduch, 2004

targeting. Finally, the paper discusses relative importance of the determinants of vulnerability together with the results of some vulnerability-reducing policy simulations. The last section concludes.

2 Concept of Vulnerability

Vulnerability of a person is conceived as the prospect a person has now of being poor in the future, i.e. the prospect of becoming poor if currently not poor, or the prospect of continuing to be poor if currently poor. Vulnerability is defined independently from the person's current poverty or welfare status. Yet, vulnerability and poverty are conceptually closely related. Poverty concerns the *ex post* realization of a stochastic focal variable (e.g. well being) with respect to a socially determined minimum threshold (poverty line), while vulnerability is the *ex ante* expectation of that focal variable relative to this threshold. In this approach, vulnerability is seen as expected poverty, akin to the safety-first risk measures developed by Fishburn (1977). In what follows, we take consumption as our measure of well being.

Formally, let $p_{it}(z, c_{it})$ be the poverty index for a person i at time t, defined over his consumption c_{it} and the poverty line z. The vulnerability level of person i at t with respect to his future consumption $(c_{i,t+1})$ can then be expressed as:

$$V_{it} = E[p_{it+1}(z,c_{it+1})|F(c_{it+1})] \tag{1}$$

$$= \int_{\underline{c}_{t+1}}^{z} p_{it+1}(z,c_{it+1})dF(c_{it+1})$$

$$= F(z) \int_{\underline{c}_{t+1}}^{z} p_{it+1}(z, c_{it+1}) \frac{f(c_{i,t+1})}{F(z)} dc_{it+1}$$

with $\underline{c}_{t+1}$ the lower bound of future consumption c_{t+1} and F(.) the cumulative distribution function associated with density function f(.). A person's vulnerability is measured as the current probability of becoming poor (F(z)), multiplied by the conditional expected poverty. Using the common Foster, Greer and Thorbecke (FGT) family of poverty measures as our poverty index $p_{it}(z,c_{it}) = [\max(0, \frac{z - c_{it}}{z})]^{\gamma}$, we can write (1) as:

$$V_{it\gamma} = F(z) \int_{\underline{c}_{t+1}}^{z} \left[\frac{z - c_{it+1}}{z} \right]^{\gamma} \frac{f(c_{i,t+1})}{F(z)} dc_{it+1} \qquad (2)$$

A person's vulnerability is measured as the product of the probability that a person's consumption falls below the poverty line (F(z)) times the probability-weighted function of relative consumption shortfall. Depending on γ, different aspects of shortfall are emphasized (Christiaensen and Boisvert, 2000). If $\gamma=0$, equation (2) simplifies to F(z), and vulnerability is measured as the probability of consumption shortfall ($V_{t,0}$). If $\gamma=1$, vulnerability ($V_{t,1}$) is measured as the product of probability of shortfall and the conditional expected gap. We account for the average depth of shortfall. By setting $\gamma>1$, we convert larger shortfalls into greater vulnerability, given the same conditional probability of occurrence, and account for the spread of the distribution of shortfalls. This is important given the detrimental and irreversible consequences of large consumption shortfalls.

While $V_{t,0}$ has a straightforward and intuitive interpretation, $V_{t,\gamma>1}$ is the preferred measure as $V_{t,0}$ does not account for the depth of shortfall and would allow policymakers to reduce vulnerability by shifting risks from the non-poor to the very poor. In the empirical application, we focus on the expected squared poverty gap ($V_{\gamma=2}$) as our measure of vulnerability, though we will also present findings using V_0 and V_1 given their intuitive appeal.

Other vulnerability measures proposed in the literature include vulnerability as the ability to smooth consumption measured by observed changes in consumption over time in response to shocks (Glewwe and Hall, 1998; Dercon and Krishnan, 2000) and vulnerability as expected utility (Ligon and Schechter, 2002). The consumption smoothing ability approach differs essentially from the expected poverty approach in that future consumption is evaluated using an internal threshold, i.e. the person's current consumption level, as opposed to an external threshold, i.e. a socially defined poverty line. As a result, people at the very bottom may not be considered vulnerable as they may not have experienced a large change in their consumption in response to a shock, even though small drops are likely to cause great damage (even death). At the same time, those among the non-poor who face a high probability of large adverse shocks (e.g. a person whose wealth is largely tied up in the stock market) resulting in large consumption changes may be considered vulnerable even though they are currently sufficiently well-off not to become poor in the face of such shocks.

Ligon and Schechter define vulnerability within the expected utility framework as $V_{it+1}=U_i(z)-EU_i(c_{it+1})$ thereby explicitly accounting for individual risk preferences through the choice of the utility function U_i. As indicated by Chaudhuri (2003) and

Calvo and Dercon (2004) the proposed vulnerability measure is in fact also a measure of expected poverty though with a different poverty index[2]. Vice versa, the expected poverty measure could also be interpreted within the expected utility framework. Their measure essentially differs from the expected poverty approach followed in this paper through: 1) its explicit consideration of risk preferences in evaluating vulnerability; and 2) its inclusion of states of the world when c_{it+1} exceeds z. Ligon and Schechter point out that the Foster-Greer-Thorbecke poverty measure P_2 is ill suited to represent risk preferences as it implies increasing absolute risk aversion.

Yet, for practical and ethical reasons we prefer not to interpret the vulnerability measures within the utilitarian framework. Arguably, application of the expected utility approach really makes sense only if one can actually estimate individual risk preferences. Decades of empirical research have shown that eliciting individual risk preferences is a daunting task in terms of both data and methodology, and standard risk analysis can severely overestimate risk aversion if observed risk response is entirely attributed to utility function curvature (Just and Pope, 2003).

More importantly, it is not obvious that risk attitudes, even if they could be elicited empirically, should be accounted for in evaluating people's expected poverty. While moral hazard behavior could rightly be invoked to justify inclusion of risk preference in vulnerability measures, individuals are often ill-informed about their preferences (Griffin, 1986) and, as Shackle (1965) and Kanbur (1987) point out, it is

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[2] To see this, let $p_{it}(z, c_{it}) = [u_i(z)-u_i(c_{it})]/|u(z)|$ with $u(.)$ an increasing function. Consequently, vulnerability as expected poverty is $V_{it}=Ep_{it}(z, c_{it}) = [u_i(z)-Eu_i(c_{it})]/|u(z)|$ which equals the vulnerability measure proposed by Ligon and Schechter when dropping the scaling factor $|u(z)|$. Given its desirable features in representing individual risk preferences, Ligon and Schechter use the CRRA utility function $u_i(c_{it})=[c_{it}^{(1-\gamma)}]/(1-\gamma)$ in their empirical application and $V_{it}= [1/(1-\gamma)]*[z^{(1-\gamma)}-E(c_{it}^{(1-\gamma)})]$. In contrast, we use $u_i(c_{it})=z^{\alpha}-[max(0,z-c_{it})]^{\alpha}$, resulting in $p_{it}(z,c_{it})= \{max[0,(z-c_{it})/z]\}^{\alpha}$, the familiar Foster-Greer-Thorbecke poverty index, and $V_{it} = E[(z-c_{it})/z]$.

hard to imagine that human knowledge can be so perfect that tomorrow's hunger or pain can be felt today. Acknowledging that people cannot fully anticipate nor appreciate the consequences of their choices, societies often develop rules and schemes which override their risk preferences (e.g. obligatory pension schemes). As a result, we prefer not to cast our vulnerability measure in an individual utilitarian framework, but rather like to think of a social planner who accounts for the depth of consumption shortfalls in a consistent and uniform manner across all individuals, irrespective of their risk preference, and set γ equal to 2.

We also opt not to incorporate states of the world in which c_{it+1} exceeds z, as this would violate the well-accepted focus axiom in poverty measurement. Incorporation of these states in the evaluation of a person's vulnerability may lead us to underestimate the person's vulnerability and generate a false impression of security as "negative" states of the world would be compensated by "positive" ones. To illustrate, consider two poor subsistence farmers A and B who are both poor today and highly likely to be poor tomorrow. They only differ in that A buys a lottery ticket each week with a probability smaller than 0.001 of a very large prize of 1 million US\$[3]. Is A indeed to be considered less vulnerable than B? Not in our approach.

3   Measuring vulnerability empirically

Empirical estimation of the vulnerability measure $V_{it\gamma}$ described in equation 2 implies a number of steps. First, we must define the time horizon over which we will assess the potential of future shortfalls. We focus on the probability that a person will

become poor one period ahead. Second, in assessing vulnerability we must choose an indicator of well-being. As indicated above, we take consumption as our indicator of well-being. Other indicators include educational achievements, health outcomes, and malnutrition. Third, a threshold for well-being must be defined (z), in our case a consumption poverty line. Fourth, to classify a person or a household in vulnerable and non-vulnerable group we also need to determine a probability threshold (θ) such that a person or household will be considered vulnerable if that person's probability of shortfall exceeds θ. In our study we assume this threshold to be 50 percent. Fifth, we must estimate an ex ante probability distribution ($f_t(.)$) of ex post consumption, the major challenge in determining a person's vulnerability empirically.

3.1 *Consumption generating process*

To draw inferences about a household's (or person's) future consumption prospects, we must obtain knowledge about the current endowments and risk factors of the household and its locality, and understand the household's stochastic income and consumption generating process[4]. Households reside in environments characterized by risks such as illness and death, weather related or natural shocks (droughts, floods and earthquakes), price fluctuations, terms of trade shocks, as well as theft and violence. These risk factors affect the level and variability of the household's endowments and income. In the face of these risks, households allocate their endowments to activities which generate income.

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[3] Example suggested by Calvo and Dercon (2004).
[4] We make abstract from intra household resource allocation and treat the household as an undifferentiated unit. For an overview of the theoretical and empirical literature on intra household resource allocation we refer to Haddad, Hoddinott and Alderman (1997).

Yet, it is unlikely that income maps one to one onto consumption as households try to protect their consumption from income shocks by engaging in consumption smoothing behavior (Deaton, 1992; Morduch, 1995). This can happen through asset depletion (Fafchamps, Udry and Czukas, 1998), through borrowing (Udry, 1995), participation in government insurance schemes such as public work programs (Ravallion, 1991, Subbarao,1997), activation of informal insurance networks (Townsend, 1994; Grimard, 1997), a reallocation of the labor supply to the labor market (Kochar, 1995), a temporal geographical reallocation of a household's labor supply (Lambert, 1994), a reconfiguration of spending patterns away from investment in human capital (Jacoby and Skoufias, 1997) or a combination of all of the above. Households engage in such consumption smoothing behavior ex post, after income has been realized.

However, conscious of their limited ex post consumption smoothing capacity, households often also reduce their risk exposure by smoothing their income ex ante. They diversify their income sources (Ellis, 1998) and engage in low risk, low return activities (Rosenzweig and Binswanger, 1993). In sum, the level and variability of a household's future consumption stream depend on the stochastic nature of the risk factors, the extent to which these affect its income (i.e. its risk exposure) and the capacity and desire of the household to protect its consumption from income shocks (i.e. their coping capacity). This suggests the following reduced-form expression for household consumption:

$$C_{ijt+1} = c(X_{ijt}, S_{ijt+1}, \phi_{t+1}, \theta_{ij}, u_{ijt}) \tag{3}$$

where X_{ijt} represents the bundle of observed household and locality characteristics of household i in locality j at time t. S_{ijt+1} represent observed locally covariant and idiosyncratic shocks (e.g. weather related shocks and illness respectively) experienced by the household between t and t+1. ϕ_{t+1} is a vector of parameters describing the returns to the locality and household endowments, and the effect of the shocks S_{ijt}. It reflects the overall state of the economy at time t+1. ϕ_{t+1} follows some stochastic process which is unaffected by the locally covariant shocks (e.g. rainfall) as this is explicitly controlled for (directly and through inclusion of interaction terms). In the remainder, we will assume ϕ_{t+1} constant. θ_{ij} and u_{ijt} are unobserved time invariant household and locality effects, and unobserved idiosyncratic shocks respectively, that contribute to differential welfare outcomes for households who are otherwise observationally equivalent.

Given the prevailing absence of well functioning credit and insurance markets in most developing countries (Besley, 1995), it is clear from (3) that household consumption will follow a stochastic process and that its stochastic properties will depend on the household characteristics and those of its environment (X_{ijt}) as well as the stochastic properties of the risk factors (S_{ijt+1}). In particular, we will assume that consumption is lognormally distributed.[5] This corresponds to what is typically found in the data. In addition, lognormal distributions are completely determined by two parameters: their mean and variance. It thus suffices to estimate the conditional mean and variance of a

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[5] This assumption could be relaxed by using a non-parametric approach akin to Kamanou and Morduch (2004). They use a Monte Carlo approach to simulate the distribution of future consumption, where the simulations are based on bootstrapping the empirical distribution of observable shocks and estimated residuals. However, while not strictly necessary, in their empirical implementation, they implicitly assume the same distribution of shocks for all households. This assumption is tenuous given that households face very different volatility in their consumption depending on their risk exposure and coping capacity. A heteroscedastic specification of consumption is called for. The lognormality assumption further permits us to examine how household and community characteristics affect the level and variability of consumption differently. This information is very useful from a policy perspective.

household's future consumption to obtain an estimate of its ex ante distribution and its vulnerability or expected poverty ($V_{it\gamma}$).

3.2   Econometric specification

Extending the approach followed by Just and Pope (1979) in examining how farm inputs independently affect the mean and the variance of farm production, we specify the demand function using the following flexible heteroskedastic form:

$$lnc_{ijt+1} = X_{ijt}\beta + S_{ijt+1}\gamma + S_{ijt+1}\varphi'X'_{ijt} + u_{ijt+1} \tag{4}$$

$$= X_{ijt}\beta + S_{ijt+1}\gamma + S_{ijt+1}\varphi'X'_{ijt} + \theta_{ij} + h^{1/2}(X_{ijt,};\alpha)* e_{ijt+1}$$

with $e_{ijt+1} \sim N(0, \sigma^2_e)$ and $\sigma^2_e=0$. The conditional mean and variance of (4) can then be expressed as:

$$E(lnc_{ijt+1} \mid X_{ijt}) = X_{ijt}\beta + E(S_{ijt+1})[\gamma + \varphi'X'_{ijt}] + E(\theta_{ij}) \tag{5}$$

$$V(lnc_{ijt+1} \mid X_{ijt}) = [\gamma + \varphi'X'_{ijt}]'V(S_{ijt+1})[\gamma + \varphi'X'_{ijt}] + \sigma^2_\theta + h(X_{ijt}; \alpha)*\sigma^2_e \tag{6}$$

This specification has several attractive features[6]. First, in contrast to traditional demand specifications which append the error term in an additive manner and assume the variance of the disturbance term of consumption to be constant across households, the heteroskedastic specification used here combined with the explicit modeling of the

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[6] The specification does not imply that the regressors X_{ijt} have to be the same in the mean and variance equations. In other words, exclusion restrictions on β for a particular X ($\beta=0$) do not imply a similar restriction for α and vice versa.

shocks allows the variance of each household's consumption to differ across households depending on their characteristics and those of its locality ($h(X_{ijt}; \beta)*\sigma^2_e$), the variance of the shocks the household faces $\gamma^2 V(S_{ijt+1})$ and the differential effect of the shock on the household $[\varphi'X'_{ijt}]'V(S_{ijt+1})[\varphi'X'_{ijt}]$.

Second, the flexible heteroskedastic specification used allows the marginal effects of the regressors on the ex ante mean and variance of future consumption to differ in sign (Just and Pope, 1979). This property is crucial to capture, for example, how the possession of assets facilitates consumption smoothing. Having more assets today decreases a household's ex ante variance of future consumption, while it increases its ex ante mean.

Third, by explicitly modeling the shocks, the variance of consumption can be decomposed in its idiosyncratic and covariant components, yielding important information in guiding the design of vulnerability reducing interventions. To illustrate, assume two uncorrelated observable shocks, an idiosyncratic one s_i and a covariant one s_c and fixed unobserved household and locality characteristics θ ($\sigma^2_\theta=0$). Consequently, the variance of consumption (6) can be decomposed (5') into: 1) the variance resulting from observed covariant shocks; 2) the variance yielded by observed idiosyncratic shocks, and 3) the variance from unobserved idiosyncratic shocks.

$$V(\ln c_{ijt+1} \mid X_{ijt}) = [\gamma_{sc} + \varphi_{sc}'X'_{ijt}]^2 \sigma^2_{sc} + [\gamma_{si} + \varphi_{si}'X'_{ijt}]^2 \sigma^2_{si} + h(X_{ijt}; \alpha)*\sigma^2_e \qquad (6)$$

Fourth, through inclusion of interaction terms between the characteristics of the household and its locality and the shocks, shocks are not forced to affect all households in

the same manner. This flexibility is important, as the effect of a shock on a household's consumption depends on its earnings structure and its consumption smoothing capacity. For example, the effect of a drought on a farmer's consumption clearly depends on the extent to which his fields are irrigated and the amount of assets he has at his disposal.

The power of the flexible consumption specification presented in (4) becomes readily apparent when investigating hypotheses regarding the role of small (goat/sheep) and large (cattle) livestock assets in alleviating household vulnerability. Because cattle are generally very productive, possession of cattle is assumed to increase mean consumption. Yet, cattle appear less effective in smoothing consumption both in the face of covariant (droughts) and idiosyncratic (illness) shocks due to their limited liquidity in poorly integrated livestock markets. It is thus hypothesized that possession of cattle increases a household's average consumption ($\beta_{cattle}>0$), while it does not affect the variance, either through its effect on the unobserved idiosyncratic variance ($\alpha_{cattle}=0$), or through its interaction with covariant shocks ($\varphi_{sc,cattle}=0$).

Sheep and goats on the other hand are assumed not to affect the mean ($\beta_{sheep}=0$), as they are less productive. However, they are more liquid than cattle and so more likely to smooth consumption against idiosyncratic shocks ($\alpha_{sheep}<0$). Yet, as livestock prices often collapse in the face of covariant shocks (drought) due to sharp declines in local demand and sharp increases in supply, especially when markets are poorly integrated, they are assumed to be ineffective in protecting household consumption from covariant shocks ($\varphi_{sc,sheep}=0$).

3.3 *Empirical strategy*

Using equations (5) and (6), we can estimate the ex ante mean and variance of a household's future consumption as a function of 1) its ex ante household and locality characteristics (X_{ijt}), 2) the mean, variance and covariance of the observed covariant and idiosyncratic shocks S_{ijt+1} which can be obtained from historical data and the survey itself, and 3) the regression parameters β, γ, φ, and α of the mean and variance equations.

To estimate the parameters β, γ, φ, and α, we assume that $h(X_{ijt};\alpha)$ is exponential with $E(u_{ijt+1} \mid X_{ijt}) = E(\theta_{ij})$ and $V(u_{ij,t+1} \mid X_{ij,t,}) = \sigma^2_\theta + \sigma^2_e * \exp(X_{ijt}'\alpha)$. The model reflects multiplicative heteroskedasticity and β, γ, φ, and α are estimated by a three-step heteroskedastic correction procedure (Judge *et al.*, 1988). In a first step, we obtain consistent estimates of β, γ, φ and α by an OLS regression of $\ln c_{ijt+1}$ on X_{ijt} and $S_{ijt+1.}$ Using the estimated error terms[7] $\hat{u}_{ijt+1} = \ln c_{ijt+1} - X_{ijt}\beta_{ols} - S_{ijt+1}\gamma_{ols} - S_{ijt+1}\varphi_{ols}'X'_{ijt}$ from the first step we obtain an estimate of the variance σ^2_{cijt+1} for each household by squaring $\hat{u}_{ijt+1.}$ Consistent estimates of α can then be obtained in a second step by regressing $\ln \hat{u}^2 ijt_{+1}$ on $X_{ijt.}$ In a third and last step we apply a weighed least squares regression of $\ln c_{ijt+1} * [\exp(X_{ijt}'\alpha_{ols})]^{-1/2}$ on $X_{ijt} * [\exp(X_{ijt}'\alpha_{ols})]^{-1/2}$ and $S_{ijt+1} * [\exp(X_{ijt}'\alpha_{ols})]^{-1/2}$ yielding efficient estimates of β, γ, φ.

From (4), it is clear that estimation of the parameters requires at least a two-period household panel. Estimation of the parameters is further complicated by the potential presence of $\theta_{ij,}$ which has been introduced to capture unobserved household heterogeneity, but could also be thought to represent measurement error related to $c_{ijt+1,.}$ Consumption is often measured with substantial error in developing countries. To

address potential biases in the estimated coefficients (β, γ, φ) arising from unobserved heterogeneity, a household level fixed-effects model could be applied that would require at least a three-period household level panel, which is unavailable for rural Kenya, and is unlikely to be available in most developing countries. Moreover, the within estimator used in fixed-effects panel data estimation exacerbates problems related to measurement error in the dependent variable, leading to overestimates of the variance.

Instead, we construct a pseudo panel by exploiting the fact that the cross-sectional household consumption surveys were conducted on repeated random samples from the same communities and apply the between estimator. Averaging the observations over households i in each community j in (4) yields:

$$\ln c^*_{jt+1} = X^*_{jt}\beta + S^*_{jt+1}[\gamma + \varphi'X^{*'}_{jt}] + \theta^*_j + h^{1/2}(X^*_{jt},;\alpha)^* e^*_{jt+1} \qquad (7)$$

where c^*_{jt+1} represents the population average of c_{ijt+1} over all households belonging to community j at t+1. The more homogeneous the groups, the more precise our estimates will be and the more the estimated parameters will resemble those obtained using the individual household observations. Analysis of our data suggests that depending on the variable, between 55 and 70 percent of the variation is explained by the variation across the communities, confirming the homogenous character of the communities.[8]

By averaging, the between estimator also substantially reduces potential overestimation of the variance of consumption due to measurement error; $V(\theta^*_j) = \sigma^2_\theta / n_j$ declines as n_j (the size of group j) increases. Pseudo panel econometric techniques

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[7] To represent estimated parameters, we use the subscript "OLS".

(Deaton, 1985; Verbeek and Nijman, 1993) can be used to control for unobserved heterogeneity. Due to data limitations (we only have two repeated cross sections with comparable consumption estimates, while a minimum of three would be needed) these have not been applied in this study[9].

By combining the estimated coefficients with the household and community characteristics (X_{ijt}) and the mean, variance and covariance of the shocks ($E(S_{ij})$, $V(S_{ij})$, $Cov(S_{ij},S_{kl})$ with $i \neq k$, $j \neq l$), we can predict the mean and variance of future consumption for each household and, assuming lognormality, estimate each household's vulnerability $V_{it\gamma}$.

4   Households in Kenya: Risk Factors, Risk Exposure and Coping Capacity

To empirically construct a vulnerability profile and examine the determinants of vulnerability, we use the 1994 and 1997 Welfare Monitoring Surveys. Household vulnerability depends on the nature of risks households face, their exposure to these risks and their consumption-smoothing capacity. These are closely linked to their livelihood systems. We distinguish between urban dwellers, rural subsistence farmers and pastoralists and focus in particular on rural subsistence farmers, which represent the majority of the Kenyan population. Among the rural subsistence farmers, we further distinguish between non-pastoralist farmers in the arid and the semi-arid zones and those

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[8] Other potential groupings using time invariant characteristics used in the literature but not explored here include age and location cohorts.

[9] This may lead to biased estimates of the mean equation coefficients if the unobserved characteristics are correlated with the observed ones. In practice however, population means will be replaced by sample means, and $\bar{\theta}_{jt+1}$ will vary over time because it will be averaged over different households in each time period. Consequently, potential bias induced by potential correlation between individual unobserved and observed characteristics will be mitigated as the averages will be obtained from (partly) different households.

in the non-arid zones. We measure and analyze vulnerability for each of these groups separately[10].

Households in rural areas were selected following a three-stage stratified sampling scheme.   Each district served as a stratum and was divided in the 1989 Census Enumeration Areas (1989 CEA).   The 1989 CEA were subsequently selected with probability proportionate to size and divided into segments (=clusters) of about 100 households following easily identifiable features such as roads, rivers, power lines, hills, and so on.   One cluster was selected out of each CEA and within each cluster 10 households were randomly chosen for the 1994 WMS and 12 for the 1997 WMS.   This resulted in a total of 981 rural clusters and 9,171 households in 1994 and 872 clusters and 8,960 households in 1997.   Both the 1994 and 1997 WMS data were collected on the same clusters. We exploit this feature of the data to construct a short panel of clusters or communities. In particular, we take 1997 as our point in the future (i.e. t+1) and 1994 as the current period (i.e. t).

The WMS contain modules on household demographics, occupation, health, education, housing amenities, assets, income, transfers and loans, expenditures, and distance to facilities. The 1994 WMS was conducted from June to August, the peak of the "hungry season" when most households experience severe shortfalls in the consumption of staple foods, and the 1997 WMS from April to June, the period following the harvests from the short rains, for those districts which enjoy two agricultural seasons and the onset of the hunger season, in those districts with one agricultural season.   We

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[10] Districts were considered as arid or semi-arid when annual rainfall was 612.5 mm or less in more than 75 % of the total arable land area. They are primarily located in the Eastern province and inland areas of the Coast province. Other districts were classified as non-arid.

complemented the WMS data with historical rainfall data which we merged at the district level.

Table 1 presents descriptive statistics across the households for the variables used in the analysis by non-arid and arid zones.[11] To examine the probability of future consumption shortfall we take regionally deflated average household expenditures per adult equivalent as our proxy of consumption, using the regional deflators and adult equivalent scales adopted by the Ministry of Finance and Planning, Kenya, 2000. Consistent with the Kenyan poverty report, we exclude expenditures for rent as they are mostly absent in rural areas, or marginal when paid.

A series of variables were used to proxy risks, risk exposure, and households' coping capacity. The main covariant and idiosyncratic risk factor for subsistence farmers in rural areas in Kenya are rainfall and health respectively (FEWS, 1995; Smith, Barrett and Cox, 2001).[12] Rainfall data were obtained from weather stations and matched at the district level. As climatic conditions are usually similar across a district, this is appropriate. In the absence of rainfall data for a particular district, rainfall was imputed from other districts based on their geographical proximity and their correspondence in historical rainfall patterns.[13] The rainfall shock was measured as the percentage deviation in 1996, the preceding agricultural year, from the historical average.

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[11] The regression parameters however were estimated using community averages of these variables across the community households. Where necessary, household averages were first calculated across the individual household members.

[12] Other risk factors include food price shocks and violence. Yet, as rainfall patterns and food prices are closely correlated and as physical violence has been especially affecting pastoralists in the arid districts neighboring Somalia and Sudan (FEWS, 1995) which have been excluded from our sample, omission of these factors is a lesser concern.

[13] District level rainfall data was available for slightly more than half the districts (25 out of 47) covered in the study.

In 1996, rainfall shocks across both non-arid and arid and semi-arid districts ranged from more than 60% below normal to slightly above normal, providing sufficient variation in the cross-section to identify the effect of negative rainfall shocks on consumption. Figure 1 further shows that historically both rainfall levels and fluctuations have varied widely across the districts and that average rainfall and coefficients of variations are strongly negatively correlated (correlation coefficient = -0.82). In other words, the challenges related to limited rainfall faced by households in drier areas are compounded by high rainfall variability.

 In considering health shocks, we focus on the exposure to malaria/fever, which accounts for more than half the reported sickness incidence in Kenya. On average 14 percent of the adult members in each household reported to suffer from malaria in the non-arid areas, while only 7.6 percent did so in the arid and semi-arid areas. This is not surprising as malaria incidence appears especially high in areas around water concentrations such as the Victoria Lake. Both zones also record a substantial variation in exposure among different households.

To eliminate potential correlation with unobserved community effects through simultaneity bias we use non self district averages in estimating the effect of illness on future consumption, i.e. the district average of community malaria incidence exclusive the concerned community. For similar reasons we used community information about malaria/fever incidence in 1994, which reflects exposure to sickness as opposed to actual incidence of fever/malaria experienced in 1997. The mean ($E(S_{ij})$) and variance ($V(S_{ij})$) of malaria incidence necessary to calculate each household's vulnerability were obtained by taking the mean and variance of adult malaria incidence in the household's

community over the 1992, 1994, and 1997 welfare monitoring surveys to also capture seasonal variation in malaria incidence.

To capture a household's risk exposure, we include proxies for land ownership, a dummy variable for fertilizer use, both indicators of the household's dependence on agriculture and rainfall, and several indicators of income diversification. In both arid and non-arid zones, households posses on average 1.5 acres per adult equivalent (or about 2.5 ha per household), though land is unequally divided, especially in the non-arid areas, reflecting the existence of plantations. Fertilizer forms a proxy for the overall level of production technology, though the quantities used are limited. The income share derived from non-agricultural activities (excluding pensions and transfers), amounts on average to about one-third of total household income. Given a larger set of observations we explore the role of non-agricultural activities in the non-arid zones in more detail, and look at the separate effect of the proportions of adults employed as unskilled public sector, as unskilled private sector, or as skilled private sector worker. We also include the share of income from pension, a relatively secured source of income.

We proxy the consumption smoothing capacity of households, by examining their demographic characteristics, their livestock possessions and community infrastructure. Larger households are often associated with higher poverty rates. Yet, depending on their age composition they may also be more flexible in reacting to shocks. In both the arid and non-arid zones, about a quarter of the households are headed by a woman and about 72 percent of the adult community is literate. Schultz (1975) hypothesizes that educated individuals are less vulnerable because they adapt more easily to changing circumstances, i.e. they have a greater ex post coping capacity, even though education does not

necessarily reduce their ex ante exposure to risks. The variable "animal possession" is measured by the average number of cattle and sheep/goats owned by the household. Animals are often seen as important assets to help smooth consumption especially in Asia (Rosenzweig and Wolpin, 1993; Kurosaki, 1995), though no conclusive supporting evidence has been reported for Africa (Fafchamps et al., 1998). From the means and distribution parameters in table 1, we see that animal ownership is unequal and more prominent in the arid than in the non-arid zones.

Community infrastructure is proxied by the average time spent to reach the food market, and access to electricity, which in 1994 was very limited in rural Kenya. Only 20 % of the communities had access to electricity and only 2 % of the households reported actually using electricity either for lighting or cooking. Time to reach the market is registered as a categorical variable with markets near the dwelling taking value one, those at 10 minutes taking value two, and so forth with those at 60 minutes or more taking value seven. In non-arid areas households find themselves on average about half an hour away from the market, while they are on average about 40 minutes removed from food markets in the arid zones. Lack of market integration prevents households from benefiting from overall economic growth (Christiaensen, Demery and Paternostro, 2004) as well as from insurance opportunities provided through the factor and product markets.

5 A Profile of Vulnerability of Non-Pastoralist Households in Rural Kenya

5.1 A profile of household vulnerability in 1994

To calculate each household's vulnerability ($V_{it,\gamma}$) we adopted the official poverty line which was set at 14,853 Kenyan Shilling (Ksh.) for rural Kenya in 1997 (Ministry of

Finance and Planning, 2000). [14] Table 2 presents the resulting vulnerability profile as observed in 1994.

In 1994, households faced on average a chance of 40 percent of falling below the poverty line in 1997 ($V_{0 \text{ total}} = 0.40$). Taking 50 percent as the vulnerability threshold (θ)[15], i.e. a household is classified as vulnerable if it has a chance of 50 % or more to fall below the poverty line in the future, we classify 26 percent of all households as vulnerable in 1994. Put differently, over a period of 10 years, holding 1994 socio-economic characteristics constant, about one-quarter of all households would be poor in at least 5 out of these 10 years. To obtain some idea about the depth of shortfall, we also calculated the expected gap (V_1) and the conditional expected gap (V_1/V_0) (not reported in the table). We find that households are expected to fall on average 2253 Ksh. below the poverty line (V1) and that if they fall below the poverty line, they would on average experience a shortfall of 5300 Ksh (V_1/V_0), which corresponds to a shortfall of 36 percent below the poverty line[16]. Thus, not only were 40 percent of all households to become poor, but also, once rendered poor they stood to suffer substantially. Households in rural Kenya are clearly vulnerable.

Further inspection of table 2 indicates that the vulnerability ranking of the arid and non-arid groups switches depending on the vulnerability measure. While the average probability of shortfall (V_0) is smaller in the arid zones, for the expected normalized gap squared (V_2) zones it is much larger. The latter result follows from the much larger variance of household consumption in arid zones due to the much larger rainfall

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[14] 1 US$=61.18 Kenyan Shillings (mean exchange rate on June 30, 1997)
[15] While any vulnerability threshold is ultimately somewhat arbitrary, 50 % appears as a natural focal point in that a household whose probability of falling below the poverty line (V_0) exceeds 0.5 is more likely than not to be poor in the future.

fluctuations and is consistent with our expectations, given the recurrent appeals for food aid in these regions, despite their higher observed average consumption (ln(cons)=10.74 versus 9.74). These findings underscore the critical importance of properly accounting for the depth of shortfall—as in V_2—when evaluating households' vulnerability. They also highlight that mere focus on poverty (as reflected by the mean) may be misleading and that the simultaneous consideration of both the level and volatility of household consumption is essential to properly target resources aimed at reducing future poverty.

Further decomposition of the variance into its sources highlights rainfall fluctuations as the overriding risk factor in the arid and semi-arid areas and malaria incidence as a key risk factor in the non-arid areas. Nonetheless, in both areas the contribution of idiosyncratic shocks to consumption volatility is substantial. Almost half of consumption volatility among households in non-arid areas arises from idiosyncratic shocks, and their importance in absolute terms is even larger in the arid and semi-arid areas—idiosyncratic shocks raise the standard deviation of log consumption on average by 0.67 and 0.43 standard deviations in arid and non-arid areas respectively. These results underscore the need for a differentiated approach to reducing vulnerability by agro-climatic zone and highlight the importance of uninsured idiosyncratic shocks as a key source of household vulnerability in addition to the vulnerability arising from the more commonly discussed covariant risk factors such as drought.

Disaggregating household vulnerability across administrative zones, we find households in the Coastal Province much more vulnerable, despite their larger consumption on average, than the Central Province. This result follows again from the much larger variance in the Coastal Province, mainly due to more variable rainfall

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[16] Recall that V_1 is the product of the probability of becoming poor and the conditional expected shortfall.

patterns, illustrating once again the interplay between the mean and variance of (log) consumption in determining a household's vulnerability. Household vulnerability in the other provinces is similar, apart from Rift Valley, where households are found to be slightly less vulnerable.

Headship of the household does not significantly affect household vulnerability, though households with more dependent members were found to be slightly more vulnerable, largely because of their lower average consumption. When classifying households by their occupational predominance, we find, somewhat surprisingly, subsistence farmers less vulnerable on average than unskilled workers, with unskilled private sector workers slightly more vulnerable than unskilled public sector workers, largely due to lower average earnings. Commercial farmers, skilled workers and business men appear on average less vulnerable, though these results need to be interpreted with caution given the small number of observations in each of these occupational categories.

5.2   *Determinants of Vulnerability in Non-Arid and Arid Rural Areas*

We now turn to the relative importance of the different factors contributing to vulnerability, i.e. the estimated coefficients on the determinants of the ex ante mean and variance of future consumption presented in table 3. Exposure to malaria emerges as the major risk factor for households in the non-arid zones, largely affecting average consumption, while households in drought prone areas are clearly unable to protect their consumption from rainfall shocks. This result echoes findings by Dercon (2004b) who traces lower economic growth paths among villages in Ethiopia back to the severity of

the drought in 1984-5. However, the importance of malaria as key risk factor has received much less attention.

Further exploration of the effect of drought shocks through interaction with possession of either goat/sheep or cattle (not reported) indicates that their presence in the household does not mitigate the effect of drought shocks. This is consistent with the lack of spatial integration of the Kenyan livestock markets and the resulting livestock price pattern reported by Barrett et al. (2001) – high and stable in good rainfall years and low and unstable in bad rainfall years. Livestock price fluctuations exacerbate rather than prevent entitlement losses during droughts. Similarly, Fafchamps, Udry and Czukas (1998) find livestock ineffective as insurance instrument against drought shocks in West Africa.

Landholdings and fertilizer use (a proxy for technology) positively affect average consumption in the non-arid areas, though not in the arid ones. Non-farm sources of income appear to be a promising risk-mitigating strategy for rural dwellers in the arid and semi-arid areas of Kenya; they enhance the mean and reduce the variance of (future) consumption, though the latter effect is estimated with less precision.[17] Ceteris paribus, access to non-farm employment also reduces households' vulnerability in the non-arid areas, especially for skilled private sector workers who experience on average a higher consumption and a lower variance. Unskilled private sector workers on the other hand tend to experience higher mean consumption, but also a higher variance, as they are less secure of their income. Pensions seem to serve a variance-reducing role in the non-arid

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[17] The Vulnerability Assessment done by FEWS (1995) writes that "with the exception of the two divisions in Siaya District, the most vulnerable subsistence farmers live in the semi-arid regions of eastern Kenya………the vulnerability of subsistence farmers in Kitui and Makueni districts is reduced by the high share of nonagricultural income in those districts." P. 8.

zones; the larger is the share of income from pensions, the lower is the variance. Pensions appear not to affect average consumption. Given the small number of recipients and the small size of pensions, this result is not surprising. We have not studied the role of pensions in the low-rainfall zone owing to small number of observations.

A large household size reduces average consumption per adult equivalent in the non-arid zones, thereby increasing vulnerability. It is well-known that families with many children are on average poorer. Yet, a larger family size is also associated with a decrease in the variance of future consumption. Many factors may be responsible for this result: for example, more family members (generous labor supply) contributes to greater flexibility and time savings in times of high economic activity; or during times of consumption stress, children may be drafted to contribute to income earning activities or temporarily placed with relatives. The larger is the dependency ratio, the larger is a household's vulnerability, as manifested by a lower mean and a larger variance of future consumption, though both results are estimated with large imprecision. When controlling for all other characteristics, female headed households do not emerge as more vulnerable. Finally, adult literacy has a mean enhancing effect on future consumption especially in the non-arid arid zones, though its effect on the variability of consumption is not statistically significant.   Thus, the vulnerability reducing effect of education works primarily through its effect on the mean and not the variance as suggested by Schultz's hypothesis.

We already indicated that small and large ruminants appeared ineffective as a buffer against covariant shocks. Yet, we do find that the possession of cattle increases mean consumption, especially in the arid and semi-arid areas where livestock rearing is a

key economic activity. The result (omitted) does not hold for small ruminants, presumably because they are generally less productive. Yet, small ruminants were found to be effective in protecting consumption from idiosyncratic shocks, especially in the arid areas. They are usually more liquid, and in the face of idiosyncratic shocks, lack of market integration is less problematic..

We find a large positive effect of access to electricity in improving the mean of future consumption. However, because of lack of variation[18], the effect is only statistically significant in the non-arid areas. Our results confirm that the time spent in reaching markets enhances households' vulnerability by reducing their average consumption, in both high and low rainfall areas, with the effect being four times larger in the arid than in the non-arid zones. Lack of infrastructure hurts both subsistence farmers (who are generally net buyers of food – often at higher prices because of poor infrastructure) and cash crop farmers who fail to deliver their goods to urban markets on time (thus sustaining income losses). It further impedes diversification out of low-yielding food crops into cash crops with higher market returns, locking subsistence farmers in low return but high risk food crop production, as illustrated by evidence from the Siaya district (Omamo, 1998).

6   Policies to Reduce Vulnerability

Vulnerability reducing policies either aim to eliminate the risk factors in the household's environment, mitigate the household's exposure to them, or strengthen its capacity to cope with them. We simulate in particular the vulnerability reducing effect of: (a) reducing the malaria/fever incidence, (b) enhancing off-farm employment

opportunities, (c) promoting literacy, and (d) reducing the time to reach the market (by improving rural infrastructure). We gauge the effect of these interventions by improving (i.e. reducing or increasing) the status of those households that score worse on the respective intervention variables, and compare the vulnerability measure V_2 pre- and post-intervention. We further decompose the overall change in vulnerability into the share contributed by changes in the mean and the variance.[19] The simulations are done separately for communities located in non-arid and arid zones.

In 1994, 52 percent of all households in the non-arid areas lived in communities with more than 10 % of the adults reporting suffering from malaria/fever. An intervention that succeeds in reducing the malaria/fever incidence to less than 10 percent in each community would reduce household vulnerability, as measured by V_2, by 22 percent (Table 4). A large part of the vulnerability reduction results from the reduction in the variance (9 out of 22 percent). Consequently, mere examination of the effect of a reduction in malaria incidence would lead us to seriously underestimate the benefits derived from this intervention. To estimate the eventual impact on consumption, we also calculated V_1 before and after the intervention and find that the average expected consumption gap declines from 2173 Ksh to 1838 Ksh. Clearly a policy that reduces malaria incidence must be an important component of a policy framework to reduce vulnerability.

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[18] In the arid and semi-arid zones, only six communities reported access to electricity.
[19] Let subscripts 1 and 2 represent the pre-and post intervention state and m and s denote the mean and standard deviation of consumption respectively. The share of change in vulnerability due to changes in the mean following the intervention is calculated as follows [{$V_\gamma (m_2,s_2)-V_\gamma (m_1, s_2)$} + {$V_\gamma (m_2,s_1)-V_\gamma (m_1, s_1)$}]/(2* $V_\gamma (m_1, s_1)$)]. Similarly, the share of change in vulnerability due to changes in the standard deviation following the intervention is calculated as: [{$V_\gamma (m_2,s_2)-V_\gamma (m_2, s_1)$} + {$V_\gamma (m_1,s_2)-V_\gamma (m_1, s_1)$}]/(2* $V_\gamma (m_1, s_1)$)].

Earlier we adopted different modeling strategies in arid and non-arid areas to estimate the effect of income diversification on vulnerability. Accordingly, we use different simulations for each area. We examine the vulnerability reducing potential of policies promoting income diversification in non-arid zones by assuming that at least 5 percent of all adult members in the household (or equivalently 5 % of the household's total adult labor time) were employed as skilled workers in the private sector and at least 10 percent as unskilled workers. This compares to the 1994 situation when 87 percent of all households had less than 5 percent of its adult members employed as skilled worker in the private sector and 79 % of all households spent less than 10 percent of their adult labor time as unskilled worker.

We simulate the effect of income diversification promoting strategies in the arid and semi-arid zones by ensuring that all households derived at least 25 percent of their income from non-agricultural activities. In 1994, this was not the case in about one-half of the households. Such an increase in income diversification by households in non-arid and arid areas would reduce their vulnerability on average by 8 and 7 percent, respectively, largely as a result of the positive effect on their average income. One important policy intervention to diversify sources of income as well as enhance access to markets (see below) is public workfare programs. Subbarao (2001) shows that there is much that countries in Sub-Saharan Africa can gain from the experience of public workfare programs in South Asia and Latin America.

Adult literacy campaigns also prove to be quite promising, especially in the non-arid areas. We find that if 75 percent or more of the adult members in each household were literate, household vulnerability would decline by 20 percent in the non-arid areas

and by 4 percent in the arid areas. Currently, less than three-quarters of the adults are literate in 38 percent of the households in the non-arid areas, and this percentage is about double in the arid areas. The policy would also bring the average expected consumption shortfall from 2,172 to 1,834 Ksh in non-arid areas and from 3,141 to 3,046 Ksh in arid areas. While clearly a lot could be gained from adult literacy campaigns to reduce household vulnerability, such policies prove less effective in arid areas than in non-arid areas. This may be related to the remote nature of the latter areas which results in less opportunities to valorize one's education.

Finally, we study the vulnerability reducing effect of improved market accessibility. Currently 44 and 58 percent of all households in the non-arid and arid zones, respectively, are at least half an hour removed from the market. Vulnerability in these zones would be reduced by 4 and 8 percent, respectively, if each community could reach its market within less than half an hour. Improving market accessibility arises as an important component of an effective vulnerability reducing policy in rural Kenya. As noted above, public workfare programs play an important role in improving access to markets.

In conclusion, while these results do not provide information on what interventions can achieve the simulated results nor their cost effectiveness, they do suggest that public policy can and should play a role in reducing vulnerability among rural non-pastoralist communities in Kenya. In particular, the appropriate mix of vulnerability reducing policies should include targeted interventions aimed at reducing malaria/fever incidence, campaigns to promote adult literacy and efforts to improve market accessibility. Promotion of income diversification, also emerges as an important

vulnerability reducing instrument. It further appears that improved market accessibility and off-farm employment generation hold more promise in the arid areas, while the non-arid areas might focus more on reducing malaria incidence and adult literacy campaigns.

7   Summary and Concluding Remarks

In this study we discussed the concept of household vulnerability and illustrated an empirical methodology to measure and assess household vulnerability. It showed in particular how repeated cross-sectional surveys augmented with historical information on shocks could be suitably used to assess household vulnerability by constructing pseudo panels and historical distributions of the shock.

Our estimated results show that in 1994 households faced on average a chance of 40 percent of falling below the poverty line in the future. Moreover, those becoming poor would on average experience a shortfall of 5,300 Ksh, or a 36 percent fall below the poverty line. Even though the average probability of suffering from consumption poverty was lower in the arid areas, when accounting for the depth of shortfall (as in V_2), households in arid areas appear much more vulnerable, mainly due to their larger exposure to rainfall shocks causing huge fluctuations in their consumption. Malaria emerges as the key risk factor in the non-arid areas. Decomposition of the variance further shows that a non-negligible part of consumption volatility arises from idiosyncratic shocks.

Together these results highlight the gains that can be obtained from directly including information on the shocks together with historical information on their distribution in the analysis. They further highlight that joint consideration of the

determinants of both the level and volatility of household consumption will be essential to develop appropriate strategies aimed at reducing poverty and targeting resources.

Important insights were gained regarding other determinants of vulnerability. Households with access to non-farm employment consume more on average, and tend to face less fluctuations in their income, especially in the arid and semi-arid areas. Possession of cattle is found to be ineffective in protecting households' consumption against both covariant and idiosyncratic shocks, but augments average consumption. Possession of goats/sheep, on the other hand, helps households smooth their consumption in the face of idiosyncratic shocks, though not against covariant ones. It does not augment consumption on average. Among the different structural factors that help households cope with consumption shocks, we identified the role of adult literacy, accessibility of the markets, and the availability of electricity. The effect of the latter is especially pronounced in the humid and sub-humid areas. Market accessibility promotes market integration, which permits a wider spatial distribution of more localized shocks. It substantially reduces transaction costs, thereby facilitating, for example, food and food aid flows, which stabilize and lower food prices, as well as temporary (urban) out-migration in case of droughts.

Of the various policy instruments we simulated, we found that policies directed at reducing the incidence of malaria, promoting adult literacy, and improving market accessibility could go a long way in reducing vulnerability in rural Kenya both in the non-arid and arid zones. For example, a reduction of the incidence of malaria in communities in the non-arid zones to a maximum of 10 percent would reduce average vulnerability among households by 22 percent, while bringing all households in the arid

zones within half an hour distance from a food market would diminish household vulnerability on average by 8 percent. Literacy campaigns achieving a 75 percent adult literacy rate across all households would reduce household vulnerability by 20 percent. Promotion of non-agricultural activities is also found to have important vulnerability reducing potential. With the right mix of policies, vulnerability can be substantially reduced among rural non-pastoralist households. Public workfare programs directed at generating access to markets could be an important part of such a mix. When properly designed, they provide insurance in times of stress through the generation of off-farm employment, while simultaneously making markets more accessible through the construction of infrastructure (e.g. roads).

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Table 1: Descriptive statistics on the risk factors, risk exposure and coping capacity of non-pastoralist households in rural Kenya in 1994

	Non-Arid				Arid and Semi-Arid			
	Mean	Std. Dev.	25 percentile	75 percentile	Mean	Std. Dev.	25 percentile	75 percentile
Dependent variable								
Real expenditure (Ksh) per adult equivalent 1997	16126	12196	8278	20229	16793	12930	8492	21484
Risk Factors[1]								
1996 rainfall shock (% deviation from historical average)	-0.16	0.15	-0.31	-0.02	-0.27	0.22	-0.61	-0.10
% adult members/household with fever/malaria during last 2 weeks in 1994	13.75	22.43	0.00	20.00	7.37	17.20	0.00	6.62
Risk Exposure								
Landholdings (acres) per adult equivalent in 1994	1.46	12.81	0.33	1.23	1.50	3.82	0.26	1.21
Fertilizer use (1=yes) in 1994	0.39	0.49	0.00	1.00	0.29	0.45	0.00	1.00
% adult unskilled public sector workers/household 1994	2.33	11.71	0.00	0.00	3.39	15.05	0.00	0.00
% adult skilled private sector workers/household in 1994	4.56	15.46	0.00	0.00	3.64	13.44	0.00	0.00
% adult unskilled private sector workers/household 1994	9.48	23.50	0.00	0.00	8.10	22.16	0.00	0.00
Income share from pensions in 1994	0.00	0.03	0.00	0.00	0.00	0.03	0.00	0.00
Income share from non-agricultural activities (exc. Pensions and transfers) in 1994	0.31	0.33	0.03	0.57	0.35	0.34	0.05	0.62
Coping Capacity								
Household size in 1994	5.61	2.80	4.00	7.00	5.43	2.73	3.00	7.00
Dependency ratio in 1994	0.52	0.23	0.40	0.67	0.52	0.24	0.40	0.67
Female headed household (1=yes) in 1994	0.27	0.44	0.00	1.00	0.26	0.44	0.00	1.00
% literate adults/household in 1994	72.33	35.67	50.00	100.00	73.59	37.13	50.00	100.00
# cattle owned per household	2.56	25.21	0.00	3.00	3.05	9.38	0.00	3.00
# goat/sheep owned per household	2.01	6.38	0.00	2.00	5.59	13.65	0.00	5.00
Use of electricity by household either for lightning or cooking (1=yes) in 1994	0.02	0.14	0.00	0.00	0.02	0.12	0.00	0.00
Time to food market (1= near dwelling, 2=10 minutes, …, 7= 60 minute or more)[1]	4.21	1.51	3.00	5.30	4.80	1.70	3.58	6.27
# observations	6538				571			

[1] Time to food market as recorded in 1997 WMS.

Table 2: Vulnerability profile in 1994 of non-pastoralist rural households in Kenya by location, demographics and employment

	#obser-vations	Prob. of shortfall (V_0)	Pro-portion $V_0 > 0.5$	Exp. Normalized gap squared (V_2)	Ratio V_2/V_2(tot)	Log cons. per adult equivalent		%variance due to		
						Predicted mean	Predicted standard deviation	Covariant rainfall shocks	Malaria incidence	Idiosyncratic shocks
Location										
Agro-climatic										
arid and semi-arid	567	0.33	0.03	0.16	2.03	10.74	2.47	0.89	0.01	0.10
non-arid	6,323	0.41	0.28	0.07	0.91	9.74	0.64	0.01	0.51	0.48
Province										
Central	1,424	0.30	0.08	0.04	0.49	9.90	0.56	0.02	0.39	0.58
Coast	534	0.45	0.42	0.13	1.61	10.09	1.48	0.29	0.36	0.35
Eastern	1,135	0.45	0.36	0.08	1.03	9.68	0.65	0.02	0.54	0.43
Nyanza	1,376	0.46	0.36	0.09	1.17	9.66	0.70	0.01	0.59	0.40
Rift Valley	1,642	0.36	0.17	0.08	1.05	9.97	0.98	0.23	0.34	0.44
Western	779	0.45	0.36	0.09	1.07	9.68	0.67	0.00	0.62	0.38
Demographic										
Male headed household	5,121	0.41	0.27	0.08	1.02	9.81	0.78	0.09	0.43	0.48
Female headed households	1,769	0.39	0.24	0.08	0.95	9.85	0.80	0.08	0.56	0.36
Dependency ratio ≤ 0.5	3,371	0.38	0.21	0.07	0.93	9.87	0.79	0.08	0.46	0.46
Dependency ratio > 0.5	3,519	0.42	0.31	0.09	1.07	9.77	0.78	0.09	0.48	0.43
Employment household head										
Commercial farmer	10	0.33	0.20	0.05	0.63	9.87	0.61	0.02	0.41	0.57
Subsistence farmer	876	0.36	0.19	0.07	0.84	9.89	0.76	0.08	0.42	0.51
Skilled public sector worker	73	0.40	0.29	0.08	0.94	9.77	0.71	0.02	0.46	0.51
Unskilled public sector worker	254	0.39	0.26	0.08	1.03	9.85	0.83	0.09	0.44	0.47
Skilled private sector worker	25	0.40	0.32	0.09	1.10	9.84	0.87	0.07	0.46	0.47
Unskilled private sector worker	4,233	0.42	0.31	0.09	1.10	9.77	0.80	0.09	0.48	0.43
Business man	9	0.35	0.22	0.05	0.68	9.88	0.60	0.02	0.42	0.57
Total	6,881	0.40	0.26	0.08	1	9.82	0.79	0.09	0.47	0.45

Table 3: Determinants of vulnerability in arid and non-arid zones in rural Kenya

	Non-arid zones		Arid and semi-arid zones	
	E(log(real exp97/ae)|Xt)	log [var log(real exp97/ae)|Xt)]	E(log(real exp97/ae)|Xt)	log [var log(real exp97/ae)|Xt)]
Risk Factors				
non self district mean proportion of adult members/hh w/fever/malaria during l/2 weeks 1994	-0.01565		-0.00858	
	(-5.35)**		(-0.25)	
1996 rainfall shock (% deviation from historical average)	-0.21096		4.08811	
	(-0.57)		(2.04)*	
1996 rainfall shock (% deviation from historical average) squared	-0.15437		6.72556	
	(-0.2)		(2.20)*	
Risk Exposure				
Landholdings (acres) per adult equivalent in 1994	0.00504		-0.01324	
	(1.87)		(-1.03)	
Fertilizer use (1=yes) in 1994	0.08846		-0.05259	
	(2.61)**		(-0.44)	
% adult unskilled public sector workers/household 1994	-0.00055	-0.03685		
	(-0.26)	(-2.09)*		
% adult skilled private sector workers/household in 1994	0.00445	-0.01525		
	(2.06)*	(-1.19)		
% adult unskilled private sector workers/household 1994	0.00229	0.0089		
	(1.62)	(1.39)		
Income share from pensions in 1994	-1.27475	-12.69468		
	(-1.62)	(-1.87)		
Income share from non-agricultural activities (exc. Pensions and transfers) in 1994			1.04153	-2.27298
			(4.05)**	(-1.53)
Coping capacity				
Household size in 1994	-0.03456	-0.11665	-0.01085	-0.6516
	(-2.78)**	(-1.58)	(-0.27)	(-2.62)*
Dependency ratio in 1994	-0.11491	0.22048	-0.4538	3.14773
	(-0.7)	(0.24)	(-1.03)	(1.26)
Female headed household (1=yes) in 1994	0.07288	-0.75882	0.30352	0.75233
	(0.89)	(-1.62)	(0.85)	(0.5)
% literate adults/household in 1994	0.00448	-0.0071	0.00386	0.01606
	(4.82)**	(-1.59)	(1.61)	(1.17)
# cattle owned per household	0.00331		0.01524	
	(1.51)		(4.13)**	
# goat/sheep owned per household		-0.03015		-0.09505
		(-1.33)		(-3.79)**
use of electricity by household either for lightning or cooking (1=yes) in 1994	0.59685		0.40501	
	(3.14)**		(0.88)	
Time to food market (1= near dwelling, 2=10 minutes, …, 7= 60 minute or more)[1]	-0.02468		-0.10913	
	(-2.45)*		(-4.32)**	
Constant	9.87315	-1.69729	10.26671	-1.26062
	(71.39)**	(-2.76)**	(26.86)**	(-0.79)
Observations	731	731	68	68
R-squared	0.26	0.03	0.87	0.34
F-value	15.56	2.18	28.54	5.23

Absolute value of t-statistics in parentheses; * significant at 5%; ** significant at 1%

Table 4**:** The vulnerability reducing effect of risk reducing, mitigation enhancing and coping power strengthening interventions for non-pastoralist households in rural Kenya

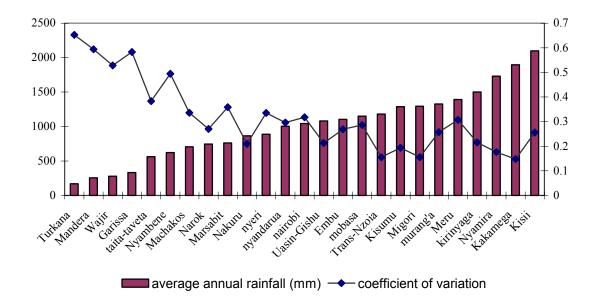| % change after intervention	Non arid zones			Arid and semi-arid zones		
	% decline in V_2	% decline due to reduction in the mean	% decline due to reduction in the variance	% decline in V_2	% decline due to reduction in the mean	% decline due to reduction in the variance
All households ≤ 10% malaria/fever incidence in their community during past 2 weeks	-0.22	-0.13	-0.09			
All non-arid households ≥5% of adult members as skilled worker in private sector and ≥ 10% as unskilled worker; all arid & semi arid households ≥ 25 % of income from non-agriculture activities	-0.08	-0.09	0.00	-0.07	-0.06	-0.01
All households ≥ 75 % of adult members literate	-0.20	-0.16	-0.04	-0.03	-0.04	0.02
All households within 30 minutes from market	-0.04	-0.04	0.00	-0.08	-0.08	0.00

Figure 1: Rainfall pattern by district in Kenya (1960-1990)

average annual rainfall (mm) — coefficient of variation