ESTIMATING DEVELOPMENT RESILIENCE: A CONDITIONAL MOMENTS-BASED APPROACH[*]

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Abstract: Despite significant spending on 'resilience' by international development agencies, no theory-based method for estimating or measuring development resilience has yet been developed. This paper introduces an econometric strategy for estimating individual or household-level development resilience from panel data. Estimation of multiple conditional moments of a welfare function—itself specified to permit potentially nonlinear path dynamics—enables the computation and forecasting of individual-specific conditional probabilities of satisfying a normative minimum standard of living. We then develop a decomposable resilience measure that enables aggregation of the individual-specific estimates to targetable subpopulation- and population-level measures. We illustrate the method empirically using household panel data from pastoralist communities in northern Kenya. The results demonstrate the method and its potential for targeting resilience-building interventions.

Keywords: Panel data, Poverty dynamics, Resilience, Risk

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I. INTRODUCTION

Over the past several years, natural disasters, food price and macroeconomic shocks, and conflict have prompted recurring humanitarian emergencies in many of the world's lowest income countries. In direct response, international development and relief agencies have become preoccupied with the concept of *resilience,* committing increasingly large amounts of funding, programming, and research toward "building resilience." They struggle, however, to develop methods to implement the concept empirically so as to guide policy and project design, measure progress, and evaluate interventions. At the same time, the concept of development resilience has the potential to draw together the strengths of several distinct economics literatures on the estimation of stochastic well-being dynamics. The opportunity is thus ripe for methodological contributions to help advance both operational and research agendas.

In his seminal work on poverty measurement, Sen (1979) discusses the need for both poverty "identification" (i.e., determining who is poor) and "aggregation" (i.e., establishing how characteristics of the poor can be combined into an aggregate indicator) to guide policy. The emergent development resilience agenda has similar measurement needs. Toward that end, we introduce an econometric strategy to estimate individual or household-level development resilience, so as to identify the targetable characteristics of those who are (and are not) resilient, and then demonstrate how to aggregate those micro-level estimates into policy-relevant measures useful for targeting and impact evaluation purposes. This approach usefully synthesizes the distinct poverty dynamics, risk, and vulnerability literatures active within economics more broadly.

We follow the Barrett & Constas (2014, p.14626, hereafter BC) conceptualization of development resilience[1] as "the capacity over time of a person, household or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks. If and only if that capacity is and remains high over time, then the unit is

[1] Although the term is the same, different fields employ different concepts of 'resilience.' See Folke (2006) for a nice review of the concept in the ecology and engineering literatures and Barrett & Constas (2014) for a discussion of why that concept must be adapted for international development or broader economic applications.

resilient." By couching resilience in terms of stochastic well-being dynamics, BC point towards a definition that can be implemented empirically. To do so, we draw on the risk literature to estimate multiple conditional moments of a welfare function specified, following the poverty traps literature, to include potentially nonlinear path dynamics. Like the vulnerability literature, the aim is a forward-looking, probabilistic measure of well-being that can be used for targeting and program evaluation. Then, like the poverty measurement literature, we demonstrate how the individual-specific estimates can be aggregated into a decomposable measure useful for policy and operational purposes, such as targeting scarce resources or evaluating the potentially-heterogeneous impacts of policies and programs on different sub-populations.

We close by illustrating the method with an empirical example using household panel data from pastoralist communities in northern Kenya. The results demonstrate the method's potential for identifying who is and is not resilient and when, as well as for generating aggregate measures of development resilience. We also briefly discuss prospective extensions of this approach to impact evaluation, multidimensional well-being measures, more sophisticated estimation of the underlying conditional moments, and the data needs to permit more widespread empirical implementation of such methods.

II. Development Resilience Estimation

Despite a growing, primarily non-economic, recent literature on development resilience (e.g., Cannon & Müller-Mahn 2010, Robinson & Berkes 2010, Davoudi 2012, BC, Béné et al. 2014, Levine 2014, d'Errico & Pietrelli 2017, Smith & Frankenberger 2018), no peer-reviewed, theory-grounded measures[2] have been proposed and applied empirically in the development context. The BC approach suggests a path forward based on integration of several distinct empirical literatures in economics. BC explicitly motivate their approach from the poverty dynamics and traps literatures that emphasize the possibility of nonlinear well-being dynamics and asset-based poverty traps (Carter & May 2001; Lybbert et al. 2004; Carter & Barrett 2006; Barrett & Carter 2013; McKay &

[2] Several atheoretical empirical papers have emerged in the grey literature, for example, Alinovi, Mane, & Romano (2010), Smith et al. (2015), Vaitla et al. (2012), Alfani et al. (2015), and Vollenweider (2015).

Perge 2013). However, that literature focuses largely on *ex post* analysis of well-being. The vulnerability literature (e.g., Christiaensen & Boisvert 2000; Pritchett et al. 2000; Chaudhuri, Jalan, & Suryahadi 2002; Hoddinott & Quisumbing 2003; Ligon & Schechter 2003), on the other hand, emphasizes probabilistic *ex ante* measures, although it overlooks the prospective importance of nonlinear path dynamics. But it is unnecessary to forsake dynamics in order to generate forward-looking estimates. BC's definition implies that an economic measure of development resilience ought to be both probabilistic (building on the vulnerability literature) and allow for the possibility of nonlinear well-being dynamics (as per the poverty traps literature). By tapping established methods for estimating conditional moment functions, as developed in the empirical risk literature (Just & Pope 1979, Antle 1983), we offer an approach to estimating probabilistic *ex ante* well-being dynamics. Then by adapting the seminal work of Foster, Greer & Thorbecke (1984, hereafter FGT), we can turn the individual estimates into aggregate measures decomposable into subgroups that naturally lend themselves to targeting for policy and project interventions. We emphasize that none of the component methods we use are original; the novelty of the method arises from their integration into implementable, theory-based measures of development resilience.

BC represent development resilience using a conditional moment function for well-being, specifically $m_i^k\left(W_{i,t+s}\middle|W_{it},\boldsymbol{X}_{i,t+s},\epsilon_{i,t+s}\right)$, where m_i^k is the k^{th} moment of individual i's well-being, W, in period $t+s$ (for $s>0$), a function of well-being in period t, a set of individual-, household- and community-level covariates, $\boldsymbol{X}$, and random disturbances, ϵ. An individual's well-being is therefore considered a random variable, with its own distribution in each period. One might use any of a host of well-being measures, depending on the context, from stock measures such as asset holdings or anthropometric indicators of health status to flow measures such as expenditures or income. The convention in the empirical poverty traps literature is to estimate only the first moment, the expected path dynamics of well-being, but to allow for potentially nonlinear path dynamics, as reflected either in a high-order polynomial in W_t (Lokshin & Ravallion 2004, Barrett et al. 2006, Antman & McKenzie 2007) or nonparametric or semiparametric estimation of a first-order Markov process (Lybbert et al., 2004; Adato, Carter, & May 2006; Naschold 2013).

Allowing for potentially nonlinear path dynamics is essential in studying development resilience, for two fundamental reasons. First, while an active academic literature debates how widespread poverty traps are,[3] the places where development organizations have focused on resilience are precisely those areas where even the scholars most skeptical of poverty traps concede the evidence in favor of poverty traps is strong. For example, Kraay & McKenzie (2014) concede that poverty traps would most likely be found among "poor households in remote rural regions" (p. 143) and also in crisis situations, i.e., precisely the populations and circumstances that motivate resilience as a domain of study and programming. Second, a specification that allows for the possibility of poverty traps can accommodate nonlinear persistence of shocks, which is essential to identify potentially heterogeneous, wealth-dependent responses to a covariate event such as flood, drought, or conflict. Such heterogeneity is one of the central targeting challenges in resilience programming.

To date, however, the poverty traps literature has largely ignored heteroscedasticity and other non-constant higher-order central moments in estimated path dynamics. The standard approach in the vulnerability literature, by contrast, is to estimate both the conditional mean and the conditional variance but to ignore prospective nonlinearity in the path dynamics by assuming, at best, a linear first-order autoregressive process (although in fact often estimated using cross-sectional data). The development and humanitarian agencies' current focus on resilience originates in the intersection of vulnerability to shocks and the apparent existence of poverty traps among the remote (commonly drylands pastoralist) populations on which much of the resilience discourse focuses. Even in the absence of poverty traps, nonlinear path dynamics may indicate differences in returns to assets for relatively asset-rich and asset-poor households, impacting the resilience of asset-poor households and their ability to quickly escape poverty. So it seems sensible to take an approach to measurement that integrates the distinct strengths of each of these two literatures, as BC's theory allows.

[3] For contrasting views, see Barrett and Carter (2013) and Kraay and McKenzie (2013). For a current summary of the literature, including how catastrophic shocks may generate psychosocial effects that reinforce the poverty resulting from adverse events, see Barrett, Carter and Chavas (2018).

We model the mean (indicated by the *M* subscript) stochastic well-being of individual or household *i* (household hereafter because in our empirical illustration we use a household-level indicator of well-being) in period *t* (W_{it}) parametrically as a polynomial function (g) of lagged well-being ($W_{i,t-1}$), and a vector of household characteristics, $\boldsymbol{X_{it}}$, including shocks directly experienced by *i* or risks to which *i* is exposed:

(1) $$W_{it} = g_M(W_{i,t-1}, \boldsymbol{X_{it}}, \beta_M) + \boldsymbol{\delta}_{\mathbf{M}}\boldsymbol{X_{it}} + u_{Mit}.$$

We assume a first-order Markov process for both conceptual and practical reasons. Conceptually, a lag is necessary to allow for persistence in the impact of previous period well-being on the future. At the same time, well-being (like wealth) is a state variable which summarizes all prior states, meaning only one lag is necessary. Empirically, incorporating a second lag would decrease the number of rounds of panel data available for analysis; the use of a single lag is economical while also addressing possible autocorrelation in the errors of the panel data. A cubic specification would be the most parsimonious parametric specification that allows for the S-shaped dynamics typical of systems characterized by multiple equilibria poverty traps (Barrett et al. 2006), although higher order polynomials may be used.

Using E to represent the expectation operator, a caret (^) to represent predicted values, and assuming that the random error term u_{Mit} is mean zero ($E[u_{Mit}] = 0$), the conditional mean for household *i* at time t (μ_{1it}) can be written

(2) $$\text{Conditional Mean: } \hat{\mu}_{1it} \equiv \hat{E}\left[W_{it} | W_{i,t-1}, \boldsymbol{X_{it}}\right] = g_M(W_{i,t-1}, \boldsymbol{X_{it}}, \hat{\beta}_M) + \widehat{\boldsymbol{\delta}}_{\mathbf{M}}\boldsymbol{X_{it}}.$$

Following Just & Pope (1979) and Antle (1983), and using a subscript *V* to indicate variance, the population second central moment can be expressed:

(3) $$\sigma_{it}^2 = g_V(W_{i,t-1}, \boldsymbol{X_{it}}, \beta_V) + \boldsymbol{\delta}_{\mathbf{V}}\boldsymbol{X_{it}} + u_{Vit}.$$

We can then use the mean zero squared residuals from equation (1), $\hat{u}_{Mit}$, to estimate the second central moment equation. Under the standard assumption that $E[u_{Vit}] = 0$, we can estimate the conditional variance for household *i* at time t ($\hat{\mu}_{2it}$) as:

(4) Conditional Variance: $\hat{\mu}_{2it} = \hat{\sigma}_{it}^2 = g_V(W_{i,t-1}, \boldsymbol{X_{it}}, \hat{\beta}_V) + \boldsymbol{\hat{\delta}_V X_{it}}$.

The empirical strategy, discussed below, should take into consideration that the conditional variance must be non-negative. One can accommodate this either by using the log of $\hat{\sigma}_{it}^2$ as the dependent variable in (4) or by making particular distributional assumptions that impose non-negativity.

If one is prepared to make the strong assumption that $W_{i,t-1}$ is distributed normally, lognormally, or gamma, these two predicted conditional moment estimates, $\{\hat{\mu}_{1it}, \hat{\mu}_{2it}\}$ suffice to describe household i's conditional well-being distribution at time t. It would be relatively straightforward to relax the distributional assumption and compute higher-order central conditional moments, such as skewness (μ_{3it}) or kurtosis (μ_{4it}), to accommodate asymmetries or peakedness, respectively, in a more general distribution. Accommodating more moments is somewhat more demanding computationally, but tractable for a range of distributions. For example, a generalized (four-parameter) beta distribution is a highly-flexible, unimodal distribution that could be estimated off of four estimated conditional central moments. In order to identify the household-specific distribution parameters, one could then use the method of moments, as described by Bury (1999). In the interests of brevity we impose a gamma and a lognormal distribution in the empirical illustration below and leave extension to higher-order moments to future work.

The assumed distribution functional form and the estimated moments jointly enable estimation of the household-and-period-specific conditional well-being probability density function and associated complementary cumulative density function (ccdf).[4] Once we have estimated the household-and-period-specific ccdf, we can use it to estimate

[4] An alternative approach would be to use moment generating functions (MGF) to identify the underlying conditional distribution functions, without assuming a particular distribution function. But while the MGF approach holds appeal in theory because it is less restrictive, in practice it can be difficult to identify a distribution function of unspecified form without a very large data set. In small data sets, the MGF approach often results in imprecise measures of the tails of the distribution, which are of particular concern in our case, as we explain below. To avoid these challenges, we assume a functional form for the underlying well-being distribution.

the probability of household *i* reaching some normative minimum standard of well-being in time *t*. We follow the BC framework, defining development resilience (ρ) as the probability that household i will have well-being in period t above some normative threshold, $\underline{W}$. For the time series defined by $s \geq 0$, we can therefore define a household's development resilience as the estimated complementary cumulative probability based on the sequence of estimated probabilities: $(\hat{\rho}_i)_{s=1}^{T}$ where

$$(5) \qquad \hat{\rho}_{is} \equiv P\left(W_{i,s} \geq \underline{W} | W_{i,s-1}, \boldsymbol{X}_{i,s}\right) = \bar{F}_{W_{i,s}}\left(\underline{W}; \hat{\mu}_{1i,s}(W_{i,s}, \boldsymbol{X_{i,s}}), \hat{\mu}_{2i,s}(W_{i,s}, \boldsymbol{X_{i,s}})\right),$$

where $\bar{F}(\cdot)$ is the assumed ccdf.

So what is the difference between vulnerability and this measure of development resilience? Of course, several estimation approaches have been proposed for operationalizing the concept of vulnerability (e.g., Christiaensen & Boisvert 2000; Pritchett et al. 2000; Chaudhuri, Jalan & Suryahadi 2002; Ligon and Schechter 2003). Each of those measures attempts to estimate the probability of well-being beneath some normative standard in a single future period. By subtracting $\hat{\rho}_{is}$ from 1, we could estimate vulnerability from our development resilience measure in a way that is theoretically consistent with Chaudhuri, Jalan & Suryahadi (2002). The primary difference with our method is that the inclusion of nonlinear path dynamics means that development resilience provides a potentially nonlinear, time-varying measure of vulnerability, represented as $1 - \hat{\rho}_{is}$, as we illustrate below. One can then use the time sequence of resilience estimates to estimate transition probabilities into or out of poverty conditional on one's characteristics and immediate pre- or post-shock welfare measure, an important refinement – especially for targeting – that is infeasible in existing vulnerability measures.

We can use this estimate of resilience to evaluate the impact of specific characteristics or programs today on the development resilience of households (or other units, such as individuals) at time t: $\partial\hat{\rho}_{it}/\partial X_{it}$. We empirically estimate this derivative as follows, using a subscript *R* to indicate resilience:

$$(6) \qquad \hat{\rho}_{it} = g_R(W_{i,t-1}, \boldsymbol{X_{it}}, \beta_R) + \boldsymbol{\delta}_{\mathbf{R}}\boldsymbol{X_{it}} + u_{Rit},$$

where $\hat{\rho}_{it}$ indicates the estimated probability of household *i* meeting or exceeding the normative well-being threshold $\underline{W}$ at time t.

Although same-period household development resilience can be calculated as described in (5), it is also possible to forecast household development resilience forward by computing it recursively and by updating any elements of $\boldsymbol{X_{it}}$ known to change over the forecast period (e.g., age or season). This computation replaces the lag with current period (realized) well-being W_{it}, employs the estimated coefficients $\hat{\beta}$ from (2) and (4) above and requires making only a few assumptions on the progression over time of household characteristics and shocks ($\ddot{\boldsymbol{X}}$):

(7) $$\hat{\rho}_{i,t+1} \equiv P\big(W_{i,t+1} \geq \underline{W} | W_{it}, \boldsymbol{X}_{i,t+1}\big) = \bar{F}_{W_{i,t+1}}\big(\underline{W}; \hat{\mu}_{1i,t+1}, \hat{\mu}_{2i,t+1}\big)$$

where $\hat{\mu}_{1i,t+1} = g_M(W_{it}, \ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}, \hat{\beta}_M) + \hat{\boldsymbol{\delta}}_{\mathbf{M}}\ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}$ and $\hat{\mu}_{2i,t+1} = g_V(W_{it}, \ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}, \hat{\beta}_V) + \hat{\boldsymbol{\delta}}_{\mathbf{V}}\ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}$. For periods beyond $t+1$, the household's lagged well-being should be drawn at random from the previous period's well-being distribution. This approach could also be used to simulate resilience responses to shocks by including various simulated shocks in $\ddot{\boldsymbol{X}}$.

The continuous measure, $\hat{\rho}_{it}$, can also be used to categorize a household as resilient or not resilient with reference to some normative minimal threshold probability, $\underline{P}$, at/under which we consider a household's probability of reaching or surpassing $\underline{W}$ (the minimum adequate well-being level) intolerably low. Iff $\hat{\rho}_{it} \geq \underline{P}$ then we classify household *i* as development resilient in period t. Then the $\hat{\rho}_{it}$ estimates can be turned into a dichotomous variable, θ_{it}, that takes value one if the household is deemed resilient and zero if it is not. That is,

(8) $$\theta_{it} \equiv \begin{matrix} 1 \; if \; \hat{\rho}_{it} \geq \underline{P} \\ 0 \; otherwise \end{matrix}.$$

The θ_{it} variable can be analyzed in the same way as binary poverty or other indicator variables.

A number of extensions to this approach follow reasonably directly. First, one could use interval criteria defined by two normative cut-offs in *W* space, as might be appropriate, for example, for an indicator such as body mass index for which values beneath one critical value (i.e., underweight) or above a different critical value (i.e., overweight) both signal an undesirable state of well-being. For such criteria, one simply replaces the ccdf in equation (5) with difference in the cumulative densities between the two thresholds.

Second, we can extend this approach to multidimensional well-being by joint estimation of equations (1) and (3), so as to enjoy efficiency gains in the estimation of each well-being metric's conditional moments. Then one would need to determine whether the normative criterion for a *j*-dimensional measure requires satisfaction of the minimum standard in *each* dimension *j* (i.e., $\hat{\rho}_{it}^{j} \geq \underline{P}^{j} \; \forall \, j$) – the intersection of the unidimensional criteria – or just in *any* dimension (i.e., $\hat{\rho}_{it}^{j} \geq \underline{P}^{j} \; for \; some \; j$) – the union of the unidimensional criteria.

There are also multiple prospective practical uses of the sequence $(\rho_i)_{s=0}^{T}$ in support of operational efforts to build resilience. First, if an element of the ***X*** vector is plausibly exogenous (e.g., a weather shock, a randomized policy intervention), then one can identify associated changes in the estimated probabilities, as reflected in the corresponding element of the $\boldsymbol{\delta}_{\mathbf{R}}$ vector, as causal and rigorously evaluate claims of "resilience building" using established inferential methods. We illustrate such inferential uses of this approach in the empirical example below.

Second, operational agencies routinely need to target interventions, whether by recipient characteristic, seasonal or geographical characteristics, or some other covariate. For this purpose, the associations in the $\boldsymbol{\delta}_{\mathbf{R}}$ vector can prove useful even if they cannot be interpreted as causal because the relevant elements of the *X* vector are potentially endogenous. Indeed, the ability to generate *s*-period-ahead estimates, $\hat{\rho}_{it+s}$, enables one to establish which period *t* (i.e., current) covariates are most strongly and statistically significantly correlated with that forward-looking measure. Moreover, this approach offers the possibility to improve prediction if there are predictable intertemporal patterns such as arise from path dynamics in the underlying well-being variable. Relative to the prevailing approach of assuming current (i.e., period *t*) values will equal future values in the absence of intervention – equivalent to assuming a random walk process in the *W* variable – to predict *s*-period-ahead values, this new method may achieve significant forecasting gains. Moreover, by adjusting $\underline{P}$ an operational agency can choose which sort of targeting errors it favors, errors of exclusion or of inclusion, as we demonstrate below. The prevailing approach does not allow that sort of tailoring of targeting strategies (Upton, Cissé and Barrett 2016).

Third, using appropriate discount rates, the sequence $(\rho_i)_{s=0}^{T}$ might be added up over time, providing a discounted, intertemporal measure of resilience similar to Calvo & Dercon's (2007) measure of chronic poverty. By aggregating our development resilience measure over time, one could assess the long-run impacts of shocks or policies. This type of intertemporal measure could also be used as a state variable in a dynamical system, allowing for development resilience analysis in coupled human-natural systems (Barrett & Constas 2014).

Finally, these measures can be used to identify development resilience indicators at more aggregated scales of analysis. We now turn to this task of development resilience aggregation, to follow Sen's (1979) term, which represents a straightforward adaptation of today's workhorse FGT class of decomposable poverty measures to the individual measures just introduced.

III. DEVELOPMENT RESILIENCE AGGREGATION

Sen describes the aggregation process as "some method of combining deprivations of different people into some over-all indicator" (Sen 1979, p.288). While the approach discussed in Section II allows us to identify the level of development resilience of a specific unit (such as an individual or household), we would also like to summarize the development resilience of the micro units into one overall sub-population or population-level resilience measure, the aggregate resilience index R.

Even before Foster, Greer, & Thorbecke (1984) proposed a class of decomposable poverty measures, now known simply as the FGT poverty measures, certain desirable attributes for poverty measures had been discussed in the literature. Sen (1976) highlights some of the shortcomings of the headcount ratio, such as its violation of the monotonicity and transfer axioms.[5] Sen proposed a poverty measure that meets additional desirable characteristics he sets out, including "relative equity,"[6] and conveniently lies between 0 and 1. Sen also argues that a poverty measure would ideally combine "considerations of absolute and relative deprivation even *after* a set of minimum needs and a poverty line have been fixed" (Sen 1979, p.293).

Another desirable feature of any aggregate measure is the ability to attribute shares of the overall development resilience indicator to various subgroups. The population-weighted sum of the subgroup measures would therefore equal the measure for the whole group. While the measure proposed by Sen is not decomposable in this way, FGT (1984) proposed an entire class of decomposable poverty measures and illustrated how the measures meet Sen's (1976, 1979) various axioms. The FGT (1984) poverty measures serve as a logical jumping off point in the search for an additive development resilience measure that meets Sen's axiomatic requirements.

As a quick refresher, for a vector of household incomes, y, ordered from lowest to highest, poverty line $z > 0$, and income gap $g_i \equiv z - y_i$, there are q households in a population of size n at or below the poverty line. FGT (1984) proposed the measure $P_\alpha(y;z) = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{g_i}{z}\right)^\alpha$, which meets the Sen criteria and is additively decomposable with population share weights for different subpopulations of n. When $\alpha = 0$ this is equivalent to the headcount ratio, when $\alpha = 1$ this is equivalent to the poverty gap index, and when $\alpha = 2$ it is the poverty severity index, also known as the squared poverty gap index (Haughton & Khandker 2009). By weighting each household's poverty gap by its proportion of the gap, the squared index not only considers absolute deprivation (by

[5] The Monotonicity Axiom states: "Given other things, a reduction in income of a person below the poverty line must increase the poverty measure" (Sen 1976, p.219). The Transfer Axiom states: "Given other things, a pure transfer of income from a person below the poverty line to anyone who is richer must increase the poverty measure" (Sen 1976, p.219).

[6] Relative Equity requires "that if person *i* is accepted to be worse off than person *j* in a given income configuration $\underline{y}$, then the weight v_i on the income short-fall g_i of the worse-off person *i* should be greater than the weight v_j on the income short-fall g_j" (Sen 1976, p. 221).

focusing on those below the poverty line z), but also relative deprivation (placing higher weights on those further below the poverty line).

Following FGT (1984), we propose a decomposable development resilience indicator that aggregates the individual- or household-specific development resilience probabilities, $\hat{\rho}_{it}$, developed in Section II across the population into a single economy-wide measure that is also decomposable to describe distinct sub-populations. Just as with the FGT family of measures from which the development resilience index is adapted, this measure meets the monotonicity, transfer, and relative equity axioms proposed by Sen in addition to being additively decomposable among groups. A demonstration of how this measure satisfies the various axioms set forth by Sen (1976, 1979) and FGT can be found in Appendix A.

Assume a normative resilience probability threshold of $\underline{P}$ $(1 \geq \underline{P} \geq 0)$, as discussed above, at/under which we consider a household's probability of reaching or surpassing $\underline{W}$ (the normative threshold well-being level discussed in Section II) to be intolerably low. The resilience analyst must therefore select two normative thresholds, $\underline{W}$ and $\underline{P}$, which may be context specific. Suppressing time period subscripts for now, we generate a vector $\boldsymbol{\rho}$ of household development resilience measures in time period $t + s$ ordered from lowest to highest values, $\boldsymbol{\rho} = (\hat{\rho}_1, \hat{\rho}_2, \hat{\rho}_3, \dots, \hat{\rho}_n; \underline{W})$ for a total number of n households. With this information we can count the number of non-resilient households, q, for which the household resilience probability falls at or below the resilience probability threshold $q = q(\boldsymbol{\rho}; \underline{P})$, as well as the resilience shortfall (measured in probabilities) for those households $g_i = \underline{P} - \hat{\rho}_i$. In the index, this gap is then weighted by α, a distribution sensitivity parameter that FGT refer to as the measure of poverty aversion.

The sum of the weighted gaps is subtracted from one to ensure that larger numbers signify increased resilience. The decomposable resilience index is therefore defined for period $t + s$ as

(9) $$R_{\alpha,t+s}(\boldsymbol{\rho}_{\boldsymbol{t+s}}; \underline{W}, \underline{P}) \equiv 1 - \left[\frac{1}{n}\sum_{i=1}^{q_{t+s}} \left(\frac{g_{i,t+s}}{\underline{P}}\right)^{\alpha}\right],$$

and the sequence of resilience indices, $\left(R_{\alpha,t+s}\right)_{s=0}^{T}$, would represent aggregate resilience over time to horizon period T. The measure necessarily lies on the closed interval $[0,1]$, with $R = 0$ if each household in the population has a development resilience probability estimate $\hat{\rho}_i < \underline{P}\ \forall\ i \in n$, and $R = 1$ if $\hat{\rho}_i \geq \underline{P}\ \forall\ i \in n$, implying $q = 0$. This approach allows us to calculate the population share deemed resilient (i.e., development resilience headcount ratio) when $\alpha = 0$ ($H_R \equiv \frac{n-q}{n}$), mean development resilience of non-resilient household ($\bar{\rho}_q = \frac{\sum_{i=1}^{q} \hat{\rho}_i}{q}$), as well as the resilience-gap ratio ($G \equiv \sum_{i=1}^{q} \frac{g_i}{q\underline{P}}$). It is therefore well suited for situations in which resilience indices would be useful for targeting or for policy/project evaluation. Given that the poor are the least economically resilient by the BC definition, and for any measure based on a poverty-related welfare indicator, W, the measure is inherently pro-poor.

IV. AN EMPIRICAL EXAMPLE

To illustrate this method, we now employ the development resilience estimation and aggregation techniques discussed above using household data from northern Kenya. The Horn of Africa is a particularly relevant context for the implementation of a resilience measure, as the 2011 drought in the region was one of the main drivers of governmental and non-governmental organization interest in resilience. In northern Kenya, pastoralist communities—considered to be some of the poorest and most vulnerable in the country—rely heavily on livestock (especially cattle, although also camels, goats, and sheep to a lesser extent) to generate most or all of their income. Few other livelihoods are viable given agroecological conditions and meager modern infrastructure (McPeak, Little, & Doss 2012). These households are incredibly vulnerable to weather shocks, such as drought, which can decimate herds. Prior research in the area has established, in multiple data sets, that multiple equilibrium poverty traps exist in livestock holdings, and that drought risk is a key driver of households' collapse into persistent poverty (Lybbert et al. 2004, Barrett et al. 2006, Santos & Barrett 2011). Interestingly, as we show below, in these newer data we find no unstable or higher stable dynamic equilibria, just a single, relatively low, stable dynamic equilibrium herd size, although the same nonlinear shape exists in herd dynamics as in prior studies.

To help pastoral and agro-pastoral populations manage drought-related livestock mortality, an index-based livestock insurance (IBLI) product was piloted in northern Kenya beginning in January 2010 (Chantarat et al. 2013). Rainfall there is bimodal, so the insurance product was designed to be marketed and sold twice annually, although each insurance contract protects the insured for an entire calendar year. The IBLI product uses normalized difference vegetation index (NDVI) estimates derived from satellite data to predict livestock mortality. When predicted livestock mortality due to drought, as reflected in low NDVI values, reaches catastrophic levels (contractually defined as 15% estimated area average loss), the insurance policy pays out. The benefit of an index-based insurance product is that premiums are much lower than for indemnity products, especially in remote locations. They also avoid moral hazard concerns that might prevent the development (or increase the price) of a traditional insurance product. During the five rounds of data, a catastrophic drought occurred once, between rounds two and three.

The data used in this example were collected to evaluate the impact of the insurance program by a consortium led by the International Livestock Research Institute (ILRI), in collaboration with private insurance providers, using a multi-year impact evaluation strategy (ILRI 2013). The household surveys gathered information from 924 randomly selected households in 16 sublocations[7] in Marsabit County, including general demographic variables as well as data on livestock holdings and production, risk and insurance, livelihood activities, expenditure and consumption, assets, and savings and credit. Five rounds[8] of the longitudinal annual survey have been administered each October-November, beginning in 2009 (prior to the first insurance sales window).

Table 1 presents summary statistics. We distinguish between fully settled households that do not practice transhumance and those partially or fully nomadic

[7] All administrative divisions in Marsabit were included. The sublocations vary in terms of pastoral system, ethnic group makeup, agro-ecology and market accessibility. The number of households from each sublocation was determined by proportional allocation within set minimum and maximum bounds. For more information see the survey codebook (ILRI 2013).

[8] Five rounds of the data are available and used in this analysis. Since we use lagged variables, the first round of the data is not used (with the exception of the lagged well-being (livestock) data). A sixth round of data has been collected but has not been included in this analysis.

households that relocated, at least seasonally, as they migrated their herds over longer distances in search of forage and water. Nearly two-thirds of the sample is (at least partly) nomadic. Sedentarized households have significantly fewer livestock holdings, greater (albeit still limited) educational attainment, and are much more likely to practice Islam. The pooled sample attrition rate is approximately 2%. Of these, some households are absent for a given round and then reappear in subsequent rounds.[9] Attrited households are somewhat more likely to be Catholic and have slightly fewer livestock holdings than the mean household. The dependency ratio is higher for attrited households, which may partially explain why no one was available to respond to the survey during a given round.

Table 1: Summary Statistics

	Sample Mean	Fully Settled	Nomadic[10]	T-test	Attrited	T-test
Tropical Livestock Units[11]	13.60	7.99	17.03	***	10.56	*
Female headed (=1)	0.37	0.36	0.38		0.29	*
Age of head (years)	49	50	48	***	49	
Education (years)	1.05	1.83	0.58	***	1.76	**
Dependency Ratio[12]	1.07	1.07	1.07		1.35	***
Catholic	0.31	0.34	0.29	***	0.40	**
Anglican	0.08	0.08	0.09		0.11	
Other Christian	0.06	0.10	0.04	***	0.04	
Muslim	0.24	0.37	0.16	***	0.21	
Traditional Religion	0.30	0.12	0.42	***	0.24	
No Religion	0.00	0.00	0.00		0.00	
N (5 rounds, pooled)	4619	1754 (38%)	2865 (62%)		114 (2%)	

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

[9] Due to the lagged variable in our estimation, the household that is not contacted in one round is actually absent from the estimation for that round and the next, and the household is counted as attrited in both rounds.

[10] Includes households identified as "partially nomadic" or "nomadic."

[11] A tropical livestock unit (TLU) is an aggregate measure of livestock holdings. 1 TLU = 1 cow = 0.7 camel = 10 sheep or goats.

[12] The dependency ratio gives a sense of how many individuals are being cared for by the family. In this case, the dependency ratio equals the number of children under 15 plus the number of seniors over 64 divided by the number of adults (between the ages of 15 and 64) in the household. If there are no working aged adults in the households, the number of dependents is divided by 1.

Development Resilience Estimation

Because most survey households hold a large share of their wealth in livestock and depend heavily on livestock to generate income, livestock holdings offer a logical (and commonplace) measure of well-being in pastoralist settings. The primary household well-being variable of interest, therefore, is household aggregate livestock holdings, expressed in tropical livestock units (1 TLU = 1 cow = 0.7 camel = 10 sheep or goats) in each survey round. Given that livestock are the primary productive asset in the region, and that a significant share of expenditure and income occur in the form of autoconsumed milk and blood from livestock, which herders harvest in small volumes daily or multiple times per day without any careful measurement (McPeak, Little & Doss 2012), animal holdings are the most useful measure of well-being in this context where asset dynamics are crucially important for overall well-being, asset smoothing maybe a rational response to avoid falling into a poverty trap, and expenditure and income measurement are especially prone to measurement error (Barrett et al. 2006; Barrett & Carter 2013).

TLU holdings are estimated via maximum likelihood, per equation (1), as a polynomial function of lagged well-being (i.e., TLU from the previous period), a dummy variable indicating a serious drought (i.e., area average predicted losses ≥ 15% per the IBLI index), the sex of the household head, the age and squared age of the household head to account for life cycle effects, the number of years of education completed for the household head, the household dependency ratio, and controls for religious affiliation and nomadic status:

(10) $$W_{it} = \sum_{\gamma=1}^{4} \hat{\beta}_{M\gamma} W_{i,t-1}^{\gamma} + \boldsymbol{\delta}_{\mathbf{M}} \boldsymbol{X}_{\boldsymbol{it}} + u_{Mit}.$$

Table 2: Marginal Effects at Representative Values[1] – Maximum Likelihood Estimates

VARIABLES	(1) TLU low	(1) TLU **mean**	(1) TLU high	(2) Variance(TLU) low	(2) Variance(TLU) **mean**	(2) Variance(TLU) high	(3) TLU Resilience [~Γ, W=6] low	(3) TLU Resilience [~Γ, W=6] **mean**	(3) TLU Resilience [~Γ, W=6] high
TLU_{t-1}	0.572***	**0.735*** **	0.824***	2.939***	**4.125*** **	4.976***	0.0616***	**0.0381*** **	0.0204***
	(0.0176)	**(0.0264)**	(0.0311)	(0.609)	**(0.815)**	(0.903)	(0.000494)	**(0.000236)**	(0.000311)
Drought	-1.583***	**-2.380*** **	-2.957***	-12.97*	**-19.82** **	-25.21**	-0.181***	**-0.112*** **	-0.0600***
	(0.375)	**(0.559)**	(0.693)	(6.795)	**(10.09)**	(12.76)	(0.00284)	**(0.00225)**	(0.00168)
Female Head	-1.060***	**-1.594*** **	-1.981***	6.193	**9.467**	12.04	-0.122***	**-0.0756*** **	-0.0406***
	(0.246)	**(0.369)**	(0.459)	(5.110)	**(7.924)**	(10.14)	(0.00455)	**(0.00301)**	(0.00178)
Head Age ($* 10^2$)	0.586	**0.881**	1.10	14.2	**21.7**	27.6	0.0684***	**0.0423*** **	0.0227***
	(0.901)	**(1.35)**	(1.68)	(18.7)	**(28.7)**	(36.6)	(0.0141)	**(0.00864)**	(0.00461)
Education in Yrs	0.0378	**0.0568**	0.0706	1.705	**2.607**	3.315	0.00433***	**0.00268*** **	0.00144***
	(0.0635)	**(0.0954)**	(0.119)	(1.208)	**(1.869)**	(2.396)	(0.00107)	**(0.000655)**	(0.000351)
Dependency Ratio	-0.504***	**-0.758*** **	-0.941***	-7.621**	**-11.65** **	-14.82**	-0.0564***	**-0.0349*** **	-0.0187***
	(0.150)	**(0.225)**	(0.279)	(3.710)	**(5.611)**	(7.119)	(0.00212)	**(0.00142)**	(0.000868)
Religion & Nomadic Dummies	Y	**Y**	Y	Y	**Y**	Y	Y	**Y**	Y
Model BIC		178991.48			8333433.3			-28669.092	

Robust (1) and bootstrapped[2] (2)-(3) standard errors in parentheses. Pooled Sample, n = 3,581. *** p<0.01, ** p<0.05, * p<0.10

[1] For (1) and (2), a Poisson distribution is assumed. For (3), a binomial distribution is assumed. "Low" are the marginal effects at $TLU_{t-1} = 8$, the average value for settled households. "Mean" are at the sample mean TLU value ($TLU_{t-1} = 13.6$) and "high" are at $TLU_{t-1} = 17$, the average holdings for nomadic households.

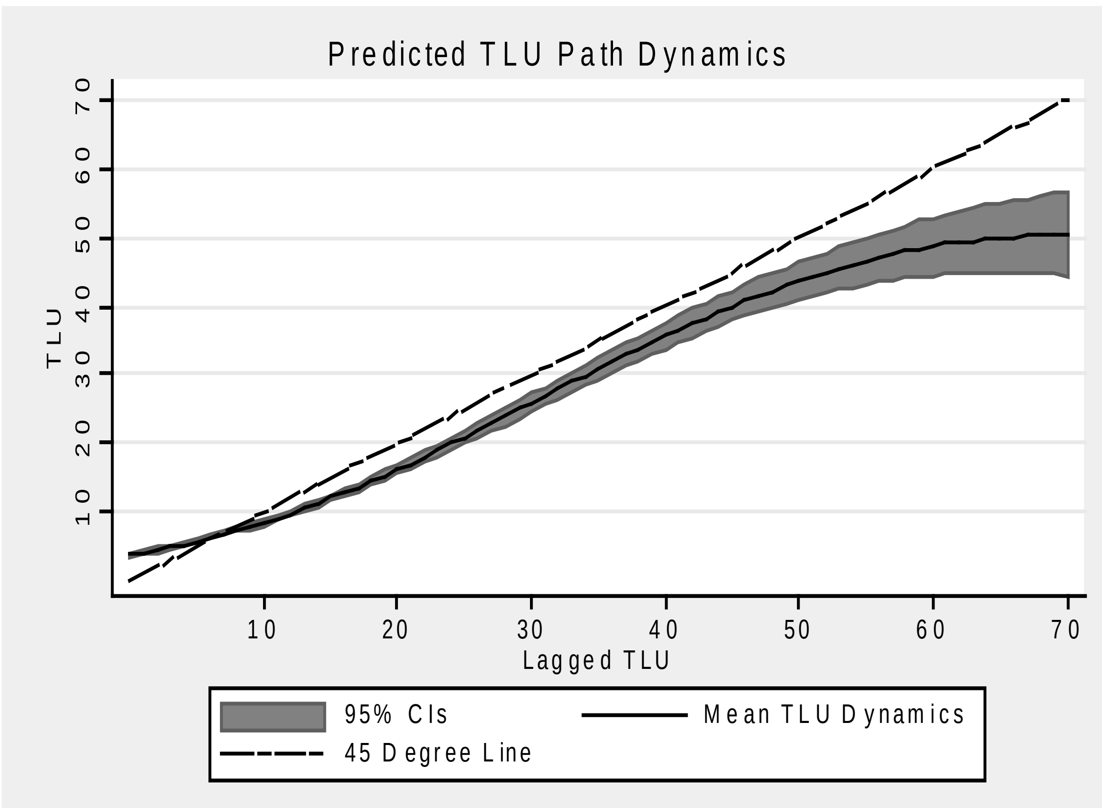
[2] B=400 repetitions chosen for the bootstrap based on Cameron & Trivedi (2010, p. 433). Bootstrapping estimates are made possible for complex survey data by calculating bootstrap weights. See Kolenikov (2010) for more information.

As mentioned above, a third order polynomial in lagged TLU holdings is the most parsimonious that can accommodate the S-shaped herd dynamics found in prior studies in the region (Barrett et al. 2006). For this empirical example, tests of the various polynomial specifications can be found in Table B1 in Appendix B. In this case, the Akaike information criterion (AIC) values are decreasing in polynomial order, suggesting a higher order specification would be preferred. However, the coefficient estimates on the higher order lagged well-being terms are effectively zero. A t-test on the equality of means between the predicted values of the higher-order specifications finds statistically insignificant differences for everything above and including the fourth order. Therefore, the fourth order specification is preferred in this case.

Given that physical livestock holdings must be non-negative, the dependent variable is assumed to be distributed Poisson. The generalized linear model (GLM) log link regression is fit using maximum likelihood and Table 2 column (1) displays the marginal effects estimates for mean TLU well-being, as well as for low and high values of lagged TLU holdings. Consistent with prior studies of east African livestock wealth dynamics, herd dynamics are statistically significantly nonlinear, as evidenced by the difference between the marginal effect at a low value of past period TLU holdings and at a high value. Marginal effects at the mean of all covariates are presented in the bolded, middle column. Figure 1 displays estimated herd dynamics based on the marginal effects calculated in Table 2 column (1), valuing other covariates at sample means. Although there is evidence of S-shaped TLU dynamics found in prior studies of the region, unlike prior empirical studies of herd dynamics using earlier datasets, there is no evidence of multiple TLU equilibria, although this could simply reflect limited recovery time from the catastrophic 2011 drought in a short sample. Rather, this parametric estimation suggests a unique stable dynamic equilibrium at approximately 6 TLU, too low to generate a non-poor income in expectation. This low, unique stable equilibrium suggests that asset transfer programs would not be sufficient to help households sustainably escape poverty in this context, but rather that investments should focus on increasing the productivity of assets.

The coefficient estimate on drought is, as expected, strongly and statistically significantly negative, with an estimated average 2.4 TLU loss in a major drought associated with a one unit increase in lagged TLU, representing an 18% average loss relative to sample mean livestock holdings. For households with low past period livestock holdings, the marginal effect of drought—while still statistically significantly negative—is smaller in absolute terms, but actually represents a slightly larger proportion of their livestock holdings (20%). Holding previous period herd size constant, female headed households have statistically significantly smaller herds than male headed households, as do households with more dependents. The coefficient estimates on the age of the household head and on his/her education are not statistically significantly different from zero.

Figure 1: Estimated Path Dynamics



Following equation (3), we capture the residuals from the mean well-being equation just reported, square them, and use these values to estimate the conditional variance equation, also via maximum likelihood,[1]

(11) $\hat{\sigma}_{it}^{2} = \sum_{\gamma=1}^{4} \hat{\beta}_{V\gamma} W_{i,t-1}^{\gamma} + \boldsymbol{\delta_{V} X_{it}} + u_{Vit}.$

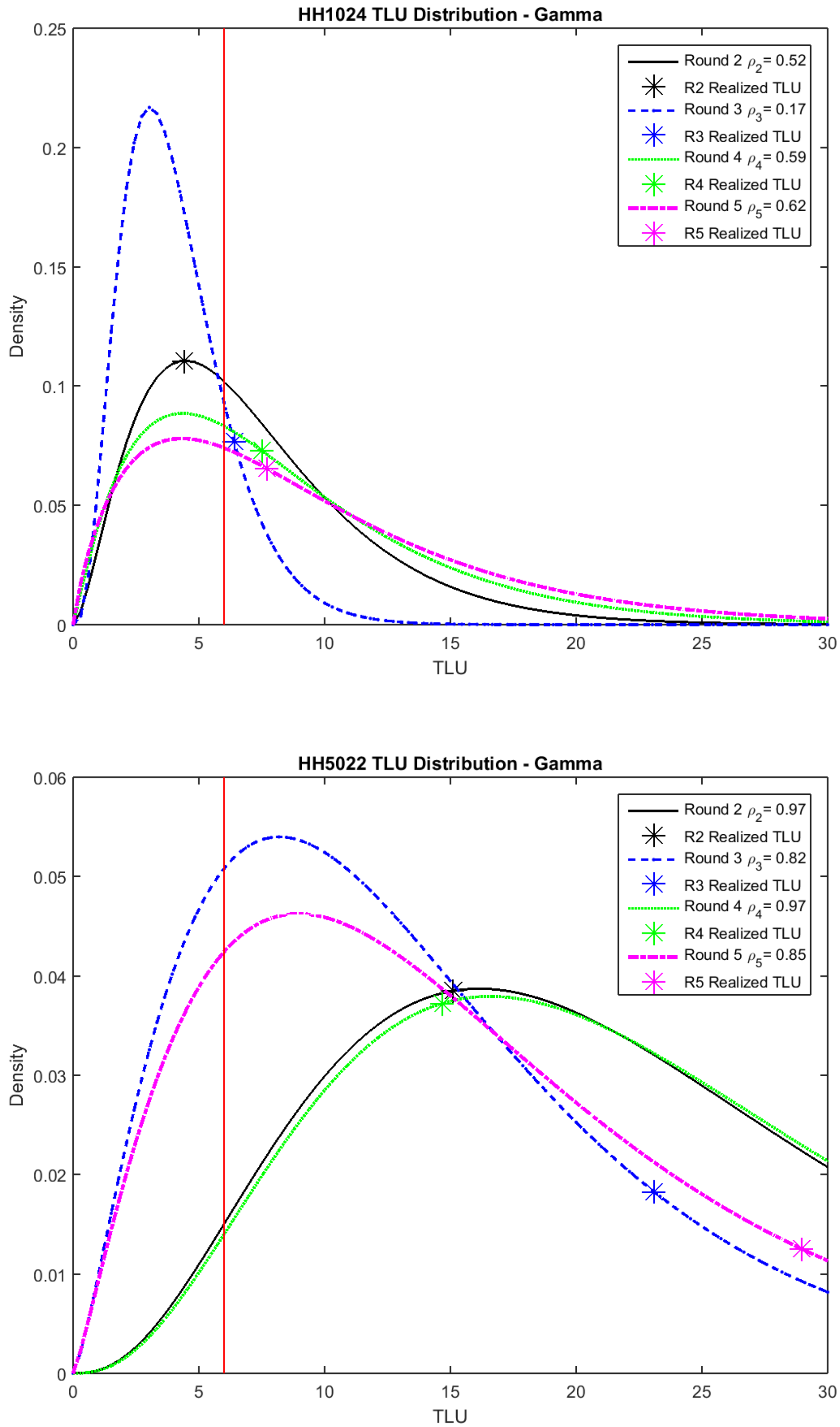
The estimates for the TLU variance equation can be found in column (2) of Table 2, again displayed at various values of lagged TLU holdings. There is statistically significant nonlinear autoregressive conditional heteroscedasticity as reflected in the coefficient estimates of lagged herd size; the marginal effect of lagged TLU on conditional variance is 60% larger for households with higher previous period TLU holdings. Drought and the dependency ratio are also statistically significantly (and negatively) related to the conditional variance of herd size, while the other covariates are not. This indicates that there is less variance in times of drought, indicating that drought suppresses variation while it also lowers mean well-being.

Using the estimates from columns (1) and (2) in Table 2, we can estimate each household's TLU probability density function (pdf) for each period. Figure 2 shows how the estimated TLU pdfs—in this case based on the gamma distribution[2]—vary, both over time and across households: Household 1024 is a female-headed, fully settled household fairly typical of that sub-group in terms of livestock holdings, education, and age, while Household 5022 is a male-headed, nomadic household with TLU holdings near that sub-group's mean. The former household is markedly poorer in terms of livestock than the latter, with lower expected TLU levels across all periods. Although the round following the drought shock (Round 3) sees a marked decrease in resilience for the female headed household, the household well-being improves markedly in the two post shock years, as reflected in leftward and rightward shifts of the pdfs, respectively. In fact, the household is able to achieve higher resilience in Rounds 4 and 5 than in the initial period. Although

[1] As with the mean equation, the dependent variable (variance) must be non-negative. As such, once again we assume the dependent variable is distributed Poisson and fit the GLM log link regression using maximum likelihood.

[2] Distribution parameters for the gamma distribution are: $W_t | W_{t-1} \sim \Gamma(\frac{\mu_{2t}}{\mu_{1t}}, \frac{\mu_{1t}^2}{\mu_{2t}})$, based on Bury (1999).

Figure 2: Conditional TLU Well-being pdfs



household 5022 is relatively well-off in terms of TLU holdings, it is also dramatically affected by the drought shock; household well-being falls to its lowest levels during Round 3. The household is able to fully recover in Round 4 before being impacted by an idiosyncratic shock in the final round.

After calculating the household-specific pdfs, the next step is to estimate each household's probability of achieving the normative minimum well-being ($\underline{W}$) in each period. We set the threshold level at 6 TLU ($\underline{W} = 6$), which is the critical, unstable livestock threshold previously identified in the literature for this region of northern Kenya (Barrett et al. 2006). This threshold is represented in Figure 2 by the vertical line. The household-specific development resilience estimate for each period, $\hat{\rho}_{it}$, is simply household i's complementary cumulative probability beyond the threshold value, $\underline{W}$, in period t, per equation (5). Each household-period-specific resilience score therefore lies in the interval [0,1].

Following equation (6), we can regress these household-and-period-specific resilience scores on the same regressors used in the mean and variance equations, as follows:

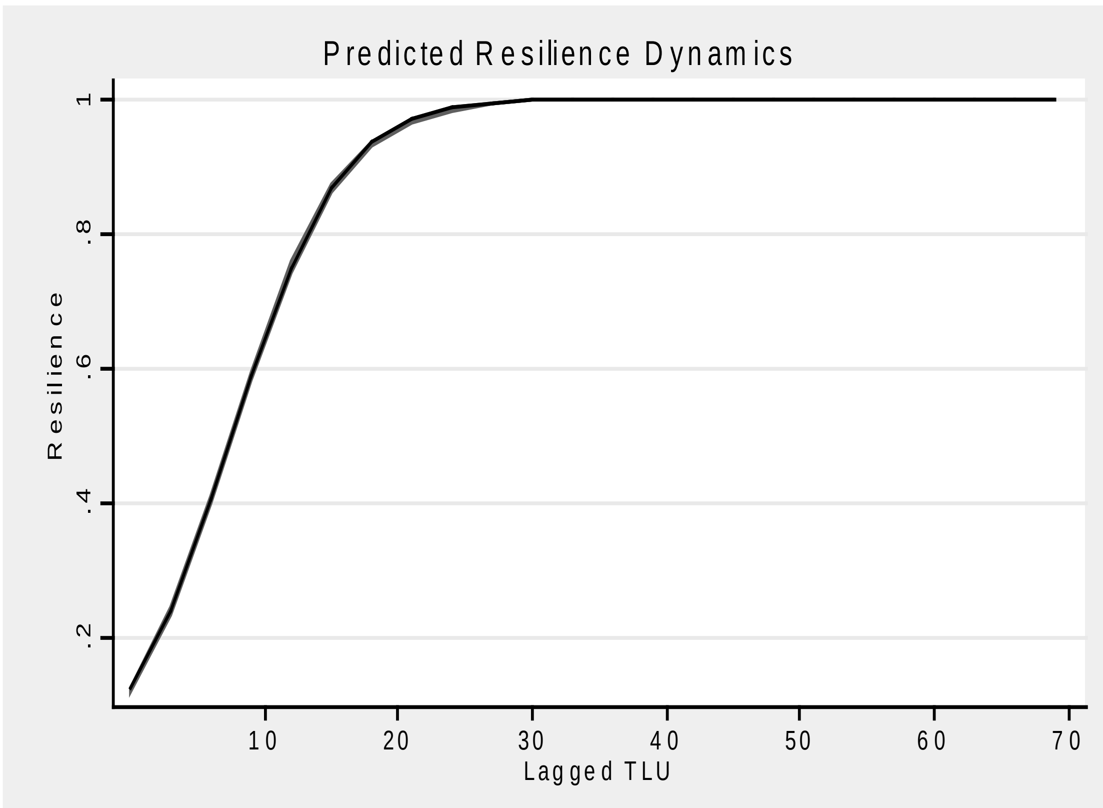
(12) $$\hat{\rho}_{it} = \sum_{\gamma=1}^{4} \hat{\beta}_{R\gamma} W_{i,t-1}^{\gamma} + \boldsymbol{\delta}_{\mathbf{R}} \boldsymbol{X}_{\boldsymbol{it}} + u_{Rit}.$$

We do this estimation because the resilience score is a nonlinear function of the (linear) estimates of the conditional mean and conditional variance. The fractional response estimates[1] for household resilience scores can be found in Table 2 column (3). We see strong evidence of non-linear relationships between lagged livestock holdings and development resilience. As seen in the coefficient estimates of the marginal effects at various lagged period livestock holding sizes, resilience increases quickly with each additional lagged TLU at first, but increases more slowly for larger lagged values. This can be clearly seen in Figure 3 by comparing the slopes of the curve at the various prior

[1] The dependent variable (resilience) is between zero and one, necessitating a fractional response specification. As such, we assume the dependent variable is distributed binomially and fit the GLM logit link regression using maximum likelihood.

period livestock holding (lagged TLU) levels.[2] Figure 3 also illustrates that, while the conditional mean regression estimates suggest a dynamic equilibrium herd size of about 6 TLU (Figure 1), household resilience actually increases monotonically in prior period herd size. This suggests that while households may incur a cost to TLU holdings larger than 6, they might overstock optimally as a form of self-insurance intended to increase resilience, following precautionary saving principles.

Figure 3: Estimated Resilience Dynamics



As intuition would suggest, drought decreases household resilience. The marginal effect of drought is much greater for households with smaller (previous period) herds.

[2] The household-specific resilience scores are, naturally, sensitive to the well-being threshold selected. Figure B1 in Appendix B illustrates how predicted resilience changes with $\underline{W}$. Resilience increases monotonically in lagged TLU holdings for all well-being thresholds $\underline{W}$, although the dynamics become more "S-shaped" as the threshold increases, indicating that—at most threshold levels—resilience increases more quickly for those with large (above average, but not huge) previous period livestock holdings.

Female headed households are less resilient, although the effect is much larger for households with lower values for lagged TLU. Households with more educated and older household heads, as well as households with fewer dependents, have statistically significantly greater resilience, although the magnitudes of the estimated effects are quite small. These resilience dynamics are robust to various distributional assumptions.[3]

As a robustness check, the mean, variance, and resilience equations were also estimated via OLS. These results can be found in Table B3 of Appendix B. In general, the two methods confirm the importance of path dynamics (in significance and magnitude) for both the variance and resilience equations, as well as the negative impact of drought on TLU well-being. The signs of coefficient estimates are not entirely consistent, however, between the different specifications. Surprisingly, the estimated coefficient on education in the OLS resilience equation is negative, although the magnitude is negligible.

Development Resilience Aggregation

In order to generate aggregate development resilience measures for a population from the set of household-specific estimates, we must first select a minimum probability threshold, $\underline{P}$, above which a household is deemed resilient and below which it is considered not resilient. This second normative threshold is necessary because development resilience is a probabilistic measure, unlike directly observable indicators such as expenditures, income or livestock holdings. We set $\underline{P} = 0.80$, meaning that we only consider household *i* resilient if it has at least an 80% probability of reaching the well-being threshold (i.e., $\hat{\rho}_{it} \equiv \Pr(W_{it} \geq \underline{W} = 6 | W_{i,t-1}, \boldsymbol{X_{it}}) \geq 0.80$). Setting the distribution sensitivity parameter, $\alpha = 0$, so as to generate a headcount estimate of the population share who are not resilient, for the entire sample, pooled across periods, we estimate

[3] As a robustness check, resilience estimates were calculated for lognormally distributed household well-being. Those results can be found in Appendix B, Table B2. The qualitative results are, naturally, very similar such that the distributional assumption does not seem to matter to the central patterns observed.

(13) $R_0(\boldsymbol{\rho_{TLU}}; 6, 0.8) \equiv 1 - \left[\frac{1}{n}\sum_{i=1}^{q}\left(\frac{g_i}{0.8}\right)^0\right] = 0.394,$

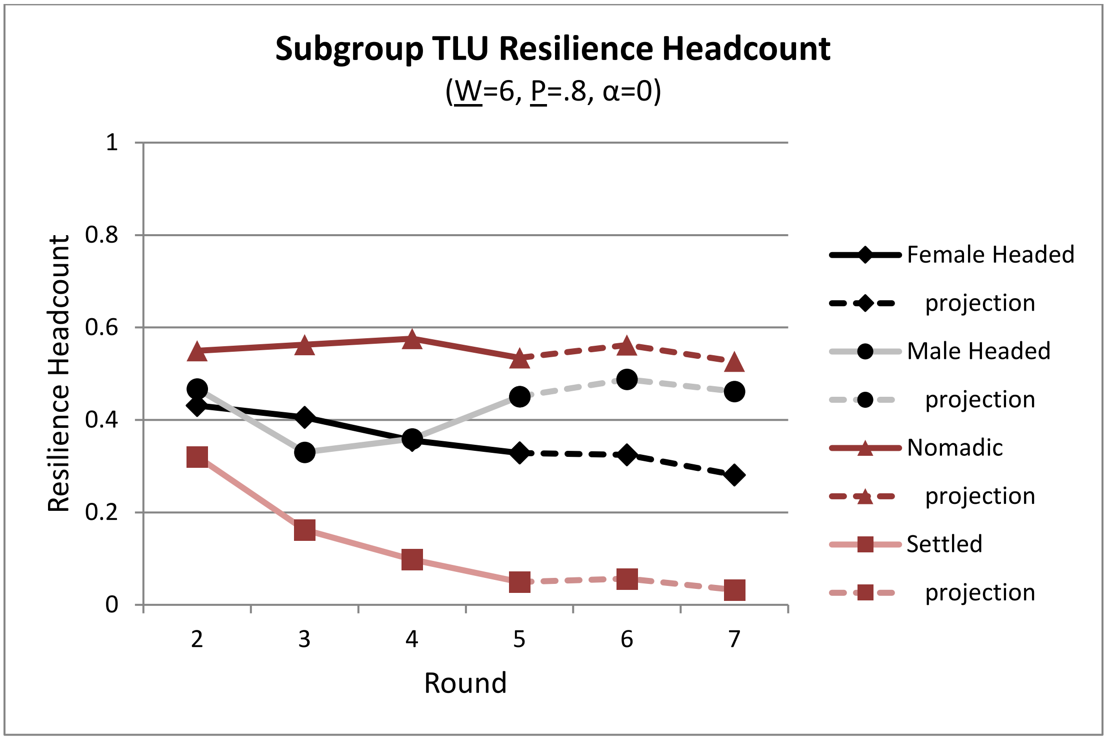
meaning that about forty percent of households in the pooled sample are development resilient by this measure.

One of the appealing features of FGT-style measures like R is their decomposability. The sample population can be broken down into various subgroups by characteristics such as sex or education of the household head, nomadic status, geographic area, etc. Another benefit of this new development resilience estimation approach is that the built-in path dynamics facilitate development resilience forecasting, projecting how resilience will evolve in future periods, given current and recently observed values. This allows us to forecast development resilience estimates for each household, and therefore the aggregate subgroup resilience measures, as well, under different scenarios. We can simulate how, for example, development resilience will develop in the absence (or presence) of another drought shock.

Given the perceived vulnerability of female headed and settled households in this region, we calculate the headcount resilience index by sex and nomadic status per equation (9) and project the measures out two years into the future based on a few reasonable assumptions about the evolution of covariates, such as that the education of the household head remains unchanged while his or her age increases by one year each year, as described in equation (7). The dashed lines from periods 5 to 7 in Figure 4 show how development resilience is predicted to evolve over the two years following the fifth survey round if households in Marsabit do not suffer another catastrophic drought.

We calculate the sex-specific headcount measure for each round so as to observe the evolution of development resilience over the course of a drought cycle. Although headcount resilience is quite similar for male and female headed households in Round 2, female headed households do not appear to be as substantially impacted by the drought as male headed households at first. Although their initial headcount resilience drop is less substantial, female headed households appear less able to recover. The headcount resilience score continues to decline over the survey period and is projected to drop even further. Male headed households, on the other hand, see a sharp drop in their headcount

Figure 4: TLU Resilience Headcount



resilience post-drought. Importantly, however, these households recover most of their lost resilience within three years of the drought and were forecast to maintain that level of resilience in subsequent years.

Given longstanding observations in the region that nomadic households are better-off and seemingly more resilient to drought due to their mobility (Barrett et al. 2006, Little et al. 2008), we also explore how this development resilience measure varies by nomadic status. As depicted in Figure 4, nomadic households are indeed consistently more resilient than are settled households. The difference in resilience among households also appears far more pronounced in the mobility/nomadism dimension than based on gender of the household head. Consistent with the aforementioned observations, the headcount resilience score for nomadic households is seemingly unaffected by the drought, while settled households see a sharp initial drop and, as with female headed households, seem unable to recover in subsequent or project rounds.

Targeting

The resilience differences based on nomadic status suggest a targetable characteristic for interventions aimed at boosting the resilience of vulnerable households.

This method and the estimates it generates can help to identify the key populations in need of assistance in order to boost and/or buffer their resilience or for targeting specific types of interventions estimated to have especially pronounced expected effects on household resilience. Because good targeting necessarily involves forecasting where a household would be in the absence of an intervention, the (potentially nonlinear) conditional path dynamics built into this method of development resilience estimation offer a significant opportunity to improve targeting. Conventional methods use the most recent observation of a household as the best estimate of the future state in the absence of an intervention. But that implicitly imposes a strong assumption of a random walk stochastic process. In the empirical example above, we can reject the null hypothesis of a random walk, suggesting that our method might enhance targeting accuracy.

The strength of the development resilience approach is that it allows us to look at the probability of maintaining well-being over time, and leverage the inter-temporal variation captured by the panel dataset to predict future outcomes. In order to assess the targeting accuracy of this approach vis-à-vis conventional approaches, we could compare targeting accuracy rates (both correctly targeted and correctly not targeted), Type I errors (errors of inclusion, i.e., those targeted who nonetheless exceeded the threshold) and Type II errors (i.e., errors of exclusion, those not targeted who nonetheless fell below the threshold), for different probability thresholds ($\underline{P}$) for a standard targeting approach (based on the most recently observed value) and a resilience-based targeting approach, as described in Upton, Cissé, & Barrett (2016).

Table 3 presents the estimates of targeting accuracy for an intervention in Round 5, based on the development resilience approach described above (using data from Rounds 1-4) and compares it to a standard targeting regime based only on realized TLU holdings in Round 4. While no probability threshold $\underline{P}$ consistently outperforms the standard approach on all measures, a probability threshold can be selected that outperforms the standard model for each of the various measures. That is, while the standard approach does not allow implementers to choose between inclusion and exclusion errors in targeting, the development resilience approach explicitly allows policymakers to choose between leakage and over-coverage depending on priorities and resource constraints. Importantly, resilience-based targeting outperforms the standard approach on the measure of interest given decision-makers' priorities.

Table 3: Estimates of Targeting Accuracy

P	Correctly Not Targeted	Correctly Targeted	TI Error	TII Error	Sum of Errors
0.45	0.539	0.342	0.059	0.059	0.119
0.5	0.519	0.358	0.079	0.044	0.123
0.55	0.505	0.363	0.093	0.038	0.132
0.6	0.485	0.368	0.113	0.034	0.147
0.8	0.384	0.386	0.214	0.015	0.229
Standard	0.526	0.352	0.072	0.049	0.122

V. CONCLUSIONS AND POLICY IMPLICATIONS

Given the disastrous impacts of increasingly frequent natural disasters, cyclical food assistance needs, and limited humanitarian budgets, international development and humanitarian agencies have recently begun to focus heavily on resilience. The empirical development resilience approach developed here provides an econometric strategy for understanding potentially nonlinear well-being dynamics in shock-prone contexts, bringing together relevant concepts from the poverty traps, risk, vulnerability, and poverty measurement literatures.

As the empirical example demonstrates, it is important to understand mean well-being dynamics in order to design appropriate interventions. As Barrett & Carter (2013) explain, well-targeted transfers to individuals just below a poverty trap threshold may help them escape poverty, but the same transfers would have negligible impacts in contexts such as the one discussed in this paper, with unique, low-level well-being equilibria. But understanding the mean well-being dynamics is not sufficient, as ignoring high-order moments obscures the impact of risk and self-insurance on well-being. In Northern Kenya, households (particularly nomadic households) acquire herds much larger than dynamic equilibrium levels, and at considerable long-run expected cost. The development resilience approach offers insight into this seemingly costly and long-run futile behavior, by uncovering the correlation between large herd sizes and higher probabilities of adequate future well-being.

While the benefits of a rigorous empirical analysis of development resilience are clear, the data are currently not available to allow this type of analysis at scale. While panel data are rapidly becoming more available in the low-income world, the full benefits of this approach can be more effectively supported by a multi-country system of sentinel sites collecting high-quality, high-frequency data over long periods of time, particularly in the most disaster-prone parts of the world (Barrett & Headey 2014, Headey & Barrett 2015). Yet the absence of such data should not prevent methodological contributions, but rather guide developments in data collection and management systems. We hope that the methods introduced in this paper provide some direction and impetus for increased data collection while also providing a template for resilience estimation in contexts with adequate data availability, which are growing increasingly common.

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APPENDICES

Appendix A: Satisfaction of Key Axioms by Resilience Index

The $R_{\alpha,t+s}(\boldsymbol{\rho}; \underline{W}, \underline{P})$index combines "considerations of absolute and relative [development resilience] deprivation" (Sen 1979, 293) even after the selection of a normative minimum development resilience threshold. We note that while the axioms are discussed with regards to individuals, they are applied in this paper almost exclusively to households. While in theory this approach could be used to aggregate individual resilience scores into a household-level aggregate, we assume for now a unitary household model and apply the axioms to the household as the most decentralized unit.

Monotonicity Axiom: *A reduction in development resilience of a person already below the resilience probability threshold, ceteris paribus, must (weakly) decrease the resilience index.*
Assume in a population of size n, that an individual j (already below the resilience probability threshold) has a reduction in development resilience from period A to period B such that $\rho_{j_A} > \rho_{j_B}$. Since $g_j = \underline{P} - \rho_j$, clearly $g_{j_A} < g_{j_B}$. Individual j remains below $\underline{P}$ and since neither the population size nor the resilience probability threshold $\underline{P}$ is changed, therefore it is easy to see that $\left[\frac{1}{n}\sum_{i=1}^{q_A}\left(\frac{g_i}{\underline{P}}\right)^{\alpha}\right] > \left[\frac{1}{n}\sum_{i=1}^{q_B}\left(\frac{g_i}{\underline{P}}\right)^{\alpha}\right]$ for all $\alpha > 0$ and therefore $R_A < R_B$. As discussed above, for $\alpha = 0$ the resilience index is the headcount ratio and therefore $R_A = R_B$.

Transfer Axiom: *A pure transfer of development resilience from a person below the resilience probability threshold to anyone who is more resilient must (weakly) decrease the resilience index, ceteris paribus.*
The transfer axiom simply ensures that the index value changes in the development resilience of the least resilient more than changes in resilience indices of more resilient individuals (even if those individuals are still below the normative threshold $\underline{P}$.

Case 1: If the transfer is made to someone with resilience above $\underline{P}$, this is effectively equivalent to the monotonicity axiom above.

Case 2: Let two individuals j and k each have a level of development resilience below the resilience probability threshold, such that $\rho_{j_A} < \rho_{k_A} \leq \underline{P}$ in period A. A pure resilience transfer in the amount of π reduces the development resilience of person j to $\rho_{j_B} = \rho_{j_A} - \pi$ in period B and increases the resilience of person k to $\rho_{k_B} = \rho_{k_A} + \pi$, which may or may not be above $\underline{P}$.

Case 2a: For this subcase let $\rho_{k_B} = \rho_{k_A} + \pi \leq \underline{P}$, so individual j's gap has increased ($g_{j_A} < g_{j_B}$) and k's gap has shrunken ($g_{k_A} > g_{k_B}$). It is immediately clear that $R_A = R_B$ when $\alpha = 0$ or $\alpha = 1$ since neither the headcount nor the cumulative resilience gap is altered by the transfer. For $\alpha > 1$, $\left[\frac{1}{n}\sum_{i=1}^{q_A}\left(\frac{g_i}{\underline{P}}\right)^{\alpha}\right] > \left[\frac{1}{n}\sum_{i=1}^{q_B}\left(\frac{g_i}{\underline{P}}\right)^{\alpha}\right]$ since greater weight is placed on larger gaps and therefore it follows that $R_A < R_B$.

Case 2b: Now let $\rho_{k_B} = \rho_{k_A} + \pi > \underline{P}$. Notice that for $\alpha = 0$, the headcount ratio, $R_A > R_B$ since fewer individuals fall below the resilience probability threshold. However, for ≥ 1 , $\left[\frac{1}{n}\sum_{i=1}^{q_A}\left(\frac{g_i}{\underline{P}}\right)^{\alpha}\right] > \left[\frac{1}{n}\sum_{i=1}^{q_B}\left(\frac{g_i}{\underline{P}}\right)^{\alpha}\right]$ as individual j's gap increases ($g_{j_A} + \pi = g_{j_B}$) and k surpasses the threshold and is considered resilient ($g_{k_B} = 0$), implying $R_A < R_B$.

Relative Equity Axiom: *If person j is accepted to be less resilient than person k in a given resilience configuration $\boldsymbol{\rho}$, then the weight on the resilience gap g_j of the less resilient person j should be greater than the weight on the resilience gap g_k.*
While the headcount ratio with $\alpha = 0$ ignores resilience gaps completely and gaps are given equal weights when $\alpha = 1$, for all $\alpha > 1$ the resilience index $R(\boldsymbol{\rho}; \underline{W}, \underline{P}) \equiv 1 - \left[\frac{1}{n}\sum_{i=1}^{q}\left(\frac{g_i}{\underline{P}}\right)^{\alpha}\right]$ weighs larger gaps more heavily than smaller gaps.

Decomposability: *The resilience index is decomposable with population share weights.*

Suppose we break the population into two (or more) subpopulations such that $n = n_1 + n_2$ and $q = q_1 + q_2$. It is clear that $R_\alpha(\boldsymbol{\rho}; \underline{W}, \underline{P}) \equiv 1 - \left[\frac{1}{n}\sum_{i=1}^{q}\left(\frac{g_i}{\underline{P}}\right)^\alpha\right] = 1 - \frac{1}{n}\left[\sum_{i=1}^{q_1}\left(\frac{g_i}{\underline{P}}\right)^\alpha + \sum_{i=1}^{q_2}\left(\frac{g_i}{\underline{P}}\right)^\alpha\right] = \left(\frac{n_1}{n}\right) - \frac{1}{n}\sum_{i=1}^{q_1}\left(\frac{g_i}{\underline{P}}\right)^\alpha + \left(\frac{n_2}{n}\right) - \frac{1}{n}\sum_{i=1}^{q_2}\left(\frac{g_i}{\underline{P}}\right)^\alpha = \left(\frac{n_1}{n}\right)\left(1 - \left[\frac{1}{n_1}\sum_{i=1}^{q_1}\left(\frac{g_i}{\underline{P}}\right)^\alpha\right]\right) + \left(\frac{n_2}{n}\right)\left(1 - \left[\frac{1}{n_2}\sum_{i=1}^{q_2}\left(\frac{g_i}{\underline{P}}\right)^\alpha\right]\right) = \left(\frac{n_1}{n}\right)R_{\alpha 1} + \left(\frac{n_2}{n}\right)R_{\alpha 2}$.

The development resilience measure satisfies each of the four important axioms above.

Appendix B: Robustness

Table B1: Poisson Estimates of TLU Well-Being – Polynomial Specifications

VARIABLES	(1) TLU	(2) TLU	(3) TLU	(4) TLU	(5) TLU	(6) TLU	(7) TLU	(8) TLU
TLU_{t-1}	1.55***	3.43***	5.73***	9.69***	12.2***	20.0***	22.2***	27.5***
$(*\,10^{2})$	(-0. 145)	(0. 606)	(0.556)	(0.396)	(0.978)	(1.14)	(1.21)	(1.47)
TLU^{2}_{t-1}		-0.0864**	-0. 36***	- 1.21***	- 2.08***	- 5.82***	-7.28***	- 11.4***
$(*\,10^{3})$		(0.0436)	(0.0759)	(0.0865)	(0.343)	(0.604)	(0.717)	(1.05)
TLU^{3}_{t-1}			0.646***	5.80***	15.8***	82.4***	119***	243***
$(*\,10^{6})$			(0.167)	(0.500)	(4.06)	(12.2)	(16.6)	(31.2)
TLU^{4}_{t-1}				- 0.86***	- 5.19***	- 56.6***	-98.7***	- 280***
$(*\,10^{8})$				(0.0810)	(1.80)	(10.7)	(17.5)	(44.7)
TLU^{5}_{t-1}					1.00**	18.0***	42.3***	180***
$(*\,10^{10})$					(0.252)	(3.98)	(8.81)	(33.7)
TLU^{6}_{t-1}						- 2.08***	-8.81***	- 64.6***
$(*\,10^{12})$						(0.507)	(2.06)	(13.6)
TLU^{7}_{t-1}							0.702***	12.0***
$(*\,10^{14})$							(0.179)	(2.74)
TLU^{8}_{t-1}								- 8.97***
$(*\,10^{17})$								(2.17)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
AIC	136.2	119.5	109.2	99.0	97.1	91.3	90.3	89.2
T-test[4]	0.0211**	0.0000***	0.0143**	0.1244	0.575	0.3557	0.3369	-

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

[4] P-value of the t-test on the equality of means between predicted values from the specific estimation and the 8th order polynomial specification.

Table B2: Marginal Effects at Representative Values – A Comparison of Two Well-Being Distributions

VARIABLES	(1) TLU Resilience [~Γ, W=6][5]			(2) TLU Resilience [~ln*N*, W=6][6]		
	low	low	low	low	**mean**	high
TLU_{t-1}	0.0616***	**0.0381*** **	0.0204***	0.0613***	**0.0353*** **	0.0194***
	(0.000494)	**(0.000236)**	(0.000311)	(0.000461)	**(0.000830)**	(0.000475)
Drought	-0.181***	**-0.112*** **	-0.0600***	-0.149***	**-0.0925*** **	-0.0535***
	(0.00284)	**(0.00225)**	(0.00168)	(0.00482)	**(0.00314)**	(0.00213)
Female Head	-0.122***	**-0.0756*** **	-0.0406***	-0.0860***	**-0.0535*** **	-0.0310***
	(0.00455)	**(0.00301)**	(0.00178)	(0.00451)	**(0.00297)**	(0.00178)
Head Age	0.0684***	**0.0423*** **	0.0227***	0.0142	**0.00774**	0.00413
$(*10^2)$	(0.0141)	**(0.00864)**	(0.00461)	(0.0145)	**(0.00900)**	(0.00521)
Education in	0.00433***	**0.00268*** **	0.00144***	0.000777	**0.000483**	0.000280
Yrs	(0.00107)	**(0.000655)**	(0.000351)	(0.000712)	**(0.000443)**	(0.000256)
Dependency	-0.0564***	**-0.0349*** **	-0.0187***	-0.0453***	**-0.0282*** **	-0.0163***
Ratio	(0.00212)	**(0.00142)**	(0.000868)	(0.00225)	**(0.00145)**	(0.000928)
Religion & Nomadic Dummies	Y	**Y**	Y	Y	**Y**	Y
Model BIC	-28669.092			2727.261		

Bootstrapped[7] (1) and robust (2) standard errors in parentheses. Pooled Sample, n = 3,581.

*** p<0.01, ** p<0.05, * p<0.10

[5] These are the same estimates as presented in Table 2 column (3).

[6] Distribution parameters for the lognormal distribution are: $W_t|W_{t-1} \sim \ln N\left(\ln(\mu_{1t}) - \frac{1}{2}\ln\left(1 + \frac{\mu_{2t}}{\mu_{1t}^2}\right), \ln\left(1 + \frac{\mu_{2t}}{\mu_{1t}^2}\right)\right)$. Given convergence issues with the estimator, these estimates are not bootstrapped and exclude survey weights. The specification was also only able to include a third order polynomial. The fractional response model uses a logit model for the conditional mean.

[7] B=400 repetitions chosen for the bootstrap based on Cameron & Trivedi (2010, p. 433).

Table B3: OLS Estimates of TLU Well-Being

VARIABLES	(1) IHS[8](TLU)	(2) Variance (IHS(TLU))	(3) Resilience [~Γ, W=6]
TLU_{t-1}	0.155***	-0.0160**	0.00626***
	(0.00577)	(0.00775)	(0.00101)
$\mathrm{TLU}_{t-1}^{2}(*\,1000)$	-2.40***	0.395	-0.0994**
	(0.172)	(0.336)	(0.0477)
$\mathrm{TLU}_{t-1}^{3}(*\,10^{6})$	12.8***	-1.75	0.563
	(1.35)	(4.34)	(0.647)
$\mathrm{TLU}_{t-1}^{4}(*\,10^{9})$	-20.1***	2.17	-0.917
	(2.54)	(16.4)	(2.55)
Drought	-0.164***	0.0551	-0.00529***
	(0.0404)	(0.0477)	(0.000852)
Female Head (=1)	-0.234***	0.107**	-0.0133***
	(0.0460)	(0.0452)	(0.00149)
Head Age	0.0161**	-0.00185	0.000787***
	(0.00753)	(0.00802)	(0.000220)
Head $\mathrm{Age}^2(*\,10^5)$	-15.7**	3.33	-0.841***
	(6.97)	(7.32)	(0.199)
Education in Yrs	-0.00753	0.0145*	-0.000463*
	(0.00925)	(0.00859)	(0.000263)
Dependency Ratio $(*\,100)$	1.42	-0.0956	0.0111
	(2.29)	(2.05)	(0.0584)
Religion & Settled Dummies	Y	Y	Y
Constant	0.827***	0.668***	0.0278***

[8] The inverse hyperbolic sine of TLU.

	(0.205)	(0.226)	(0.00658)
Observations	3,581	3,581	3,581
R-squared	0.70	0.05	0.86

Robust standard errors in parentheses, standard errors for (2) & (3) are bootstrapped w/400 reps. *** p<0.01, ** p<0.05, * p<0.10

Figure B1. Estimated Resilience Dynamics for Selected *W*