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Estimating Development Resilience: A Conditional Moments-Based Approach

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1 | Introduction

Natural disasters, food price and other economic shocks, and conflict have resulted in recurring humanitarian emergencies in many of the world's lowest income countries. In direct response, international development and relief agencies have recently become focused on the concept of *resilience*, committing increasingly large amounts of funding, programming, and research toward “building resilience.” They struggle, however, to define the concept rigorously in order to guide policy and project design, measure progress, and evaluate interventions. 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.

This work is intended as a response to researchers and the development community's need for resilience measurement. We use Barrett and Conostas' (2014) definition of “development resilience” 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, then the unit is resilient.** We draw on multiple distinct aca-

demical literatures to develop an econometric strategy to measure development resilience. Poverty traps approaches allow for the possibility of non-linear well-being dynamics and path dependency, but focus largely on *ex post* analysis of well-being. Meanwhile vulnerability approaches emphasize probabilistic *ex ante* measures at the expense of considering non-linear path dynamics. Our work combines both approaches to estimate probabilistic *ex ante* well-being dynamics. Then by adapting the seminal poverty measurement work of Foster, Greer & Thorbecke (1984, hereafter FGT), we turn the individual-level resilience 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.

2 | Method

Development resilience estimation methods are best illustrated through an empirical example. We therefore illustrate our new method by looking at pastoralist communities in

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northern Kenya, which rely heavily on livestock for their livelihoods and are extremely vulnerable to weather shocks, such as drought. In this region, prior research has convincingly established that drought risk is a key driver of households' collapse into persistent poverty. The regional focus is appropriate as the 2011 drought across the Horn of Africa motivated governmental and non-governmental interest in resilience.

We first construct each household's individual well-being conditional probability density function. Specifically, we estimate the function's mean, conditional on their past well-being and other characteristics, allowing for highly non-linear dynamics, Poisson-distributed generalized linear model using a maximum likelihood estimator. We subsequently estimate the conditional variance of well-being. Together, these first two conditional moments describe the household well-being function (please refer to the full paper for a detailed description of this process). Because most survey households in northern Kenya hold a large share of their wealth in livestock and depend heavily on livestock to generate income, livestock holdings offer a logical measure of well-being in pastoralist settings. The primary 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. We then select a normative well-being threshold, basically a poverty line, which in this case is set at six TLU—a previously identified critical livestock threshold in northern Kenya (Barrett et al., 2006). The period- and household-specific resilience score is the household's probability of being above the six-TLU threshold in the given period.

In order to generate aggregate FGT-like development resilience measures for a population from the set of household-specific estimates, we must first determine at what probability of surpassing the six-TLU threshold a household should own in order to be deemed resilient (and below which it is considered not resilient). In our example, we place this probability threshold at 80%, meaning that we only consider a household resilient if it has at least an 80% probability of having six or more TLU at a given point in time. We then estimate the population share that is not resilient; in this case 40%. One appealing feature of this particular measure is its decomposability; the sample population can be broken down into subgroups of interest (by sex, educational attainment, etc.). Another benefit 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 forward-

looking scenarios. We can simulate how, for example, development resilience will develop in the absence (or presence) of another drought shock.

To illustrate this, we calculate the headcount measure for each round, disaggregated by the sex of the household head and also by nomadic status) to observe the evolution of development resilience over the course of a drought cycle (Figure 1). Although headcount resilience is quite similar for male and female headed households in period 2, when a major drought hit after period 2, female headed households do not appear to have been as substantially impacted at first as male headed households were. But then female headed households' headcount resilience score continues to decline over the subsequent survey period and is projected to drop even further in periods 6 and 7. Male headed households, on the other hand, see a sharp drop in their headcount resilience post-drought. But unlike their female headed counterparts, male headed households recover most of their lost resilience within three years of the drought and are 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 the development resilience measure varies by nomadic status. As also depicted in Figure 1, 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 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.

3 | Applications

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. The resilience differences based on nomadic status and household head gender suggest that there are targetable characteristics for interventions aimed at boosting the resilience of vulnerable households. Because good targeting necessarily involves forecasting where a household would be in the absence of

an intervention, the (potential) nonlinear 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, which imposes a strong assumption not required by our method, 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 repeated observations of individuals and households to predict future outcomes. In order to assess the targeting accuracy of this approach versus conventional approaches, we also compare targeting accuracy rates, Type I errors (errors of inclusion) and Type II errors (errors of exclusion), for different probability thresholds for a standard targeting approach and a resilience-based targeting approach, as described in Upton, Cissé, and Barrett (2016). We estimate targeting accuracy for an intervention in period 5 using the development resilience approach that draws from periods 1-4 and compare it to a standard targeting regime based only on data from period 4. We find that, for each measure, there is a probability threshold that outperforms the standard model. Put differently, targeting based on resilience forecasts generated by this method outperforms the standard approach on the measure of interest, given decision-makers' priorities. The development resilience approach explicitly allows policymakers to choose between leakage to unintended beneficiaries and under-coverage of intended recipients, depending on priorities and resource constraints.

Another application of the development resilience measure itself is to aggregate it over time, using appropriate discount rates, to provide an intertemporal measure of resilience simi-

lar to Calvo & Dercon's (2007) measure of chronic poverty. 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. In places where program managers are concerned about the co-evolution of natural resource stocks—soils, forests, wildlife, fisheries, etc.—along with human well-being, such methods show considerable promise.

4 | Conclusions

With many efforts being undertaken by African countries and their partners to build resilience, particularly in areas of cyclical climatic shock, this paper provides an approach for evaluating the impact of those interventions. In particular, this work highlights the need for resilience initiatives to be evaluated in terms of their impacts not only on mean well-being, but on the variance of well-being as well. The approach also highlights how policymakers can use longitudinal data to assess the resilience of various subgroups in order to target resilience-building interventions.

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. We support calls for 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 (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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Figure 1 Subgroup TLU Resilience Headcount

