DEVELOPMENT RESILIENCE ESTIMATION: THEORY AND APPLICATIONS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Jennifer Denno Cisse

August 2017

DEVELOPMENT RESILIENCE ESTIMATION: THEORY AND APPLICATIONS

Jennifer Denno Cisse, Ph.D.

Cornell University 2017

The past five to ten years has seen the emergence of a new term on the humanitarian and development economics landscapes, *resilience*. While this term holds considerable promise, international development practitioners and the academic community have yet to reach consensus on a consistent definition of resilience and few, if any, theory-based methods for estimating resilience in a development context have been developed. This dissertation introduces an econometric strategy for estimating individual or household-level development resilience from panel data and applies this strategy to two different contexts. The first, more theoretical, paper proposes a conditional moments-based approach to development resilience estimation and illustrates the method empirically using household panel data from pastoralist communities in northern Kenya. The results demonstrate not only the method and its potential as a targeting tool for resilience-building interventions, but also help explain the behavioral paradox of apparent herd overstocking in pastoral communities.

The second paper of the dissertation applies the development resilience approach to evaluate the impact of an index insurance product on resilience. Taking advantage of an experimental, multi-round, household panel dataset, the paper employs an instrumental variable approach to evaluate the impact of an index-based livestock insurance product in Northern Kenya on development resilience in terms of both household herd size, the primary productive asset in the region, and child health. The results indicate that index-based livestock insurance increases household resilience to drought in terms of household livestock holdings. Insurance is

also associated will substantially higher nutritional resilience in the children of drought-affected households.

The final paper of the dissertation evaluates the empirical relationship between livelihood diversification—both on-farm crop diversification and income diversification—and well-being, measured as monthly household expenditures per adult equivalent, in rural Uganda. Results indicate that income diversification is negatively associated with resilience. Crop diversification is associated with increased resilience, but only when considering poverty thresholds above the rural absolute poverty line. Diversification into cash crops and non-farm income does not increase resilience. These results indicate that crop diversification (although not diversification into cash crops) should be considered in similar contexts as a tool for increasing resilience, although not necessarily for the poorest households. More generally, it demonstrates the importance of applying a development resilience approach when evaluating the potential benefits of risk management strategies and resilience-building activities.

BIOGRAPHICAL SKETCH

Jennifer Denno Cisse is a development economist and aid worker, currently serving as the Senior Risk Advisor in the Bureau for Food Security at the US International Development Agency. Prior to completing her Ph.D., Dr. Cisse worked for Catholic Relief Services, managing development projects and writing grant proposals for activities in Africa and Asia. She holds a B.A. in Mathematics from Smith College and an M.A. in International Relations from the Johns Hopkins School of Advanced International Studies (SAIS). Dr. Cisse served as a Peace Corps Volunteer in Guinea.

DEDICATION

To my husband and children,

Thank you for joining me on this adventure.

I would be lost without you.

Je vous aime.

ACKNOWLEDGEMENTS

I would like to thank Christopher B. Barrett, Mark A. Constas, and Shanjun Li for their comments, guidance and support. I would also like to thank participants in several Cornell University seminars and academic conference presentations for comments on various drafts of this research. This dissertation uses two primary sources of data: 1) data collected by a consortium led by the International Livestock Research Institute, funded by the UK Department for International Development through FSD Trust Grant SWD/Weather/ 43/2009, the United States Agency for International Development grant No: EDH-A-00-06-0003-00 and the World Bank's Trust Fund for Environmentally and Socially Sustainable Development and 2) data collected by the World Bank Living Standard Measurement Study—Integrated Surveys on Agriculture (LSMS-ISA) program.

I am grateful for financial support from the USAID BASIS Research Program at the University of California at Davis, the USAID-funded Technical Consortium for Building Resilience to Drought in the Horn of Africa, a CGIAR project, and the African Development Bank.

Finally, I would like to thank my husband and children for their love and patience on this journey; my parents for their love and support; my committee for their guidance and collaboration; and my friends, particularly JBR and the indomitable ladies of 410 Warren Hall, for their strength and infinite emotional support. Without you this would not have been possible.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the supporting agencies. All errors are my own.

TABLE OF CONTENTS

PREFACE

I. Introduction

Over the past twenty years, scholars have made considerable progress in understanding poverty and its counterpart, well-being. In economics, seminal contributions include theoretical explanations for persistent poverty; approaches to understanding the interplay between risk, vulnerability, and poverty; and methods for calculating intertemporal and multidimensional poverty. Despite the richness of the poverty dynamics/traps and vulnerability literatures, the past five to ten years has seen the emergence of a new term on the development economics landscape, resilience. While this term holds considerable promise, much of the economic literature on development resilience to date has failed to incorporate many of the poverty and vulnerability measurement lessons of the past twenty years.

The goal of this dissertation summary is threefold; 1) to critically examine the poverty dynamics and vulnerability literatures in order to identify both critical elements and central issues; 2) to build a consistent lexicon for the economics of development resilience that highlights the conceptual foundations of development resilience and a resilience approach to well-being estimation; and 3) to clarify the contribution of my dissertation to these literatures. This document is organized as follows: The second section contains the literature review, which is organized conceptually around the three topics mentioned above and is focused on the theoretical insights they provide. The third section highlights how I bring together the strengths of these various research fields and discusses my general contribution to the literature. Finally, the fourth section briefly summarizes each of the three chapters of my dissertation.

II. Literature Review

Our current understanding of how poverty evolves over time, particularly in the face of shocks, comes from three distinct but related literatures: the poverty dynamics and traps, vulnerability, and resilience literatures. The following section works through each of these literatures, with an eye to highlighting the key strengths and lessons of each.

Poverty dynamics and traps

While the literature on economic growth and poverty reduction is vast, I will focus here on theoretical micro-economic contributions from the past twenty or so years, with a particular emphasis on models that incorporate dynamics and/or risk explicitly. Although a bit older, Loury (1981) describes the potential theoretical impacts on human capital investment of stochastic income and incomplete credit markets for educational loans. Rosenzweig and Binswanger (1993) provide the first, as far as I am aware, empirical study of farmer risk aversion in the context of incomplete insurance markets and informal idiosyncratic risk sharing, finding that utility-maximizing farmers with higher levels of risk exposure self-insure against covariate weather shocks through the selection of lower mean production, lower variance portfolios. The authors examine *ex ante* behavior during a single period only. Building on this, Banerjee and Newman (1994) outline perhaps the first micro-economic model of poverty traps resulting from (credit) market failures and demonstrate that, in a simple two period model, poor households pass on poverty to their children. Similarly, Barham (1995) describes a three period model in which liquidity constraints among poor households (also a form of credit market failure) limit human capital investments and therefore trap future generations in poverty.

In his seminal paper, Dasgupta (1997) explores how nutrition and income are mutually (and deterministically) reinforcing, and describes the possibility of two distinct stable equilibria:

adequate nutrition to sustainably meet needs through economic participation and perpetual malnutrition. Dasgupta argues that these “lock-in effects” may be found even without credit market failures, although he acknowledges that market imperfections certainly exacerbate poverty traps. Dercon (1998) proposes a model of asset accumulation in the face of credit constraints and risk, and implements it empirically using a very small panel (80 households) in rural Tanzania. He theorizes that credit market imperfections and the indivisibility of livestock assets cause barriers to entry into animal rearing (which he considers a high-return investment), causing poorer households to continue low return, low risk non-farm activities and eventually leading to growing inequality.

Baulch and Hoddinott (2000), in their introduction to a special issue of the Journal of Development Studies, describe the multiple “dimensions” of economic mobility and poverty: 1) metrics of interest, 2) temporal concerns, and 3) additionality. They highlight problems, in a stochastic world, with cross-sectional poverty measures that fail to differentiate between the “sometimes poor” and the “always poor” although they point out that even with multiple rounds of data 1) measurement error leads to an overstatement of the number of transitorily poor households and 2) the heterogeneity of the transitorily poor may hide important distinctions in terms of welfare, suggesting a permanent income approach may be more appropriate in some circumstances. Further, Naschold and Barrett (2011) demonstrate that much of the empirical evidence on transitory poverty is overstated due to the relatively short windows between rounds in many panel datasets. With regards to measures, Baulch and Hoddinott (2000) emphasize that different welfare measures may lead to very different conclusions about the magnitude of chronic or transitory poverty. They differentiate between short term poverty dynamics and long term economic mobility, the latter of which they argue also must incorporate initial conditions, shocks, macroeconomic conditions, the impact of asset stocks on welfare.

Carter and May (2001) expand the standard single-period poverty line intertemporally using a formula for discounted present value and classify households as dynamically poor if the "maximal discounted stream of [the household's] future livelihoods" (p. 1989) given its initial asset endowment is below the multiperiod poverty line. Although the authors do not include measures of shocks specifically, they do include a stochastic component which allows them to classify families as either stochastically or structurally poor (or non-poor). Zimmerman and Carter (2003) explore a dynamic, stochastic model with subsistence constraints and revitalize Lipton's (1993) concept of a Micawber threshold around which asset dynamics bifurcate between asset accumulation and decumulation. The authors demonstrate that poor but rational actors will alter consumption patterns to smooth assets in response to shocks (and with missing insurance markets). Lybbert et al. (2004) study stochastic well-being dynamics among Ethiopian pastoralists, building on the hypothesis that "history dependence" may drive poverty dynamics in situations of multiple equilibria, they offer an empirical estimation of multiple dynamic wealth (in terms of livestock assets) equilibria using a non-parametric approach which is able to capture non-linearities in asset dynamics. On the other hand, Kraay and McKenzie (2014) argue that, despite the value and advancement of the literature, there is a lack of evidence for the existence of poverty traps in practice—remote rural areas, such as the one studied by Lybbert et al., perhaps being the primary exception.

Prior to 2006, the poverty dynamics and measurement literatures were focused on *ex post* poverty measurement, identifying who was poor in the past. Carter and Barrett (2006) pull together the previous literatures on asset accumulation and stochastic versus structural poverty, laying the groundwork for a “forward-looking” (*ex ante*) poverty measure that builds on the strengths of the vulnerability literature (discussed below) as well. Hoddinott (2006) furthers the literature on poverty dynamics and asset accumulation, pointing out that the previous literature inadequately examined intra-household aspects of poverty dynamics. He also recasts the consumption versus asset smoothing debate by noting that households simply decide which capitals (including between human capital and physical assets or between the human capital of children and adults) to conserve and which to draw down in response to shocks.

Vulnerability

Although much has been written on vulnerability in recent years, the literature primarily began as a series of (sometimes still unpublished) working papers responding to critics that the poverty measurement literature was too backward-looking and that the poor themselves consider vulnerability to be an important aspect of poverty (Kanbur & Squire 1999). One of the earliest of these was Pritchett, Suryahadi and Sumarto (2000), who propose, as far as I am aware, the first probabilistic measure of vulnerability. The authors define vulnerability as the probability (or risk) that a household will fall below the poverty line in the future (three years). This focus on the near future distinguishes the vulnerability literature from much of the poverty dynamics literature. While the authors do construct a headcount measure, they do not examine depth of vulnerability per se. Christiaensen and Boisvert (2000) highlight that the well-being can be measured using a variety of “focal variables,” a probability distribution, a well-being threshold, and a probabilistic vulnerability threshold. They also suggest an FGT-type aggregator can be used to measure the depth of vulnerability. Chaudhuri, Jalan, and Suryahadi (2002) also consider vulnerability as the probabilistic interpretation of a stochasitic process. Although they suggest a framework for measuring vulnerability, their reliance on cross-sectional data means that the estimates are actually *ex post* estimates of the probability of a household being in poverty and cross-sectional variation is assumed to resemble variation over time.

The pieces above can all be grouped into one approach to vulnerability measurement, which Hoddinott and Quisumbing (2003) refer to as the vulnerability as expected poverty (or VEP) approach. The VEP approach has multiple strengths, particularly its forward-looking nature and explicit focus on risk and shocks. Hoddinott and Quisumbing (2003) identify two other approaches to vulnerability measurement in their review, vulnerability as low expected utility (VEU) and vulnerability as uninsured exposure to risk (VER). Gisele and Morduch (2002) are perhaps the earliest proponents of the VEU approach. Their framework uses Monte Carlo simulations combined with bootstrapping to nonparametrically generate a household's future well-being distribution. In general, the VEU and VER approaches to vulnerability measurement are further removed from the poverty measurement literature, and my work builds primarily on the VEP approach.

Resilience

As the vulnerability literature was developing in the early 2000s, the concept of resilience—previously a concept in the ecology and ecosystems literature (Holling 1996)—began to draw the attention of researchers working on social problems, from socioecological systems (Carpenter et al. 2001, Folke 2006), including pastoral systems (Robinson and Berkes 2010), to planning (Davoudi 2012). As cyclical shocks, disaster risk reduction, and climate change became more of a focus of the international development and humanitarian communities, the concept of resilience became increasingly central in donor thinking (e.g., USAID 2012). Some argued that the focus on resilience risked to leave vulnerable populations behind by ignoring the power dynamics that contributed to poverty and vulnerability (Cannon & Müller-Mahn 2010), while others argued that the concept of resilience allowed development actors to refocus on the most vulnerable populations (Levine 2014).

Despite significant focus in the past five years, the development community has still not reached a consensus on the definition of resilience, how it relates to vulnerability, whether resilience should be considered an attribute or an outcome, and whether resilience is a latent concept or is measured by observable well-being outcomes. Important work in this direction has been carried out by the Resilience Measurement Technical Working Group, who proposed a set of resilience measurement principles, including connections between resilience and vulnerability (Constas, Frankenburger, & Hoddinott 2014). Constas provides a convenient framework for thinking about different definitions (or interpretations) of resilience: resilience as a multidimensional construct, resilience as a predictor, resilience as a property, and resilience as a paradigm (Constas (2016) as cited in d'Errico, Garbero, and Constas (2016)).

In terms of empirical applications, Béné et al. (2014) provide a review of the early application of resilience to the field of international development, and begin to develop the concept of resilience as a set of capacities. The view that resilience was about agency and quite separate from vulnerability was further developed by Béné et al. (2016). Barrett and Constas (2014), on the other hand, view resilience as an outcome and emphasize the need for a resilience measure that allows for nonlinear well-being dynamics.

Recent empirical papers, most of which are focused on the Horn of Africa or the Sahel, have used latent variable techniques to construct food security resilience indices (Alinovi, Mane, & Romano 2010; FAO 2015), principal component analysis to construct vectors of resilience capacities (Smith et al. 2015), household welfare dynamics to measure resilience (Vaitla et al. 2012), imputed counterfactual measures to categorize households based on predicted consumption (Alfani et al. 2015), classifications of households by the speed to which they bounce back from shock (Tesso, Emana, & Ketema 2012), and developed a methodology for using panel precipitation data to examine the effects of climate shocks on Ethiopian households (Vollenweider 2015). Yet despite the view that that resilience must be based around shocks (Régibeau & Rockett 2012), few of these empirical papers integrate shocks into their analysis.

III. Synthesis and Contribution

The key contribution of my dissertation is a pulling together of these three literatures into an empirical framework that acknowledges the importance of assets, path dynamics, and stochasticity—as highlighted in the poverty dynamics literature—together with probabilistic well-being measurement and prediction. A probabilistic, moments-based approach explicitly models mean, variance, and potentially even higher order moments of well-being, much as proposed by supporters of vulnerability approaches. This is particularly important as development actors increasingly focus on activities that promote resilience by helping farmers manage risk. Assessing the impact of these activities on mean well-being without an understanding of the conditional variance of well-being limits our ability to understand the risks vulnerable populations face and how best to address these risks.

At the same time, incorporating lagged well-being acknowledges the importance of initial asset or well-being conditions. Higher order polynomial lagged well-being terms allow for nonlinearities in these path dynamics, as emphasized in the poverty traps literature. Finally, the probabilistic development resilience approach I develop in my dissertation, building on the VEP approach discussed above, allows researchers and policy-makers to predict out over time, making the resilience approach a potentially powerful targeting tool. At the same time, the approach explicitly controls for observed shocks and climactic stress, which is necessary to assess resilience in the face of shocks.

IV. Dissertation Papers

Paper 1 – Estimating Development Resilience: A Conditional Moments-Based Approach

For the first paper of my dissertation, Chris Barrett and I develop an empirical strategy for estimating resilience based on theoretical work by Barrett and Constas (2014). The issue of resilience measurement involves two distinct but related tasks: development resilience estimation and aggregation. Resilience estimation is the process by which researchers identify who is resilient and who is not. Several methodologies have been proposed in the literature on resilience measurement and we review desirable resilience model characteristics, such as stochasticity and nonlinearity, as discussed above.

This dissertation chapter demonstrates how to empirically implement the moments-based approach proposed by Barrett and Constas (2014), which allows us to identify who in a given population is resilient and who is not, as well as how specific interventions impact resilience or how certain characteristics are correlated with household resilience. Although individual- or household-level resilience scores are necessary for understanding the micro impacts of policies and behaviors, it is useful to be able to aggregate these various household level scores into an overall resilience index that is decomposable (and comparable) across subgroups.

The second part of the paper tackles the resilience aggregation issue, building on the seminal poverty measurement work of Foster, Greer, and Thorbecke (1984). As in the first section, the aggregation section begins by laying out desirable characteristics for an aggregate measure and then demonstrates how an appropriate resilience index can be constructed. Finally, we describe how we can predict resilience in order identify targetable characteristic for interventions aimed at boosting the resilience of vulnerable households. We conclude the paper with an example of resilience estimation and aggregation using data on livestock holdings from Northern Kenya, demonstrating how the empirical strategy discussed in the paper can be carried out in practice.

Paper 2 – The Impacts of Index Insurance On Resilience In Northern Kenya

In this paper with Munenobu Ikegami, we implement the empirical strategy discussed in Paper 1 (above) to evaluate the impact of a livestock insurance program in Northern Kenya on participant well-being. Taking advantage of five rounds of panel data from Kenya, including a 2011 insurance payout following extreme drought, we evaluate the impact of livestock insurance on household well-being and resilience in Marsabit.

The East African context is a particularly interesting setting in which to implement an empirical analysis of resilience, given that stochastic poverty traps have been discussed in the East African pastoral context for over a decade (e.g., McPeak & Barrett 2001). In order to dampen the alarming impacts of drought on livestock-dependent households, an index-based livestock insurance (IBLI) program was piloted in Marsabit District (Northern Kenya) beginning in January 2010. Households in the IBLI program area decide whether or not to purchase the product, as well as how many animals to insure. Should drought cause the normalized difference vegetation index (NDVI) to fall below a certain level — a level associated with high animal mortality (Chantarat et al. 2013) — the insurance holder receives a payout. IBLI can therefore be considered a resilience-building program because it aims to protect against catastrophic livestock mortality by allowing households to insure their most important assets against shock.

Building on previous work by Barrett and Constas (2014), we propose a third order polynomial parametric regression model of stochastic well-being in order to evaluate the impact of the insurance product on resilience. The well-being dependent variables of interest are child anthropometry (in terms of mid-upper arm circumference) and household livestock holdings (in terms of tropical livestock units). The dynamic model describes current well-being as a function of lagged well-being and a series of explanatory variables. Since the insurance uptake decision is likely endogenous to any measure of household welfare, we exploit the random distribution of coupons, which in this context can serve as an exogenous shifter of insurance demand, as an instrument for insurance participation. We also use predicted catastrophic livestock mortality data as a proxy for weather shocks.

We find that insurance in the previous season increases a household's resilience in terms of livestock holdings, whether a drought occurred or not. We explore how changing the well-being threshold impacts the results and find that the positive impacts of past season insurance on TLU resilience are statistically significant for thresholds of 20 TLU and above. Shifting the well-being threshold allows us to determine that IBLI it does not effectively increase the resilience of the poorest households with the smallest initial herds. It does, however, dramatically increase the resilience of slightly better-off households and appears to allow them to invest more in their herds while avoiding protective over-stocking.

Given the small sample size of young children and the survey design, we are not able to exploit the instrumental variable for our analysis of the impact of insurance on child health. We do however see a positive association between insurance and child health resilience during droughts. There appears to be no relationship between past season's IBLI coverage and probabilities of subsequently becoming severely acutely malnourished in non-drought years.

Paper 3 –Livelihood Diversification and Well-Being in Uganda: A Development Resilience Approach

In this final paper, I use a large-scale, nationally representative household survey to explore the relationship between livelihood diversification and development resilience in terms of household per adult equivalent expenditures in rural Uganda. Despite the fact that diversification is often cited as an important risk management strategy with potential for increasing resilience, this paper provides one of the first empirical assessments of the relationship between crop and income diversification and resilience in the face of shocks.

I begin by reviewing the literature on diversification, including theories about whether farming households are pulled into diversification as they enter into higher return activities, or whether they are pushed into diversification as a strategy for managing risks and coping with shock. I briefly discuss various measures of diversification used in the literature, before proposing a transformed Herfindahl index to measure crop and income diversification at the household level.

Holding total income, as well as shares of wage and self-employment income, constant, I find that income diversification is negatively associated with increased resilience. For the least resilient households, crop diversification is also negatively associated with resilience. Once the poverty threshold is increased, however, crop diversification is positively and statistically significantly associated with increases in resilience. This is not as a result of diversification into cash crops, which are associated with decreases in conditional mean expenditures and with decreased resilience, as well.

References

Adato, Michelle, Michael R. Carter, and Julian May. 2006. "Exploring Poverty Traps and Social Exclusion in South Africa using Qualitative and Quantitative Data." Journal of Development Studies 42(2): 226–47.

Alfani, Federica, Andrew Dabalen, Peter Fisker, and Vasco Molini. 2015. "Can We Measure Resilience? A Proposed Method and Evidence from Countries in the Sahel." Policy Research Working Paper #7170, World Bank Group – Poverty Global Practice Group.

Alinovi, Luca, Erdgin Mane, and Donato Romano. 2010. "Measuring Household Resilience to Food Insecurity: Application to Palestinian Households." In Agricultural Survey Methods, edited by Roberto Benedetti, Marco Bee, Giuseppe Espa, and Federica Piersimoni. Chichester, U.K.: John Wiley & Sons.

Banerjee, Abhijit V. and Andrew F. Newman. 1994. "Poverty, Incentives, and Development." The American Economic Review, Papers and Proceedings of the Hundred and Sixth Annual Meeting of the American Economic Association, 84(2): 211-5.

Barham, Vicky. 1995. "Education and the Poverty Trap," European Economic Review, 39(7): 1257-75.

Barrett, Christopher B. and Mark A. Constas. 2014. "Toward a Theory of Resilience for International Development Applications." Proceedings of the National Academy of Sciences 40(111): 14625–14630.

Baulch, Bob, and John Hoddinott. 2000. "Economic Mobility and Poverty Dynamics in Developing Countries." Journal of Development Economics Special issue: 1–24.

Béné , Christophe, Derek Headey, Lawrence Haddad, and Klaus von Grebmer. 2016. "Is resilience a useful concept in the context of food security and nutrition programmes?

Some conceptual and practical considerations." Food Security 8(1): 123-38. doi:10.1007/s12571-015-0526-x

Béné, Christophe, Andrew Newsham, Mark Davies, Martina Ulrichs, and Rachel Godfrey-Wood. 2014. "Review Article: Resilience, Poverty and Development." Journal of International Development 26: 598-623.

Cannon, Terry and Detlef Müller-Mahn. 2010. "Vulnerability, resilience and development discourses in context of climate change." Natural Hazards 55(3): 621-35. doi: 10.1007/s11069-010-9499-4

Carpenter, Steve, Brian Walker, J. Marty Anderies, and Nick Abel. 2001. "From Metaphor to Measurement: Resilience of What to What?" Ecosystems 4: 765-81.

Carter, Michael R. and Chistopher B. Barrett. 2006. "The economics of poverty traps and persistent poverty: An asset-based approach." Journal of Development Studies 42(2): 178-199.

Carter, Michael R. and J. May. 2001. "One Kind of Freedom: Poverty Dynamics in Postapartheid South Africa." World Development 29(12): 1987-2006.

Chantarat, Sommarat, Andrew G. Mude, Christopher B. Barrett, and Michael R. Carteret. 2013. "Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya." Journal of Risk and Insurance 80: 205–237. doi: 10.1111/j.1539-6975.2012.01463.x

Chaudhuri, Shubham, Jyotsna Jalan, and Asep Suryahadi. 2002. "Assessing Household Vulnerability to Poverty from Cross-sectional Data: a Methodology and Estimates for Indonesia." Discussion Paper Series No. 0102-52, Department of Economics, Columbia University, New York.

Christiaensen, Luc J. and Richard N. Boisvert. 2000. “On Measuring Household Food Vulnerability: Case Evidence from Northern Mali.” Cornell University Department of Economics Working Paper. WP 2000-05.

Constas, Mark A. 2016. “The four versions of resilience for development: Implications for programming and measurement.” Unpublished manuscript.

Constas, Mark A., Timothy R. Frankenburger, and John Hoddinott. 2014. “Resilience Measurement Principles: Toward an Agenda for Measurement Design.” Published by the Food and Agriculture Organization and the World Food Program under the Food Security and Information Network as Technical Series No. 1.

Dasgupta, P. 1997. “Nutritional status, the capacity for work, and poverty traps,” Journal of Econometrics 77: 5-37.

Davoudi, Simin. 2012. “Resilience: A Bridging Concept or a Dead End?” Planning Theory & Practice 13(2): 299-333.

Dercon, S. 1998. "Wealth, risk and activity choice: cattle in Western Tanzania." Journal of Development Economics 55: 1-42.

d’Errico, Marco, Alessandra Garbero, and Mark A. Constas. 2016. “Quantitative Analyses for Resilience Measurement: Guidance for constructing variables and exploring relationships among variables.” Published by the Food and Agriculture Organization and the World Food Program under the Food Security and Information Network as Technical Series No. 7.

Folke, Carl. 2006. “Resilience: The emergence of a perspective for social–ecological systems analyses.” Global Environmental Change 16: 253-67.

Food and Agriculture Organization. 2015. “Resilience Analysis in Senegal 2005.” FAO Resilience Analysis Team, Agricultural Development Economics Division (ESA), FAO Resilience Analysis No. 1.

Foster, James, Joel Greer, and Erik Thorbecke. 1984. “A Class of Decomposable Poverty Measures.” Econometrica 52(3): 761-66.

Gisele, Kamanou and Jonathan Morduch. 2002. “Measuring vulnerability to poverty.” World Institute for Development Economics, WIDER Discussion Paper No 2002/58.

Hoddinott, John and Agnes Quisumbing. 2003. “Methods for Microeconomic Risk and Vulnerability Assessments.” World Bank Social Protection Discussion Paper Series No. 0324.

Hoddinott, John. 2006. “Shocks and their Consequences Across and Within Households in Rural Zimbabwe.” Journal of Development Studies, 42(2): 301-21.

Hoddinott, John. 2014. “Understanding Resilience for Food and Nutrition Security.” International Food Policy Research Institute, 2020 Conference Paper.

Holling, C.S. 1996. “Surprise for Science, Resilience for Ecosystems, and Incentives for People.” Ecological Applications 6(3): 733-5.

Kanbur, Ravi, and Lyn Squire. 2001. “The evolution of thinking about poverty: exploring the interactions.” Frontiers of Development Economics The Future Perspective. 183-226.

Kraay, Aart and David McKenzie. 2014. “Do Poverty Traps Exist? Assessing the Evidence.” Journal of Economic Perspectives 28(3): 127-48.

Levine, Simon. 2014. “Assessing resilience: why quantification misses the point.” Overseas Development Institute, Humanitarian Policy Group Working Paper.

Lipton, Michael, 1994. “Growing points in poverty research: Labour issues.” Institute of Development Studies, Sussex University.

Loury, Glenn C. 1981. “Intergenerational Transfers and the Distribution of Earnings.” Econometrica 49(4): 843-67.

Lybbert, Travis, Christopher Barrett, Solomon Desta, and D. Layne Coppock. 2004. “Stochastic Wealth Dynamics and Risk Management among a Poor Population.” Economic Journal 114(498): 750–77.

McPeak, John and Christopher B. Barrett. 2001. “Differential Risk Exposure and Stochastic Poverty Traps among East African Pastoralists.” American Journal of Agricultural Economics, 83(3): 674-679.

Naschold, Felix and Christopher B. Barrett. 2011. “Do Short-Term Observed Income Changes Overstate Structural Economic Mobility?” Oxford Bulletin of Economics & Statistics 73(5): 705-17.

Pritchett, Lant, Asep Suryahadi and Sudarno Sumarto. 2000. “Quantifying Vulnerability to Poverty: A Proposed Measure, Applied to Indonesia.” World Bank, Policy Research Working Paper 2437

Régibeau, Pierre and Katharine Rockett. 2012. “Economic Analysis of Resilience: A Framework for Local Policy Response Based on New Case Studies.” Centre for Research in Economic Sociology and Innovation (CRESI) Working Paper 2012-01, University of Essex: Colchester.

Robinson, Lance W. and Fikret Berkes. 2010. “Applying Resilience Thinking to Questions of Policy for Pastoralist Systems: Lessons from the Gabra of Northern Kenya.” Human Ecology 38:335-50. doi: 10.1007/s10745-010-9327-1

Rosenzweig, M. R. and H. P. Binswanger .1993. “Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments.” Economic Journal 103(416): 56-78.

Smith, Lisa, Tim Frankenberger, Ben Langworthy, Stephanie Martin, Tom Spangler, Suzanne Nelson, and Jeanne Downen. 2015. Ethiopia Pastoralist Areas Resilience Improvement and Market Expansion (PRIME) Project Impact Evaluation: Baseline Survey Report. Prepared for USAID’s Feed the Future FEEDBACK project.

Tesso, Gutu, Bezabih Emana, and Mengistu Ketema. 2012. “Analysis of vulnerability and resilience to climate change induced shocks in North Shewa, Ethiopia.” Agricultural Sciences 3(6): 871-88. doi:10.4236/as.2012.36106

US Agency for International Development. 2012. “Building Resilience to Recurrent Crisis: USAID Policy and Program Guidance.”

Vaitla, Bapu, Girmay Tesfay, Megan Rounseville, and Daniel Maxwell. 2012. “Resilience and livelihoods change in Tigray, Ethiopia.” Somerville, MA: Tufts University, Feinstein International Center.

Vollenweider, Xavier. 2015. “Measuring Climate Resilience and Vulnerability: A Case Study from Ethiopia.” Final Report prepared for the Famine Early Warning Systems Network (FEWS NET) Technical Support Contract (TSC), Kimetrica LLC.

Zimmerman, Frederick J. and Michael R. Carter. 2003. “Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints.” Journal of Development Economics, 71: 233-60.

CHAPTER 1

ESTIMATING DEVELOPMENT RESILIENCE:
A CONDITIONAL MOMENTS-BASED APPROACH

Jennifer Denno Cissé and Christopher B. Barrett

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 and 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 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

---

[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 and Constas (2014) for a discussion of why that concept must be adapted for international development or broader economic applications.

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), no peer-reviewed 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 & Perge 2013). However, that literature focuses largely on *ex post* analysis of well-being. The vulnerability literature (e.g., Christiaensen & Boisvert 2000; Chaudhuri, Jalan, & Suryahadi 2002; Hoddinott & Quisumbing 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

[2] Several 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).

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, ***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). That literature to date has largely ignored heteroscedasticity and other non-constant higher-order central moments in the 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. 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. 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.

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

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

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

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).[3] Once we have estimated the household-and-period-specific ccdf, we can use it to estimate the probability of household *i* reaching some normative minimum standard of well-being in time *t*. We follow the BC framework, defining development resilience 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

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

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

---

[3] 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.

We can use this estimate 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:

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

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. 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 ($\ddot{\boldsymbol{X}}$):

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

where $\hat{\mu}_{1i,t+1} = g_M(W_{it}, \ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}, \hat{\beta}_M) + \widehat{\boldsymbol{\delta}}_{\mathbf{M}}\ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}$ and $\hat{\mu}_{2i,t+1} = g_V(W_{it}, \ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}, \hat{\beta}_V) + \widehat{\boldsymbol{\delta}}_{\mathbf{V}}\ddot{\boldsymbol{X}}_{\boldsymbol{i,t+1}}$. 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. If and only if $\hat{\rho}_{it} \geq \underline{P}$ 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 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 $\boldsymbol{X}$ 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.

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.

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.[4] Sen proposed a poverty measure that meets additional desirable characteristics he sets out, including "relative equity,"[5] and conveniently lies between 0 and 1. Sen also argues that a

---

[4] 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).

[5] 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).

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 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 of household development resilience measures in time period $t + s$ ordered from lowest to highest values, $\boldsymbol{\rho} = (\hat{\rho}_1, \hat{\rho}_2, \hat{\rho}_3, \ldots, \hat{\rho}_n; \underline{W})$ 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) $R_{\alpha,t+s}\left(\boldsymbol{\rho_{t+s}}; \underline{W}, \underline{P}\right) \equiv 1 - \left[\frac{1}{n}\sum_{i=1}^{q_{t+s}}\left(\frac{g_{i,t+s}}{\underline{P}}\right)^{\alpha}\right],$

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 and Barrett 2011).

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 in Northern Kenya 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 from sixteen sublocations[6] in Marsabit County, including general demographic

[6] 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).

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[7] of the longitudinal annual survey have been administered each October-November, beginning in 2009 (prior to the first insurance sales window).

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. During the five rounds of data, a catastrophic drought occurred once, between rounds two and three.

Table 1 presents summary statistics. We distinguish between fully settled households that never relocated do not practice transhumance and those partially or fully nomadic 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.[8] 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

---

[7] 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 recently been collected but has not yet been included in this analysis.

[8] 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.

attrited households, which may partially explain why no one was available to respond to the survey during a given round.

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.

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 for the household head, the household dependency ratio, and controls for religious affiliation and nomadic status:

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

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, unlike prior empirical studies of herd dynamics using earlier datasets from the region, 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. 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.

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,[9]

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

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[10]—vary, both over time and

---

[9] 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.

[10] 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).

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 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 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:

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

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[11] 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 period livestock holding (lagged TLU) levels.[12] 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.

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

---

[11] 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

[12] 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.

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.[13]

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 are not 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

[13] 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.

headcount estimate of the population share who are not resilient, for the entire sample, pooled across periods, we estimate

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

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 unable 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 resilience post-drought. Importantly, 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, and 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.

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 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 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. 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 (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.

References

Adato, Michelle, Michael R. Carter, and Julian May. 2006. "Exploring Poverty Traps and Social Exclusion in South Africa Using Qualitative and Quantitative Data." The Journal of Development Studies 42(2): 226-47.

Alfani, Federica, Andrew Dabalen, Peter Fisker, and Vasco Molini. 2015. "Can We Measure Resilience? A Proposed Method and Evidence from Countries in the Sahel." Policy Research Working Paper #7170, World Bank Group – Poverty Global Practice Group.

Alinovi, Luca, Erdgin Mane, and Donato Romano. 2010. "Measuring Household Resilience to Food Insecurity: Application to Palestinian Households." In Agricultural Survey Methods, edited by Roberto Benedetti, Marco Bee, Giuseppe Espa, and Federica Piersimoni. Chichester, U.K.: John Wiley & Sons.

Antle, John M. 1983. "Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach." Journal of Business & Economic Statistics 1(3): 192-201.

Antman, Francisca and David McKenzie. 2007." Poverty traps and nonlinear income dynamics with measurement error and individual heterogeneity." Journal of Development Studies 43(6): 1057-83.

Barrett, Christopher B. and Michael R. Carter. 2013. "The Economics of Poverty Traps and Persistent Poverty: Empirical and Policy Implications." Journal of Development Studies 49(7): 976-990.

Barrett, Christopher B. and Mark A. Constas. 2014. "Toward a Theory of Resilience for International Development Applications." Proceedings of the National Academy of Sciences 40(111): 14625–14630.

Barrett, Christopher B. and Derek Headey. 2014. “Measuring Resilience in a Volatile World: A Proposal for a Multicountry System of Sentinel Sites.” Paper prepared for the 2020 Vision Initiative. Washington: International Food Policy Research Institute.

Barrett, Christopher B., Paswel Phiri Marenya, John McPeak, Bart Minten, Festus Murithi, Willis Oluoch-Kosura, Frank Place, Jean Claude Randrianarisoa, Jhon Rasambainarivo, and Justine Wangila. 2006. "Welfare Dynamics in Rural Kenya and Madagascar." Journal of Development Studies 42(2): 248-77.

Béné, Christophe, Andrew Newsham, Mark Davies, Martina Ulrichs, and Rachel Godfrey-Wood. 2014. “Review Article: Resilience, Poverty and Development.” Journal of International Development 26: 598-623.

Bury, Karl. 1999. Statistical Distributions in Engineering. Cambridge, UK: Cambridge University Press.

Calvo, Cesar and Stefan Dercon. 2007. “Chronic poverty and all that: the measurement of poverty over time.” CPRC Working Paper 89, Chronic Poverty Research Centre.

Cameron, A. Colin and Pravin K. Trivedi. 2010. Microeconomics Using Stata: Revised Edition. College Station, TX: Stata Press.

Cannon, Terry and Detkef Müller-Mahn. 2010. “Vulnerability, Resilience and Development Discourses in the Context of Climate Change.” Natural Hazards 55(3): 621-635.

Carter, Michael R. and Christopher B. Barrett. 2006. “The economics of poverty traps and persistent poverty: An asset-based approach.” Journal of Development Studies 42(2): 178-199.

Carter, Michael R. and Julian May. 2001. “One Kind of Freedom: Poverty Dynamics in Post-apartheid South Africa.” World Development 29(12): 1987-2006.

Chantarat, Sommarat, Andrew G. Mude, Christopher B. Barrett, and Michael R. Carteret. 2013. “Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya.” Journal of Risk and Insurance 80: 205–237. doi: 10.1111/j.1539-6975.2012.01463.x

Chaudhuri, Shubham, Jyotsna Jalan, and Asep Suryahadi. 2002. “Assessing Household Vulnerability to Poverty from Cross-sectional Data: a Methodology and Estimates for Indonesia.” Discussion Paper Series No. 0102-52, Department of Economics, Columbia University, New York.

Christiaensen, Luc J. and Richard N. Boisvert. 2000. “On Measuring Household Food Vulnerability: Case Evidence from Northern Mali.” Cornell University Department of Economics Working Paper. WP 2000-05.

Constas, Mark A., Timothy R. Frankenberger, and John Hoddinott. 2014. “Resilience Measurement Principles: Toward an Agenda for Measurement Design.” Food Security Information Network, Resilience Measurement Technical Working Group, Technical Series No. 1.

Davoudi, Simin. 2012. “Resilience: A Bridging Concept or a Dead End?” Planning Theory & Practice 13(2): 299–333.

Folke, Carl. 2006. “Resilience: The Emergence of a Perspective for Social-Ecological Systems Analyses.” Global Environmental Change 16 (2006): 253-67.

Foster, James, Joel Greer, and Erik Thorbecke. 1984. “A Class of Decomposable Poverty Measures.” Econometrica 52(3): 761-66.

Haughton, Jonathan and Shahidur R. Khandker. 2009. Handbook on Poverty and Inequality. Washington, DC: The World Bank.

Headey, Derek and Christopher B. Barrett. 2015. “Measuring Development Resilience in the World’s Poorest Countries.” Proceedings of the National Academy of Sciences 112(37): 11423-5.

Hoddinott, John and Agnes Quisumbing. 2003. “Methods for Microeconometric Risk and Vulnerability Assessments.” Social Protection Discussion Paper No 0324, Human Development Network, the World Bank.

International Livestock Research Institute. 2013. “Index Based Livestock Insurance for Northern Kenya’s Arid and Semi-Arid Lands: The Marsabit Project - Codebook for IBLI Evaluation Survey (Round 1, Round 2, Round 3 and Round 4 Surveys).” http://data.ilri.org/portal/dataset/ibli-marsabit-r1

Just, Richard E. and Rulon D. Pope. 1979. “Production Function Estimation and Related Risk Considerations.” American Journal of Agricultural Economics 61(2): 276-84.

Kolenikov, Stanislav. 2010. Resampling Variance Estimation for Complex Survey Data. The Stata Journal 10(2): 165-99.

Levine, Simon. 2014. “Assessing Resilience: Why Quantification Misses the Point.” HPG Working Paper. London: Overseas Development Institute.

Little, Peter D., John McPeak, Christopher B. Barrett, and Patti Kristjanson. 2008. “Challenging orthodoxies: understanding poverty in pastoral areas of East Africa.” Development and Change 39(4): 587-611.

Lokshin, Michael and Martin Ravallion. 2004. “Household Income Dynamics in Two Transition Economies.” Studies in Nonlinear Dynamics & Econometrics 8(3).

Lybbert, Travis J., Christopher B. Barrett, Solomon Desta, and D. Layne Coppock. 2004. “Stochastic Wealth Dynamics and Risk Management among a Poor Population.” Economic Journal 114: 750-77.

McKay, Andy and Emilie Perge. 2013. “How Strong is the Evidence for the Existence of Poverty Traps? A Multicountry Assessment.” Journal of Development Studies 49(7): 877-97.

McPeak, John, Peter D. Little, and Cheryl R. Doss. 2012. Risk and Social Change in an African Rural Economy: Livelihoods in Pastoralist Communities. London, UK: Routledge.

Naschold, Felix. 2013. “Welfare Dynamics in Pakistan and Ethiopia – Does the Estimation Method Matter?” Journal of Development Studies 49(7): 936-54.

Robinson Lance W. and Fikret Berkes. 2010. “Applying Resilience Thinking to Questions of Policy for Pastoralist Systems: Lessons from the Gabra of Northern Kenya.” Human Ecology 38: 335-50.

Santos, Paulo and Christopher B. Barrett. 2011. “Persistent Poverty and Informal Credit.” Journal of Development Economics 96(2):337-47.

Sen, Amartya. 1976. “Poverty: An Ordinal Approach to Measurement.” Econometrica 44(2): 219-231.

------. 1979. “Issues in the Measurement of Poverty.” Scandinavian Journal of Economics 81(2): 285-307.

Smith, Lisa, Tim Frankenberger, Ben Langworthy, Stephanie Martin, Tom Spangler, Suzanne Nelson, and Jeanne Downen. 2015. Ethiopia Pastoralist Areas Resilience Improvement and Market Expansion (PRIME) Project Impact Evaluation: Baseline Survey Report. Prepared for USAID’s Feed the Future FEEDBACK project.

Upton, Joanna B., Jennifer Denno Cissé, and Christopher B. Barrett. 2016. "Food Security as Resilience: Reconciling Definition and Measurement." Working Paper.

Vaitla, Bapu, Girmay Tesfay, Megan Rounseville, and Daniel Maxwell. 2012. "Resilience and livelihoods change in Tigray, Ethiopia." Somerville, MA: Tufts University, Feinstein International Center.

Vollenweider, Xavier. 2015. "Measuring Climate Resilience and Vulnerability: A Case Study from Ethiopia." Final Report prepared for the Famine Early Warning Systems Network (FEWS NET) Technical Support Contract (TSC), Kimetrica LLC.

Tables

Table 1: Summary Statistics

	Sample Mean	Fully Settled	Nomadic[14]	T-test	Attrited	T-test
Tropical Livestock Units[15]	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[16]	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

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

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

[16] 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.

Table 2: Marginal Effects at Representative Values[17] – 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[18] (2)-(3) standard errors in parentheses. Pooled Sample, n = 3,581. *** p<0.01, ** p<0.05, * p<0.10

[17] 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.

[18] 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.

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

Figures

Figure 1: Estimated Path Dynamics

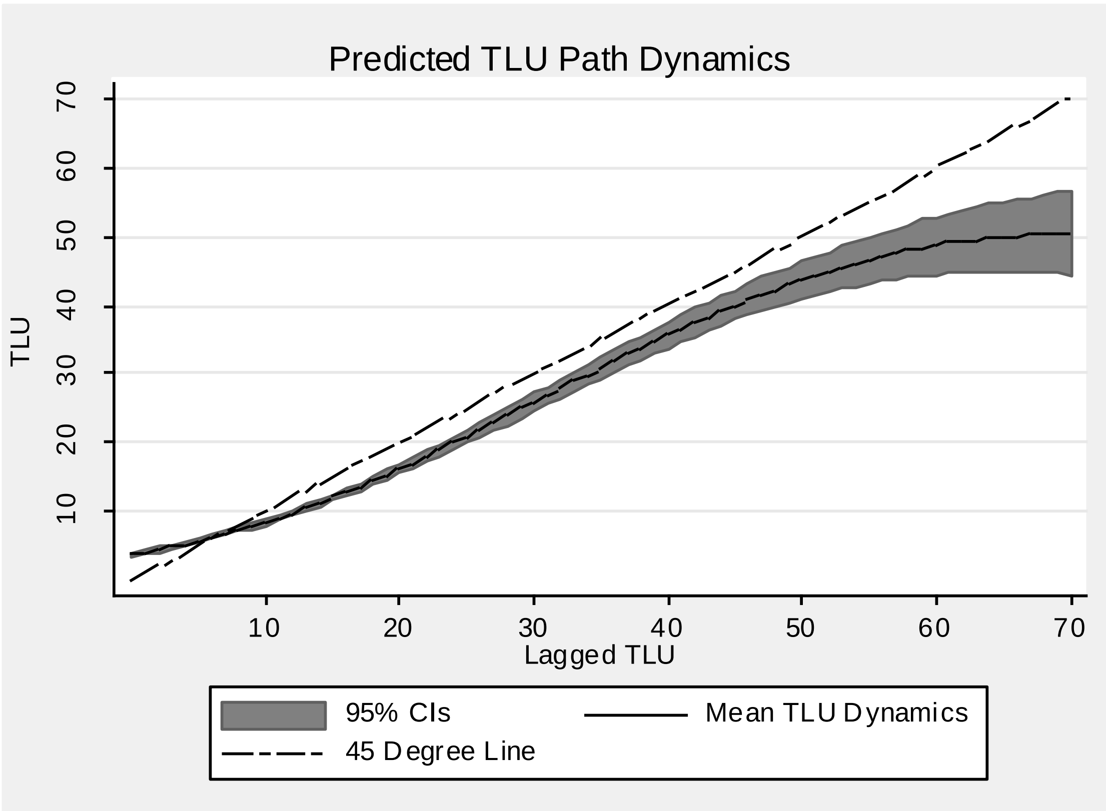
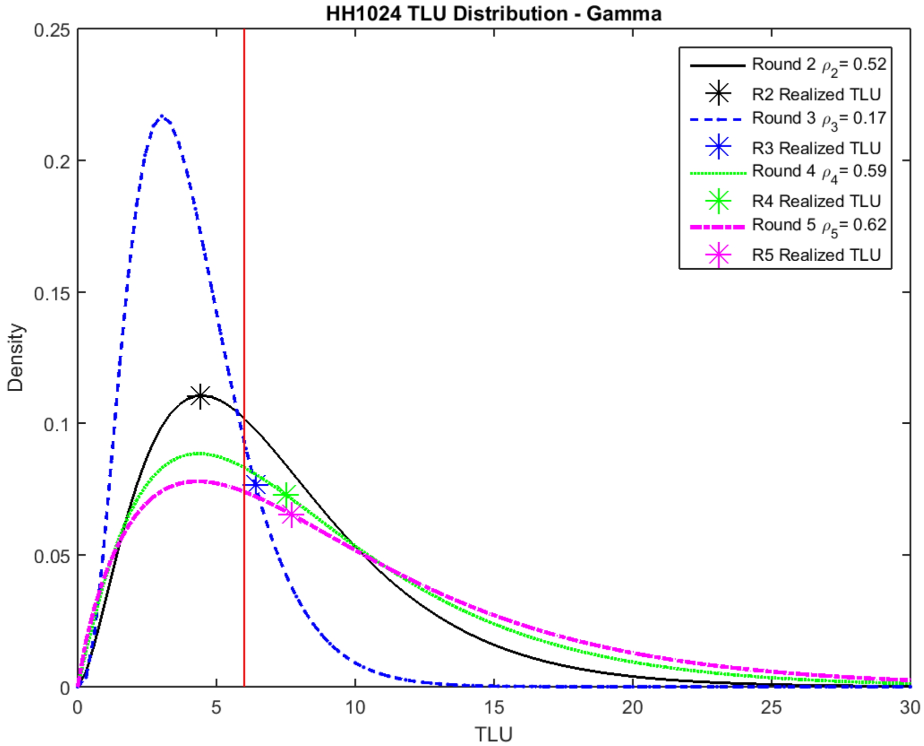


Figure 2: Conditional TLU Well-being pdfs



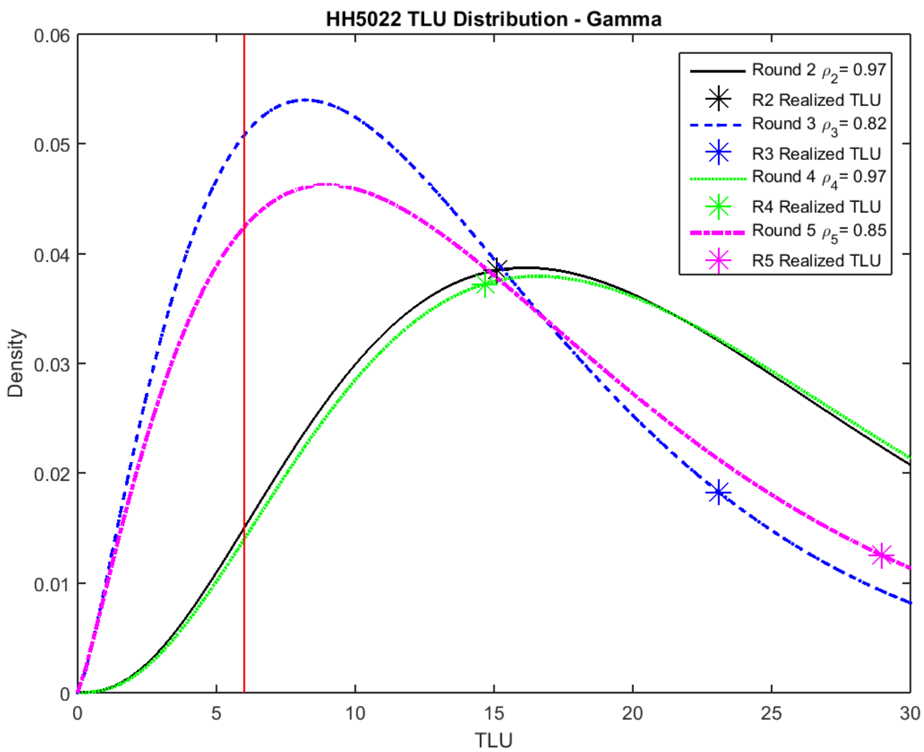


Figure 3: Estimated Resilience Dynamics

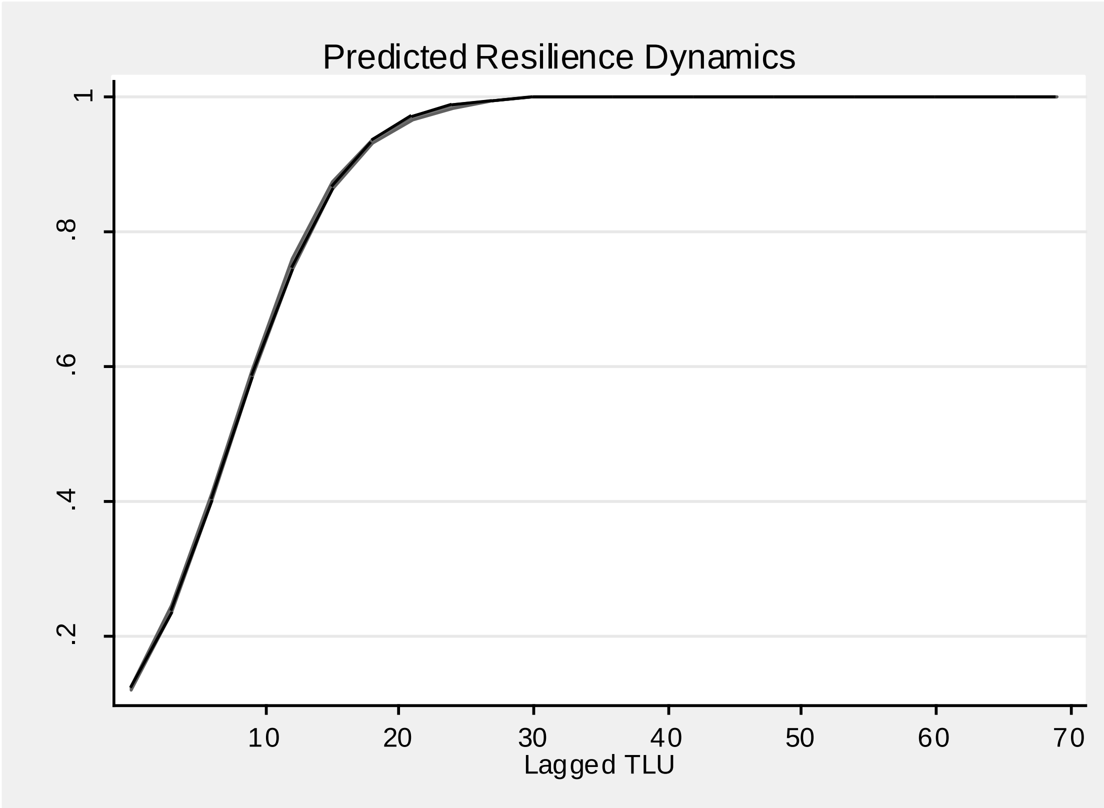
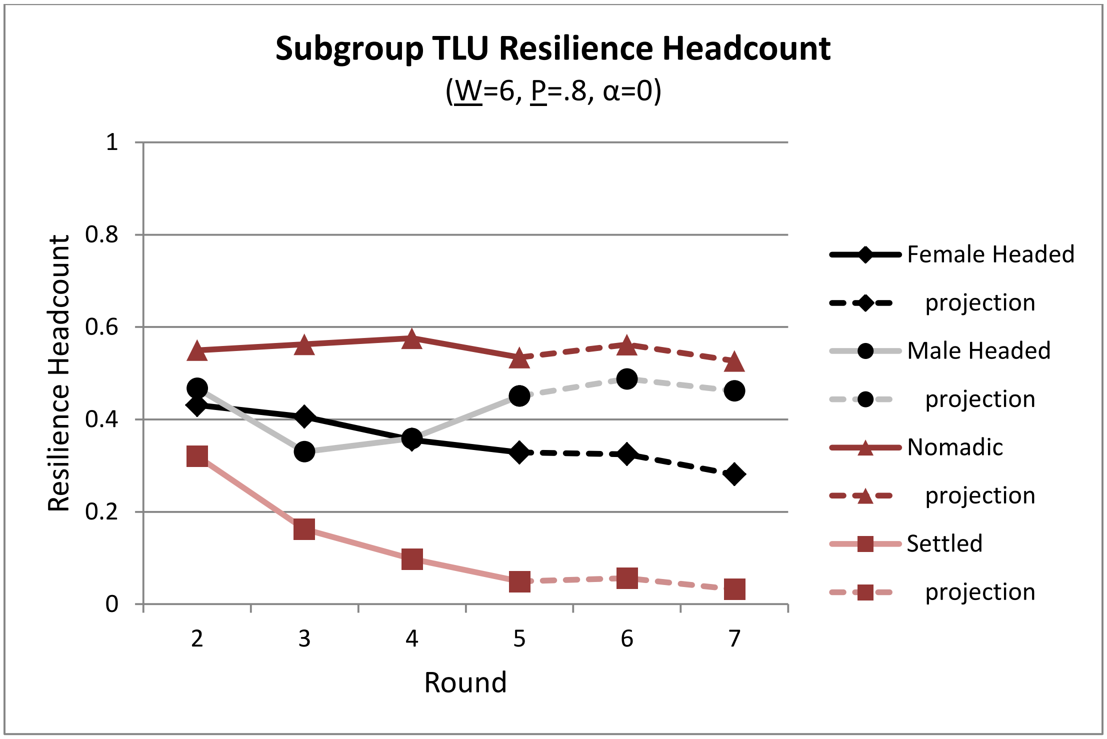


Figure 4: TLU Resilience Headcount



Appendix

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_{t-1}^{2}		-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_{t-1}^{3}			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_{t-1}^{4}				-0.86***	-5.19***	-56.6***	-98.7***	-280***
$(* 10^{8})$				(0.0810)	(1.80)	(10.7)	(17.5)	(44.7)
TLU_{t-1}^{5}					1.00**	18.0***	42.3***	180***
$(* 10^{10})$					(0.252)	(3.98)	(8.81)	(33.7)
TLU_{t-1}^{6}						-2.08***	-8.81***	-64.6***
$(* 10^{12})$						(0.507)	(2.06)	(13.6)
TLU_{t-1}^{7}							0.702***	12.0***
$(* 10^{14})$							(0.179)	(2.74)
TLU_{t-1}^{8}								-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[19]	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

[19] 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][20] low	low	low	(2) TLU Resilience [~ln*N*, W=6][21] 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[22] (1) and robust (2) standard errors in parentheses. Pooled Sample, n = 3,581.
*** p<0.01, ** p<0.05, * p<0.10

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

[21] 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.

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

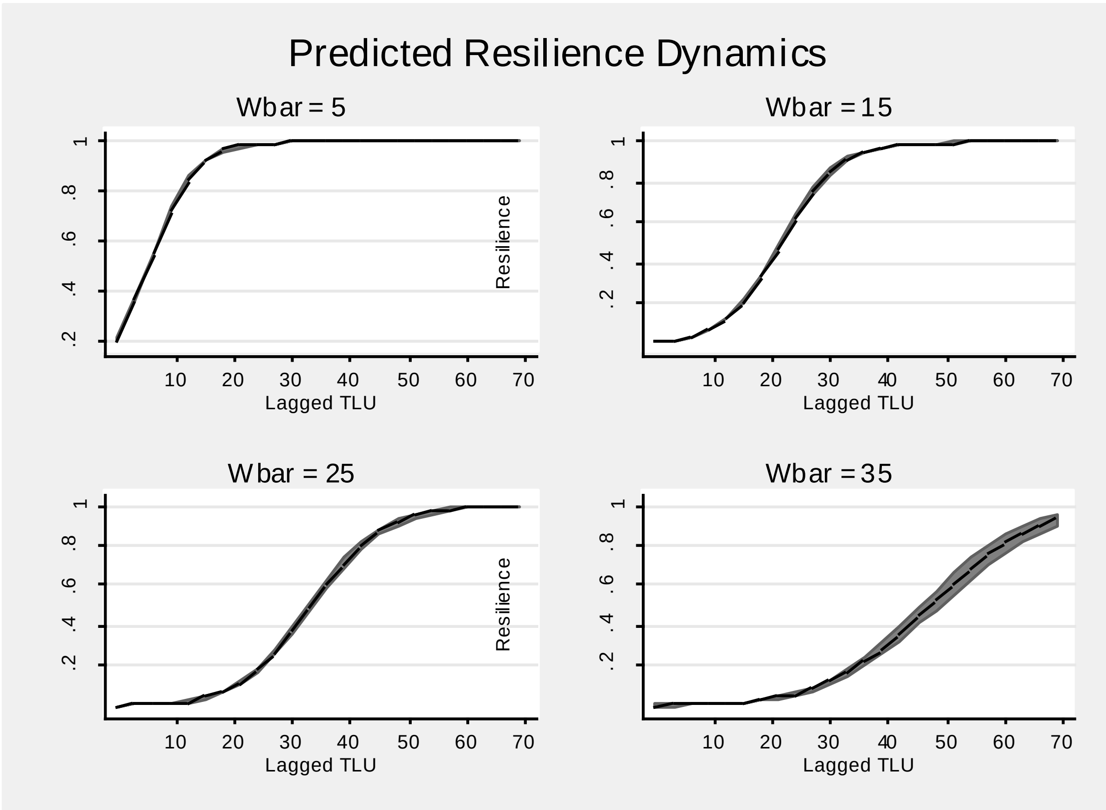
Table B3: OLS Estimates of TLU Well-Being

VARIABLES	(1) IHS[23](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)
$TLU_{t-1}^{2}(*1000)$	-2.40***	0.395	-0.0994**
	(0.172)	(0.336)	(0.0477)
$TLU_{t-1}^{3}(*10^{6})$	12.8***	-1.75	0.563
	(1.35)	(4.34)	(0.647)
$TLU_{t-1}^{4}(*10^{9})$	-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 $Age^{2}(*10^{5})$	-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	1.42	-0.0956	0.0111
$(*100)$	(2.29)	(2.05)	(0.0584)
Religion & Settled Dummies	Y	Y	Y
Constant	0.827***	0.668***	0.0278***
	(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

[23] The inverse hyperbolic sine of TLU.

Figure B1. Estimated Resilience Dynamics for Selected $\underline{W}$



CHAPTER 2

THE IMPACTS OF INDEX INSURANCE ON RESILIENCE IN NORTHERN KENYA

Jennifer Denno Cissé and Munenobu Ikegami

I. Introduction

Northern Kenya is one of the poorest regions of the world. The primary livelihood in the region is nomadic pastoralism, although some households have become sedentarized in recent decades. While sedentarized households may still rely on animal husbandry for their livelihoods, they no longer migrate with their herds. These pastoral and agro-pastoral households are incredibly vulnerable to weather shocks, particularly drought. Yet, as is common in remote rural communities in developing countries, formal insurance and credit markets are highly imperfect in northern Kenya. As a result, households must employ a variety of *ex ante* risk mitigation and *ex post* risk coping strategies, including excess livestock accumulation and sales, asset smoothing, and informal borrowing. In the most extreme cases, these multiple financial market failures create poverty traps (Barrett & Carter 2013).

Recurrent droughts and humanitarian appeals in the Horn of Africa have propelled calls for resilience building and other interventions to help pastoral communities manage drought risk and cope with shocks without falling into poverty traps or relying on increasingly scarce humanitarian assistance. One such intervention, an index-based livestock insurance (IBLI), was commercially piloted in Northern Kenya in 2009. The multi-year project was introduced to help vulnerable pastoral and agro-pastoral populations manage drought risk by allowing them to insure their livestock against drought. Given that pastoralism is the predominate livelihood strategy in the region, livestock was the natural asset to insure.

In this paper, we implement the empirical strategy for estimating development resilience proposed by Cissé & Barrett (2016) in order to evaluate the impact of IBLI on participant resilience in terms of herd size and child health. If a household has a high probability of achieving or maintaining satisfactory well-being with regards to those measures, it is considered resilient. As the first (as far as we are aware) paper evaluating the causal impacts of an insurance program on empirically-measured resilience, this paper contributes to two nascent literatures. First, we contribute to the resilience measurement literature, demonstrating that resilience estimation can and should have an important role in evaluating the well-being of vulnerable populations. Secondly, we contribute to the index insurance literature. The literature on index insurance is primed to expand rapidly as increasing access to affordable, high quality, high-resolution satellite data is driving interest in—and the affordability of—index and microinsurance products around the world. This paper, therefore, will help guide the development of this literature by documenting the causal impacts of an index insurance product on well-being and resilience in a developing country.

We begin by identifying household- and child-level conditional distributions of well-being. We predict household and child development resilience by evaluating the probability, based on their individual distributions, that a household or child will achieve a satisfactory level of well-being based on specific, normative thresholds. We then evaluate the impact of insurance on resilience (probabilities) and explore how changing the normative well-being thresholds affect the impacts of the index insurance product.

We find that, for a well-being threshold of just over two animals per capita, holding an IBLI contract in the previous season increases a household's resilience in terms of livestock holdings, regardless of whether a drought occurred. The impact of insurance on resilience is significantly greater, however, during droughts. For large herd sizes of over five animals per capita, we find that having insurance during a drought increases the probability that a household will achieve the threshold by a statistically significant fifteen percentage points. We also find that IBLI is positively associated with child health resilience during droughts, increasingly the probability that a child will be well-nourished by four percentage points. There appears to be no relationship between insurance holdings and probabilities of subsequently becoming severely acutely malnourished in non-drought years.

The paper is organized as follows: section II provides a brief background on the extant pastoralist risk and insurance literatures in development economics. Section III describes the context and presents information on the IBLI project. Section IV overviews the Cissé & Barrett (2016) empirical approach for development resilience estimation. Section V empirically evaluates the impact of index insurance in terms of development resilience and presents results. Section VI concludes.

II. Risk, Insurance, and Resilience

Pastoral Livelihoods and Risk

Although different pastoral strategies[24] are practiced by the various pastoral ethnic groups (Fratkin 1986) in Africa's arid and semi-arid lands (ASALs), African pastoralists are generally

[24] Pastoralism is the practice of raising livestock (i.e., animal husbandry). Pastoralists are often classified by the types of movement and distance covered as they care for their herds. Nomadic pastoralists general do not practice crop agriculture and are able to travel long distances to accommodate the needs of their herds. Transhumant pastoralists, generally referred to in this paper as semi-nomadic pastoralists, may have an established settlement and travel only to fixed locations according to seasonal needs. Semi-nomadic pastoralists often practice herd-splitting, leaving women and children at the primary settlement with lactating animals while the men migrate with the larger

considered to be among the poorest and most-vulnerable populations in the world (Rass 2006). Many pastoralist households in Northern Kenya earn most or all of their income from their livestock. Unfortunately, these households, who have few other livelihood options, are incredibly vulnerable to weather shocks, such as drought, which can decimate animal populations (Chantarat et al. 2013). As such, households rationally accumulate large herds, as income increases in herd size and large herds serve as self-insurance in the face of shock (McPeak 2005). This phenomenon is not unique to Sub-Saharan Africa; for example, there is evidence of path dynamics in reindeer herd size and protective herd accumulation practices in Norway (Næss & Bårdsen 2010).

Herd stocks are commonly aggregated in terms of tropical livestock units, allowing researchers to compare aggregate livestock holdings across a variety of species. In this context, one tropical livestock unit (TLU) is equivalent to one cow, 0.7 camel, ten sheep, or ten goats. Although estimates differ, there is substantial evidence of asset thresholds and asset-based poverty traps among pastoral households in Northern Kenya and Ethiopia, with five to six animals or TLU per capita needed to sustain subsistence pastoral households in Northern Kenya (Pratt & Gwynne 1977; Barrett et al. 2006). The estimates in neighboring Ethiopia are a bit lower, ranging anywhere from one to five TLU per person (Coppock 1994), although more recent work in Southern Ethiopia finds evidence for the existence of at least two stable dynamic equilibria, with an unstable equilibrium between 10 and 15 animals (about two TLU per capita), above which households are able to engage in extensive pastoralism (Lybbert et al. 2004).

---

herd. Finally, agro-pastoralists are settled households that practice both animal husbandry and crop agriculture. See Blench (2001) for an excellent summary of the types of pastoralism being practiced around the world.

Given the potential impact of drought on herd size and the presence of poverty trap thresholds, some argue there is a need for safety net programs that protect livestock assets above the critical threshold level to prevent households from falling into a low equilibrium poverty trap (Barrett et al. 2006). In the absence of such programs, dramatic decreases in livestock herd size as a result of severe shocks prevents pastoralists from maintaining nomadic or semi-nomadic livelihoods, pushing households towards sedentarization (McPeak & Barrett 2001). Unfortunately, sedentary households who have lost the productive assets necessary for pastoral production are general considered the most vulnerable in the region, and face increased competition for unskilled or low-cost non-pastoral livelihoods (Little et al. 2008). Perhaps of even greater concern, child anthropometric measures from Northern Kenya demonstrate that children in nomadic pastoral communities are much healthier than those in sedentarized communities (Fratkin, Roth, & Nathan 2004). Other research shows that children from sedentary households are much more likely to suffer from malnutrition during dry years, as nomadic children are able to consume more milk than their sedentary counterparts are, even during drought (Nathan, Fratkin, & Roth 1996).

Resilience

Soon after much of the empirical work discussed above was completed, the Horn of Africa suffered the worst drought in sixty years, causing famine in the most politically and geographically isolated regions (Maxwell & Fitzpatrick 2012). The 2011 drought was followed soon after by drought and famine in the Sahel in 2012. Citing projections showing continued need for humanitarian intervention in these vulnerable regions in the future, exacerbated by shocks of increasing frequency and severity, the United States Agency for International Development (USAID) launched guidance in 2012 aimed at "Building Resilience to Recurrent

Crisis” (USAID 2013). USAID and other humanitarian actors quickly called for the need to bridge the humanitarian-development divide by implementing projects that would reduce drought risk and increase the resilience of families living in the Sahel and the Horn of Africa (Hillier & Dempsey 2012). Since then, hundreds of millions of dollars have been spent on resilience building initiatives in the two regions. Given this focus on resilience, it makes sense to evaluate potential safety net programs, including index insurance interventions, through a resilience lens, as we will describe below.

Risk Management, Coping, and Insurance

Despite the cyclical nature of droughts and crisis in the ASALs, households in Northern Kenya have similar risk mitigation and coping strategies available to them as in other part of the continent. Those with access to credit and/or insurance may employ intertemporal risk sharing in order to smooth consumption and investments (Besley 1995) while avoiding asset-based poverty traps (Carter & Barrett 2006). While actuarially-fair, formal insurance is often the preferred risk-management mechanism in the absence of market failures, most poor, rural households do not have access to formal insurance (Skees & Barnett 2006; Barnett, Barrett, and Skees 2008). Insurance- and credit-constrained households in developing countries have developed a variety of second-best insurance strategies, including informal borrowing, selling off assets, and risk-averse production decisions (Morduch 1994). Some of these risk mitigation strategies—such as on-farm diversification, on- and off-farm production, migration—can be considered *ex ante* risk management while others—borrowing, saving, selling off assets, etc.—are primarily concerned with *ex post* risk coping (Alderman & Paxson 1992). Insurance, therefore, can be expected to impact behavior both 1) in response to shock and 2) via *ex ante* production and investment decisions (Mobarak & Rosenzweig 2012; Janzen & Carter 2013; Karlan et al. 2014).

Although there is evidence from other countries in Sub-Saharan African that asset sales in response drought (a covariate shock) do appear to temper the impacts of shock for some households and in some situations (Hoddinott 2006), asset sales generally provide more protection against idiosyncratic shocks, as increased supply in times of covariate shock will likely decrease the asset price (Morduch 1994), In fact, droughts in the area of study in Northern Kenya have been found to decrease the price of female camels, cattle, goats, and sheep by 5, 52, 17, and 34% , respectively (Barrett et al. 2003). Informal, community-based mechanisms are also more suited to insuring against idiosyncratic shocks than covariate shocks (Dercon 2002). For example, by separating non-food from food consumption, Skoufias & Quisumbing (2005) show that idiosyncratic income shocks are correlated with non-food consumption in Ethiopia, but that food consumption is partially shielded from these shocks, which they presume to be the result of informal food consumption insurance mechanisms.

On the other hand, even relatively mild covariate shocks may have permanent impacts, particularly for poorer households (Hoddinott 2006). Index insurance is one mechanism that has been proposed to deal with covariate weather-related risk in poor, primarily agricultural communities (Barnett & Mahul 2007; Chantarat et al. 2007). Index insurance works by insuring households or individuals against bad weather, as opposed to insuring them against particular outcomes. Weather can be monitored remotely by satellite, reducing the cost substantially compared to traditional insurance (Mude et al. 2009). These index-based risk transfer products, as they are also known, may allow households to avoid poverty traps by correcting a critical market failure (Barnett, Barrett, and Skees 2008).

Given this potential to provide market-based solutions to weather-related vulnerability in developing countries, index insurance products have received considerable attention in the past fifteen years. Well-designed, experimental approaches have found promising results. Karlan et al. (2014) evaluated the impact of rainfall insurance piloted in northern Ghana in 2009 and found uninsured risk to be the primary barrier to farmer investment. Similarly, Mobarak & Rosenzweig (2012) find that rice farmers in India offered index insurance in 2010-2011 invest in higher yielding portfolios that are less resistant to drought.

One of the earliest examples of weather-based index insurance was the rainfall insurance project piloted in Andhra Pradesh, India in 2003 by ICICI Lombard with technical assistance from the World Bank (Giné et al. 2010). This and other early example of index insurance were characterized by low take-up, in part due to limited understanding of the products, long lag periods between the weather shock and receipt of indemnity payments, and high levels of basis risk (Giné et al. 2010). As far as we are aware, the first example of predicted mortality-based livestock insurance was the index-based livestock insurance product in Mongolia, which the World Bank piloted in 2006. The lessons learned over the course of the implementation in Mongolia, including the need for high quality data as well as education around the product for potential consumers (DeAngelis 2013), informed the development of the Kenya and Ethiopia IBLI projects.

Increasing access to affordable, high quality, high-resolution satellite data is partly responsible for booming interest in and availability of index-based insurance products in recent years. For example, in the past ten years the Index Insurance Innovation Initiative (I4), a project of the USAID-supported Feed the Future Innovation Lab for Assets and Market Access, has piloted or researched index insurance products in Bangladesh, Burkina Faso, the Dominican Republic, Ethiopia, Ghana, Guatemala, Haiti, India, Mali, Nepal, Peru, and Tanzania. This is in addition to their support for research related to the Ethiopia and Kenya IBLI projects.

Although index insurance has many supporters, some have pointed out the potential weaknesses of index-based insurance products. Households already caught in poverty may not be able to benefit from un-subsidized insurance (Kovacevic & Pflug 2011). In addition to the cost to insure, the main limitation of index insurance is basis risk, *i.e.*, that some shock-affected households may not receive an indemnity or that non-affected households may receive a payout (Barnett, Barrett, and Skees 2008; Jensen, Barrett, & Mude 2016). However, informal insurance mechanisms can help share the burden of basis risk where they exist (Mobarak & Rosenzweig 2012). Nonetheless, among pastoral communities in Southern Ethiopia, Lybbert et al. (2004) find that household-specific idiosyncratic shocks and characteristics account for more variability in well-being dynamics than do covariate shocks, which calls into questions the appropriateness of weather-based index insurance in some settings.

III. Context and Project Background

Despite the limitations of index insurance mentioned above, an index-based livestock insurance (IBLI) product was commercially piloted in Northern Kenya beginning in January 2010 in order to help pastoral and agro-pastoral populations manage drought-related livestock mortality. The ASALs of Northern Kenya experience frequent drought, and the arid conditions make crop-based livelihoods infeasible for the majority of the population. The climate is better suited to extensive pastoralism and Northern Kenyan communities rely heavily on livestock for their livelihoods. (McPeak, Little, & Doss 2012) Still, households are heavily exposed to climactic shock and Kenya's pastoralists communities are considered to be the most vulnerable in the country. Given these vulnerabilities and the cyclical nature of shocks in the region, IBLI aims to protect against catastrophic livestock mortality by allowing households to insure their most important assets against shock (Mude et al. 2009).

This paper evaluates the impact of IBLI on the development resilience of households in the project implementation zone. We provide the technical definition of resilience in the next section but, in general, we define resilience as the probability that a household will achieve a satisfactory level of well-being in a particular period (following Barrett & Constas (2014)). We are therefore interested in evaluating how holding an IBLI contract increases (or not) households' probabilities of achieving well-being above a particular threshold (e.g., poverty line).

Some previous work has studied the impact of IBLI on well-being. Janzen & Carter (2013) examine how insured households anticipate reducing coping behaviors during a drought. They explore how these expected behavioral responses may differ around a critical livestock asset threshold. Other impact assessments find positive impacts of IBLI on material well-being—particularly in terms of reduced risk exposure through reductions in herd size and investments in herd health (Jensen, Barrett, & Mude 2015; Jensen, Ikegami, & Mude 2015)—and on subjective well-being (Tafere et al. 2015).

The IBLI project was implemented in Northern Kenya, in the semi-arid county of Marsabit (see Figure 1). According to the 2005-2006 Kenya Integrated Household Budget Survey, Marsabit is the second-poorest district in Kenya, with a poverty rate[25] of 91.7% (Kenya National Bureau of Statistics, National Data Archive). Marsabit is a large county that borders Ethiopia to the north and Lake Turkana to the west. The county contains six administrative divisions, all of which were targeted by the program: Central, Gadamoji, Laisamis, Loiyangalani, Maikona, and North Horr.

[25] Based on the rural Kenya poverty line of 1,562 Kenyan shillings per month.

Beginning in 2009, five annual rounds[26] of the survey were administered in Marsabit, covering the period before the introduction of IBLI and four subsequent periods, including an indemnity payout period. In general, insurance contracts are offered for sale prior to each rainy season (two sales periods per year) and each contract lasts for a full year. Insurance is available to all residents and information about the insurance product was shared during village assemblies and by insurance promoters. Households choose how many TLU to insure and premium payments vary by administrative division, as the risk of catastrophic drought varies by location. IBLI payouts are based on a statistical model that identifies the relationship between the normalized difference vegetation index (NDVI) and livestock mortality. NDVI is a satellite-derived measure of vegetative greenness, which is correlated with rainfall and pasture conditions. When the NDVI falls below a certain pre-determined threshold, catastrophic livestock mortality is predicted and insurance holders receive an indemnity payout of 15,000 KSH for each insured TLU (Jensen, Barret & Mude 2016), which is generally distributed in cash following the next data collection round. The IBLI project piloted a 15 percent strike contract, meaning that when the statistical model predicted that livestock mortality would surpass 15%, the insurance product would pay out (Chantarat et al. 2013). Given that only predicted covariate risk can be insured through IBLI, idiosyncratic risk remains formally uninsured. See Chantarat et al. (2013) for a full description of the IBLI index design.

Figure 2 illustrates the timing between the seasons, survey (data) collection rounds, insurance contract coverage, and weather shocks. Each Rainfall in Northern Kenya is bimodal and each survey round covers two climactic seasons, the short-rainy-short-dry (SRSD) season

---

[26] A sixth round has recently become available, but it differs from previous rounds in a few important ways and therefore is not included in this analysis.

and the long-rainy-long-dry season (LRLD). Although the survey was administered after each LRLD season, the enumerators asked respondents to recall livestock sales, deaths, births, etc. that occurred during the SRSD season, allowing us to construct ten seasons of livestock holdings over the five year period. IBLI insurance sales occur in the two months prior to the contract periods shown in the figure. Note that while IBLI sales occurred prior to both the LRLD and SRSD seasons, each contract lasts for a full year, insuring the purchaser through both upcoming seasons (and therefore theoretically allowing for someone to be covered by two different insurance contracts simultaneously). A total of five contract periods are evaluated here.

The baseline survey (Round 1) was conducted in October and November 2009, prior to the first round of IBLI sales for the first contract period (Contract 1). Additional survey rounds were conducted in October and November of subsequent years. As indicated by the red line on Figure 2, a catastrophic drought occurred in 2011 when the predicted livestock mortality (PLM) index surpassed the 15% threshold and triggered indemnity payments for all holders of Contract 2 (in all six divisions) and some holders of Contract 3 (only in select divisions).

Insurance uptake was encouraged through the use of premium discount coupons, which were randomly provided to 60% of the surveyed households. Among those households that received a coupon in a given round, the coupon amount varied randomly, with approximately equal numbers of households receiving coupons for 10%, 20%, 30%, 40%, 50%, and 60% off the IBLI insurance premium amounts for the first 15 TLU insured. Households were re-randomized in each sales period (meaning that prior coupon receipt had no impact of the probability of receiving a coupon in any given period), ensuring within-household random variation in insurance premiums over time. Coupons were distributed during each sales period, in the two months prior to the contract sales windows listed in Figure 2. The randomization of the coupon distribution was largely achieved. For more information, see Jensen, Barrett, and Mude (2015).

IV. Empirical Approach to Development Resilience Estimation

As mentioned above, this paper evaluates the impact of IBLI on development resilience. Estimating household resilience is a multi-step process. In the first step, we employ the approach described by Cissé & Barrett (2016) to estimate household-level conditional probability density functions (pdfs) of well-being, otherwise known as the development resilience approach, in order to estimate the impact of index insurance on well-being. The benefit of this approach is that it looks beyond simple mean effects to understand the impact of a program on households' probabilities of achieving some minimum standard of well-being. These are conditional probabilities, based on the household's well-being in the previous period, allowing us to account for path dynamics of well-being.

In order to allow for nonlinear path dynamics, including S-shaped dynamics, as suggested by Barrett & Constas (2014), Cissé & Barrett (2016) model well-being (W_{it}) parametrically as a polynomial function of lagged well-being ($W_{i,t-1}$), and a series of household characteristics, including shocks and insurance coverage, $\boldsymbol{X_{it}}$:

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

The first central moment (conditional mean, or μ_{1it}) is:

(2) $$\hat{\mu}_{1it} \equiv E\left[W_{it} | W_{i,t-1}, \boldsymbol{X_{it}}\right] = g_M(W_{i,t-1}, \boldsymbol{X_{it}}, \hat{\beta}_M).$$

where E represents the expectation operator and the random error term u_{Mit} is mean zero. In the second step, we take the residuals from equation (1) and square them. The conditional variance (μ_{2it}) is thus:

(3) $$\hat{\mu}_{2it} = E[u_{Mit}^2] = \hat{\sigma}_{it}^2,$$

where $\sigma_{it}^2 = g_V(W_{i,t-1}, \boldsymbol{X_{it}}, \beta_V) + u_{Vit}$ and $E[u_{Vit}] = 0$.

Following the Barrett & Constas (2014) conceptual framework, in the third step we define development resilience (ρ) as the probability that household *i* will have well-being in a future period (*t*) above some normative threshold, $\underline{W}$. Assuming that the conditional well-being pdf for each household comes from a two parameter distribution (e.g., normal, lognormal, gamma, or Weibull), the conditional mean (μ_{1it}) and conditional variance (μ_{2it}) are sufficient to completely describe the conditional distribution and therefore the conditional probability of achieving well-being greater than $\underline{W}$. This permits us to estimate their resilience:

(4) $$\rho_{it} \equiv \Pr\left(W_{it} \geq \underline{W} | W_{i,t-1}, X_{it}\right) = \bar{\mathrm{F}}_{\mathrm{W_{it}}}\left(\underline{W}; \hat{\mu}_{1it}(W_{it}, X_{it}), \hat{\mu}_{2it}(W_{it}, X_{it})\right),$$

where $\bar{\mathrm{F}}_{\mathrm{it}}$ is the complementary cumulative distribution function. As explained by Cissé & Barrett (2016), the impact of any plausibly exogenous component of ***X*** on resilience may be estimated: $\partial \hat{\rho}_{it} / \partial X_{it}$.

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

Aside from demonstrating how to measure development resilience at the household level, Cissé & Barrett (2016) develop a decomposable development resilience measure similar to the class of poverty measures developed by Foster, Greer, and Thorbecke (1984). This feature allows us to attribute shares of the overall development resilience measure to various subgroups, as we demonstrate below.

V. Impact of Insurance on Development Resilience

Data

The data used in this analysis were collected in order to evaluate the impact of the insurance by the International Livestock Research Institute (ILRI), Cornell University, University of California-Davis, and Syracuse University in collaboration with private sector insurance providers using an elaborate multi-year impact evaluation strategy (Ikegami & Sheahan 2016). The household surveys were designed to capture a wealth of household livelihood and welfare variables for survey households and include general demographic questions as well as questions regarding livestock holdings and production, risk and insurance, livelihood activities, expenditure and consumption, assets, and savings and credit. Researchers determined the number of households that would need to be surveyed in order to identify the impacts of the project, and randomly selected households from the divisions mentioned above (with the exception of North Horr) to ensure representativeness. This resulted in a final sample of 924 households for all sixteen sublocations in Marsabit County that were followed over the length of the project.[27]

---

[27] Details on the sample household selection methodology are available in the IBLI survey codebook (ILRI 2013) and Ikegami & Sheahan (2016). There are population differences by sublocation, including ethnic group makeup, pastoral system and agro-ecology, and market accessibility. Proportional allocation relative to sublocation population size was used to determine the number of households from each sublocation to survey within set minimum and maximum bounds.

Table 1 provides household-level summary statistics. The first column presents the sample mean (all ten seasons pooled) for household-level covariates. All 924 households are included, but some are lost to attrition (discussed below), so there are 8,670 observations across the ten seasons. On average, households have 14.3 TLU. However, six percent of households have zero animals, so the average TLU holdings conditional on having any animals is 15.3. A histogram of TLU holdings can be found in Figure 3. The PLM index varies by division and season, with mean predicted livestock mortality at about 12%. The *contract* variable is an indicator variable taking the value of one if a household purchases any IBLI insurance during a given season. On average, one in eight households holds an insurance contract in a given season. Household can insure any number of animals, but the average number of TLU insured is about 0.6, however conditional on purchasing insurance the average number of TLU insured is nearly five TLU. The treatment indicator takes a value of one if a household receives a coupon to purchase insurance in a given season. On average across the ten seasons, the treatment rate is just under 50% (this includes two baseline seasons when no coupons were distributed).

The remaining summary statistics provide information on household characteristics. Over a third of households are headed by women. The dependency ratio[28] is just about two, meaning the average household has twice as many dependents as able-bodied adults of working age. Household heads have very little formal education (about one year). Over a third of households are fully settled, although some of these may be formerly nomadic or partially-nomadic. Given the reliance on animal products in the region and the poor conditions for agricultural production, milk production is important for home consumption, sale, and consumption at satellite camps by

[28] 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 18, plus seniors over 55 and disabled or chronically ill household members, divided by the number of able-bodied adults (between the ages of 18 and 55) in the household.

those moving with the animals. On average, households produce about two-thirds of a liter of milk a day at the primary homestead or base camp, while production at satellite camps is about twice as much. Average weekly food consumption expenditure is nearly 5,000 Kenyan shillings (nearly $60/week), although the median is about a third of that. Information on where the households live and insure is also provided.

Since our identification strategy, discussed below, relies of the random distribution of the insurance coupons, we check to ensure balance between households that received coupons and those that did not. Panel A presents Season 1 summary statistics, broken down by future treatment. Untreated households are those who would not receive a coupon for IBLI purchases in Season 4, while treated households are those who would receive a coupon in Season 4. There is no statistically significant difference in means between treated and untreated households.

Table 1, Panel B provides summary statistics for households that appear in all rounds of the survey and those who attrit. We see a statistically significant difference between the means of the two groups in terms of dependency ratios, education, nomadism, and milk production at satellite camps. Note that while only 89% of the sample appears in all rounds, most of the "attrited" households do not drop out completely, but rather are missing for one or more rounds before reappearing in the sample. All analyses below control for the possibility of non-random attrition; see Appendix A for more information on our method.

Table 2 provides summary statistics at the child level. Data was collected during each round for all children in surveyed households under the age of five, for a total of 1,083 eligible children. Since new children are born and some children age out of the sample (or their households attrit), the same children are not present in all rounds. The first column presents sample averages for the eligible children as often as they are present (for a total of 2,358 observations). We are interested in child health, measured anthropometrically using the child's mid-upper arm circumference (MUAC). While other common child anthropometric measures such as weight-for-height and height-for-age are relevant, these measures are more prone to measurement error. In community-based management of malnutrition, children (aged 6 – 59 months) are generally at risk for acute malnutrition when their MUAC falls below 13.5 cm. The sample mean MUAC is 14.4 cm, which is considered well-nourished. Figure 4 presents a histogram of MUAC, which is relatively normally distributed, if a bit peaked towards the mean. Just under half of the children are girls. Most of the sample means are close to the household-level means presented in Table 1, although the dependency ratio is slightly higher in the child sample (not surprisingly). Milk production at both the homestead and satellite camp is higher in the child sample.

Panel A compares pooled summary statistics for children in untreated and treated households in any given round. This is not a balance test since randomization was not at the child level and because some of the covariates may be impacted by the treatment. In fact, we do see that MUAC is higher for children in treated households. The means for consumption and milk production at the base camp are also statistically significantly higher among children in treated households, although milk production at the satellite camp and TLU holdings overall are lower. There are also some differences in terms of where the household lives and insures. Panel B presents the means for children that are present in each round for which they are eligible (as long as their family did not attrit) and for "missing" children, or children that are not surveyed, despite being eligible and their family not attriting. Thankfully, according to survey results none of the children are missing due to death nor have they been sent away to live with their biological parents. We see that children from female headed households are more likely to be missing, as are children from settled households. The mean weekly food expenditure is much higher in households from which children are subsequently missing. There is also a geographical component to missingness. Panel B demonstrates that missing children are not missing at random. We therefore correct survey weights to control for this missingness, as discussed in Appendix A.

IBLI and Mean Well-being

Households in the IBLI program area decide whether or not to purchase the product, as well as how many animals to insure. As mentioned above, should the predicted livestock mortality index surpass contractual 0.15 strike point, the insurance holder receives a payout. In order to evaluate the impact of insurance on mean well-being, we estimate a nonlinear polynomial parametric regression model of stochastic well-being, W, for household i ($i = 1, \dots, N$) in season s ($t = 1, \dots, S$):

(6) $$W_{is} = g_M\big(\beta_M W_{i,s-1}, \delta_{M1} PLM_{s-1}, \delta_{M2} I_{s-1}, \delta_{M3}(D_{s-1} * I_{s-1}), \boldsymbol{\delta_{M4} H_{is}}\big) + u_{Mis}.$$

Suppressing household subscripts for now, the regression model describes current well-being as a possibly nonlinear function of lagged well-being (W_{s-1}) and a series of explanatory variables, including previous season predicted livestock mortality (PLM_{t-1}), an indicator for holding an IBLI contract in the previous season (I_{s-1})[29], and an interaction term indicating holding an IBLI contract in the previous season when the PLM surpassed the 0.15 strike point ($D_{s-1} * I_{s-1}$). For simplicity we shall henceforth refer to seasons in which the PLM surpasses the

[29] For robustness, regressions were also computer controlling instead for the number of TLU insured in the past season, interacted with the drought. These estimates are available from the author by request.

indemnity threshold as droughts, indicated here by the indicator variable D. Since the impact of PLM on mean well-being is potentially nonlinear, PLM_{s-1}^2 is also included in all specifications. Current season household level characteristics ($\boldsymbol{H_{is}}$) such as education and nomadic status (as described in the summary statistics) are also included. As discussed below, polynomial terms for lagged well-being are included in most specifications to capture nonlinearities, with a minimum third-order polynomial required to capture S-shaped well-being dynamics.

The βs and δs are coefficients and u_{Mit} is the household- and season-specific residual for this mean (*M*) estimation. The coefficients of primary interest are therefore those on the indicator for holding and IBLI contract (δ_{M2}) and for holding a contract during a drought (δ_{M3}). The dependent well-being variables of interest (W_{it}) are household livestock holdings in TLU and child anthropometry. Using both a productive asset/wealth measure and a health measure allows us to understand how insurance impacts the two key aspects of household wealth holdings in this context: their livestock and their children. Household aggregate livestock holdings are measured in TLUs (recall 1 TLU = 1 cow, 0.7 camel, 10 sheep, or 10 goats) held by each household in each round of the survey. In Northern Kenya, TLUs (which we will also refer to as herd size) allow households to store wealth, as there is limited access to formal banking. Animal are also productive assets, providing milk for household consumption and offspring, which can be sold for cash or saved. TLU holdings in any given period is strongly associated with past period TLU holdings (correlation coefficient = 0.8700), as demonstrated by the kernel regression of lagged TLU holdings on current period holdings (Figure 5). The second dependent variable of interest is child anthropometry (measured in MUAC). We check to see if there is evidence of dynamics in MUAC. Figure 6 provides the kernel regression of lagged MUAC on MUAC, showing a positive association between the two (correlation coefficient = 0.4135).

Given that TLU are necessarily non-negative, we assume the dependent variable is distributed Poisson and estimate a generalized linear model (GLM)[30] log link regression using maximum likelihood. Table 3 presents the marginal effects at mean values of all covariates. In all specifications, we cluster standard errors at the household level and include attrition-corrected survey weights and season fixed effects. While there are important theoretical reasons why lagged dependent variables should be included in dynamic well-being models, it is necessary to test empirically whether there is evidence of path dynamics in our well-being indicators, as well as to evaluate the extent to which serial correlation may cause us to underestimate standard errors on our coefficient estimates. Column (1) provides coefficient estimates and standard errors estimated without including a lagged dependent variable on the right hand side, while column (2) includes polynomial terms up to the third-order and column (3) up to the fourth-order. The marginal effects of the lagged terms are statistically significant in both cases where they are included, and the fit in improves substantially (as evidenced by the increased pseudo R^2). The final row shows the correlation coefficient between the residuals and lagged residuals. We see incredibly strong serial correlation in column (1), but we control for serial correlation fully when the first- through fourth-order lagged terms are included in the specification.

It is not possible to include household fixed effects in a nonlinear model due to the incidental parameters problem. To avoid this issue, Table 3 columns (4) through (6) include the Mundlak (1978) cluster-level means of all covariates. We will henceforth refer to these simply as household fixed effects (FE) for the nonlinear models. Otherwise, columns (4)-(6) are identical to (1)-(3). Marginal effects for the lagged dependent variables continue to be positive and

[30] We prefer the GLM estimator over a simple log linear regression since we do not need to transform zero-valued dependent variables, of which there are many. Nor do we need to adjust predicted values to transform them from ln(TLU) to TLU.

statistically significant in the FE models. Serial correlation is a problem, as evidenced by the very large correlation coefficient on the FE specification in column (4). We can almost completely correct for the serial correlation by including the polynomial lagged terms up to the fourth-order as in column (6), although the correlation coefficient is still higher than in column (3).

We retain the third specification (with up to a fourth-order lagged dependent variable, no household FE) as our preferred specification. In that specification (column (3)) we see that the coefficient on insurance in a non-drought season is negative, but not statistically significant. Holding an IBLI contract during a drought, however, is positively and statistically significantly associated with increased future herd size. A Wald test confirms that the two coefficients are statistically significantly different from each other ($Prob > \chi^2 = 0.0797$). Ordinary least squares (OLS) and fixed-effects (using the within regression estimator) estimates are provided in Appendix B, Table B1 for robustness. Signs and magnitudes are similar between the nonlinear and linear estimators, although serial correlation in the linear model in minimized without the fourth-order polynomial term. Many of the coefficients in the preferred nonlinear specification are statistically significant while they are not in the corresponding (Table B1, column (3)) OLS estimate.

In order to make a causal statement about the impact of IBLI on average herd size, we take advantage of the experimental design of the data to instrument for endogenous insurance uptake. As discussed above, the project randomly distributed coupons to decrease the cost of insurance to a subset of the sample. The coupons introduce the random variation needed to instrument for the endogenous decision to purchase insurance. Table 4 presents the first stage and two-stage least squares (2SLS) estimation results, including the first-, second-, and third-order lagged dependent variables found to minimize serial correlation (Appendix Table B2). There are three instrumental variables (IVs): past season coupon values when there was no drought, past season coupon values when there was a drought, and current season coupons received, which are used to instrument for current period insured TLU, which is used as a control variable. We do not instrument for lagged well-being given the correlation between TLU and its lagged values. We see that the signs in the 2SLS model are consistent with those in the nonlinear model we prefer and although the magnitudes are larger in the 2SLS specification, they are not statistically significantly different from zero. However, a Wald test confirms that the coefficients on IBLI during drought and not during drought are statistically significantly different from each other ($Prob > \chi^2 = 0.0506$).

Turning to child health, we similarly run serial correlation tests on the MUAC mean well-being regressions using Poisson MLE (Table 5) and OLS (in Appendix B, Table B2). Enumerators collected child health information annually, during each survey round. Therefore, MUAC data is only available for even seasons. We still regress MUAC on previous season PLM and insurance holdings, as in equation (6), but must proxy previous season MUAC ($W_{i,s-1}$) with previous round MUAC (*i.e.*, $W_{i,s-2}$), which is only available for seasons 4, 6, 8, and 10. Once again, we assume the dependent variable is distributed Poisson and estimate a GLM regression with a log link using maximum likelihood. Table 5 presents the marginal effects at mean values for all covariates, using survey weights corrected as described in Appendix A and standard errors clustered at the child level. Despite the longer lag period between rounds, we continue to see evidence of path dynamics in child health. The serial correlation in the specification without lags (column (1)) is lower than we see with TLU, but still sufficiently high to be concerned about the impact on our standard errors. Including the lagged terms, however, substantially reduces the serial correlation[31]. There is no different in serial correlation between the third-order (column (2)) and up to fourth-order (column (3)) specifications, although the pseudo R^2 is slightly higher in the former specification. The marginal effect coefficients on our variables of interest in the fixed effects models (columns (4) through (6)) do not change, although we lose magnitude and statistical significance on some of the time-invariant child characteristics, as we would expect. We select the specification in column (2) as the preferred nonlinear MUAC specification and note that the coefficients on the two variables of interest—the association between previous season insurance holdings and child MUAC during non-drought and drought seasons—are both negative, but small in magnitude and not statistically significantly different than zero. Nor are they statistically significantly different from each other. Appendix B, Table B2 presents the OLS and FE results. The coefficients of interest are similar in sign, magnitude, and significance. Serial correlation is a particular problem in the FE specifications.

We would like to explore the causal impact of insurance on child health, and attempt to do so using 2SLS using the same IVs discussed above. Table 6 presents the first stage regressions and 2SLS estimates of the impact of insurance on child MUAC with and without drought. While there is positive coefficient on the impact of insurance during non-drought seasons on MUAC, the coefficient on insurance during drought is negative. Neither coefficient is statistically significant, although the F statistics indicate that at least two of the IVs are incredibly weak.

---

[31] In fact, it appears to over correct to the point that serial correlation becomes negative. The magnitude is smaller however, and negative serial correlation is less of a concern as it may cause us to overstate rather than underestimate standard errors.

The Variance of Well-being

As described in Section III, there are three steps involved in predicting households' well-being pdfs. We begin by predicting their mean well-being, using equation (6). In order to ensure that predictions are non-negative, we predict mean well-being values from our preferred nonlinear specifications discussed above (i.e., the TLU specification in Table 3 column (3) and the MUAC specification in Table 5 column (2)). Given the nonlinear nature of these estimates, we present the marginal effects at important representative values of the PLM index in the first panels of Tables 7 and 8, which we discuss below.

As described above, the second step is to predict household well-being variance. We square the residuals estimated in equation (6) and regress them on the polynomial lagged well-being terms, last season PLM, last season insurance holdings disaggregated by non-drought and drought seasons, and the same vector of household or child characteristics. Using the subscript V to indicate this is the variance equation, we estimate:

$$(7) \qquad \hat{u}_{Mis}^2 = g_V\left(\beta_V W_{i,s-1}, \delta_{V1} PLM_{s-1}, \delta_{V2} I_{s-1}, \delta_{V3}(D_{s-1} * I_{s-1}), \boldsymbol{\delta_{V4} H_{is}}\right) + u_{Vis}.$$

Variance is necessarily non-negative, so we estimate equation (7) for both the squared TLU residuals and squared MUAC residuals using Poisson MLE. The right panels of Tables 7 and 8 provide the marginal effects for variables of interest at representative values of the PLM index. Specifically, we provide marginal effects at $PLMindex = 0.039$ and $PLMindex = 0.265$, which are the sample mean PLM for non-drought and drought years, respectively. Table 7 panel (1), therefore, shows the marginal effects of various covariates during average non-drought (column (A)) and drought (column (B)) years. All other covariates are taken at their means. Recall that this is the same specification as Table 3 column (3), with marginal effects presented at specific values of the PLM index rather than at its mean. Coefficients are therefore consistent with the previously discussed analysis, although it is interesting to note that the marginal effect on mean herd size of increasing predicted livestock mortality is much greater at lower values of the index, demonstrating the importance of allowing PLM to impact herd size nonlinearly.

Panel (2) reports the marginal effects, again at two PLM index values, associated with increases in the variance or herd size. Since we previously estimated the dependent variable, report bootstrapped standard errors, clustered at the household or child level, for all variance equations. We see that holding insurance during a non-drought season is correlated with increased variance in herd size, while holding an IBLI contract during a drought is associated with a large decrease in the variance of herd size. Despite these interesting correlations, the coefficients are not statistically significant. We predict the variance of herd size for each household in each season and use this, along with the predicted mean TLU to parameterize the household's TLU well-being distribution, as discussed below.

Turning to child anthropometry in Table 8, panel (1) presents the marginal effects at the two (non-drought and drought) PLM index levels from the preferred MUAC specification (i.e. Table 5, column (2)). The association between IBLI and mean child MUAC is negative, small, and not statistically significant, regardless of drought conditions. Increased past season PLM is associated with higher MUAC, which is surprising, although the marginal effect does fall for high PLM. Panel (2) presents the variance estimates per equation (7). We see that IBLI in associated with decreases in the future variance of MUAC, both in drought and non-drought seasons, although the marginal effects are not statistically significant. The pseudo R2 on the variance estimates is very low, meaning there is a lot of variation in the variance of child anthropometry that we do not explain.

Development Resilience Estimation

We use the household-season conditional predicted means from equation (6) and variances from equation (7) to parameterize household well-being distributions, which we assume to be distributed gamma[32]. As described in Section 3, we must select a well-being threshold, $\underline{W}$, for each of our well-being indicators. Given a household's well-being distribution in a particular season, the household's resilience (in that season) as the probability that the household surpasses the threshold $\underline{W}$, as in equation (4) above. So household i's TLU resilience in season s (ρ_{is}) is the area under its TLU well-being distribution beyond the threshold $\underline{W}$.

Figure 6 provides a concrete example, using a specific household from our dataset. For simplicity, we display only four rounds (rather than eight seasons). The household's TLU holdings in each round are marked with the stars. The four distributions show the household TLU well-being distribution for the given round. Naturally, the realized TLU holdings lie on each of the curves. The red vertical line marks the TLU threshold $\underline{W}^{TLU} = 14$. So for a threshold of 14 TLU, Household 5008's TLU resilience in Round 2 is the integral of their distribution beyond $\underline{W}$ (this can also be calculated using the complementary cumulative distribution function, as in equation (4)). We can see from the legend that 46% of the area under the black Round 2 curve lies to the right of $\underline{W}$, meaning $\hat{\rho}^{TLU}_{5008,2} = 0.46$. We can see that the household is affected by the drought, as their Round 3 distribution shifts to the left, causing a decrease in their TLU resilience. The household begins to recover in Round 4 and has achieved nearly complete resilience in Round 5.

---

[32] For a two-parameter distribution, the gamma distribution is much more general than the normal, and is entirely non-negative.

As the figure clearly demonstrates, the resilience scores depend on the selection of $\underline{W}$. In order to identify the impact of IBLI on TLU and MUAC resilience for any given threshold, the household- and child-specific development resilience scores are regressed on the same set of regressors used in the well-beings equations, as in equation (8), below.

$$(8) \qquad \hat{\rho}_{is} = g_R\left(\beta_R W_{i,s-1}, \delta_{R1} PLM_{s-1}, \delta_{R2} I_{s-1}, \delta_{R3}(D_{s-1} * I_{s-1}), \boldsymbol{\delta_{R4} H_{is}}\right) + u_{Ris}.$$

Since the resilience scores are necessarily between zero and one, we would prefer to use a fractional response specification. Unfortunately, the estimation of binomially distributed dependent variables using maximum likelihood is currently infeasible in the presence of endogenous explanatory variables. For the TLU specification, we instead estimate the impact of IBLI on TLU resilience via 2SLS, instrumenting for endogenous past season IBLI holdings interacted with drought with past season coupon receipts interacted with drought, as discussed above.[33] Table 9 presents that 2SLS estimates for the impacts of IBLI on TLU resilience at various values of $\underline{W}^{TLU}$. Figure 7 presents these coefficients visually. We see in Table 9 that the coefficients on IBLI holdings in non-drought seasons are smaller in magnitude than those during drought. In terms of interpretation, the -0.0497 coefficient on drought/IBLI interaction in Table 9 column (1) means that holding IBLI in the past season, a drought season, increased a household's probability of having at least two TLU by nearly 5 percentage points.

The coefficients on both variables appear to drop initially before rising and remaining above zero. Interestingly, the coefficient on holding insurance during a drought season is not

---

[33] We do not instrument in the mean and variance equations since our goal in the first two stages is to maximize goodness of fit (predict household distributions of well-being well), not inference. We instrument in the final stage as causal inference is desired.

statistically significant unless our threshold value $\underline{W}^{TLU} \geq 20$, above which the coefficient estimates are large and positive. This is consistent with recent work showing that IBLI is ineffective at preventing poverty backslides for households whose livestock holdings are below the critical herd growth threshold of approximately 15 TLU (Chantarat et al. 2017). As we can see clearly in Figure 7, the coefficients on both variables are maximized when the threshold is set around 30 or 31 TLU. This means that we see the largest causal impact of IBLI on TLU resilience when we consider households' probabilities of maintaining or accumulating at least 30 TLU. The 30 TLU threshold is economically meaningful, as it is the lower bound on the bifurcation point identified non-parametrically in a similar context by Barrett et al. (2006). For robustness, we provide the full regressions results for $\underline{W}^{TLU} = 14$ estimated via 2SLS and MLE Tobit[34], each with and without household FE in Appendix B, Table B4. The results are incredibly robust; the 2SLS and Tobit estimates are nearly identical.

Given the weak IV problem in the MUAC estimates, we assume MUAC resilience is distributed binomially and fit the GLM logit link regression using maximum likelihood without using any instruments. Table 10 presents the coefficients and standard errors for our two explanatory variables of interest for different values of $\underline{W}^{MUAC}$. The coefficients are plotted visually in Figure 8. Note that the various threshold values are important indicators of child health; in community-based management of severe acute malnutrition (SAM), children under five are generally admitted for treatment of SAM when their MUAC falls below 11.5 cm (Binns et al. 2014). With MUAC below 12.5 cm children are considered at risk for acute malnutrition, while above 13.5 cm child are considered well nourished.

[34] ivtobit in Stata, censoring at 0 and 1.

We see that the coefficient on IBLI without drought is initially positive and significant for very low threshold levels ($\underline{W}^{MUAC} = 11.5$, column(1)), although the magnitude is very small. There appears to be no relationship between past seasons IBLI holdings and probabilities of subsequently becoming severely acutely malnourished in non-drought years. As the threshold increases, the coefficient on IBLI in non-drought seasons drop precipitously. However, the coefficients on IBLI during drought are positive and statistically significant, taking their maximum coefficient value around a threshold of $\underline{W}^{MUAC} = 13.5$. This indicates that in both drought and non-drought seasons, IBLI is associated with positive (but small) increases in the probability of a child not being severally acutely malnourished the following season. Holding an IBLI contract during a drought season is associated with a nearly 4 percentage point increase in the probability of a child being well-nourished the following season, but holding an IBLI contract during a non-drought season is associated with a 2.5 percentage point decrease in the child's probability of being well-nourished the following season. For robustness, Table B5 in Appendix B provides the full binomial MLE specification, presented in panel (1) at representative values of the PLM index. Panel (2) presents the intent-to-treat impact of randomly receiving a coupon in a given season on the following season's child MUAC. While not statistically significant, the signs are consistent with those in the binomial specification.

VI. Conclusion

This paper evaluates the impacts of the IBLI insurance product on the development resilience of children and households in pastoral areas of Northern Kenya. Like much of the ASALs in Sub-Saharan Africa and the Horn, Marsabit County is prone to droughts. Although the climate is more suited to pastoralism than agricultural cultivation, pastoral and agro-pastoral households are nonetheless extremely vulnerable to drought. The index-based livestock insurance program was designed to "manage the [weather] risks faced by vulnerable pastoral and agro-pastoral populations and provide them with a productive safety net" (Mude et al. 2009).

The cycle of droughts and humanitarian response in this region, and in the ASALs in general, has motivated donor and governmental interest in building resilience with the goal of improving vulnerable populations' abilities to manage risk and cope with shocks and in the hopes of reducing demands for humanitarian assistance. Given the goals of the IBLI project and the focus on resilience in the region, it is appropriate to evaluate the impacts of IBLI in terms of resilience. In order to do so, we predict household distributions of well-being in terms of two highly important indicators, livestock holdings and child health. Using both linear and nonlinear methods, we assess the impact of insurance on the probability that a household or child will have a high level of well-being, that is of their resilience.

We find that holding an IBLI contract in the previous season increases a household's TLU resilience—whether a drought occurred or not—when we consider the probability of having more than 15 TLU (close to mean TLU holdings), although the household's resilience is increased more if the previous season was a drought season. The positive impacts of past season insurance on TLU resilience are statistically significant for thresholds of 20 TLU and above. This indicates that while index-based livestock insurance does increase the resilience, in terms of TLU holdings, of pastoralists in Northern Kenya, it does not effectively increase the resilience of the poorest households with the smallest initial herds. IBLI does, however, dramatically increase the resilience of slightly better-off households and appears to allow them to invest more in their herds while avoiding protective over-stocking.

With regards to child health, we see a positive association between past season IBLI holdings and resilience during droughts. However, during non-drought season there is a negative association between insurance and future MUAC resilience for higher thresholds of child well-being. There appears to be no relationship between past season's IBLI holdings and probabilities of subsequently becoming severely acutely malnourished in non-drought years.

There are a few limitations to this analysis. Unfortunately, the small sample of children and weak instruments prevented us for looking at the causal impact of IBLI on child MUAC resilience, although the intent-to-treat analysis was consistent with the associational analysis. Future studies of this kind may increase the number of households surveyed with a particular focus on households with small children if they are interested in understanding the impact of policies or projects on child health and resilience. It may be worth following children even after their fifth or sixth birthdays in order to avoid highly unbalanced panels of children. Secondly, this paper emphasizes inference, taking advantage of the experimental nature of the IBLI data. We focus on variables that are typically associated with well-being in the rural Kenyan context, but future work may substantially improve on the predictive performance of our analysis using ensemble learning methods.

Despite these shortcomings, this paper contributes to the body of evidence demonstrating the positive impact of IBLI on well-being. The relatively low cost of IBLI compared to safety net programs of similar impact (Jensen, Barrett, & Mude 2015) recommends it as the primary means of managing covariate drought risk in pastoral communities. While the findings are encouraging, IBLI should be piloted and assessed in other ASALs, such as in Burkina Faso, Mali, and Niger[35], in order to establish the external validity of these findings.

[35] Mills et al. (2016) provide a nice classification of countries by TLUs supply and insurance infrastructure that could be used to inform future locations for IBLI pilots.

Future work on index insurance and resilience would benefit from randomizing access to a suite of products, including insurance, credit, and savings, particularly in combination with social protection programs that protect the poorest households from shocks. In combination, these activities may be able to protect households from climatic risk while incentivizing increased savings, prudent risk-taking, and investment in production activities that would allow households to increase standards of living while increasing their own resilience to the shocks they face.

Tables

Table 1: Household Summary Statistics

	Pooled	Panel A: Season 1 only			Panel B: Season 1 only		
	Sample Mean	Untreated Season 4	Treated Season 4	T*	Unattrited	Attrited	T*
TLU[36]	**14.3**	15.9	17.1		17.1	13.9	
Conditional TLU	**15.3**	17.1	18.4		18.2	15.9	
PLM Index	**0.119**						
Contract (0/1)	**0.125**						
# Insured TLU	**0.595**						
Conditional # Insured TLU	**4.77**						
Treatment (0/1)	**0.456**						
Female headed	**0.376**	0.369	0.388		0.377	0.327	
Dependency Ratio[37]	**2.03**	1.97	2.05		2.03	1.74	*
Education (yrs)	**1.03**	1.20	0.947		0.970	2.59	***
Settled (0/1)[38]	**0.375**	0.258	0.221		0.229	0.317	**
Milk Prd [39]- Base	**0.644**	0.764	0.775		0.775	0.816	
Milk Prd - Sat	**1.21**	1.54	1.41		1.45	1.93	**
Consumption[40]	**4620**	1400	1420		1430	1280	
Division[41]							
Central and Gadamoji	**0.240**	0.239	0.244		0.244	0.202	
Laisamis	**0.147**	0.139	0.132		0.137	0.125	
Loiyangalani	**0.325**	0.336	0.340		0.330	0.346	
Maikona	**0.282**	0.286	0.284		0.289	0.327	
North Horr	**0.007**						
N (households)	**8,670 (924)**	**360 (40.5%)**	**529 (59.5%)**		**820 (88.7%)**	**104 (11.3%)**	

*T-test on difference of means: *** p<0.01, ** p<0.05, * p<0.10

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

[37] 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 18, plus seniors over 55 and disabled or chronically ill household members, divided by the number of able-bodied adults (between the ages of 18 and 55) in the household. If there are no working aged adults in the households, the number of dependents is divided by 1.

[38] Indicates that a household is fully settled. "Partially nomadic" (i.e. agro-pastoral) and nomadic households not settled.

[39] Daily average milk production in liters. This is disaggregated for the base camp (homestead) and satellite camp.

[40] Winsorized (top 1%) weekly food consumption expenditure in Kenyan shillings, including value of produced foods consumed at home. The mean value is approximately $60/week. Median expenditure is much lower – closer to $20/week.

[41] For households that insured, the division is listed as the division in which the household chose to insure, not the division of residence. For all other households, the division of residence is used.

Table 2: Child Summary Statistics

	Pooled	Panel A: Pooled (5 rounds)			Panel B: Pooled		
	Sample Mean	Untreated in round	Treated in round	T*	Not missing	Missing[42]	T*
MUAC[43] (cm)	**14.4**	14.3	14.5	**	14.4	14.3	
PLM Index	**0.136**						
Contract (0/1)	**0.124**						
# Insured TLU	**0.636**						
Conditional # Insured TLU	**5.12**						
Treatment (0/1)	**0.412**						
Female headed	**0.328**	0.335	0.305		0.318	0.458	**
Girl (0/1)	**0.481**	0.468	0.500		0.483	0.417	
Dependency Ratio	**2.33**	2.36	2.28		2.33	2.22	
Head Educ (yrs)	**1.12**	1.16	1.05		1.12	1.04	
Settled (0/1)	**0.362**	0.355	0.373		0.356	0.556	***
Milk Prd - Base	**1.15**	1.08	1.25	*	1.16	0.847	
Milk Prd - Sat	**2.41**	2.54	2.23	**	2.42	2.24	
Consumption	**4960**	3080	7660	***	4800	10000	***
HH TLU holdings	**15.2**	16.3	13.5	***	15.1	16.6	
Division[44]							
Central and Gadamoji	**0.210**	0.203	0.220		0.208	0.278	
Laisamis	**0.160**	0.154	0.170		0.163	0.0694	**
Loiyangalani	**0.352**	0.379	0.314	***	0.347	0.500	***
Maikona	**0.272**	0.263	0.284		0.276	0.153	**
North Horr	**0.006**	0.001	0.011	***	0.006	0	
N (children<5)	**2,358 (1,083)**	**1,387 (58.8%)**	**971 (41.2%)**		**2,286 (96.9%)**	**72 (3.1%)**	
*T-test on difference of means: *** p<0.01, ** p<0.05, * p<0.10							

[42] A child may not reappear for many reasons, including (random) aging out and (non-random) household attrition. Missingness here means unexplained missingness not caused by aging out or household attrition (which is already corrected for in the probability weights).

[43] Mid upper arm circumference in cm.

[44] For households that insured, the division is listed as the division in which the household chose to insure, not the division of residence. For all other households, the division of residence is used.

Table 3: Poisson MLE[45] of mean TLU – specification and serial correlation checks (marginal effects at mean values)

VARIABLES	(1) MLE TLU	(2) MLE TLU	(3) MLE TLU	(4) MLE TLU	(5) MLE TLU	(6) MLE TLU
TLU_{s-1} [46]		0.449***	0.663***		0.363***	0.557***
		(0.0287)	(0.0251)		(0.0250)	(0.0251)
PLMindex_{s-1}	-13.07***	-10.03***	-8.410***	1.347	-3.377*	-2.721
	(2.734)	(1.702)	(1.726)	(3.318)	(1.808)	(1.954)
(No drought # insurance) $_{s-1}$	**-0.192**	**0.285**	**-0.0830**	**-0.361**	**-0.0713**	**-0.0801**
	(0.630)	**(0.350)**	**(0.338)**	**(0.423)**	**(0.291)**	**(0.309)**
(Drought # insurance) $_{s-1}$	**0.734**	**1.096****	**0.899****	**0.186**	**0.451**	**0.626**
	(0.855)	**(0.427)**	**(0.409)**	**(0.616)**	**(0.389)**	**(0.417)**
Female Headed HH (indicator)	0.0170	-0.448	-0.517**	-0.544	-0.185	0.0160
	(0.758)	(0.273)	(0.222)	(0.729)	(0.670)	(0.672)
Dependency Ratio	-0.411*	-0.0859	-0.159**	-0.182	-0.238	-0.209
	(0.227)	(0.0798)	(0.0722)	(0.208)	(0.146)	(0.164)
Education of head in yrs	-0.135	-0.0774	-0.0141	0.199	0.269**	0.297**
	(0.181)	(0.0568)	(0.0623)	(0.205)	(0.129)	(0.116)
Settled HH (indicator)	-6.543***	-1.904***	-1.717***	0.229	0.566	0.153
	(0.772)	(0.323)	(0.321)	(0.665)	(0.415)	(0.365)
Milk Production at Base	0.362	0.235***	0.222***	0.0633	-0.0252	0.00369
	(0.234)	(0.0797)	(0.0777)	(0.111)	(0.0713)	(0.0767)
Milk Production at Satellite Camp	1.291***	0.524***	0.453***	0.228*	0.282***	0.280***
	(0.233)	(0.115)	(0.112)	(0.117)	(0.0827)	(0.0852)
Ln(consumption)	0.549**	0.170	0.103	0.0266	0.0958	0.127
	(0.237)	(0.123)	(0.100)	(0.147)	(0.112)	(0.109)
# Insured TLU $_s$	0.00386	0.00597	0.00588**	-0.00504	0.000715	0.00311
	(0.00905)	(0.00372)	(0.00242)	(0.00772)	(0.00396)	(0.00284)
HH FE[47]	N	N	N	Y	Y	Y

[45] TLU is assumed to be distributed Poisson and fit using the canonical log link. This is essentially a log-linear model estimated using maximum likelihood.

[46] First, second, and third order polynomial terms included in (2) and (5) and up to fourth order terms included in (3) and (6).

Pseudo R^2 [48]	0.0441	0.664	0.679	0.234	0. 699	0.701
Correlation Coefficient	**0.7666**	**0.2405**	**-0.0089**	**0.8027**	**0.2752**	**0.0420**

Clustered (HH) standard errors in parentheses. Season fixed effects included in all specifications. N=6,807.
*** p<0.01, ** p<0.05, * p<0.10

[47] In the nonlinear setting, rather than including HH fixed effects, household-level mean values of all covariates are included (Mundlak 1978).

[48] All MLE pseudo R^2 values are the correlation between the response and the fitted or predicted response, calculated using Stata's *glmcorr* by Nicholas J. Cox.

Table 4: 2SLS estimates of mean TLU

VARIABLES	(1) 1st Stage I_{s-1}	(2) 1st Stage $(D_{s-1} * I_{s-1})$	(3) 1st Stage # Insured TLU	(4) 2SLS TLU
IV1: (No drought # coupon) $_{s-1}$	0.00323***	-0.000811***	0.00820	
	(0.000497)	(0.000119)	(0.0165)	
IV2: (Drought # coupon) $_{s-1}$	-0.000864***	0.00423***	0.0106	
	(0.000263)	(0.000716)	(0.0128)	
IV3: Coupon $_s$	6.17e-06	5.86e-05	-0.0111	
	(0.000218)	(0.000162)	(0.0152)	
TLU_{s-1}	0.000863	0.000508	0.0281	0.904***
	(0.000725)	(0.000390)	(0.0237)	(0.0373)
TLU^2_{s-1}	-1.50e-05**	-6.65e-06*	-0.000381	-0.00201***
	(7.38e-06)	(3.87e-06)	(0.000258)	(0.000618)
TLU^3_{s-1}	3.38e-08**	1.57e-08*	8.90e-07	3.92e-06***
	(1.56e-08)	(8.16e-09)	(5.81e-07)	(1.46e-06)
$\mathrm{PLMindex}_{s-1}$	-0.358***	0.641***	2.253	-21.62***
	(0.0944)	(0.0811)	(7.695)	(5.706)
$\mathrm{PLMindex}^2_{s-1}$	0.599***	-1.150***	-1.756	42.09***
	(0.191)	(0.174)	(15.42)	(11.38)
(No drought # insurance) $_{s-1}$				**-1.812**
				(2.532)
(Drought # insurance) $_{s-1}$				**3.003**
				(2.822)
Female Headed HH (indicator)	-0.0121	-0.0198***	0.778	-0.385
	(0.0135)	(0.00732)	(0.716)	(0.470)
Dependency Ratio	-0.00414	-0.00103	-0.220	-0.184*
	(0.00443)	(0.00207)	(0.134)	(0.112)
Education of head in yrs	-0.000572	-0.00149	-0.0161	-0.0184
	(0.00230)	(0.00110)	(0.0153)	(0.0389)
Settled HH (indicator)	0.0378***	-0.000544	-0.331	0.145
	(0.0124)	(0.00807)	(0.317)	(0.420)
Milk Production at Base	-0.000127	0.00194	-0.145	0.0782
	(0.00415)	(0.00210)	(0.166)	(0.151)
Milk Production at Satellite Camp	0.00483	-0.00167	-0.0578	1.035***
	(0.00403)	(0.00187)	(0.136)	(0.165)
Ln(consumption)	-0.000853	-0.00689**	-0.177	0.194
	(0.00676)	(0.00334)	(0.212)	(0.132)
# Insured TLU $_s$				-0.0323
				(0.511)
Constant	0.0349	-0.0110	1.103	0.686
	(0.0495)	(0.0274)	(2.072)	(1.916)
R^2	0.13	0.19	0.01	0.75
F-stat / Wald χ^2	25.59	41.12	0.73	12018.85
				(0.0000)

Clustered (HH) standard errors in parentheses. Season fixed effects included in all specifications. N=6,807. *** p<0.01, ** p<0.05, * p<0.10

Table 5: Poisson MLE[49] of mean MUAC – specification and serial correlation checks (marginal effects at mean values)

VARIABLES	(1) MLE MUAC	(2) MLE MUAC	(3) MLE MUAC	(4) MLE MUAC	(5) MLE MUAC	(6) MLE MUAC
MUAC_{s-2}		0.393***	0.394***		0.383***	0.384***
		(0.0573)	(0.0576)		(0.0556)	(0.0526)
PLMindex_{s-1}	3.062***	3.487***	3.519***	2.420***	3.369***	3.401***
	(0.711)	(0.891)	(0.894)	(0.697)	(0.883)	(0.887)
(No drought # insurance) $_{s-1}$	**-0.0202**	**-0.174**	**-0.179**	**-0.0532**	**-0.165**	**-0.170**
	(0.132)	**(0.156)**	**(0.154)**	**(0.130)**	**(0.155)**	**(0.153)**
(Drought # insurance) $_{s-1}$	**0.189**	**-0.138**	**-0.148**	**0.172**	**-0.113**	**-0.123**
	(0.194)	**(0.209)**	**(0.208)**	**(0.188)**	**(0.211)**	**(0.210)**
Female Headed HH (indicator)	-0.255**	-0.356***	-0.349***	0.286	0.301	0.308
	(0.113)	(0.0991)	(0.0994)	(0.338)	(0.359)	(0.359)
Girl (indicator)	-0.0492	-0.0867	-0.0945	-0.0631	-0.0971	-0.105
	(0.0906)	(0.0832)	(0.0833)	(0.0893)	(0.0848)	(0.0849)
Dependency Ratio	-0.0723***	-0.0246	-0.0251	0.00204	-0.0138	-0.0161
	(0.0277)	(0.0286)	(0.0281)	(0.0467)	(0.0487)	(0.0484)
Education of head in yrs	0.0685***	0.0421***	0.0433***	0.0274	0.0164	0.0168
	(0.0171)	(0.0132)	(0.0134)	(0.0520)	(0.0501)	(0.0503)
Settled HH (indicator)	0.217**	0.0925	0.0881	0.120	0.0468	0.0431
	(0.0923)	(0.0912)	(0.0915)	(0.0967)	(0.104)	(0.104)
Milk Production at Base	-0.00857	-0.00862	-0.00834	-0.0144	-0.0130	-0.0127
	(0.0155)	(0.0154)	(0.0152)	(0.0199)	(0.0206)	(0.0205)
Milk Production at Satellite Camp	-0.0124	-0.00376	-0.00255	0.00465	-0.00279	-0.00176
	(0.0125)	(0.0135)	(0.0135)	(0.0142)	(0.0172)	(0.0172)
Ln(consumption)	0.114**	0.0232	0.0259	0.00616	-0.0417	-0.0396
	(0.0485)	(0.0622)	(0.0617)	(0.0560)	(0.0802)	(0.0796)
TLU	-0.000405	0.00111	0.000884	-2.32e-05	-0.000766	-0.000978
	(0.00193)	(0.00165)	(0.00164)	(0.00553)	(0.00632)	(0.00650)
# Insured TLU $_s$	0.00239	0.0147***	0.0146***	0.00246***	0.0137***	0.0135***

[49] MUAC is assumed to be distributed Poisson and fit using the canonical log link. This is essentially a log-linear model estimated using maximum likelihood.

	(0.00152)	(0.00505)	(0.00500)	(0.000938)	(0.00502)	(0.00498)
Child FE[50]	N	N	N	Y	Y	Y
Observations	1,882	1,257	1,257	1,882	1,257	1,257
Pseudo R^2	0.0851	0.246	0.244	0.132	0.255	0.253
Correlation Coefficient	**0.3667**	**-0.1237**	**-0.1237**	**0.3463**	**-0.1205**	**-0.1199**

Clustered (child) standard errors in parentheses. Round FE included in all specifications. *** p<0.01, ** p<0.05, * p<0.10

[50] In the nonlinear setting, rather than including child fixed effects, child-level mean values of all covariates are included (Mundlak 1978).

Table 6: 2SLS estimates of mean MUAC

VARIABLES	(1) 1st Stage I_{s-1}	(2) 1st Stage $(D_{s-1} * I_{s-1})$	(3) 1st Stage # Insured TLU	(4) 2SLS MUAC
IV: (No drought # coupon) $_{s-1}$	0.00248***	-0.00107***	-0.00884	
	(0.000687)	(0.000252)	(0.00705)	
IV: (Drought # coupon) $_{s-1}$	-0.000623	0.00641***	0.00365	
	(0.000710)	(0.00174)	(0.00505)	
IV: Coupon $_s$	-2.23e-05	0.000351	0.00456	
	(0.000426)	(0.000322)	(0.00588)	
MUAC_{s-2}	1.136	-0.218	0.824	-8.806
	(1.040)	(0.430)	(3.864)	(11.52)
MUAC^2_{s-2}	-0.0803	0.0175	-0.0182	0.588
	(0.0776)	(0.0310)	(0.290)	(0.763)
MUAC^3_{s-2}	0.00187	-0.000442	-0.000448	-0.0124
	(0.00192)	(0.000733)	(0.00720)	(0.0168)
$\mathrm{PLMindex}_{s-1}$	-1.006***	1.541***	-4.048	13.16
	(0.383)	(0.390)	(5.677)	(20.09)
$\mathrm{PLMindex}^2_{s-1}$	1.431**	-2.118***	4.496	-15.66
	(0.609)	(0.545)	(8.464)	(27.13)
(No drought # insurance) $_{s-1}$				**3.324**
				(7.917)
(Drought # insurance) $_{s-1}$				**-0.328**
				(1.334)
Female Headed HH (indicator)	-0.0235	-0.00428	-0.235*	-0.00234
	(0.0258)	(0.0144)	(0.138)	(0.638)
Girl	0.0191	0.0211	0.187	-0.346
	(0.0210)	(0.0144)	(0.215)	(0.631)
Dependency Ratio	0.00227	0.000392	-0.00722	-0.0231
	(0.00652)	(0.00367)	(0.0508)	(0.0661)
Education of head in yrs	-0.00300	-0.00281	-0.0163	0.0691
	(0.00323)	(0.00268)	(0.0184)	(0.0562)
Settled HH (indicator)	0.0406*	-0.0202	-0.0382	-0.0114
	(0.0210)	(0.0157)	(0.120)	(0.261)
Milk Production at Base	-0.00182	0.00705**	0.0481	-0.0494
	(0.00460)	(0.00333)	(0.0363)	(0.0849)
Milk Production at Satellite Camp	0.00798	-0.00421*	-0.00783	-0.0237
	(0.00514)	(0.00230)	(0.0491)	(0.0478)
Ln(consumption)	0.0155	-0.00202	0.0395	-0.0670
	(0.0132)	(0.00615)	(0.0479)	(0.182)
TLU	-0.000469	0.000186	0.00364	-0.00163
	(0.000503)	(0.000228)	(0.00626)	(0.00846)
# Insured TLU $_s$				1.075
				(1.548)
Constant	-5.268	0.592	-5.804	55.44
	(4.589)	(1.952)	(17.59)	(56.41)
R^2	0.11	0.38	0.01	
F-stat / Wald χ^2	4.87	23.37	3.94	104.44
				(0.0000)

Clustered (child) standard errors in parentheses. Round fixed effects included in all specifications. N=1,257. *** p<0.01, ** p<0.05, * p<0.10

Table 7: Poisson MLE of TLU and its variance– marginal effects at representative values of the PLM index

VARIABLES	(1) MLE TLU		(2) MLE V(TLU)	
	(A)	(B)	(A)	(B)
PLM =	**.039**	**0.265**	**.039**	**0.265**
TLU_{s-1}	0.642***	0.543***	4.875	2.889
	(0.0142)	(0.0188)	(65.14)	(38.32)
$PLMindex_{s-1}$	-20.56***	0.815	-624.7	5.834
	(4.336)	(1.739)	(7,728)	(123.4)
(No drought # insurance) $_{s-1}$	**-0.118**	**-0.0998**	**8.192**	**4.855**
	(0.479)	**(0.406)**	**(105.9)**	**(62.31)**
(Drought # insurance) $_{s-1}$	**1.275****	**1.080****	**-62.64**	**-37.13**
	(0.588)	**(0.492)**	**(762.8)**	**(448.6)**
Female Headed HH	-0.733**	-0.621**	58.83	34.86
	(0.318)	(0.268)	(715.1)	(420.5)
Dependency Ratio	-0.225**	-0.191**	-4.520	-2.679
	(0.104)	(0.0875)	(58.67)	(34.49)
Education of head in yrs	-0.0201	-0.0170	3.511	2.081
	(0.0885)	(0.0749)	(41.99)	(24.69)
Settled HH (indicator)	-2.436***	-2.063***	-9.826	-5.823
	(0.470)	(0.400)	(125.3)	(73.58)
Milk Production at Base	0.316***	0.267***	2.828	1.676
	(0.110)	(0.0938)	(35.67)	(20.99)
Milk Pr, Satellite Camp	0.643***	0.545***	20.91	12.39
	(0.163)	(0.137)	(257.4)	(151.4)
Ln(consumption)	0.146	0.123	-5.670	-3.360
	(0.142)	(0.120)	(67.77)	(39.86)
Insured TLU $_s$	0.00834**	0.00706**	-0.0182	-0.0108
	(0.00346)	(0.00291)	(3.157)	(1.871)
Pseudo R^2	0.679		0.614	

Clustered (HH) standard errors in parentheses. Variance standard errors are bootstrapped (reps=400). Season fixed effects included in all specifications. N=6,807.

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

Table 8: Poisson MLE of MUAC and its variance– marginal effects at representative values of the PLM index

VARIABLES	(1) MLE MUAC		(2) MLE V(MUAC)	
	(A)	(B)	(A)	(B)
PLM =	**.039**	**0.265**	**.039**	**0.265**
$MUAC_{s-2}$	0.351***	0.370***	0.108	0.134
	(0.0401)	(0.0434)	(0.0732)	(0.114)
$PLMIndex_{s-1}$	4.588***	2.058***	1.533	0.794
	(1.261)	(0.710)	(2.536)	(1.707)
(No drought # insurance) $_{s-1}$	**-0.169**	**-0.178**	**-0.308**	**-0.383**
	(0.152)	**(0.161)**	**(0.290)**	**(0.361)**
(Drought # insurance) $_{s-1}$	**-0.134**	**-0.141**	**-0.533**	**-0.664**
	(0.203)	**(0.215)**	**(0.355)**	**(0.586)**
Female Headed HH	-0.346***	-0.365***	0.0870	0.108
	(0.0961)	(0.102)	(0.190)	(0.230)
Girl	-0.0845	-0.0890	0.239	0.297
	(0.0811)	(0.0853)	(0.170)	(0.240)
Dependency Ratio	-0.0240	-0.0253	0.0287	0.0357
	(0.0278)	(0.0294)	(0.0581)	(0.0695)
Education of head in yrs	0.0410***	0.0432***	-0.0184	-0.0229
	(0.0129)	(0.0135)	(0.0248)	(0.0328)
Settled HH (indicator)	0.0902	0.0950	0.246	0.307
	(0.0888)	(0.0936)	(0.180)	(0.227)
Milk Production at Base	-0.00840	-0.00885	-0.0610	-0.0760
	(0.0150)	(0.0158)	(0.0376)	(0.0541)
Milk Pr, Satellite Camp	-0.00366	-0.00386	0.000414	0.000515
	(0.0131)	(0.0138)	(0.0228)	(0.0284)
Ln(consumption)	0.0226	0.0238	0.0348	0.0434
	(0.0605)	(0.0639)	(0.120)	(0.159)
TLU	0.00108	0.00114	-0.00290	-0.00361
	(0.00160)	(0.00169)	(0.00321)	(0.00451)
# Insured TLU $_s$	0.0144***	0.0151***	-0.00604	-0.00752
	(0.00491)	(0.00520)	(0.0257)	(0.0319)
Pseudo R^2	0.246		0.022	

Clustered (child) standard errors in parentheses. Variance standard errors are bootstrapped (reps=400). Round fixed effects included in all specifications. N=1,257.

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

Table 9: 2SLS Coefficient Estimates on TLU resilience at various values of $\underline{W}^{TLU}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\underline{W}^{TLU}$**:**	**2**	**8**	**14**	**20**	**26**	**32**	**38**
(No drought # insurance) $_{s-1}$	-0.019	-0.0442	-0.00675	0.0311	0.0554	0.0627	0.0502
	(-0.0322)	(-0.0391)	(-0.0446)	(-0.0474)	(-0.0476)	(-0.0428)	(-0.0362)
(Drought # insurance) $_{s-1}$	0.0497	-0.0447	0.00522	0.0861*	0.141***	0.154***	0.133***
	(-0.0345)	(-0.0405)	(-0.0424)	(-0.0467)	(-0.0499)	(-0.0475)	(-0.0405)

Clustered (HH), bootstrapped (reps=400) standard errors in parentheses. N=6,807.
*** p<0.01, ** p<0.05, * p<0.10.

Table 10: Binomial MLE Coefficient Estimates on MUAC resilience at various values of $\underline{W}^{MUAC}$

	(1)	(2)	(3)	(4)
$\underline{W}^{MUAC}$**:**	**11.5**	**12.5**	**13.5**	**14.5**
(No drought # insurance) $_{s-1}$	0.000356*	-0.000755	-0.0254***	-0.0808***
	(0.000205)	(0.00114)	(0.00348)	(0.00593)
(Drought # insurance) $_{s-1}$	0.00430***	0.0238***	0.0386***	-0.0215***
	(0.000551)	(0.00241)	(0.00707)	(0.00776)

Clustered (child), bootstrapped (reps=400) standard errors in parentheses. N=1,257.
*** p<0.01, ** p<0.05, * p<0.10.

Figures

Figure 1: Map of Kenya and Marsabit County

Adapted from Wikipedia

Figure 2: Timeline of IBLI Sales and Data Collection Rounds

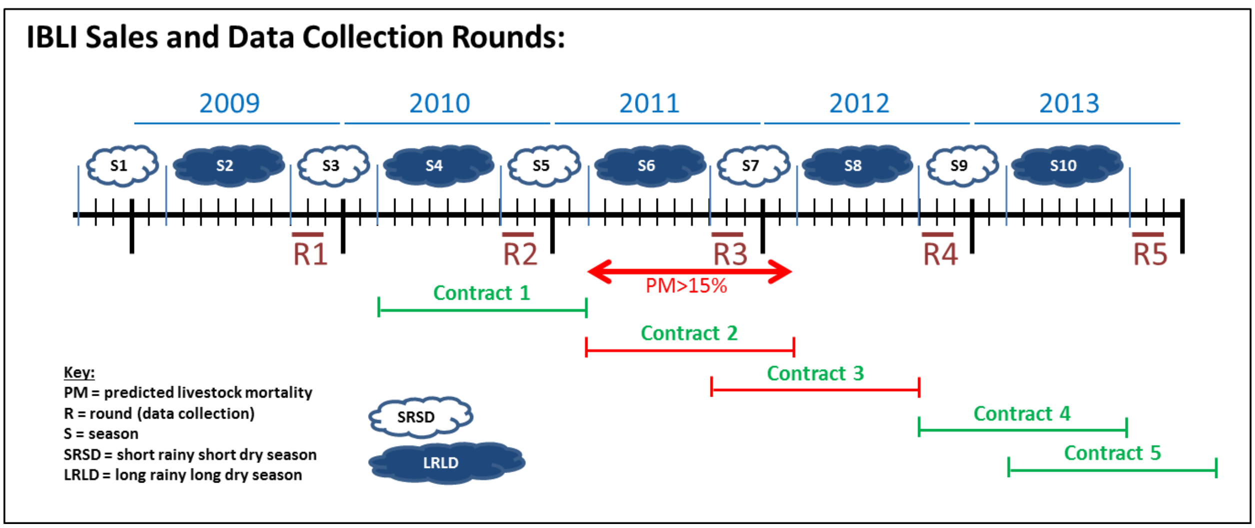


Figure 3: Histogram of TLU[51]

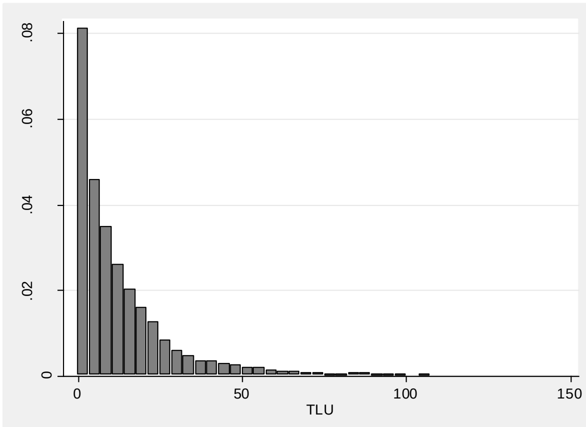


Figure 4: Histogram of MUAC

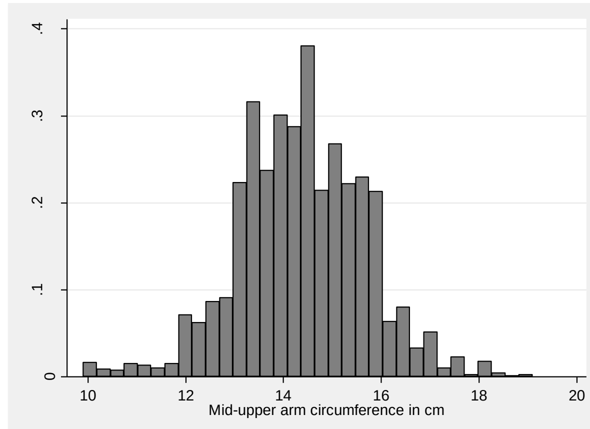
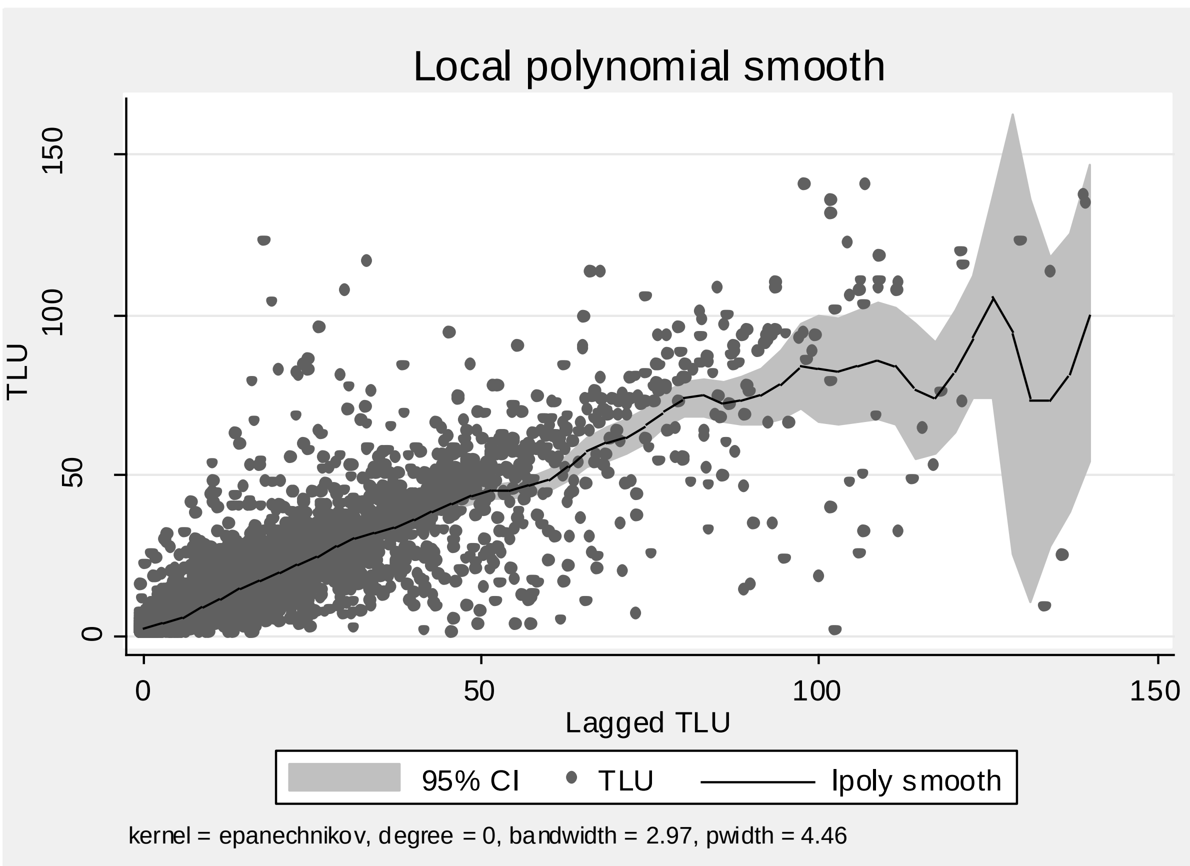


Figure 5: Kernel Regression of Lagged TLU and TLU



[51] In order to facilitate interpretation, outliers above 150 TLU have been censored from all figures.

Figure 5: Kernel Regression of Lagged MUAC and MUAC

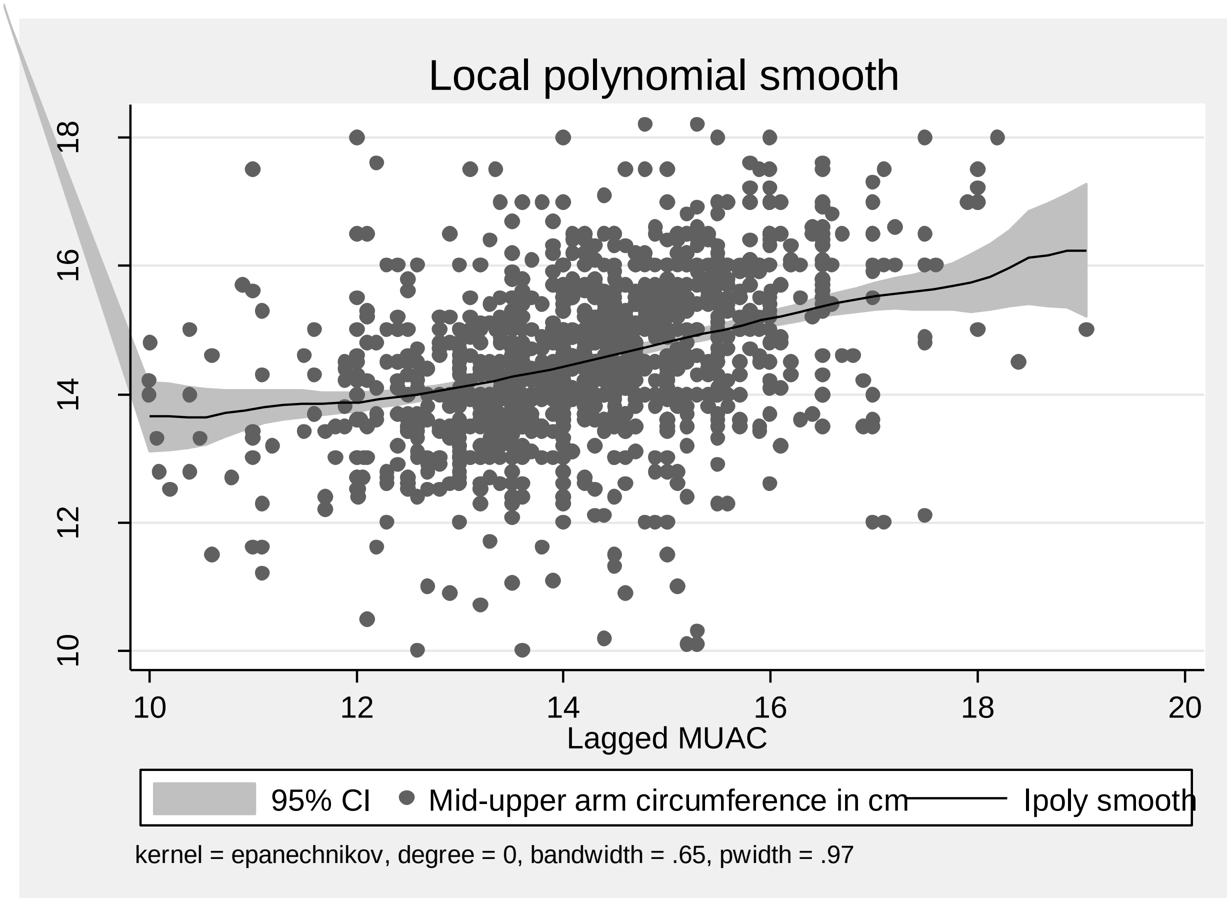


Figure 6: Household 5008's distributions of TLU well-being over time

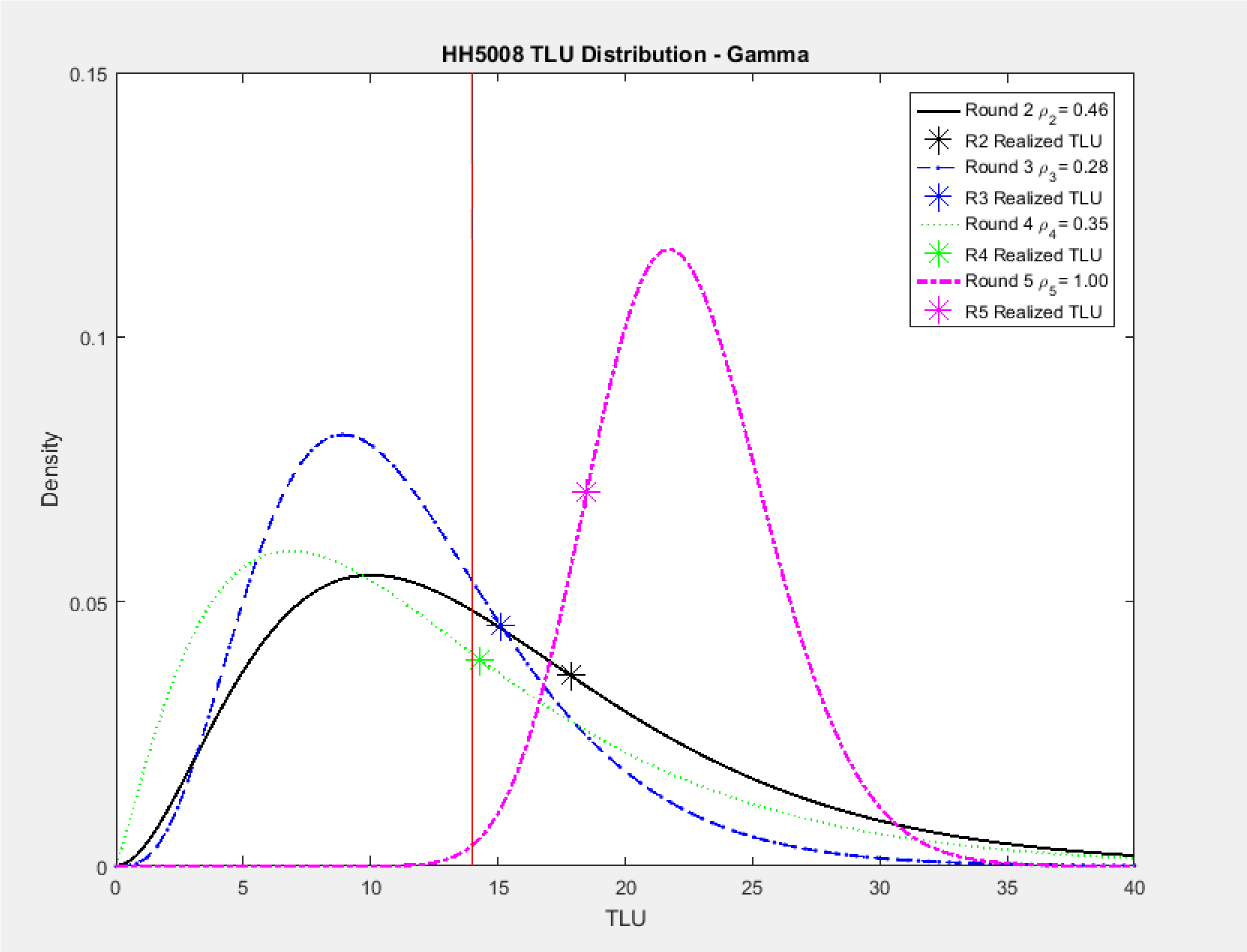


Figure 7: 2SLS Coefficients Estimates of IBLI on TLU resilience

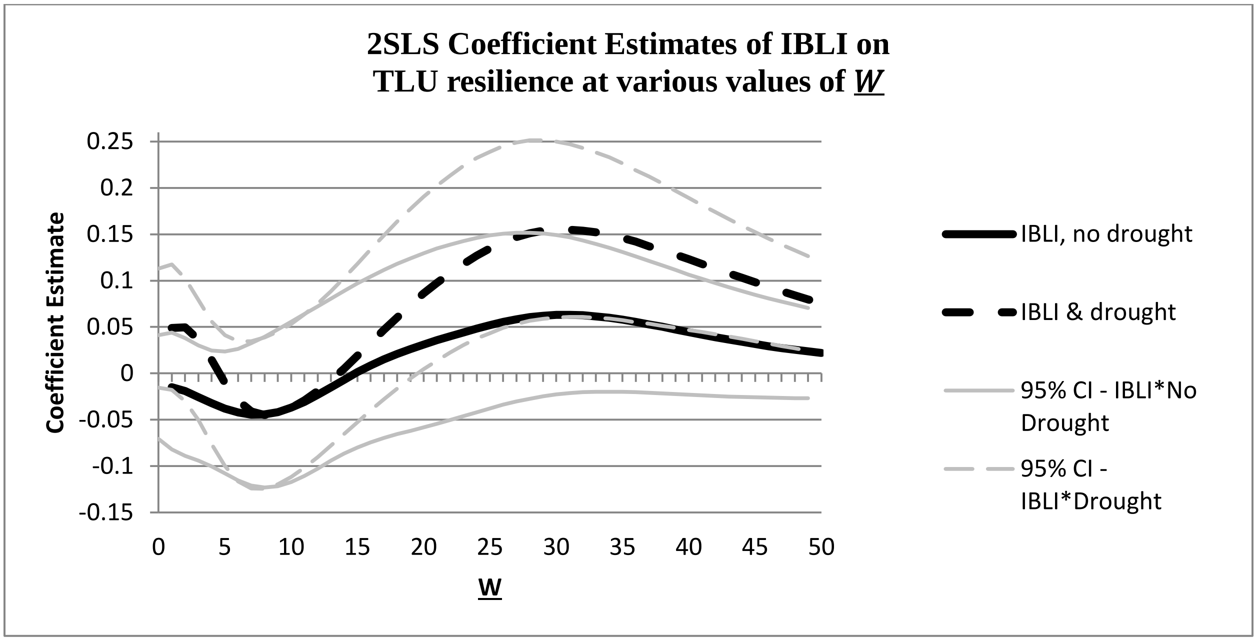
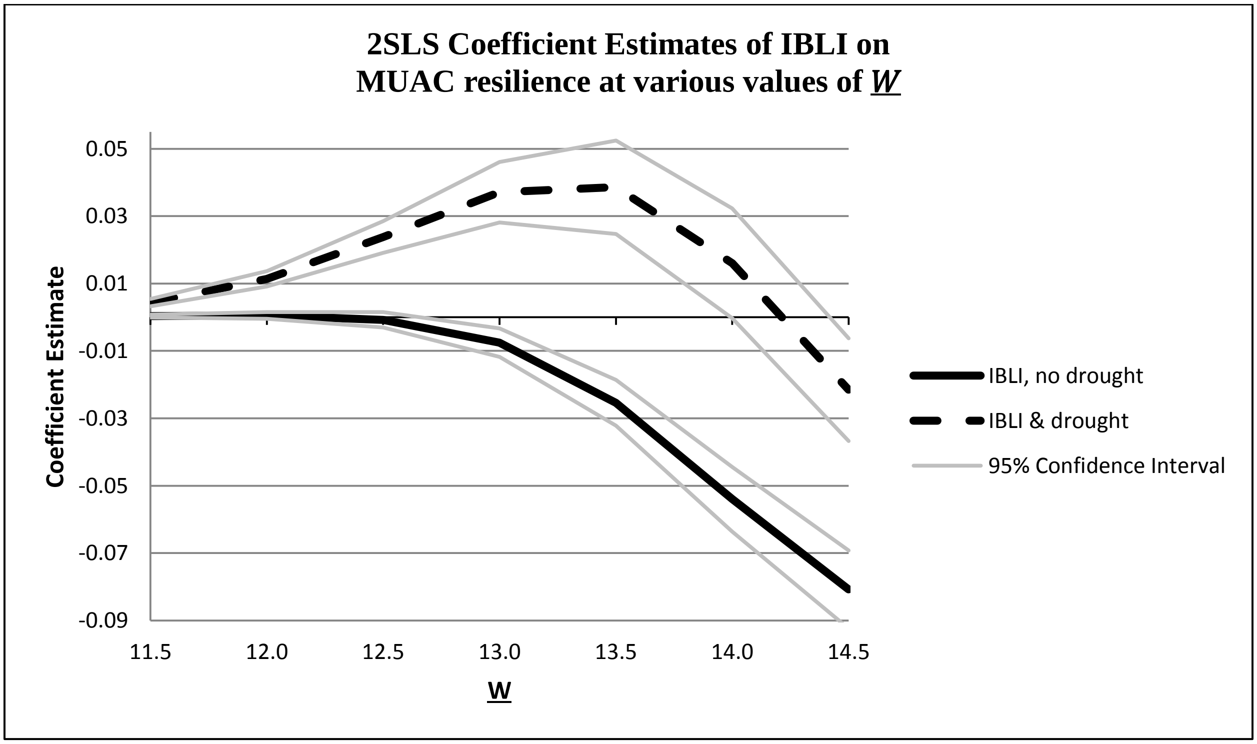


Figure 8: Binomial MLE Coefficients Estimates of IBLI on MUAC resilience



References

Alderman, Harold and Christina H. Paxson. 1992. “Do the Poor Insure? A Synthesis of the Literature on Risk and Consumption in Developing Countries.” Policy Research Working Paper. Agriculture and Rural Development Department. The World Bank.

Barnett, Barry J., Christopher B. Barrett, and Jerry R. Skees. 2008. “Poverty Traps and Index-Based Risk Transfer Products.” World Development 36(10): 1766-85.

Barnett, Barry J. and Olivier Mahul. 2007. “Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries.” American Journal of Agricultural Economics, 89(5): 1241-7.

Barrett, Christopher B. and Michael R. Carter. 2013. “The Economics of Poverty Traps and Persistent Poverty: Policy and Empirical Implications.” Journal of Development Studies 49(7): 976-990.

Barrett, Christopher B., Francis Chabari, DeeVon Bailey, Peter D. Little, and D. Layne Coppock. 2003. “Livestock Pricing in the Nothern Kenyan Rangelands.” Journal of African Economies 12(2): 127-155. doi: 10.1093/jae/12.2.127

Barrett, Christopher B. and Mark A. Constas. 2014. “Toward a theory of development resilience for international development applications.” Proceedings of the National Academy of Sciences 111(40): 14625-14630.

Barrett, Christopher B., Paswel Phiri Marenya, John McPeak, Bart Minten, Festus Murithi, Willis Oluoch-Kosura, Frank Place, Jean Claude Randrianarisoa, Jhon Rasambainarivo, and Justine Wangila. 2006. "Welfare Dynamics in Rural Kenya and Madagascar." Journal of Development Studies 42(2): 248-77.

Baulch, Bob and Agnes Quisumbing. 2011. "Testing and Adjusting For Attrition In Household Panel Data." CPRC Toolkit Note, Chronic Poverty Research Centre.

Besley, Timothy. 1995. "Savings, Credit, and Insurance." In Handbook of Development Economics, edited by Jere Behrman and T.N. Srinivasan, 2123-207. Elsevier.

Binns, Paula, Nancy Dale, Theresa Banda, Chrissy Banda, Bina Shaba, and Mark Myatt. 2014. "Safety of Using Mid-Upper Arm Circumference as a Discharge Criterion in Community-Based Management of Severe Acute Malnutrition in Children Aged 6–59 Months." Oxford, England: Valid International.

Blench, Roger M. 2001. Pastoralism in the new millennium. FAO: Animal Health and Production Series, No 150.

Carter, Michael R. and Christopher B. Barrett. 2006. "The economics of poverty traps and persistent poverty: An asset-based approach." Journal of Development Studies 42(2): 178-99.

Chantarat, Sommarat, Christopher B. Barrett, Andrew G. Mude, and Calum G. Turvey. 2007. "Using Weather Index Insurance to Improve Drought Response for Famine Prevention." American Journal of Agricultural Economics 89(5): 1262-8.

Chantarat, Sommarat, Andrew G. Mude, Christopher B. Barrett, and Michael R. Carter. 2013. "Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya." Journal of Risk and Insurance 80(1): 205–237. doi:10.1111/j.1539-6975.2012.01463.x

Chantarat, Sommarat, Andrew G. Mude, Christopher B. Barrett, and Calum G. Turvey. 2017. "Welfare Impacts of Index Insurance in the Presence of a Poverty Trap." World Development 94: 119–38. https://doi.org/10.1016/j.worlddev.2016.12.044

Cissé, Jennifer Denno and Christopher B. Barrett. 2016. "Estimating Development Resilience: A Conditional Moments-Based Approach." African Development Bank Group, Working Paper No 236.

Constas, Mark A. and Christopher B. Barrett. 2013." Principles of Resilience Measurement for Food Insecurity: Metrics, Mechanisms, and Implementation Plans." Cornell University working paper.

Coppock, D. Layne. 1994. The Borana Plateau of Southern Ethiopia: Synthesis of Pastoral Research, Development and Change, 1980-91. International Livestock Centre for Africa, Addis Ababa. Ethiopia.

DeAngelis, Kate. 2013. "Index-based livestock insurance: The case of Mongolia." Climate & Development Knowledge Network: Inside Stories on Climate Compatible Development series.

Dercon, Stefan. 2002. "Income Risk, Coping Strategies, and Safety Nets." The World Bank Research Observer 17(2): 141-166.

Foster, James, Joel Greer, and Erik Thorbecke. 1984. "A Class of Decomposable Poverty Measures." Econometrica 52(3): 761-66.

Fratkin, Elliot. 1986. "Stability and Resilience in East African Pastoralism: The Rendille and the Ariaal of Northern Kenya." Human Ecology 14(3): 269-86.

Fratkin, Elliot, Eric Abella Roth, and Martha A. Nathan. 2004. "Pastoral Sedentarization and Its Effects on Children's Diet, Health, and Growth among Rendille of Northern Kenya." Human Ecology 32(5): 531-59. doi: 10.1007/s10745-004-6096-8.

Giné, Xavier, Lev Menand, Robert Townsend, and James Vickery. 2010. "Microinsurance: A Case Study of the Indian Rainfall Index Insurance Market." World Bank, Policy Research Working Paper No. WPS 5459.

Greene, William. 2004. "The Behavior of the Maximum Likelihood Estimator of Limited Dependent Variable Models in the Presence of Fixed Effects." Econometrics Journal 7: 98-199.

Hillier, Debbie and Benedict Dempsey. 2012. "A Dangerous Delay: The cost of late response to early warnings in the 2011 drought in the Horn of Africa." Oxfam Policy and Practice: Agriculture, Food and Land 12(1): 1-34.

Hoddinott, John. 2006. "Shocks and their Consequences Across and Within Households in Rural Zimbabwe." Journal of Development Studies, 42(2): 301-21.

Ikegami, Munenobu and Megan Sheahan. 2016. "Index Based Livestock Insurance (IBLI) Marsabit Household Survey Codebook." International Livestock Research Institute. Available at https://ibli.ilri.org/.

International Livestock Research Institute. 2013. "Index Based Livestock Insurance for Northern Kenya's Arid and Semi-Arid Lands: The Marsabit Project - Codebook for IBLI Evaluation Survey (Round 1, Round 2, Round 3 and Round 4 Surveys)." http://data.ilri.org/portal/dataset/ibli-marsabit-r1

Janzen, S.A. and M.R. Carter. 2013. "The Impact of Microinsurance on Consumption Smoothing and Asset Protection: Evidence from a Drought in Kenya." Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, selected paper.

Jensen, Nathaniel D., Christopher B. Barrett, and Andrew G. Mude. 2016. "Index Insurance Quality and Basis Risk: Evidence from Northern Kenya." American Journal of Agricultural Economics 98(5): 1450-69. doi: 10.1093/ajae/aaw046

Jensen, Nathaniel D., Christopher B. Barrett, and Andrew G. Mude. 2015. "Index Insurance and Cash Transfers: A Comparative Analysis from Northern Kenya." Cornell University Working Paper.

Jensen, Nathaniel D., Munenobu Ikegami, and Andrew Mude. 2016. "Integrating Social Protection Strategies for Improved Impact: A Comparative Evaluation of Cash Transfers and Index Insurance in Kenya." International Livestock Research Institute Working Paper.

Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. 2014. "Agricultural Decisions After Relaxing Credit and Risk Constraints." The Quarterly Journal of Economics 129 (2): 597-652.

Kenya National Bureau of Statistics, Ministry of Planning and National Development. "Kenya Integrated Household Budget Survey 2005-2006." National Data Archive online at http://statistics.knbs.or.ke/nada/index.php/catalog/8.

Kolenikov, Stanislav. 2010. "Resampling Variance Estimation for Complex Survey Data." The Stata Journal 10(2): 165-99.

Kovacevic, Raimund M., and Georg C. Pflug. 2011. "Does Insurance Help to Escape the Poverty Trap?--A Ruin Theoretic Approach." Journal of Risk and Insurance, 78(4): 1003-27.

Little, Peter D., John McPeak, Christopher B. Barrett, and Patti Kristjanson. 2008. "Challenging Orthodoxies: Understanding Poverty in Pastoral Areas of East Africa." Development and Change 39(4): 587–611.

Lybbert, T.J., C.B. Barrett, S. Desta, and D.L. Coppock. 2004. “Stochastic Wealth Dynamics and Risk Management among a Poor Population.” Economic Journal 114: 750-777.

Maxwell, Daniel and Merry Fitzpatrick. 2012. “The 2011 Somalia Famine: Context, Causes, and Complications” Global Food Security 1: 5-12.

McPeak, John. 2005. “Individual and Collective Rationality in Pastoral Production: Evidence From Northern Kenya.” Human Ecology 33(2): 171-97. doi: 10.1007/s10745-005-2431-Y

McPeak, John and Christopher B. Barrett. 2001. “Differential Risk Exposure and Stochastic Poverty Traps among East African Pastoralists.” American Journal of Agricultural Economics, 83(3): 674-679.

McPeak, John, Peter D. Little, and Cheryl R. Doss. 2012. Risk and Social Change in an African Rural Economy: Livelihoods in Pastoralist Communities. London, UK: Routledge.

Mills, Christopher J., Nathaniel D. Jensen, Christopher B. Barrett, and Andrew G. Mude. 2016. Characterization for index based livestock insurance. International Livestock Research Institute, ILRI Research Report 39.

Mobarak, A. Mushfiq and Mark Rosenzweig. 2012. “Selling Formal Insurance to the Informally Insured.” Yale University Economics Department Working Paper No. 97.

Morduch, Jonathan. 1994. “Poverty and vulnerability.” American Economic Review Papers and Proceedings 84(2): 221-5.

Mude, Andrew, Christopher B. Barrett, Michael R. Carter, Sommarat Chantarat, Munenobu Ikegami, and John McPeak. 2009. “Index Based Livestock Insurance for Northern Kenya’s Arid and Semi-Arid Lands: The Marsabit Pilot.” International Livestock Research Institute Project Summary.

Mundlak, Yair. 1978. “On the pooling of Time Series and Cross Section Data.” Econometrica, 46(1): 69-85.

Næss, Marius Warg and Bård-Jørgen Bårdsen. 2010. “Environmental Stochasticity and Long-Term Livestock Viability—Herd-Accumulation as a Risk Reducing Strategy.” Human Ecology 38(3): 3-17. doi:10.1007/s10745-009-9288-4

Nathan, Martha A., Elliot M. Fratkin, and Eric Abella Roth. 1996. “Sedentism and Child Health among Rendille Pastoralists of Northern Kenya.” Social Science & Medicine 43(4): 503-15.

Pratt, D. J, and M. D Gwynne. 1977. Rangeland Management and Ecology in East Africa. London: Hodder and Stoughton.

Rass, Nikola. 2006. “Policies and Strategies to Address the Vulnerability of Pastoralists in Sub-Saharan Africa.” Pro-Poor Livestock Policy Initiative Working Paper No. 37.

Roberfroid, Dominique, Naima Hammami, Carl Lachat, Zita Weise Prinzo, Victoria Sibson, Benjamin Guesdon, Sylvie Goosens, and Patrick Kolsteren. 2013. “Utilization of mid-upper arm circumference versus weight-for-height in nutritional rehabilitation programmes: a systematic review of evidence.” World Health Organization.

Sen, Amartya. 1976. “Poverty: An Ordinal Approach to Measurement.” Econometrica 44(2): 219-231.

------. 1979. “Issues in the Measurement of Poverty.” Scandinavian Journal of Economics 81(2): 285-307.

Skees, Jerry R. and Barry J. Barnett. 2006. “Enhancing microfinance using index-based risk-transfer products.” Agricultural Finance Review 66(2): 235-250.

Skoufias, Emmanuel, and Agnes R. Quisumbing. 2005. "Consumption Insurance and Vulnerability to Poverty: A Synthesis of the Evidence from Bangladesh, Ethiopia, Mali, Mexico and Russia." European Journal of Development Research 17(1): 24-58.

Taferea, Kibrom, Christopher B. Barrett, Erin Lentz, and Birhanu T. Ayana. 2015. “The Subjective Well-being Gains from Insurance That Doesn’t Pay Out.” Cornell University Working Paper.

Terza, Joseph V., Anirban Basu, and Paul J. Rathouz. 2008. “Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling.” Journal of Health Economics 27: 531–43.

Wooldridge, Jeffery M. 2002. Econometric Analysis of Cross-sectional and Panel Data. Cambridge MA: MIT Press.

World Health Organization (2015). Child Growth Standards: Methods and development: Head circumference-for-age, arm circumference-for-age, triceps skinfold-for-age and subscapular skinfold-for-age. World Health Organization. On line at: http://www.who.int/childgrowth/publications/technical_report_2/en/

United States Agency for International Development. 2012. “Building Resilience to Recurrent Crisis: USAID Policy and Program Guidance.” Washington DC: U.S. Agency for International Development.

Appendix

Appendix A: Attrition

There is evidence of non-random attrition by households, as shown in the summary statistics. To avoid bias due to attrition, we adjust the survey probability weights to oversample households similar to those who attrited based on observables. We calculate these attrition-correcting inverse probability weights following Baulch & Quisumbing (2011) and multiply them by the survey probability weights. The probits used in this calculation are below (Columns (1) and (2)). Note that following Wooldridge (2002), only households that are surveyed at baseline (in Round 1) are included in the analysis (throughout the paper) despite the inclusion of replacement households when originally surveyed households could not be resurveyed.

Columns (3) and (4) present the probit results on non-missingness for children. As mentioned in above, children may (randomly) enter and leave the child survey sample as they are born or age out. Some children are lost to follow-up because their families attrit. Eligible (age appropriate) children that are missing from the child sample and whose households have not attrited are considered missing. The household survey confirms that no children are missing due to death or moving back home to live with their biological parents. Nonetheless, child missingness is not random, as can be seen in the probit below. The predicted missingness from columns (3) and (4) are used to correct survey weights for missingness in the MUAC regressions above.

Table A1: Probit estimates on non-attrition and non-missingness

VARIABLES	(1) Probit HH remains	(2) Probit HH remains	(3) Probit Child not missing	(4) Probit Child not missing
Female Headed HH (indicator)	-0.167	-0.0873		
	(0.136)	(0.115)		
Girl (indicator)			0.0965	0.134
			(0.110)	(0.106)
Dependency Ratio	0.0594	0.0373	0.0278	0.0297
	(0.0397)	(0.0348)	(0.0446)	(0.0400)
Education of head in yrs	-0.0560*	-0.0541***	0.0437	0.0231
	(0.0337)	(0.0166)	(0.0591)	(0.0188)
Head literate (indicator)	-0.128		-0.328	
	(0.310)		(0.520)	
HH head age (yrs)	-0.00625		-0.00153	
	(0.00382)		(0.00407)	
Child age (months)			0.00789**	0.00799**
			(0.00340)	(0.00330)
Settled HH (indicator)	-0.0859	-0.0730	-0.403***	-0.378***
	(0.0834)	(0.0781)	(0.130)	(0.116)
Sublocation attrition rate	-4.973***		-0.649	
	(1.113)		(0.938)	
Sublocation child missing rate			-4.664*	
			(2.592)	
Milk Production at Base	-0.00217	0.0216	0.00208	0.0272
	(0.0336)	(0.0335)	(0.0336)	(0.0297)
Milk Production at Satellite Camp	0.00168	0.00530	0.00797	-0.00444
	(0.0225)	(0.0228)	(0.0217)	(0.0189)
Ln(consumption)	0.0309	0.0762	-0.114*	-0.0824
	(0.0473)	(0.0550)	(0.0599)	(0.0582)
HH TLU Holdings				-0.00254
				(0.00189)
Season FE	Y	Y	N	N
Division FE	Y	N	Y	N
Religion FE	Y	N	Y	N
Constant	2.283***	0.709*	3.341***	2.239***
	(0.490)	(0.405)	(0.586)	(0.492)
Observations	8,664	8,664	2,348	2,355
Pseudo R^2	0.1575	0.0901	0.0781	0.0344

Clustered standard errors in parentheses, clustered at HH ((1) & (2)) and child-level ((3) and (4).
*** p<0.01, ** p<0.05, * p<0.10

Appendix B: Robustness Checks

Table B1: Linear estimates of mean TLU – specification and serial correlation checks

VARIABLES	(1) OLS TLU	(2) OLS TLU	(3) OLS TLU	(4) FE[52] TLU	(5) FE TLU	(6) FE TLU
TLU_{s-1}		0.903***	1.001***		0.448***	0.693***
		(0.0324)	(0.0651)		(0.0823)	(0.106)
TLU^2_{s-1}		-0.00199***	-0.00480**		0.000572	-0.00549*
		(0.000553)	(0.00196)		(0.00114)	(0.00308)
TLU^3_{s-1}		3.87e-06***	2.39e-05*		3.71e-07	4.07e-05*
		(1.31e-06)	(1.31e-05)		(2.46e-06)	(2.16e-05)
TLU^4_{s-1}			-3.60e-08			-7.00e-08*
			(2.25e-08)			(3.81e-08)
$PLMindex_{s-1}$	-52.83***	-18.46***	-16.98***	-4.635	-9.826*	-9.537*
	(12.65)	(4.810)	(4.848)	(9.487)	(5.719)	(5.677)
$PLMindex^2_{s-1}$	131.0***	37.07***	33.75***	19.35	20.37	20.00
	(30.81)	(10.30)	(10.51)	(21.07)	(12.70)	(12.68)
(No drought # insurance) $_{s-1}$	**-0.753**	**-0.0939**	**-0.135**	**-0.358**	**-0.207**	**-0.249**
	(0.753)	**(0.379)**	**(0.378)**	**(0.699)**	**(0.519)**	**(0.520)**
(Drought # insurance) $_{s-1}$	**0.794**	**0.626**	**0.551**	**1.227**	**0.842***	**0.786**
	(1.054)	**(0.479)**	**(0.476)**	**(0.751)**	**(0.510)**	**(0.507)**
Female Headed HH (indicator)	-0.549	-0.444**	-0.389**	0.618	0.690	0.797
	(0.857)	(0.182)	(0.196)	(1.003)	(0.858)	(0.842)
Dependency Ratio	-0.548**	-0.173***	-0.173***	-0.340	-0.264	-0.250
	(0.248)	(0.0646)	(0.0660)	(0.282)	(0.201)	(0.203)
Education of head in yrs	-0.0900	-0.0201	-0.0116	-0.0637	0.0784	0.0743
	(0.147)	(0.0379)	(0.0383)	(0.251)	(0.153)	(0.149)
Settled HH (indicator)	-5.440***	0.106	0.267	0.744	0.705	0.709
	(0.784)	(0.307)	(0.362)	(1.008)	(0.551)	(0.538)

[52] Probability weights in the fixed effects equations are average household-level probability weights.

Milk Production at Base	0.650	0.0863	0.0519	0.0797	0.0326	0.0347
	(0.453)	(0.126)	(0.126)	(0.200)	(0.150)	(0.150)
Milk Production at Satellite Camp	4.118***	1.023***	0.979***	1.234***	0.959***	0.931***
	(0.443)	(0.157)	(0.151)	(0.280)	(0.184)	(0.185)
Ln(consumption)	0.574**	0.182*	0.172*	0.144	0.136	0.146
	(0.275)	(0.0983)	(0.0975)	(0.193)	(0.140)	(0.140)
# Insured TLU $_s$	0.00484	0.00202	0.00126	-0.00929	-0.00179	-0.000299
	(0.0162)	(0.00558)	(0.00542)	(0.0190)	(0.0104)	(0.00929)
HH FE	N	N	N	Y	Y	Y
Constant	14.65***	3.478***	2.919***	13.67***	7.482***	5.977***
	(2.527)	(0.939)	(1.031)	(2.006)	(1.329)	(1.603)
Adjusted R^2	0.232	0.754	0.755	0.0541	0.407	0.412
Number of HH				889	889	889
Correlation Coefficient	**0.7434**	**0.0152**	**0.0207**	**0.8347**	**0.3872**	**0.3640**

Clustered (HH) standard errors in parentheses. Season fixed effects included in all specifications. N=6,807.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table B2: Linear Estimates of mean MUAC – specification and serial correlation checks

VARIABLES	(1) OLS MUAC	(2) OLS MUAC	(3) OLS MUAC	(4) FE[53] MUAC	(5) FE MUAC	(6) FE MUAC
MUAC_{s-2}		-3.729	-38.08		6.332	-55.01
		(3.809)	(30.43)		(5.565)	(35.69)
MUAC^2_{s-2}		0.273	3.994		-0.446	6.231*
		(0.280)	(3.317)		(0.393)	(3.759)
MUAC^3_{s-2}		-0.00600	-0.183		0.00970	-0.310*
		(0.00682)	(0.159)		(0.00921)	(0.174)
MUAC^4_{s-2}			0.00314			0.00568*
			(0.00283)			(0.00301)
$\mathrm{PLMindex}_{s-1}$	5.024***	5.290***	5.314***	5.459***	6.130***	6.123***
	(1.277)	(1.540)	(1.540)	(1.357)	(1.562)	(1.519)
$\mathrm{PLMindex}^2_{s-1}$	-7.190***	-6.158**	-6.154**	-10.29***	-13.88***	-13.76***
	(2.545)	(2.767)	(2.762)	(2.857)	(3.604)	(3.531)
(No drought # insurance) $_{s-1}$	**-0.0207**	**-0.178**	**-0.182**	**-0.173**	**-0.142**	**-0.126**
	(0.130)	**(0.155)**	**(0.153)**	**(0.144)**	**(0.142)**	**(0.144)**
(Drought # insurance) $_{s-1}$	**0.192**	**-0.140**	**-0.150**	**-0.218**	**-0.0429**	**-0.0757**
	(0.201)	**(0.216)**	**(0.215)**	**(0.207)**	**(0.266)**	**(0.262)**
Female Headed HH (indicator)	-0.252**	-0.351***	-0.344***	-0.112	0.625	0.625
	(0.111)	(0.0977)	(0.0978)	(0.404)	(0.583)	(0.573)
Girl (indicator)	-0.0484	-0.0874	-0.0942			
	(0.0906)	(0.0834)	(0.0833)			
Dependency Ratio	-0.0712***	-0.0239	-0.0242	0.0438	-0.0171	-0.0216
	(0.0271)	(0.0282)	(0.0278)	(0.0467)	(0.0546)	(0.0547)
Education of head in yrs	0.0707***	0.0442***	0.0452***	0.0232	0.0491	0.0451
	(0.0180)	(0.0139)	(0.0141)	(0.0469)	(0.0545)	(0.0530)
Settled HH (indicator)	0.215**	0.0922	0.0878	0.102	-0.0451	-0.0459
	(0.0925)	(0.0916)	(0.0918)	(0.0922)	(0.106)	(0.106)
Milk Production at Base	-0.00864	-0.00865	-0.00835	0.0146	-0.0594**	-0.0568**
	(0.0153)	(0.0153)	(0.0151)	(0.0240)	(0.0248)	(0.0250)
Milk Production at Satellite Camp	-0.0120	-0.00360	-0.00244	-0.00447	-0.00657	-0.00476
	(0.0123)	(0.0134)	(0.0134)	(0.0170)	(0.0165)	(0.0167)
Ln(consumption)	0.115**	0.0250	0.0273	-0.0305	0.0361	0.0373

[53] Probability weights in the fixed effects equations are average child-level probability weights.

	(0.0497)	(0.0634)	(0.0629)	(0.0674)	(0.0565)	(0.0557)
HH TLU holdings	-0.000407	0.00108	0.000864	0.000792	-0.00446	-0.00478
	(0.00192)	(0.00163)	(0.00162)	(0.00356)	(0.00535)	(0.00523)
# Insured TLU $_s$	0.00239	0.0153***	0.0150***	0.00457***	-0.0116	-0.0113
	(0.00155)	(0.00537)	(0.00529)	(0.000845)	(0.0278)	(0.0289)
Child FE	N	N	N	Y	Y	Y
Constant	12.83***	28.48*	146.1	13.44***	-14.52	194.4
	(0.438)	(17.14)	(103.6)	(0.597)	(26.00)	(125.9)
Observations	1,882	1,257	1,257	1,882	1,257	1,257
Adjusted R^2	0.112	0.246	0.247	0.132	0.250	0.257
Number of children				941	730	730
Correlation Coefficient[54]	**0.3672**	**-0.1244**	**-0.1245**	**0.4122**	**0.7049**	**0.7109**

Clustered (child) standard errors in parentheses. Round fixed effects included in all specifications.

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

[54] The correlation coefficient is the pairwise correlation coefficient between the regression residual and the lagged value of the regression residual. Higher correlations indicate serial correlation.

Table B3: Binomial[55] MLE of TLU resilience – marginal effects at representative values of the PLM index

VARIABLES	(1) MLE $\hat{\rho}_{is}^{TLU}, \underline{W} = 14$		(2) MLE $\hat{\rho}_{is}^{TLU}, \underline{W} = 14$	
	(A)	(B)	(A)	(B)
PLM =	**.039**	**0.26**	**.039**	**0.26**
TLU_{s-1}	0.0183***	0.0158***	0.0183***	0.0158***
	(0.00129)	(0.000934)	(0.00129)	(0.000948)
PLMindex_{s-1}	-0.397***	0.0416***	-0.385***	0.0434***
	(0.0476)	(0.00705)	(0.0472)	(0.00707)
(No drought # insurance) $_{s-1}$	**-0.00321**	**-0.00288**		
	(0.00217)	**(0.00194)**		
(Drought # insurance) $_{s-1}$	**0.00791***	**0.00710***		
	(0.00441)	**(0.00395)**		
(No drought # treatment) $_{s-1}$			**0.00111**	**0.001000**
			(0.00190)	**(0.00171)**
(Drought # treatment) $_{s-1}$			**-0.00227**	**-0.00205**
			(0.00328)	**(0.00296)**
Female Headed HH	-0.00746***	-0.00670***	-0.00768***	-0.00692***
	(0.00190)	(0.00171)	(0.00194)	(0.00175)
Dependency Ratio	-0.00391***	-0.00351***	-0.00392***	-0.00354***
	(0.000655)	(0.000564)	(0.000655)	(0.000567)
Education of head in yrs	0.000477	0.000428	0.000494	0.000445
	(0.000402)	(0.000357)	(0.000399)	(0.000356)
Settled HH (indicator)	-0.0379***	-0.0341***	-0.0379***	-0.0342***
	(0.00288)	(0.00203)	(0.00287)	(0.00205)
Milk Production at Base	0.00534***	0.00480***	0.00535***	0.00482***
	(0.000644)	(0.000533)	(0.000647)	(0.000537)
Milk Pr, Satellite Camp	0.0119***	0.0107***	0.0118***	0.0107***
	(0.00133)	(0.000974)	(0.00133)	(0.000984)
Ln(consumption)	0.00159*	0.00143*	0.00145*	0.00131*
	(0.000850)	(0.000762)	(0.000843)	(0.000758)
Insurance TLU	0.000207	0.000186	0.000207	0.000187
	(0.000127)	(0.000114)	(0.000159)	(0.000143)
Pseudo R^2	0.983		0.983	

Clustered (HH) standard errors in parentheses. Variance standard errors are bootstrapped (reps=400). Season fixed effects included in all specifications. N=6,807.

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

[55] $\hat{\rho}_{is}^{TLU}$ is assumed to be distributed binomially and fit using the canonical logit link. This is essentially a fraction response logistic regression.

Table B4: 2SLS and IV Tobit Estimates of TLU resilience

VARIABLES	(1) 2SLS $\hat{\rho}_{is}^{TLU}, \underline{W} = 14$	(2) 2SLS FE $\hat{\rho}_{is}^{TLU}, \underline{W} = 14$	(3) ivtobit [0,1] $\hat{\rho}_{is}^{TLU}, \underline{W} = 14$	(4) ivtobit [0,1] $\hat{\rho}_{is}^{TLU}, \underline{W} = 14$
TLU_{s-1}	0.0371***	0.0429***	0.0371***	0.0403***
	(0.00349)	(0.000914)	(0.00455)	(0.000915)
TLU_{s-1}^2	-0.000390**	-0.000521***	-0.000391*	-0.000444***
	(0.000157)	(1.76e-05)	(0.000206)	(2.05e-05)
TLU_{s-1}^3	1.51e-06	2.34e-06***	1.52e-06	1.82e-06***
	(1.98e-06)	(1.09e-07)	(2.61e-06)	(1.38e-07)
TLU_{s-1}^4	-1.93e-09	-3.32e-09***	-1.94e-09	-2.42e-09***
	(7.10e-09)	(1.86e-10)	(9.29e-09)	(2.44e-10)
PLMindex_{t-1}	-0.515***	-0.597***	-0.502***	-0.468***
	(0.0680)	(0.0687)	(0.0677)	(0.114)
PLMindex_{t-1}^2	1.121***	1.314***	1.094***	1.075***
	(0.159)	(0.164)	(0.158)	(0.219)
(No drought # insurance) $_{s-1}$	**-0.00675**	**-0.0253**	**-0.00592**	**-0.0570**
	(0.0446)	**(0.0292)**	**(0.0446)**	**(0.0394)**
(Drought # insurance) $_{s-1}$	**0.00522**	**0.00309**	**0.00779**	**-0.0439**
	(0.0424)	**(0.0267)**	**(0.0429)**	**(0.0488)**
Female Headed HH (indicator)	0.0163**	0.00413	0.0159**	0.00156
	(0.00683)	(0.0143)	(0.00683)	(0.0147)
Dependency Ratio	-0.00183	-0.00274	-0.00184	-0.00496**
	(0.00204)	(0.00187)	(0.00201)	(0.00227)
Education of head in yrs	0.00101	0.000871	0.00101	2.41e-07
	(0.00113)	(0.00287)	(0.00110)	(0.00219)
Settled HH (indicator)	0.00372	-0.0325***	0.00393	-0.0276***
	(0.00636)	(0.00400)	(0.00731)	(0.00526)
Milk Production at Base	-0.000240	0.00777***	-0.000156	0.00682**
	(0.00317)	(0.00173)	(0.00323)	(0.00274)
Milk Production at Satellite Camp	0.0117***	0.0158***	0.0118***	0.0152***
	(0.00193)	(0.00194)	(0.00205)	(0.00196)
Ln(consumption)	0.000680	0.000236	0.000829	-0.000186
	(0.00253)	(0.00158)	(0.00251)	(0.00180)
HH FE	N	Y	N	Y[56]
Constant	-0.0181	-0.0387**	-0.0208	-0.0505
	(0.0243)	(0.0160)	(0.0270)	(0.0907)
Overall R^2	0.90	0.896		
Number of HH		889		
Wald χ^2		471036.22	14152.05	16822.65
		(0.0000)	(0.0000)	(0.0000)

Clustered (HH) standard errors in parentheses. (1) & (3) are bootstrapped (reps=400). (2) does not contain survey weights. Season fixed effects included in all specifications. N=6,807.

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

[56] Fixed effects in column (4) are implemented using household-level means for all covariates.

Table B5: Binomial[57] MLE of MUAC resilience – marginal effects at representative values of the PLM index

VARIABLES	(1) MLE $\rho_{it}^{MUAC}, \underline{W}^{MUAC} = 13.5$		(2) MLE $\rho_{it}^{MUAC}, \underline{W}^{MUAC} = 13.5$	
	(A)	(B)	(A)	(B)
PLM =	**.039**	**0.265**	**.039**	**0.265**
MUAC_{s-2}	0.0892***	0.0565***	0.0903***	0.0551***
	(0.00180)	(0.00118)	(0.00187)	(0.00136)
PLMindex_{s-1}	1.195***	0.324***	1.321***	0.335***
	(0.0426)	(0.0111)	(0.0567)	(0.0113)
(No drought # insurance) $_{s-1}$	**-0.0318*** **	**-0.0201*** **		
	(0.00439)	**(0.00276)**		
(Drought # insurance) $_{s-1}$	**0.0485*** **	**0.0307*** **		
	(0.00879)	(0.00570)		
(No drought # treatment) $_{s-1}$			**-0.00187**	**-0.00114**
			(0.00335)	**(0.00205)**
(Drought # treatment) $_{s-1}$			**0.00906**	**0.00552**
			(0.00759)	**(0.00467)**
Female Headed HH	-0.111***	-0.0703***	-0.111***	-0.0678***
	(0.00307)	(0.00195)	(0.00331)	(0.00216)
Girl	-0.0479***	-0.0303***	-0.0485***	-0.0296***
	(0.00269)	(0.00177)	(0.00296)	(0.00189)
Dependency Ratio	-0.00744***	-0.00471***	-0.00762***	-0.00465***
	(0.000872)	(0.000554)	(0.000920)	(0.000574)
Education of head in yrs	0.0163***	0.0103***	0.0164***	0.0100***
	(0.000815)	(0.000545)	(0.000858)	(0.000552)
Settled HH (indicator)	0.00197	0.00125	-0.000502	-0.000306
	(0.00275)	(0.00174)	(0.00293)	(0.00179)
Milk Production at Base	0.00239**	0.00151**	0.00268**	0.00163**
	(0.00116)	(0.000736)	(0.00119)	(0.000732)
Milk Pr, Satellite Camp	-0.00127**	-0.000801**	-0.00178***	-0.00109***
	(0.000512)	(0.000324)	(0.000531)	(0.000324)
Ln(consumption)	0.00376***	0.00238***	0.00353**	0.00215**
	(0.00141)	(0.000890)	(0.00154)	(0.000939)
TLU	0.000629***	0.000398***	0.000658***	0.000401***
	(6.80e-05)	(4.30e-05)	(7.13e-05)	(4.42e-05)
# Insured TLU $_s$	0.00640***	0.00405***	0.00550***	0.00335***
	(0.000848)	(0.000542)	(0.00108)	(0.000669)
Pseudo R^2	0.967		0.932	

Clustered (child), bootstrapped (reps=400) standard errors in parentheses. Round fixed effects included in all specifications. N=1,257.

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

[57] $\hat{\rho}_{is}^{MUAC}$ is assumed to be distributed binomially and fit using the canonical logit link. This is essentially a fraction response logistic regression.

CHAPTER 3

LIVELIHOOD DIVERSIFICATION AND WELL-BEING IN UGANDA: A DEVELOPMENT RESILIENCE APPROACH

Jennifer Denno Cissé

I. Introduction

It is commonly accepted that households in Sub-Saharan Africa (SSA), particularly rural households, employ diversified livelihood strategies. But why do these households choose to diversify? In an early publication, Binswagner (1983) lays out a clear story of the road from subsistence agriculture to specialization, pointing out that rural areas gain from specialization, which leads to significant (albeit not always well-distributed) increases in average income.

Yet households continue to diversify. While the heterogeneous nature of livelihood portfolio decision processes was pointed out some 15 years ago (Ellis 1998), much of the recent empirical work has focused on diversification as an ex-ante risk mitigation strategy. Carter (1997), for example, views diversification as conditional self-insurance, protecting households against microclimatic risk and weather shocks in the face of incomplete (insurance and credit) markets. This would indicate that diversification may have resilience-enhancing benefits, allow households to better manage risk and cope with shock. Yet while diversification may certainly be a logical risk-mitigation strategy in some contexts, decreasing absolute risk aversion would imply that the poorest households would diversify more than their wealthier neighbors. This theory is not supported by much of the empirical literature on diversification, which finds more diversification at higher income levels (Barrett, Reardon, and Webb 2001).

Others view diversification as a result of rational agents gradually entering into new and better livelihood options. Balihuta and Sen (2001) argue more effort needs to be directed toward policy measures that contribute "positively to livelihood diversification that allows households to move out of poverty" (8). As Barrett, Reardon, and Webb (2001) remind us, however, income diversification might result naturally for a variety of reasons, including diminishing returns to factors of production, market failures and incomplete markets, and risk management and coping practices. If diversification is the result of market failures, policy would have the greatest impact on poverty by addressing the root market imperfections.

The thin recent literature on diversification and resilience finds that livelihood diversification promotes resilience, particularly in the face of complex social-ecological systems (Goulden et al. 2013) and climate change (Seo 2012). This argument has also been championed by development NGOs (TANGO 2012). Yet the relationship between livelihood diversification — including diversification across sectors, functions, and space (Barrett, Reardon, and Webb 2001) — and the resilience of households in the face of shock remains unclear. Given the increasing focus by the international community on resilience building, and the promise of diversification to contribute to the resilience of vulnerable communities in SSA, empirical evidence on diversification and well-being is needed. In particular, evidence is needed not only of average associations, but also the relationship between diversification and the variability of well-being.

In order to understand the relationship between crop and income diversification in rural Uganda and development resilience, I apply the Cissé and Barrett (2016) resilience approach to a large, nationally-representative panel dataset. I find that income diversification is negatively associated with increased resilience at all expenditure threshold levels. Crop diversification is significantly and positively associated with increased resilience when considering expenditures above the absolute poverty line. However, I find that diversifying into cash crop production is associated with lower levels of resilience.

II. Risk Management and Livelihood Diversification

While there are many opinions (see Martin and Lorenzen, 2016, for a recent review) about the reasons for and role of livelihood diversification in the literature, these can broadly be classified as the "progressive success" role and the "distress diversification" role.

Progressive success is the process of gradually entering into new and better livelihood options (Martin & Lorenzen 2016) that allow households to escape poverty (Balihuta & Sen 2001). These are generally caused by "pull factors," as increased wealth allows households to overcome barriers to entry into (presumably higher-return) non-farm livelihoods and also spurs demands for non-farm goods and services (Barrett & Reardon 2000). There is a substantial literature showing that barriers to entry into non-farm livelihoods are important in SSA (Barrett & Reardon 2000), which would explain why diversification is often positively correlated with wealth (Reardon et al. 2000, Bigsten & Tengstam 2011, Martin & Lorenzen 2016), and suggest that asset-based poverty traps may be preventing households from moving into higher-return activities (Barrett & Reardon 2000). Household-level diversification is not necessarily contradictory to the theory of specialization, as individual family members may specialize within the household (Ellis 2000).

Nonetheless, there is mixed evidence on the role that non-farm activities play in rural incomes (Martin & Lorenzen 2016). This may be due, in certain contexts, to the presence of distress diversification, which includes both *ex ante* risk management through self-insurance due to incomplete financial markets (Carter 1997, Barrett & Reardon 2000)—including portfolios that have lower risk but lower average returns—and *ex post* coping due to reduced capacity to manage shocks, both of which could be considered "push factor" (Barrett & Reardon 2000). Although diversification may serve as a form of self-insurance, crop diversification may not contribute positively to risk management given the highly correlated nature of the risk profiles (Barrett & Reardon 2000). In fact, diversification based on natural resource use is viewed by some as increasing vulnerability to shocks, including climate change (Thomas & Twyman 2005).

Seasonal diversification[58], for example growing different crops at different times of the year or working off-farm during the dry season, may fall into either category. Some researchers also consider seasonal diversification as a type of distress diversification (Martin & Lorenzen 2016), as households attempt to smooth consumption over the course of the year. On the other hand, seasonal diversification (including crop diversification) may be a rational response to varying returns to labor and other inputs over the course of the year (Ellis 2000).

III. Data and Context

In order to understand the relationship between both crop and income diversification and resilient well-being in Uganda, I use three rounds of the Uganda National Panel Survey (UNPS), a household-level panel dataset collected in 2009–10, 2010–11, and 2011–12. The UNPS is representative at the national, urban/rural, and four regional levels (discussed below) and includes data on approximately 3,200 households. It is implemented jointly by the Uganda Bureau of Statistics and the World Bank Living Standard Measurement Study—Integrated Surveys on Agriculture (LSMS-ISA) program. In addition to the typical LSMS style household survey questions, the UNPS and other LSMS-ISA surveys collect high quality data on

[58] The process of diversifying the households livelihood portfolio over time such that different activities are performed during different seasons.

agriculture, including crop production and livestock earnings. The analysis additionally benefits from data aggregates on household income sources generated by the Rural Income Generating Activities (RIGA) project.

These data me to explore on-farm crop diversification as well as income diversification from on- and off-farm sources (including remittances), and how each of these relates to well-being while controlling for elevation, geo-referenced weather variables, a variety of household characteristics, assets, livestock, landholdings, and self-reported shocks. The dependent variable of interest is well-being, measured in terms of monthly household expenditure per adult equivalent (PAE). Given my interest in on-farm crop diversification, I limit the dataset to rural households included in the RIGA dataset, of which there are nearly 1,800.

Uganda contains four regions (see Figure 1): Central, Eastern, Western, and Northern. Central borders Tanzania and contains the capital, Kampala, and much of the Lake Victoria shoreline. The Eastern region borders Lake Victoria and Kenya, while the Western region borders Tanzania, Rwanda, and the Democratic Republic of Congo (DRC), as well as Lake Edward and Lake Albert. Generally speaking, these regions experience bimodal rainfall, allowing two crops annually (FAO 1999). The Northern region, on the other hand, transitions to a unimodal rainfall pattern and borders DRC to the West, South Sudan to the North, and Kenya to the East. The conditions in the North are less favorable for crop agriculture and more favorable for extensive livestock production (FAO 1999).

Table 1 shows the summary statistics for the rural RIGA dataset, broken out by round. The average household contains around six people, two or three of which are of working age (over 14 but under 60 years of age). Nearly three-quarters of households are headed by men, although the rate seems to decrease slightly over time. The average household head has completed about 5 years of formal education. In Round 1, nearly 70% of households report having experienced a shock in the last year, although this falls to below half in Rounds 2 and 3.

As mentioned above, the dependent variable of interest is monthly expenditure PAE in 2005-2006[59] Ugandan shillings (USh). Monthly expenditure, monthly expenditure PAE, acres under cultivation, acres under cash crop cultivation, wages, assets, and livestock holdings (measured in tropical livestock units, or TLU[60]) have extremely long tails and are therefore winsorized[61] (right side only) at the 1% level. Both total income and own income (income from self-employment activities) have some negative values and long tails on both ends of the distribution, so I winsorize these at the 1% level on both ends. The histogram of the winsorized density for monthly PAE expenditure can be found in Figure 2. As I show in Table 1, the average monthly expenditure in Round 1 (2009-2010) is 51,000 USh, which is about $28[62] per month, or $0.90 per (adult equivalent) person per day. This is well below the international poverty line of $1.25/day in 2005 dollars.

The primary explanatory variables of interest are crop diversification and income diversification. A major consideration when exploring the relationship between well-being and diversification is how to measure diversification. Different methods and definitions are used in

---

[59] The LSMS data are converted to 2005-2006 USh in order to compare real values to the initial survey round. I have maintained the use of 2005-2006 real values for simplicity.

[60] In this context, one tropical livestock unit is equivalent to two cattle, donkeys, or horses; five pigs; ten sheep or goats; or one hundred poultry, fowl, or rabbits. The conversations are based on Chilonda & Otte (2006) coefficients for SSA and may not be comparable to other TLU calculations for East Africa.

[61] Summary statistics for the original and winsorized variables, as well as histograms of the unwinsorized densities for PAE monthly expenditure can be found in Appendix 1.

[62] Using historical August 2005 exchange rates (1829.27 USh/$, average of the August 2005 buy and sell rates) according to the bank of Uganda:
https://www.bou.or.ug/bou/collateral/interbank_forms/2005/Aug/major_25Aug05.html.

the literature (see Barrett & Reardon 2000, Martin & Lorenz 2016 for a more thorough discussion of various measures employed in the literature). Some use combinations of different types of activities—such as farm income, non-agricultural work, and self-employment income—to explore diversification (Bigsten & Tengstam 2011), while others count the total number of activities undertaken at the household level (Martin & Lorenz 2016). Neither of these methods, however, weights according to intensification in a various activity. For this reason, I use transformed Herfindahl indices, normalized between zero and one, which sum up squared proportions of intensity in various activities, with zero meaning that a household is completely specialized in one crop (or one type of income) and one representing a highly diversified crop (or income) portfolio. I have provided more details on how the diversification indices are calculated in Appendix 2. While the transformed Herfindahl index has many strengths in this setting, it has certain drawbacks as well. The index cannot distinguish between crops or activities that have highly correlated returns, meaning that diversification into a secondary crop with a similar climate risk exposure would not be captured differently than diversification into a crop with a very different risk profile. Unfortunately, the LSMS-ISA data is not sufficient to identify the variance-covariance matrix that would be required in order for such agronomic detail to be incorporated. Given that any strategy to address this shortcoming of the transformed Herfindahl index would likely inject significant measurement error, I opt to move forward with the Herfindahl despite this concern.

The summary statistics in Table 1 show that households are moderately diversified in terms of their crop portfolio on average, and diversification increases very slightly after Round 1. Interestingly, income diversification decreases from its high in Round 1. On average, households have more diversified crop portfolios than income portfolios. This is particularly evident when examining the distributions of the two indices, as seen in Figure 3. Interestingly, a scatter plot (Figure 4) of the two shows little relationship between having a diversified crop portfolio and income diversification; the correlation coefficient is only 0.0795. As one can see in Table 1, households have between two and three acres under cultivation on average, very little of which (only an eighth of an acre) is under cash crop cultivation—meaning land used for coffee, cotton, tea, tobacco, vanilla, or cocoa. Wage and own income data is in annual USh and was aggregated by RIGA. We see higher average wage than own income, although the range for own income is larger. In terms of assets, I explore both livestock and non-productive assets, as data on productive assets is not available in the same manner across all rounds. As mentioned above, livestock holdings are measured in TLU, and the average households has 1.46 TLU in Round 1, falling slightly across rounds. Interestingly, households hold a large amount of self-reported, non-productive (non-agricultural) assets—which I will refer to simply as assets—on average. I sum these up at self-reported values, averaging nearly $6,000 in assets per household.

In the analysis, I also control for a variety of climactic and geological variables. These include rainfall in mm, rainfall difference with long-run average, the satellite-based greenness indicator Enhanced Vegetation Index (EVI), the EVI difference with long-run average, and the elevation in meters of the community in which the household lives. Both of the difference variables are calculated by taking the absolute value of the difference between the current year's value and the long-run average, divided by the district standard deviation. This is to get a sense of how different the growing conditions were in the given year from the average growing conditions.

In Table 2, I dig into the regional distribution of the sample and breakdown a few key variables. The households are pretty well-distributed across the four regions. In order to get a sense of levels of absolute poverty, as well as consistency with other sources, I calculate the share of households in each region spending fewer than 26,000 USh PAE per month (about $14). I will consider this to be the absolute rural poverty line. We can see that 11%, 20%, 30%, and 23% of rural households in Central, Eastern, Northern, and Western regions, respectively, are below this absolute poverty line. This is somewhat close to the 14%, 25%, 49%, and 23%, respectively, of rural households in 2009-2010 below the headcount poverty line (for caloric requirements plus a few non-food needs) in these regions according to the Uganda Bureau of Statistics (UBOS 2010, chapter 6). I also breakdown the crop and income diversification indices by region. Crop diversification is relatively constant across the regions, and increasing over time in Central and Western. Income diversification is highest in the Northern region, likely due to the importance of livestock income in the region.

IV. Empirical Model

This paper employs the Cissé & Barrett (2016) conditional moments-based resilience approach to understand the dynamic relationship between rural Ugandan livelihood diversification and well-being in the face of shocks. The resilience approach allows researchers to estimate household-level well-being probability density functions (pdfs) and associated predicted levels of well-being. By estimating not only the mean but also the variance of well-being, the resilience approach is well-suited to exploring the relationship between well-being and diversification.

The empirical approach below is as described in Cissé and Ikegami (2016). I begin by estimating the mean well-being equation,

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

W_{it} is the household *i*'s well-being (in terms of monthly expenditures) in round *t*. Well-being is a non-linear function of past-period well-being ($W_{i,t-1}$); household factors of production/ characteristics, assets, portfolio decisions, and weather ($\boldsymbol{X_{it}}$); parameters (β_M); and a residual (u_{Mit}). Given that the relationship between expenditure and diversification may be non-linear, I begin regressing expenditure on polynomials of crop (Table 3) and income (Table 4) diversification. Both tables clearly indicate that the relationship is highly non-linear, with the adjusted R-squared values indicating that the 5th order polynomials fit the data best. I explore the non-linearities in Figure 5, which plots the predicted expenditure at various diversification levels. For crop diversification, we see expenditure peak at low levels of diversification (although not at complete specialization) before dipping at moderate levels of diversification. Expenditure increases again for households with high levels of crop portfolio diversification, although the confidence intervals are very large. The trend is similar, although more muted, for income diversification. All remaining explanatory variables in $\boldsymbol{X_{it}}$ are included as levels only, with the exception of head age and household size. I include squared terms for each of these to allow for possible non-linearities.

Given that a household's monthly expenditure is non-negative, I assume that the dependent variable is distributed Poisson and estimate a generalized linear model (GLM)[63] log link regression using maximum likelihood. I discuss the results in the following section. The first central moment (conditional mean, or μ_{1it}) is:

(2) $$\hat{\mu}_{1it} \equiv E\left[W_{it} | W_{i,t-1}, \boldsymbol{X_{it}}\right] = g_M(W_{i,t-1}, \boldsymbol{X_{it}}, \hat{\beta}_M).$$

[63] See Cissé and Ikegami (2016) for a discussion of why GLM is preferred over ordinary least squares.

where E represents the expectation operator and the random error term u_{Mit} is mean zero. I can then take the predicted residuals from equation (1) and square them to calculate conditional variance (μ_{2it}), where $\hat{\mu}_{2it} = E[u_{Mit}^2] = \hat{\sigma}_{it}^2$ and:

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

and $E[u_{Vit}] = 0$. Regressing the conditional variance on the same explanatory variables allows me to explore not only how diversification and household characteristics are associated with mean well-being, but also how they are associated with variations in well-being.

Still following Cissé and Barrett (2016), as described in Cissé and Ikegami (2016), I define development resilience (ρ_{it}) as the probability that household *i* will have expenditure in round (*t*) above some expenditure poverty line threshold, $\underline{W}$. I assume the conditional expenditure pdf for each household comes from a two parameter gamma distribution such that:

$$(4) \qquad \rho_{it} \equiv \Pr\left(W_{it} \geq \underline{W} | W_{i,t-1}, \boldsymbol{X_{it}}\right) = \bar{\mathrm{F}}_{\mathrm{W_{it}}}\left(\underline{W}; \hat{\mu}_{1it}(W_{it}, \boldsymbol{X_{it}}), \hat{\mu}_{2it}(W_{it}, \boldsymbol{X_{it}})\right),$$

where $\bar{\mathrm{F}}_{\mathrm{it}}$ is the complementary cumulative distribution function. The association between any component of X and resilience may be therefore be estimated by regressing the $\hat{\rho}_{it}$ I calculated on $\boldsymbol{X_{it}}$:

$$(5) \qquad \hat{\rho}_{it} = g_R(W_{i,t-1}, \boldsymbol{X_{it}}, \beta_R) + u_{Rit}.$$

The histogram of ρ_{it} for $\underline{W}$ = 26,000 USh/mo can be seen in Figure 6. Recalling that I've described 26,000 USh as the absolute poverty line (roughly equivalent to PAE expenditure of $14/month), it is perhaps not surprising that a large number of households have resilience scores equal to 1, meaning that their entire expenditure pdf lies to the right of the absolute poverty threshold. It is clear that the association between expenditure resilience and diversification (or other household characteristics) likely depends on the selection of the poverty line $\underline{W}$. I therefore choose to recalculate (4) and reevaluate (5) for a variety of different well-being thresholds $\underline{W}$. This will allow me to see if crop diversification is associated with increased probabilities of surpassing, for example, low poverty line thresholds while perhaps income diversification is associated with increased resilience for higher poverty line thresholds.

V. Results

Figure 7 shows the predicted path dynamics of expenditure for two models. The complex model includes higher order polynomial terms (including a third order term of lagged expenditure and the preferred high order diversification indices. The parsimonious model retains a square lagged expenditure term and level terms for the diversification indices (equivalent to Table 5 Column 3, below). As can be seen from the path dynamics in Figure 7, the two models are virtually indistinguishable, and therefore the parsimonious model is preferred for subsequent specifications. Further, the figure demonstrates that while the path dynamics are non-linear, there is only one stable equilibrium, at just below 50,000 USh (approximately $25 PAE per month). While this is nearly twice the rural Ugandan absolute poverty line, it is still well below the international $1.25/day poverty line in 2005 dollars. It is worth noting that this equilibrium is very close to the sample mean PAE monthly expenditure level.

Table 5 presents the marginal effects (at mean values of all covariates[64]) from a Poisson MLE regression on mean (Columns 1-3) and variance (Columns 4-6)[65] of expenditure using the parsimonious model discussed above. I include survey weights, a series of households control variables (household size, labor, an indicator for having a male head, the years of education of the head, and his/her age), regional dummies, and household level Mundlak[66] fixed effects in all specifications. We can see from the statistically significant coefficients on the lagged well-being term that there are significant path dynamics in expenditure resilience. In Column 1 of Table 5, I regress expenditure on diversification and household assets and other controls without controlling for cash crop cultivation or levels of non-farm income. Neither the coefficient estimates on crop diversification nor on income diversification is statistically significant. The coefficient estimates for total income (from all sources) and assets are significantly, positively associated with well-being. Those for EVI and elevation are also statistically significantly associated with expenditure, although the coefficient estimates for rainfall and deviations from typical EVI and rainfall are not significant.

In Columns 2, I introduce area of land under cash crop cultivation in order to assess whether diversification into cash crop cultivation is confounding the relationship with crop diversification. Neither the estimated coefficient on cash crop cultivation nor on area cultivated is significant. In Column 3, I additionally include levels of two types of non-agricultural income:

[64] For robustness, I present an alternative specification, holding lagged expenditure at the absolute poverty line, in Appendix 3 Table A3. The results are largely consistent.

[65] Predicted conditional variance is calculated for Columns 4, 5, and 6 using the regressions in Columns 1, 2, and 3, respectively.

[66] Given the inclusion of a lagged variable, standard fixed effects are not appropriate. I opt instead to include Mundlak fixed effects through the inclusion of household level means of crop and income diversification indices, area under cultivation, TLU, assets, shocks, HH labor, the various income measures, and cash crop area.

wage income and own (self-employment) income. The estimates for these additional inclusions are not statistically significant and do not change the overall story presented by the data. In general, it appears that crop and income diversification are not associated with mean levels of household expenditure. Income and assets continue to be highly associated with expenditure, perhaps as should be expected.

Following equation (3), I regress the conditional variance of household monthly expenditure on the same right hand side. Results of the Poisson MLE regressions are displayed in Columns 4-6. Neither crop nor income diversification is associated with increased conditional variance of expenditure, although increased area under cultivation is positively associated with increased variance, highlighting the riskiness of agricultural livelihoods. As I show in Column 5, this relationship is even larger (and stronger) when controlling for cash crop cultivation, although the coefficient estimate for cash crop cultivation is not statistically significant. Neither the coefficient estimate for total income nor for either of the non-farm income variables is statistically significantly associated with increased conditional variance of expenditure. Somewhat surprisingly, assets are positively associated with an increase in variance, perhaps a result of the increased investment opportunities available to these households.

Using the predicted conditional mean and variance (from Columns 3 and 6), I construct well-being distributions for each household for Rounds 2 and 3 (Round 1 is used at the lagged values for Round 2) as described in equation (4), above. The resilience score for the household is the probability that the household will be above the threshold poverty line $\underline{W}$ in that period given their well-being distribution. In order to evaluate the importance of the poverty line threshold $\underline{W}$, and recalling that mean expenditure PAE is around 50,000 USh per month, I calculated eleven resilience scores per household per period, using evenly dispersed values for $\underline{W}$ between 13,000 and 143,000 USh, the latter of which is about $2.60/day, or twice the international poverty line of $1.25/day (2005 dollars). Following equation (5), I then regress these resilience scores on the right hand side variables mentioned previously using a binomial[67] GLM with a logit link via MLE.

The regressions for select values of $\underline{W}$ are provided in Table 6. As suspected, the selection of $\underline{W}$ is important in understanding the relationship between diversification and resilience. Controlling for area under cultivation (including cash crop cultivation), we see that crop diversification is not significantly associated with increased resilience when the absolute poverty line is selected as the well-being threshold (Column 1), although crop diversification is significantly associated with increased resilience for higher well-being thresholds (Columns 2 and 3). The magnitude also varies with the choice of well-being threshold selected. The table presents marginal effects (at means) which have been multiplied by 100 so that they can be interpreted as percentage points. The 2.83 estimated coefficient on crop diversification in Column 2 should be interpreted as *at average levels of all covariates, going from completely specialized to a completely diversified crop portfolio is associated with an increase in resilience by nearly three percentage points* (*i.e.*, is associated with a three percentage point increase in the probability of the household having expenditure above 78,000 USh PAE).

Coefficient estimates for area under cultivation and cash crop area are both statistically significant in all three specifications (for various well-being thresholds). Interestingly, we see that area under cultivation is negatively associated with resilience when a very low (absolute poverty line) threshold is considered. For higher thresholds, however, area under cultivation is positively associated with resilience. Meaning that *ceteris paribus* (and for mean values of all

---

[67] A binomial distribution is assumed for the dependent variable since it lies on a range from 0 to 1.

covariates), increasing the area under cultivation is associated with a decreased probability of achieving the absolute poverty line, however once a higher threshold is selected, increasing area under cultivation is positively associated with increased resilience. Increasing cash crop cultivation is negatively associated with resilience regardless of well-being threshold, although the magnitude decreases towards zero as higher well-being thresholds are considered. Increasing cash crop cultivation is therefore associated with lower levels of resilience, driven by the lower levels of mean well-being for cash crop producers.

When controlling for levels of income, including levels of wage and self-employment income, income diversification is consistently negatively (and significantly) associated with resilience, although the magnitude decreases for higher well-being thresholds. Column 1 indicates that moving from a specialized to a diversified income portfolio decreases expenditure resilience, or the probability that a household will have at least absolute poverty line expenditure, by 3.5 percentage points. So while more income is associated with increased resilience across all specifications (as one would expect), more diversified income is not. Interestingly, the signs on the estimated coefficients for wage and own (self-employment) income are negative in all specifications, so holding total income constant, increasing the share of that income that comes from wage and self-employment sources is associated with decreased resilience. This is likely a combined effect from the mean decreasing but variance increasing relationships we see with these non-farm incomes sources in Table 5.

These coefficients can be more clearly understood visually, however, so I plot the coefficient estimates for the different poverty thresholds in Figure 8, along with the 95% confidence interval. Here it is easy to see that both crop and income diversification are actually associated with lower resilience for very low well-being thresholds (below the 26,000 USh rural absolute poverty line). Crop diversification becomes increasingly associated with increased resilience for higher well-being thresholds, however, passing zero at a well-being threshold equivalent to the absolute poverty line. Plotting the coefficient estimates for different well-being thresholds allows us to see at what level diversification is most strongly associated with resilience. From Figure 8, we see that moving from a specialized to a diversified crop portfolio is associated with the largest increases in resilience when considering the probability of a household having expenditure of 52,000 USh or more per person per month (about $0.95/person/day, and close to the sample mean expenditure level). As higher well-being thresholds are considered (as it moves towards and surpasses the international poverty line) the magnitude of the association between crop diversification and resilience decreases.

For income diversification, we see a consistent negative and statistically significant relationship between income diversification and resilience, as I also showed in Table 6. From Figure 6, we see that the negative relationship is maximized around well-being thresholds of 39,000 USh of expenditure person/month. This is below the mean expenditure level in the panel, so setting the well-being threshold this low focuses the analysis on changes in well-being distributions of the least resilient households, meaning that having a diversified income portfolio is most negatively associated with resilience for the least resilient households.

VI. Conclusion

By building on the development resilience theory set forth by Barrett and Constas (2014) and the empirical research on diversification discussed above, this paper provides the first empirical analysis using the Cissé and Barrett (2016) development resilience approach of how diversification is correlated with household development resilience in Uganda. This question is not academic; as national governments, international organizations, and donors increasingly focus on building resilience to shocks and stressors in agriculturally-dependent developing countries, many are focusing on on-farm and income diversification as possible strategies for increasing resilience. For a resilience-building strategy to be successful, however, it should ideally increase mean well-being, while decreasing risk (or the variance of well-being) in the face of shocks and stressors. The Cissé and Barrett (2016) approach is particularly well-suited to undertaking this sort of analysis, as approaches based on analyses of mean associations only neglect potentially important relationships between diversification (or other risk management strategies) and the conditional variance of well-being.

The analysis herein shows that crop and income diversification are not linearly associated with conditional mean well-being in terms of monthly household expenditure in rural Uganda. Nor is there a straightforward association between increased diversification and resilience. While crop diversification is weakly associated with increased expenditure, income diversification is not. Holding levels of diversification constant, increased shares of cash crop production is negatively (although not statistically significantly) associated with increased well-being. Similarly, holding levels of income diversification constant, increased shares of self-employment and wage income are weakly, negatively associated with increased well-being.

In terms of resilience, or the probability that a household surpasses a given normative well-being threshold ($\underline{W}$) in a given period, we see that income diversification is negatively associated with increased resilience regardless of well-being threshold, possibly indicating that it is being used as a last resort strategy by these households. Crop diversification is not associated with increased resilience for these poorest households, possibly due to fixed costs or limited access to land or agricultural inputs. Once the resilience threshold is increased above the rural absolute poverty threshold of 26,000 USh PAE per month, however, crop diversification is significantly and positively associated with resilience in terms of expenditure. This positive relationship between crop diversification and increased resilience peaks at a well-being threshold of 52,000 USh. Somewhat surprisingly, area under cultivation is negative and significant for very low thresholds, possibly driven by poor access to inputs for the least resilient households or that area increases for those households are on lower quality land. The drivers of this relationship could be explored with further research. Once a well-being threshold above the rural absolute poverty line is considered, increased area under cultivation is positively associated with resilience. However, cash crop cultivation is negatively associated with resilience across the board, seemingly due to its negative relationship to mean expenditures.

Taken together, these results indicate that diversification on-farm should have a place in the resilience-building toolkit, although pushing farmers into cash crops may be counterproductive. It does not appear that income diversification on its own is sufficient to increase resilience, although increasing incomes in general is associated with increased resilience in terms of expenditure through its effects on mean expenditure. More generally, this paper demonstrates the important role this type of resilience analysis should play in identifying evidence-based strategies to increase resilience in developing countries.

Tables

Table I: Summary Stats

Variable	2009–10 – N [68] = 1,974 Mean	Std. Dev.	Min	Max	2010–11 – N = 1,828 Mean	Std. Dev.	Min	Max	2011-12 – N = 1,893 Mean	Std. Dev.	Min	Max
HH size	6.3	3.1	1	23	5.9	2.8	1	21	6.0	2.8	1	22
HH labor	2.8	1.7	0	14	2.5	1.5	0	13	2.6	1.5	0	14
Male Head (indicator)	0.73	0.45	0	1	0.71	0.45	0	1	0.70	0.46	0	1
Head school years	4.8	3.8	0	18	5.2	3.9	0	18	4.9	3.9	0	18
Head age	46.7	15.1	14	100	47.3	15.3	14	96	47.8	15.2	0	94
Shock (indicator)	0.693	0.461	0	1	0.491	0.500	0	1	0.410	0.492	0	1
Monthly expenditure (1,000 of USh)	213	168	8	892	171	146	9	892	171	135	9	892
Mo expenditure PAE (1,000)	51	36	5	218	45	37	3	218	44	34	5	218
Crop diversification	0.582	0.207	0	1	0.617	0.185	0	1	0.611	0.198	0	0.897
Income diversification	0.403	0.217	0	0.786	0.389	0.221	0	0.794	0.376	0.220	0	0.788
Acres under cultivation	2.71	2.73	0	14.1	2.55	2.32	0	14.1	2.24	1.91	0.1	14.1
Cash crop acres	0.15	0.44	0	2.8	0.17	0.45	0	2.8	0.17	0.42	0	2.8
Total income (1,000 USh)	1,674	1,948	-413	12,100	1,806	2,196	-413	12,100	1,920	2,034	-413	12,100
Wage income (1,000 USh)	531	1163	0	6734	538	1226	0	6734	364	868	0	6734
Own income (1,000 USh)	395	1263	-1680	9240	456	1404	-1680	9240	552	1543	-1680	9240
TLU	1.46	2.68	0	17	1.31	2.50	0	17	1.19	2.38	0	17
Non-ag assets (1,000 USh)	10700	23100	0	163000	10900	22200	0	163000	12200	23900	0	163000
Rainfall (mm)[69]	391	64	165	594	509	94	298	757	464	147	222	834
Rainfall difference[70]	0.138	0.085	0	0.373	0.186	0.090	0.006	0.445	0.205	0.177	0	0.910

[68] In Round 1, *income diversification* is available for 1,833 households and *head* age is missing for 2. In Round 2, income diversification is available for 1,771 households and *total income* for 1,793. *Assets* are missing for 16 households in R3, and *total income* for 32.

[69] This is the rainfall in the wettest quarter within Jan-Dec of the year in question, or Jan-Jun in places with bimodal rainfall.

[70] The absolute value of the difference between the current rainfall (mm of year's wettest quarter) and the average, divided by the average.

Enhanced Vegetation Index[71]	0.496	0.054	0.301	0.591	0.522	0.057	0.336	0.630	0.517	0.052	0.309	0.623
EVI difference[72]	0.052	0.027	0.006	0.208	0.019	0.015	433	0.111	0.030	0.025	0	0.181
Elevation (m)	1236	254	621	2297	1235	253	621	2396	1233	257	621	2396

Table 2: Summary Statistics by Region

	2009–10				**2010–11**				**2011–12**			
	Mean	Abs. Poor[73]	Crop Div.	Income Div.	Mean	Abs. Poor	Crop Div.	Income Div.	Mean	Abs. Poor	Crop Div.	Income Div.
Central	0.206	0.110	0.582	0.383	0.223	0.152	0.642	0.376	0.202	0.105	0.668	0.390
Eastern	0.271	0.199	0.607	0.419	0.279	0.424	0.636	0.389	0.273	0.405	0.627	0.367
Northern	0.283	0.303	0.564	0.426	0.278	0.452	0.564	0.422	0.291	0.452	0.529	0.407
Western	0.240	0.230	0.575	0.376	0.220	0.338	0.634	0.361	0.234	0.239	0.642	0.334

[71] Enhanced Vegetation Index (EVI) value at peak of greenness within main (or first) growing season of the current year

[72] The absolute value of the difference between the current year's EVI and the average, over the average

[73] Percentage of sample households in the region that have PAE monthly expenditure below 26,000 USh

Table 3: OLS Regressions of PAE Expenditure and Crop Diversification

VARIABLES	(1) Expenditure	(2) Expenditure	(3) Expenditure	(4) Expenditure	(5) Expenditure	(6) Expenditure
Crop diversification	-3,175	-32,847***	20,242	73,963*	175,283**	159,462
	(2,389)	(8,464)	(20,652)	(42,299)	(77,600)	(139,230)
Crop div. ^{2}		32,467***	-122,929**	-397,955**	-1,179,000**	-1,007,000
		(8,886)	(55,857)	(197,071)	(538,965)	(1,367,000)
Crop div. ^{3}			117,180***	575,848*	2,699,000*	2,018,000
			(41,584)	(317,916)	(1,400,000)	(5,171,000)
Crop div. ^{4}				-246,621	-2,000,000*	-1,419,000
				(169,472)	(1,568,000)	(9,308,000)
Crop div. ^{5}					994,841	-97,430
					(638,819)	(8,006,000)
Crop div. ^{6}						362,323
						(2,647,000)
Constant	48,658***	53,478***	51,402***	50,739***	50,250***	50,284***
	(1,516)	(2,008)	(2,138)	(2,186)	(2,208)	(2,222)
Observations	5,695	5,695	5,695	5,695	5,695	5,695
Adjusted R^2	0.00013	0.00230	0.00351	0.00371	0.00396	0.00379

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 4: OLS Regressions of Expenditure and Income Diversification

VARIABLES	(1) Expenditure	(2) Expenditure	(3) Expenditure	(4) Expenditure	(5) Expenditure	(6) Expenditure
Income diversification	3,326	-8,240	23,193	98,856***	243,361***	325,091***
	(2,183)	(7,386)	(18,127)	(36,090)	(64,967)	(107,015)
Income div. ^{2}		17,566	-101,534	-624,161***	-2,162,000***	-3,413,000**
		(10,716)	(63,635)	(224,774)	(617,199)	(1,441,000)
Income div. ^{3}			112,312*	1.248e+06***	6,830,000***	13,620,000*
			(59,152)	(472,104)	(2,140,000)	(7,385,000)
Income div. ^{4}				-776,638**	-9,141,000***	-25,970,000
				(320,366)	(3,144,000)	(17,800,000)
Income div. ^{5}					4,435,000***	23,880,000
					(1,658,000)	(20,300,000)
Income div. ^{6}						-8,492,000
						(8,836,000)
Constant	45,334***	46,329***	45,585***	44,961***	44,452***	44,313***
	(975.5)	(1,149)	(1,214)	(1,240)	(1,254)	(1,262)
Observations	5,496	5,496	5,496	5,496	5,496	5,496
Adjusted R^2	0.00024	0.00055	0.00102	0.00191	0.00302	0.00301

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 5: Poisson MLE of mean and variance of expenditure (marginal effects at means)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Expenditure			V(Expenditure) in 1,000s	
Expenditure $_{t-1}$	0.385***	0.385***	0.387***	7.407***	7.334***	7.347***
	(0.0282)	(0.0283)	(0.0282)	(1.932)	(1.915)	(1.914)
Crop diversification	3,364	3,023	3,048	269,800	253,400	240,400
	(4,046)	(4,057)	(4,084)	(217,900)	(220,900)	(223,900)
Income diversification	-3,236	-3,202	-3,218	-132,500	-130,400	-123,300
	(3,156)	(3,158)	(3,172)	(184,900)	(183,900)	(183,400)
Total Income	0.000679**	0.000677**	0.00108**	0.01423	0.01304	-0.04327
	(0.000331)	(0.000331)	(0.000514)	(0.01593)	(0.01575)	(0.02723)
Wage income			-0.00103			0.03134
			(0.000808)			(0.04411)
Own income			-0.000344			0.02515
			(0.000616)			(0.03071)
Acres under cultivation	275.8	405.2	399.7	37,900*	42,380**	41,450*
	(343.5)	(368.9)	(367.2)	(19,570)	(21,610)	(21,590)
Cash crop acres		-1,895	-2,240		-53,900	-37,510
		(2,039)	(2,049)		(95,350)	(95,490)
TLU	272.9	253.6	227.8	-28,740	-29,200	-31,530
	(789.1)	(783.1)	(782.8)	(44,360)	(44,170)	(44,100)
Assets	0.000077**	0.000078**	0.000076**	0.0044***	0.0045***	0.0048***
	(0.000031)	(0.000032)	(0.000031)	(0.0014)	(0.0014)	(0.0014)
Rainfall (mm)	-3.415	-3.523	-3.009	199.84	193.95	176.17
	(6.977)	(6.970)	(6.988)	(541.08)	(534.76)	(538.29)
Rainfall difference	1,176	1,207	1,172	28,770	30,520	29,260
	(1,090)	(1,090)	(1,089)	(88,690)	(87,700)	(88,020)
Enhanced Vegetation Index	-31,755*	-31,842**	-33,053**	-953,500	-927,700	-880,200
	(16,218)	(16,235)	(16,448)	(868,000)	(862,100)	(871,200)
EVI difference	498.6	492.3	484.4	1,932	1,013	1,791
	(584.8)	(583.0)	(580.2)	(37,820)	(37,580)	(37,550)
Elevation (m)	-3.978*	-3.945*	-3.923*	-163,430	-160,197	-156,268
	(2.371)	(2.377)	(2.372)	(181,957)	(180,699)	(180,500)
Shock	2,176	2,175	2,253	63,600	64,830	62,310
	(1,411)	(1,410)	(1,414)	(94,730)	(93,920)	(95,280)
HH characteristics[74]	Y	Y	Y	Y	Y	Y
HH FE (Mundlak)	Y	Y	Y	Y	Y	Y
Observations	3,259	3,259	3,259	3,259	3,259	3,259
BIC (in billions)[75]	64.33	64.30	64.23	9,060,000	9,038,000	9,032,000

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

[74] Characteristics include household size, labor, an indicator for having a male head, the years of education of the head, and his/her age. Region dummies are also included.

[75] Bayesian information criterion (BIC) from the GLM specification (not marginal effects).

Table 6: Binomial MLE of resilience (ME*100 at means) for select values of $\underline{W}$

	(1) $\underline{W}$ = 26,000 USh	(2) $\underline{W}$ = 78,000 USh	(3) $\underline{W}$ = 130,000 USh
VARIABLES	Resilience	Resilience	Resilience
Expenditure $_{t-1}$	0.00052***	0.00021***	0.000019***
	(0.0000031)	(0.0000025)	(0.00000055)
Crop diversification	0.0957	2.83***	0.328***
	(0.355)	(0.327)	(0.0716)
Income diversification	-3.50***	-2.33***	-0. 221***
	(0. 263)	(0.218)	(0.0371)
Total Income	0.0000022***	0.00000059***	0.000000039***
	(0.000000076)	(0.000000045)	(0.0000000065)
Wage income	-0.0000027***	-0.00000044***	-0.000000017*
	(0.000000098)	(0.000000064)	(0.0000000090)
Own income	-0.0000012***	-0.00000016***	0.000
	(0.00000012)	(0.000000054)	(0.0000000065)
Acres under cultivation	-0.315***	0.390***	0.0462***
	(0.0384)	(0.0319)	(0.0048)
Cash crop acres	-3.45***	-1.13***	-0.136***
	(0.179)	(0.177)	(0.0271)
TLU	1.27***	0.0569	0.0051
	(0.0923)	(0.0698)	(0.0097)
Assets	-0.000000015**	0.000000037***	0.0000000053***
	(0.0000000071)	(0.000)	(0.000)
Rainfall (mm)	-0.0091***	0.00043	-0.000058
	(0.00050)	(0.00038)	(0.000082)
Rainfall difference	1.55***	0. 675***	0.0808***
	(0.0773)	(0.0641)	(0.0124)
Enhanced Vegetation Index	-36.7***	-20.0***	-1.73***
	(1.32)	(1.17)	(0.172)
EVI difference	0.742***	0.186***	0.0166***
	(0.0416)	(0.0351)	(0.0043)
Elevation (m)	-0.0038***	-0.0032***	-0.00035***
	(0.00019)	(0.00016)	(0.000036)
Shock	2.49***	1.25***	0.131***
	(0.0984)	(0.0891)	(0.0183)
HH characteristics[76]	Y	Y	Y
HH FE (Mundlak)	Y	Y	Y
Observations	3,259	3,259	3,259
BIC[77]	-11687.477	-3884.2259	-13296.851

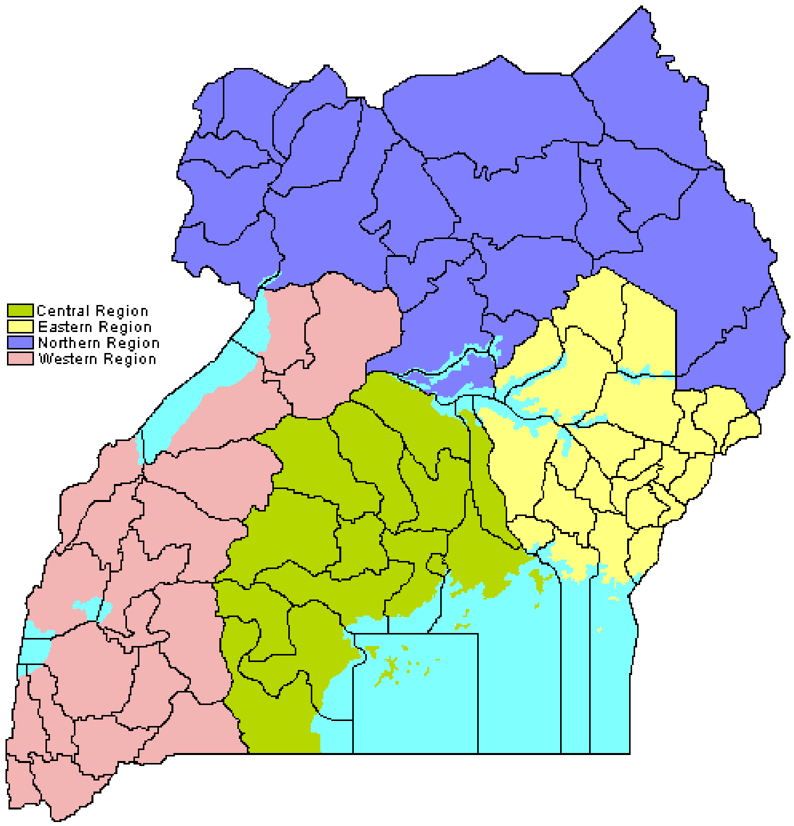
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

[76] Characteristics include household size, labor, an indicator for having a male head, the years of education of the head, and his/her age. Coefficients are available on request.

[77] Bayesian information criterion (BIC) from the GLM specification (not marginal effects).

Figures

Figure 1: Map of Uganda



Credit: CC BY-SA 3.0
https://commons.wikimedia.org/w/index.php?curid=769386

Figure 2: Histogram of monthly expenditure

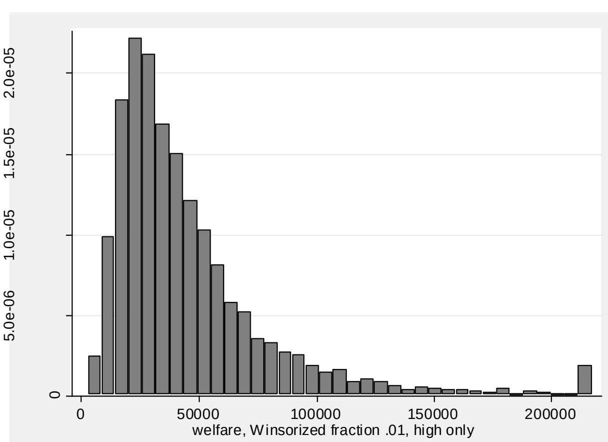


Figure 3: Histograms of crop and income diversification

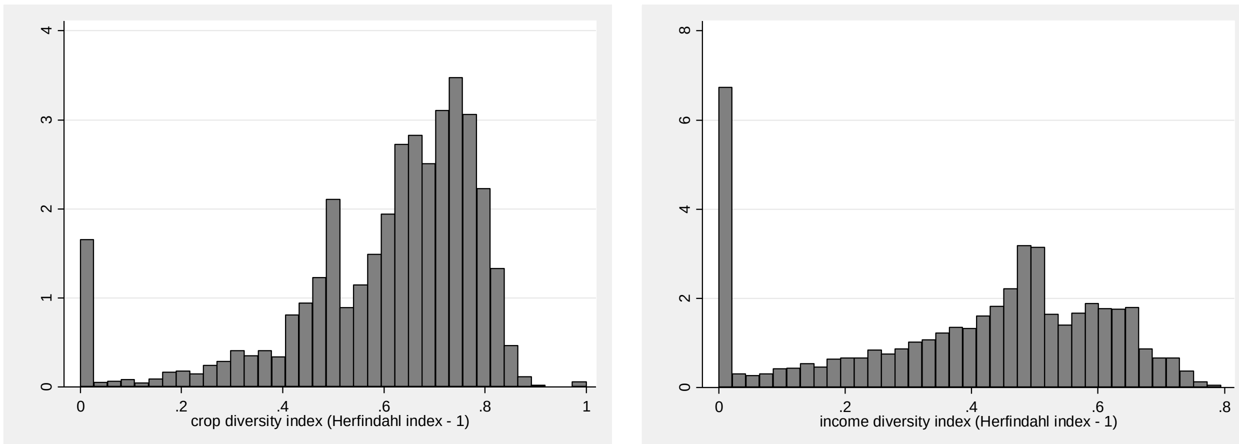


Figure 4: Scatter plot of crop (y-axis) and income (x-axis) diversification (ρ = 0.0795)

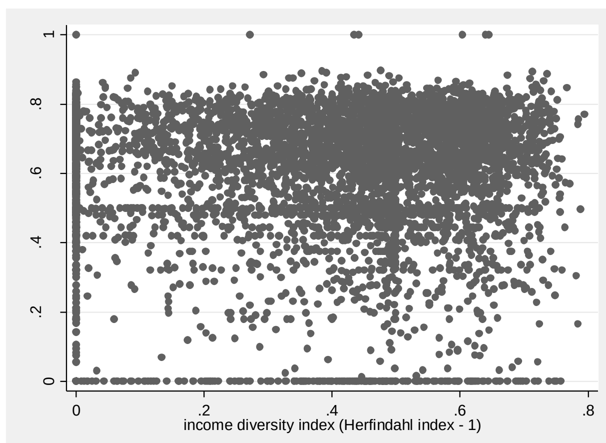


Figure 5: Predicted expenditure at various diversification levels

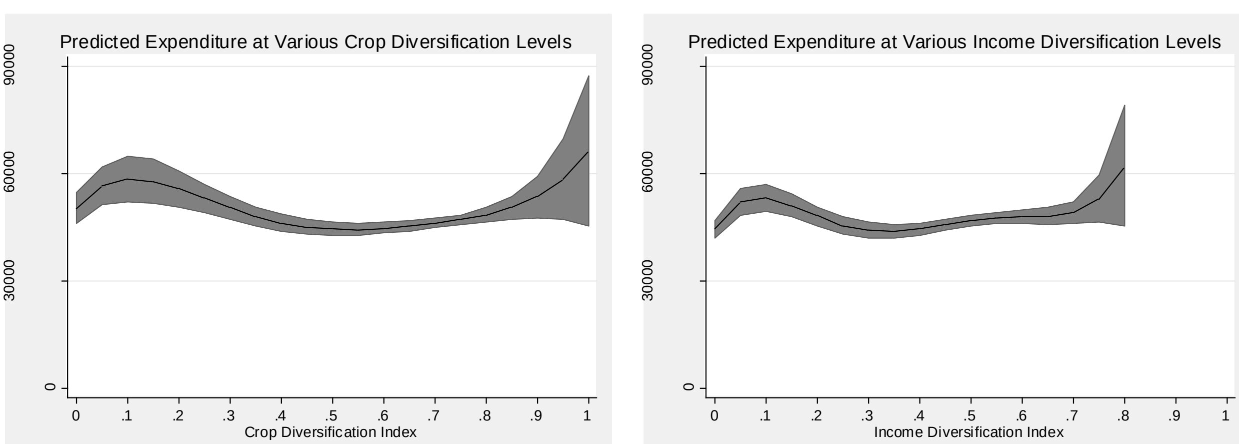


Figure 6: Histogram of expenditure resilience ρ_{it} for $\underline{W} = 26,000$

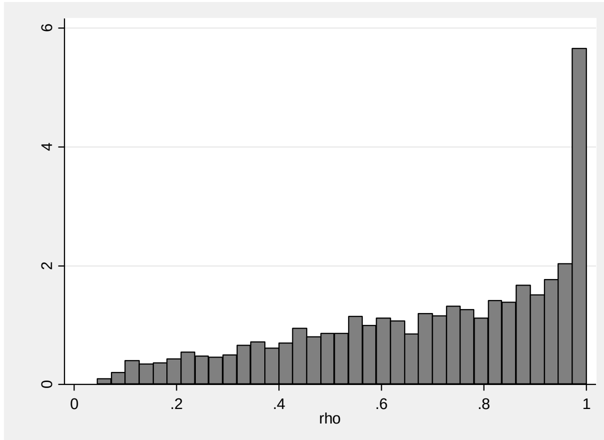


Figure 7: Predicted expenditure path dynamics

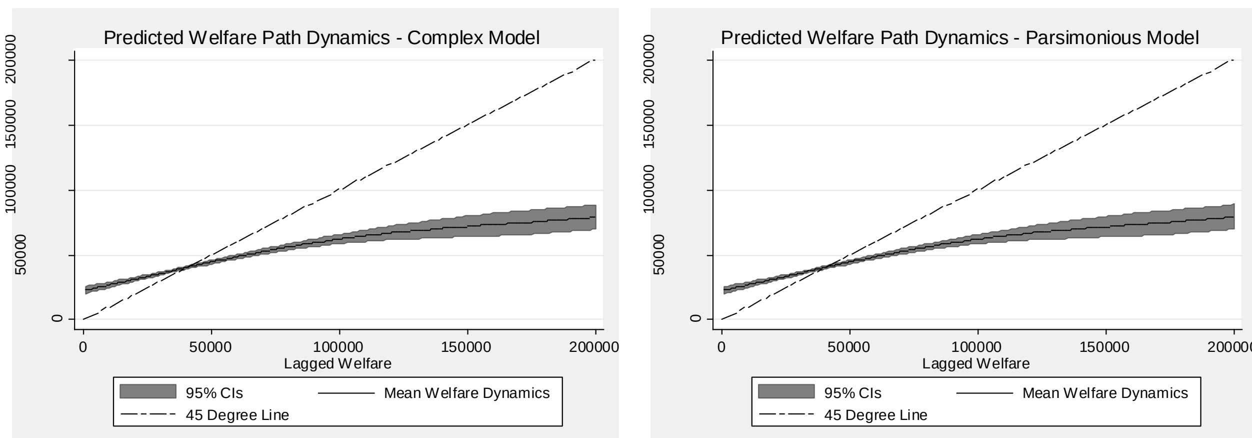
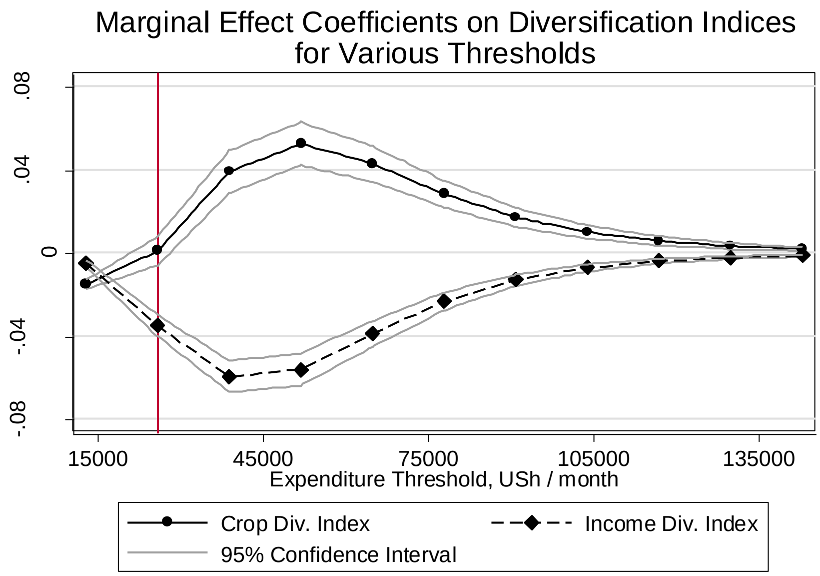


Figure 8: Threshold Analysis



References

Balihuta, Arsene M. and Kunal Sen. 2001. “Macroeconomic Policies and Rural Livelihood Diversification: An Ugandan Case-study.” LADDER Working Paper No.3: http://www.uea.ac.uk/dev/odg/ladder

Barrett, Christopher B. and Thomas Reardon. 2000. “Asset, Activity, and Income Diversification Among African Agriculturalists: Some Practical Issues.” Report for the USAID-funded Broadening Access and Strengthening Input Market Systems Collaborative Research Support Program (BASIS CRSP).

Barrett, Christopher B., Thomas Reardon, and Patrick Webb. 2001. “Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications.” Food Policy 26: 315-331.

Bigsten, Arne and Sven Tengstam. 2011. “Smallholder Diversification and Income Growth in Zambia.” Journal of African Economies 20(5): 781-822. doi:10.1093/jae/ejr017

Binswanger, Hans P. 1983. “Agricultural Growth and Rural Nonfarm Activities.” Finance and Development 20(2). 38-40.

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

Chilonda, P. and J. Otte. 2006. “Indicators to monitor trends in livestock production at national, regional and international levels.” Livestock Research for Rural Development 18: Article #117. http://www.lrrd.org/lrrd18/8/chil18117.htm

Cissé, Jennifer Denno and Christopher B. Barrett. 2016. “Estimating Development Resilience: A Conditional Moments-Based Approach.” African Development Bank Group, Working Paper No 236.

Cissé, Jennifer Denno and Munenobu Ikegami. 2016. “Does Insurance Improve Resilience? Measuring the Impact of Index-Based Livestock Insurance on Development Resilience in Northern Kenya.” Cornell University Working Paper.

Ellis, Frank. 1998. “Household strategies and rural livelihood diversification.” The Journal of Development Studies 35(1): 1-38, DOI: 10.1080/00220389808422553

Ellis, Frank. 2000. “The Determinants of Rural Livelihood Diversification in Developing Countries.” Journal of Agricultural Economics 51(2): 289-302.

Food and Agriculture Organization. 1999. Country Pasture/Forage Resource Profiles: Uganda. by Sandra M. N. Mwebaze. Available at http://www.fao.org/ag/agp/agpc/doc/counprof/uganda/uganda.htm.

Goulden, Marisa C., W. Neil Adger, Edward H. Allison, and Declan Conway. 2013. “Limits to Resilience from Livelihood Diversification and Social Capital in Lake Social–Ecological Systems.” Annals of the Association of American Geographers 103(4): 906-24, DOI: 10.1080/00045608.2013.765771.

Martin, Sarah M. and Kai Lorenzen. 2016. “Livelihood Diversification in Rural Laos.” World Development 83: 231-43. doi: 10.1016/j.worlddev.2016.01.018.

Reardon, T., Taylor, J. E., Stamoulis, K., Lanjouw, P., and Balisacan, A. 2000. “Effects of non-farm employment on rural income inequality in developing countries: An investment perspective.” Journal of Agricultural Economics 51: 266-88.

Seo, S. Niggol. 2011. “Decision Making under Climate Risks: An Analysis of Sub-Saharan Farmers’ Adaptation Behaviors.” Weather, Climate, and Society 4: 285-99, DOI: 10.1175/WCAS-D-12-00024.1.

Thomas, David S.G., and Chasca Twyman. 2005. "Equity and justice in climate change adaptation amongst natural-resource-dependent societies." Global Environmental Change 15: 115-24.

TANGO International. 2012. "Enhancing Resilience to Food Security Shocks in Africa." Discussion Paper.

Uganda Bureau of Statistics. 2010. "Uganda National Household Survey Report 2009/2010." http://www.ubos.org/UNHS0910/chapter6_%20Poverty%20trend%20estimates.html

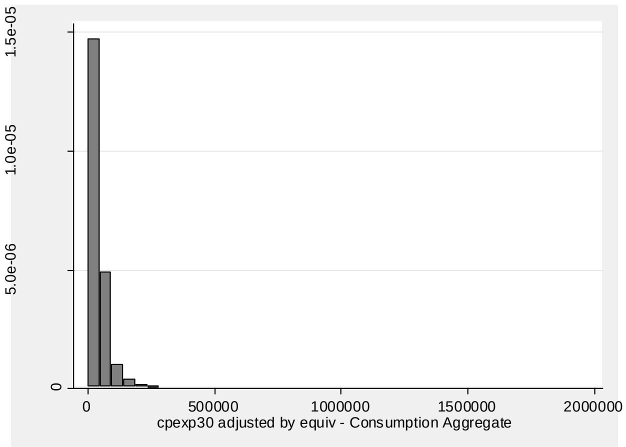
Appendix

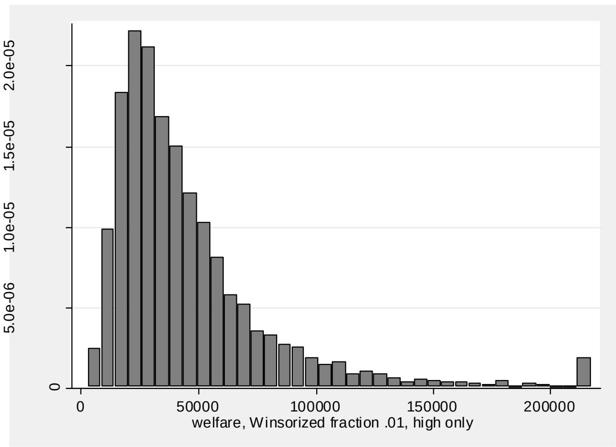
Appendix 1: Winsorization

Table A1: Unaltered and winsorized summary statistics

	Round 1				Round 2				Round 3			
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Monthly expend. (1,000 of USh)	220	227	8	5,055	175	178	9	3,755	172	146	9	1,902
Monthly expend., winzorized	213	168	8	892	171	146	9	892	171	135	9	892
Mo expenditure PAE	53	62	5	1,757	46	47	3	801	45	37	5	369
Mo expenditure PAE, winzorized	51	36	5	218	45	37	3	218	44	34	5	218
Acres under cultivation	3.58	14.5	0	406	2.69	3.96	0	101.3	2.25	2.00	0.1	24.5
Acres under cultivation, winzorized	2.71	2.73	0	14.1	2.55	2.32	0	14.1	2.24	1.91	0.1	14.1
Cash crop acres	0.20	1.0	0	30	0.19	0.81	0	26	0.20	0.74	0	18.8
Cash crop acres, winzorized	0.15	0.44	0	2.8	0.17	0.45	0	2.8	0.17	0.42	0	2.8
Total income (1,000 USh)	1,686	2,243	-6,871	37,100	1,818	2,615	-18,800	27,100	2,029	3,639	-9,782	17,100
Total income, winsorized	1,674	1,948	-413	12,100	1,806	2,196	-413	12,100	1,920	2,034	-413	12,100
Wage income (1,000 USh)	957	12,900	0	557,000	627	1,990	0	40,200	431	2,862	0	118,000
Wage income, winzorized	531	1,163	0	6,734	538	1,226	0	6,734	364	868	0	6,734
Own income (1,000 USh)	334	3,921	-74,000	51,100	397	3,471	-93,900	52,200	617	3,942	-79,000	69,500
Own income, winzorized	395	1,263	-1,680	9,240	456	1,404	-1,680	9,240	552	1,543	-1680	9,240
TLU	356	11,251	0	400,003	1.43	3.52	0	51.6	1.30	3.37	0	50.4
TLU, winzorized	1.46	2.68	0	17	1.31	2.50	0	17	1.19	2.38	0	17
Non-ag assets (1,000 USh)	14,100	85,100	0	3,210,000	12,800	40,200	0	610,000	13,700	38,100	0	719,000
Non-ag assets, winzorized	10,700	23,100	0	163,000	10,900	22,200	0	163,000	12,200	23,900	0	163,000

Figure A1: Histograms of PAE monthly expenditure in USh, original (left) and winsorized (right)





Appendix 2: Diversification Indices

Transformed Herfindahl index

Both diversification indices used in this paper are transformed Herfindahl indices, typically used as a measure of market concentration, but also used in the ecology literature as a measure of ecological diversity (or rather concentration, referred to often as the Simpson Index) and in the development literature. For household *i* in period *t*, the Herfindahl index *H* for $\alpha \in \{c, y\}$ (for crops, *c*, or income, *y*) is:

$$H_{it}^{\alpha} = \sum_{i=1}^{N} s_i^2$$

given *N* types of crops or sources of income each of share (proportion of total) *s*. Note that $\frac{1}{N} \leq H_{it}^{\alpha} \leq 1$, and so $H_{it}^{c} = 1$ if household i is entirely specialized in the production of one crop in period *t*.

In order to have a measure of diversification, rather than specialization, I calculate the crop or income diversification index:

$$D_{it}^{\alpha} = 1 - H_{it}^{\alpha}$$

where $D_{it}^{\alpha} = 0$ indicates complete specialization and higher values indicate more diversification, such that $\lim_{N\to\infty}\{D_{it}^{\alpha}\} = 1$. This measure is more appropriate that measures that simply count the number of activities that a household in engaged in, as this measure actually weights by intensity in a given activity.

Crop diversification index

The “share” *s* of a given activity can be measured in different ways. Here, I am interested in area shares. In order to calculate the share of a given crop, I use area under cultivation of that crop, divided by the entire area under cultivation by household *i*.

While impressive, the LSMS-ISA crop production data for Uganda needed significant cleaning for these purposes. The cleaning dataset is available on request. For intercropped crops, the area under cultivation is the area of the plot time the proportion of the plot under that crop. Plots under fallow, bush, pasture, forest or trees, or "other" were excluded.

Income diversification index

The income diversification measure takes advantage of RIGA aggregates and calculated variables, normalized to ensure that all proportions of total income are positive. Types of income include agricultural wage income, non-agricultural wage income, crop income, livestock income, transfers, self-employment income, and other (which includes remittances).

Appendix 3: Robustness

Table A3: Poisson MLE (marginal effects at lag expenditure = poverty line (26,000 USh))

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Expenditure			V(Expenditure) in 1,000s	
Expenditure $_{t-1}$	0.366***	0.366***	0.368***	7.361***	7.323***	7.333***
	(0.0220)	(0.0220)	(0.0219)	(1.211)	(1.208)	(1.204)
Crop diversification	2,785	2,503	2,522	224,900	212,700	201,700
	(3,351)	(3,360)	(3,380)	(187,000)	(189,700)	(191,800)
Income diversification	-2,679	-2,651	-2,662	-110,500	-109,400	-103,400
	(2,612)	(2,613)	(2,623)	(152,400)	(152,700)	(152,300)
Total Income	0.000563**	0.000561**	0.000896**	0.012	0.011	-0.0036
	(0.000273)	(0.000273)	(0.000426)	(0.013)	(0.013)	(0.023)
Wage income			-0.000855			0.026
			(0.000670)			(0.037)
Own income			-0.000284			0.021
			(0.000510)			(0.026)
Acres under cultivation	228.3	335.5	330.7	31,590*	35,580*	34,780*
	(284.1)	(304.9)	(303.3)	(16,400)	(18,590)	(18,550)
Cash crop acres		-1,569	-1,853		-45,250	-31,470
		(1,687)	(1,695)		(81,290)	(80,940)
TLU	226.0	210.0	188.5	-23,950	-24,510	-26,460
	(653.9)	(648.8)	(648.1)	(36,800)	(36,940)	(36,850)
Assets	0.000064**	0.000064**	0.000063**	0.0037***	0.0038***	0.0040***
	(0.000026)	(0.000026)	(0.000026)	(0.0012)	(0.0013)	(0.0013)
Rainfall (mm)	-2.828	-2.917	-2.489	166.574	162.811	147.806
	(5.790)	(5.784)	(5.793)	(441.398)	(439.494)	(442.769)
Rainfall difference	973.7	999.2	969.7	23,980	25,620	24,550
	(906.7)	(907.0)	(905.2)	(75,360)	(75,170)	(75,360)
EVI	-26,294**	-26,360**	-27,347**	-794.800	-778.800	-738.500
	(13,352)	(13,362)	(13,528)	(711.900)	(711.600)	(718.400)
EVI difference	412.8	407.6	400.7	1,610	850.39	1,503
	(484.5)	(482.9)	(480.4)	(31,520)	(31,540)	(31,490)
Elevation (m)	-3.294*	-3.266*	-3.246	-136.223	-134.474	-131.107
	(1.977)	(1.982)	(1.976)	(159.016)	(158.787)	(158.493)
Shock	1,802	1,801	1,864	53,020	54,420	52,280
	(1,176)	(1,174)	(1,177)	(80,250)	(80,200)	(81,210)
HH char[78] & Mundlak FE	Y	Y	Y	Y	Y	Y
Observations	3,259	3,259	3,259	3,259	3,259	3,259
BIC (in billions)[79]	64.33	64.30	64.23	9,060,000	9,038,000	9,032,000

Clustered (HH) standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

[78] Characteristics include household size, labor, an indicator for having a male head, the years of education of the head, and his/her age. Region dummies are also included. Coefficients are available on request.

[79] Bayesian information criterion (BIC) from the GLM specification (not marginal effects).