Resilience thresholds to temperature shocks in rural Tanzania: a long-run assessment

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ICID-IFAD-SITES Conference on International Development

October 3 – 4, 2018 - Rome

Motivations

- Increasing interest in the **within-country impacts of climate change** and their distributional implications (Letta, Montalbano & Tol, 2018);
- Relevance of studying **household resilience** in development economics (Barret and Constas 2014; Constas et al. 2014; Smith and Frankenberger 2017; d'Errico and Pietrelli 2017; d'Errico and Di Giuseppe 2018);
- Despite significant recent improvements in measuring resilience, no data-driven evidence has been provided yet on the potential existence of **resilience thresholds**;
- **Aim**: Filling this gap by providing empirical evidence on the presence of critical household resilience thresholds to exogenous temperature shocks in rural Tanzania
- The identification of resilience thresholds represents a key step towards a full assessment of potential resilience traps (**relevant policy implications**)

However….

1. Convergence is a long-run process
2. Short-run elasticities between temperature shocks, resilience capacity and economic growth may not hold in the long-run
3. A long-run analysis is hampered by the lack of available long panels at the household level (not just in Tanzania but in developing countries as a whole)
4. Although the welfare of risk-averse households will always be higher in a shock-free environment, the identification of the actual effects of shocks on household welfare is hampered by both theoretical and empirical constraints

Theoretical and Empirical Constraints...

- Precautionary saving literature: empirical associations between shocks and reductions in current consumption are compatible with a higher consumption growth (see : Caballero, 1990; Carroll & Kimball, 2001; Carroll & Samwick, 1998; Deaton, 1992, Paxson, 1992)
- Literature on poverty traps (Carter & Barrett, 2006; Carter, Little, Mogues, & Negatu, 2007; Carter & Lybbert, 2012; Zimmerman & Carter, 2003) highlights that voluntarily destabilizing consumption could avoid the risk of falling into poverty traps (asset-smoothing)
- As for empirical constraints, robust empirical evidence on resilience dynamics are hampered by a lack of long micro panels, measurement error and attrition (Antman & McKenzie, 2007).
- Recall the inherent inconsistency of the concept of "households" in a long-term perspective: household splits are characterized by short-term frequencies.
- **Solution:** build up **integrated pseudo-panels** covering a **thirteen-year time span**. This also minimizes attrition and smooths individuals' response errors compared to genuine panels (Deaton, 1985).

Why Tanzania?

- It is commonly accepted that the impact of weather shocks will disproportionally affect poorer, hotter and lower-lying countries… (IPCC 2014).
- …and especially people living in rural, remote and scarcely populated areas, whose main source of income is agriculture (Tol, 2015);

Why Tanzania?

- Tanzania is a poor, hot and (partially) lower-lying Sub Saharan country
- Agriculture accounts for half of gross production and employs 80 percent of the labour force (WB, 2016)
- Agriculture in Tanzania is primarily rain-fed (only 2% of arable land has irrigation facilities)
- Tanzania also exhibits large climate diversity (from tropical at the coasts to temperate at the highlands, Lobell et al., 2011)
- Temperatures in the country are predicted to rise 2–4 °C by 2100 (Rowhani, Lobell, Linderman & Ramankutty, 2011)

Data

- ✓ **Household data:**

  ✓Household Budget Surveys (HBS) by the Tanzanian NBS (2 repeated cross-sections – 2000 & 2007);

  ✓ Tanzania National Panel Survey (NPS) 2008 – 2013 (3 waves) / LSMS-ISA Database by the World Bank

- ✓ **Weather data:**

  ✓Climatic Research Unit (CRU) – University of East Anglia - 0.5 X 0.5 degree resolution (55 x 55 km)

Pseudo-panels

- We group individuals sharing some common characteristics into cohorts (Deaton, 1985) and treat averages within these cohorts as observations (Verbeek, 2008).
- The key assumption is that the mean cohort behaviour reproduces the form of an individual behaviour in that specific cohort
- each individual must be a member of exactly one cohort which stays the same for all T (time-invariant characteristics);
- Hybrid between repeated cross-sections and genuine panel data.

Advantages over genuine panels:

1) Attrition and non-response issues minimized
2) individuals' response errors smoothed
3) Longer-term dynamics can be studied

Main drawback:

The same individuals are not followed over time.

2 pseudo-panels (hetero climate areas* age of hhs head)

Version	Variables used for cohort construction	Number of cohorts (C)	Average N of observations per cohort (n_c)
1	Long-run average temperature quintiles*Year-of-birth of the household head quintiles	25	647.6
2	Long-run average precipitation quintiles*Year-of-birth of the household head quintiles	25	647.6

There is a **trade-off** between the accuracy of each cohort mean (*n*c) and the number of observations (C) of the pseudo-panel. The optimal choice minimizes the heterogeneity within each cohort (internally homogeneous) but maximizes the heterogeneity among them

Descriptive statistics

PP- vers. 1	Mean	Var	sd	Obs
Food consumption level	33.162	82.441	9.080	125
ΔFood	6.691	60.786	7.797	100
RCI	63.496	16.392	4.049	125
ΔRCI	0.887	1.222	1.106	100
Temperature	23.256	0.980	0.990	125
Precipitation	60.141	114.408	10.696	125
Long-run temperature	23.108	0.776	0.881	125
Long-run precipitation	60.470	88.037	9.383	125
ΔTemp	0.006	0.001	0.024	100
ΔPre	0.032	0.005	0.071	100

Notes:
Food consumption is cohort monthly per capita food consumption expressed in dollars at 201 Purchasing Power Parity (PPP). ΔFood is the annualised food consumption growth rate between and t-1, i.e. the average annual percentage change in (ln) cohort per capita food consumption. RC is the Resilience Capacity Index, scaled from 1 to 100. ΔRCI is the annualised change in the RC Index between t and t-1. Temperature is average monthly temperature in the years between t and 1, expressed in degree Celsius. Precipitation is average monthly precipitation in the years betwee t and t-1, expressed in mm. ΔTemp is the difference in logarithms of average temperature levels and t-1, both scaled by long-run means. ΔPre is the difference in logarithms of average precipitatio

PP- vers. 2	Mean	Var	sd	Obs
Food consumption level	32.855	88.180	9.390	125
ΔFood	6.019	28.349	5.324	100
RCI	63.378	17.644	4.201	125
ΔRCI	0.789	0.576	0.759	100
Temperature	23.197	3.430	1.852	125
Precipitation	60.088	26.546	5.152	125
Long-run temperature	23.054	3.446	1.856	125
Long-run precipitation	60.348	13.046	3.612	125
ΔTemp	0.002	0.000	0.018	100
ΔPre	0.033	0.004	0.064	100

Notes:
Food consumption is cohort monthly per capita food consumption expressed in dollars at 2010 Purchasing Power Parity (PPP). ΔFood is the annualised food consumption growth rate between t and t-1, i.e. the average annual percentage change in (ln) cohort per capita food consumption. RCI is the Resilience Capacity Index, scaled from 1 to 100. ΔRCI is the annualised change in the RCI Index between t and t-1. Temperature is average monthly temperature in the years between t and t-1, expressed in degree Celsius. Precipitation is average monthly precipitation in the years between t and t-1, expressed in mm. ΔTemp is the difference in logarithms of average temperature levels at and t-1, both scaled by long-run means. ΔPre is the difference in logarithms of average precipitation

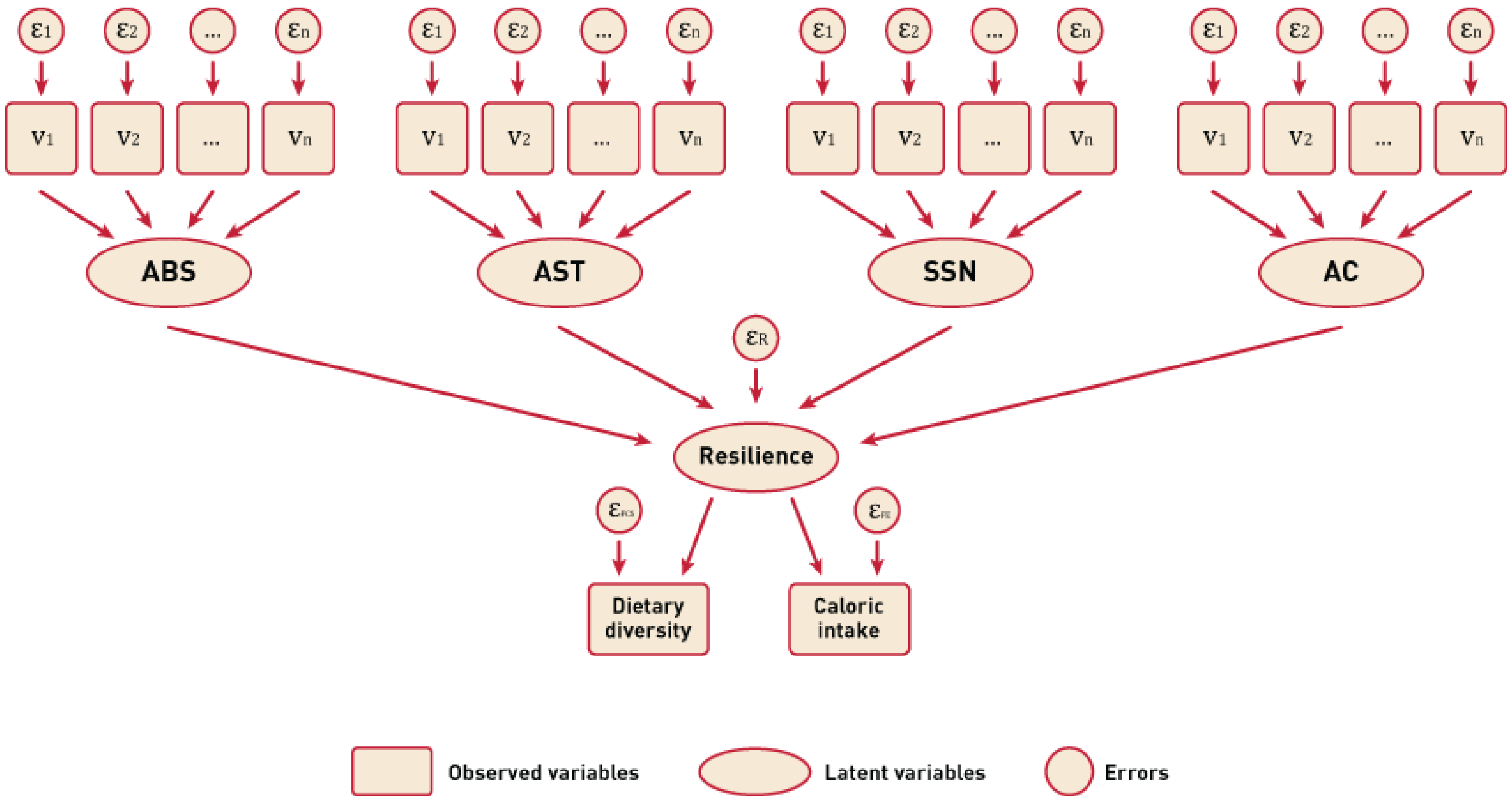
Identification strategy

1. We test for the relevance of a set of household characteristics on household resilience (Resilience Capacity Index – FAO RIMA II)
2. We then test RCI to temperature shocks (including both temperature and precipitation) in a standard empirical stochastic micro-growth model controlling for households and geographical heterogeneity,
3. We finally test for the presence of critical "resilience thresholds" in order to check for bifurcation of impacts from temperature shocks due to different resilience capacity regimes.
4. Caveats: Bifurcation of impacts (i.e., conditional on a critical level of a pre-shock level of household resilience) does not entail bifurcation of growth paths (i.e., a change of direction that translates into a permanent negative outcome for the household)
5. Results: We distinguish two impact regimes of temperature shocks (an upper and a lower regime) on food consumption growth which are conditional to specific critical values of the resilience index.

Resilience Capacity Index (RCI)

Two-step procedure:

1) Factor analysis: from observed variables to pillars
2) MIMIC: from pillars to Resilience Capacity Index



RCI Variables – Descriptive statistics

	Mean	Var	sd	Obs
Dwelling Index	-0.150	0.459	0.677	16190
Distance from hospital (inverse)	0.764	5.656	2.378	16190
Distance from primary school (inverse)	17.627	264.651	16.268	16190
Wealth Index	0.008	0.427	0.653	16190
Agricultural Wealth Index	0.151	1.508	1.228	16190
Tropical Livestock Units (per capita)	0.296	1.436	1.198	16190
Land owned (per capita)	0.424	1.533	1.238	16190
Public Transfers (per capita)	1.163	294.673	17.166	16190
Private transfers (per capita)	12.186	2017.016	44.911	16190
Participation in a saving group	0.044	0.042	0.204	10254
Average years of education	4.724	8.730	2.955	16190
Dependency ratio (inverse)	2.056	0.878	0.937	16190
Farming is not the main source of income	0.268	0.196	0.443	16190
Monthly per capita food expenditure (usd)	28.671	588.273	24.254	16190
Simpson Index	0.605	0.026	0.161	16190

Empirical strategy: empirical stochastic micro-growth model

Baseline: Solow (1965), Mankiw, Romer & Weil (1992), Dercon (2004), Carter et al. (2007), Jalan and Ravallion (2002, 2004)

1) $\Delta Y_{it} = \alpha + \beta_1 ln\, Y_{it-1} + \beta_2 RCI_{it-1} + \beta_3 \Delta RCI_{it} + \beta_4 \Delta Temp_{dt} + \beta_5 \Delta Pre_{dt} + \beta_6 X_{it} + \mu_i + \theta_t + \varepsilon_{it}$

ΔY_{it} is the annualised growth rate in cohort monthly per capita food consumption;

$ln\, Y_{it-1}$ is lagged cohort monthly per capita consumption (a proxy for time-invariant initial cons.);

RCI_{it-1} capturestreatment household resilience on food consumption growth;

ΔRCI_{it} captures possible time-varying resilience factors and/or coping mechanisms

$\Delta Temp_{dt}$ and ΔPre_{dt} are temperature and precipitation shocks, observed at the district level

(calculated as the difference in logarithms between their values at t and t-1, both scaled by long-run means)

X_{it} include other biophysical controls, namely elevation, plot slope and length of the growing period (LGP) by hhs

$\mu_i$are cohort fixed effects, θ_t are wave fixed effects and ε_{it} are error terms clustered at the cohort level.

Threshold model: Hansen (2000) threshold estimator, as implemented in a fixed-effect setting by Wang (2015).

2) $\Delta Y_{it} = \begin{cases} \alpha + \beta_1 ln\, Y_{it-1} + \beta_2 RCI_{it-1} + \beta_3 \Delta RCI_{it} + \beta_4^l \Delta Temp_{dt} + \beta_5 \Delta Pre_{dt} + \beta_6 X_{it} + \mu_i + \theta_t + \varepsilon_{it} \;\; if\; RCI_{it-1} \leq \omega \\ \alpha + \beta_1 ln\, Y_{it-1} + \beta_2 RCI_{it-1} + \beta_3 \Delta RCI_{it} + \beta_4^u \Delta Temp_{dt} + \beta_5 \Delta Pre_{dt} + \beta_6 X_{it} + \mu_i + \theta_t + \varepsilon_{it} \;\; if\; RCI_{it-1} > \omega \end{cases}$

Impacts on food consumption growth – Pseudo-panel Version 1

Dependent variable: ΔFood	(1)	(2)	(3)	(4)	(5)
L1.Food	-51.948***	-44.487***	-46.986***	-46.577***	-51.423***
	(5.238)	(4.702)	(5.438)	(6.006)	(4.569)
L1.RCI	3.776***	3.195***	3.098***	3.306***	3.658***
	(0.427)	(0.370)	(0.427)	(0.468)	(0.358)
ΔRCI	7.389***	7.418***	7.426***	7.366***	7.325***
	(0.101)	(0.122)	(0.112)	(0.129)	(0.106)
ΔTemp	-12.998	-10.697	4.966	-13.141	-255.308**
	(17.367)	(14.247)	(16.323)	(15.812)	(110.287)
Low average pre-shock RCI x ΔTemp		-24.367**			
		(10.476)			
Hot x ΔTemp		-12.371	-1.879	-15.511**	-9.262
		(8.172)	(7.035)	(7.195)	(7.260)
ΔPre	-1.959	-3.182**	-4.881**	-5.141***	20.469
	(1.494)	(1.422)	(1.933)	(1.646)	(25.403)
Low average pre-shock RCI x ΔPre		-0.999			
		(3.400)			
Hot x ΔPre		3.976*	4.180*	4.511**	6.674**
		(2.054)	(2.218)	(1.944)	(2.596)
Low pre-shock RCI x ΔTemp			-60.694***		
			(15.635)		
Low pre-shock RCI x ΔPre			6.632		
			(3.110)		
Low pre-shock RCI			0.112		
			(0.285)		
Low initial RCI x ΔTemp				-27.988***	
				(9.247)	
Low initial RCI x ΔPre				-0.506	
				(3.081)	
L1.RCI x ΔTemp					3.802**
					(1.663)
L1.RCI x ΔPre					-0.404
					(0.408)
Constant	-63.728***	-51.077***	-56.872***	-52.344***	-62.922***
	(14.159)	(10.358)	(12.971)	(12.784)	(11.543)
Observations	100	100	100	100	100
Adjusted R-squared	0.993	0.994	0.994	0.994	0.994
Biophysical controls	Yes	Yes	Yes	Yes	Yes

Threshold model – Pseudo-panel Version 1

	(1)
Dependent variable:	ΔFood
L1.Food	-52.711***
	(5.651)
L1.RCI	3.777***
	(0.445)
ΔRCI	7.363***
	(0.099)
ΔPre	-3.075*
	(1.496)
ΔTemp_Lower regime	-61.361***
	(20.920)
ΔTemp_Upper regime	-5.661
	(16.505)
Constant	-64.476***
	(14.319)
Observations	100
Adjusted R-squared	0.994
Biophysical controls	Yes

Notes: All specifications include cohort and time fixed effects. Biophysical controls include slope, elevation and length of the growing period. ΔFood is food consumption growth rate, i.e. the average annual percentage change in (ln) cohort monthly per capita food consumption between t and t-1. L1.Food is lagged (ln) cohort monthly per capita food consumption. L1.RCI is the lagged Resilience Capacity Index, scaled from 1 to 100. ΔRCI is the annualized change in the RCI Index between t and t-1. ΔTemp is the difference in logarithms of average temperature levels at and t-1, both scaled by long-run means. ΔPre is the difference in logarithms of average total precipitation levels at t and t-1, both scaled by long-run means. Hot is a dummy taking value 1 for cohorts living an area with an above mean long-run average temperature.
Standard errors are in parentheses and are clustered at the cohort level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

RCI Threshold*

Model	Threshold	Lower	Upper
RCI	54.609	53.130	55.139

* The threshold value of RCI is at time t-1.

Threshold effect test (bootstrap = 300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	13.5417	0.1411	21.08	0.0033	13.2478	15.5232	20.0510

Impacts on food consumption growth – Pseudo-panel Version 2

Dependent variable: ΔFood	(1)	(2)	(3)	(4)	(5)
L1.Food	-42.068***	-45.379***	-47.292***	-42.862***	-46.258***
	(4.448)	(3.917)	(4.360)	(3.481)	(3.957)
L1.RCI	2.996***	3.293***	3.394***	3.033***	3.258***
	(0.352)	(0.308)	(0.337)	(0.269)	(0.290)
ΔRCI	7.146***	7.266***	7.230***	7.208***	7.212***
	(0.129)	(0.145)	(0.131)	(0.118)	(0.127)
ΔTemp	-5.067	-7.918	-6.398	-5.666	-185.110**
	(4.619)	(5.566)	(7.760)	(4.323)	(70.249)
Low average pre-shock RCI x ΔTemp		-7.593			
		(9.612)			
Hot x ΔTemp		-12.772	-12.212	-18.023**	-16.717**
		(7.541)	(7.708)	(6.488)	(7.552)
ΔPre	-1.944	0.691	1.387	0.402	-42.163
	(2.519)	(2.942)	(2.686)	(2.514)	(34.675)
Low average pre-shock RCI x ΔPre		-4.326			
		(4.911)			
Hot x ΔPre		-6.972**	-6.954**	-6.859**	-6.502**
		(2.918)	(3.061)	(2.845)	(2.735)
Low pre-shock RCI x ΔTemp			-11.755		
			(8.460)		
Low pre-shock RCI x ΔPre			-4.829		
			(5.190)		
Low pre-shock RCI			0.382		
			(0.371)		
Low initial RCI x ΔTemp				-19.087***	
				(5.819)	
Low initial RCI x ΔPre				-1.262	
				(3.499)	
L1.RCI x ΔTemp					2.938**
					(1.180)
L1.RCI x ΔPre					0.692
					(0.556)
Constant	-53.564***	-65.786***	-65.701***	-58.154***	-61.601***
	(12.066)	(10.825)	(11.398)	(10.096)	(9.386)
Observations	100	100	100	100	100
Adjusted R-squared	0.996	0.997	0.997	0.997	0.997
Biophysical controls	Yes	Yes	Yes	Yes	Yes

Threshold model – Pseudo-panel Version 2

	(1)
Dependent variable:	ΔFood
L1.Food	-45.248***
	(4.568)
L1.RCI	3.211***
	(0.360)
ΔRCI	7.134***
	(0.113)
ΔPre	-1.822
	(2.261)
ΔTemp_Lower regime	-16.094***
	(4.811)
ΔTemp_Upper regime	2.288
	(5.901)
Constant	-60.330***
	(12.500)
Observations	100
Adjusted R-squared	0.997
Biophysical controls	Yes

Notes: All specifications include cohort and time fixed effects. Biophysical controls include slope, elevation and length of the growing period. ΔFood is food consumption growth rate, i.e. the average annual percentage change in (ln) cohort monthly per capita food consumption between t and t-1. L1.Food is lagged (ln) cohort monthly per capita food consumption. L1.RCI is the lagged Resilience Capacity Index, scaled from 1 to 100. ΔRCI is the annualised change in the RCI Index between t and t-1. ΔTemp is the difference in logarithms of average temperature levels at and t-1, both scaled by long-run means. ΔPre is the difference in logarithms of average total precipitation levels at t and t-1, both scaled by long-run means. Hot is a dummy taking value 1 for cohorts living an area with an above mean long-run average temperature.
Standard errors are in parentheses and are clustered at the cohort level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

RCI Threshold*

Model	Threshold	Lower	Upper
RCI	60.796	60.379	60.835

* The threshold value of RCI is at time t-1.

Threshold effect test (bootstrap = 300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	16.528	0.1722	15.78	0.0267	11.6289	13.7316	19.6328

Core findings

- Detection of critical "resilience thresholds" below which households are unable to absorb the negative effects of temperature shocks.
- Going back to the original aggregate dataset, between 25% and 47% of households (i.e. nearly one third of the population) in our sample are below the resilience threshold and consequently exposed to temperature shocks
- These thresholds are intrinsically relative and context-specific
- Still, the existence of resilience thresholds is a significant finding for policymakers, especially for policies targeting adaptation to the negative impacts of future climate change

Conclusions

- Sharp and remarkable pattern of heterogeneity of impacts: temperature shocks affect the less resilient households
- The identification of resilience thresholds represents an important step towards an assessment of the presence of potential resilience traps, i.e. regime shifts (Folke et al 2004)
- Extrapolating from weather to climate, climate change could cause a fractal increase in within-country inequality, led by a resilience capacity gap
- **Main policy message: resilience building** as a complementary strategy to greenhouse gas emission reduction in developing countries
- **Future research agenda:** exploration of the relationship between temperature shocks and crucial determinants or single drivers of resilience

Thank you!