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Article (Accepted Version)

d'Errico, Marco, Letta, Marco, Montalbano, Pierluigi and Pietrelli, Rebecca (2019) Resilience thresholds to temperature anomalies: a long-run test for rural Tanzania. *Ecological Economics*, 164. 1063652 1-14. ISSN 0921-8009

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Resilience thresholds to temperature anomalies: a long-run test for rural Tanzania

***Abstract** The existence of thresholds constitutes an important frontier topic for resilience analysis and measurement. This paper contributes to the literature by identifying critical resilience thresholds below which rural Tanzanian households are unable to absorb the negative effects of temperature anomalies on long-run growth. To make up for the lack of long micro panels, we generate a synthetic panel covering the time span 2000 – 2013. We show that 25%-47 % of households in our sample lie below the estimated thresholds. The evidence of resilience-driven regime shifts and non-linear dynamics has important implications for adaptation to climate change in developing countries and is of significant interest for policy interventions.*

Keywords: resilience thresholds, food security, household growth, temperature shocks, climate change

JEL: I32, O12, Q12, Q54

Acknowledgments: We acknowledge the collaboration with the International Food Policy Research Institute for the creation of the climatic dataset. We are grateful to Veronica Notaro for excellent research assistance. We thank Valeria Costantini, Mark Constanas, Alessio D’Amato, Stefania Di Giuseppe, Marco Sanfilippo, Richard Tol and seminar participants at the 2018 ICID-IFAD Workshop on International Development. We are also grateful to four anonymous referees for excellent comments on earlier versions of this paper. We finally thank Daniela Verona for her support on the realization of Figure 1. Usual disclaimers apply.

1. Introduction

Over the last few years, an increased interest in resilience, i.e. the ability to withstand shocks and stressors, has been paralleled by interest in how to measure the effectiveness of resilience-targeted programmes.

Despite significant improvements in measuring resilience (see, among the others, Conostas et al., (2014); Smith and Frankenberger, (2017); d'Errico and Pietrelli, (2017); d'Errico and Di Giuseppe, (2018)) and theoretical advancements on the hypothesis of resilience thresholds (Barrett and Conostas, 2014), no evidence has been provided yet on the existence of thresholds and regime shifts in response to exogenous shocks, such as ecological or climatic stress.

The concept of resilience thresholds was first introduced in the early 1970s in seminal papers on ecology (Hollings, 1973; May, 1977). Groffman et al. (2006) define a threshold as the point at which there is an abrupt change in a quality, property or phenomenon or where small changes in a driver produce large responses in a system. Thresholds are therefore fundamental to evaluate alternate states, i.e. the phenomenon whereby a system can change from one status to another (Walker & Meyers, 2004). In this respect, thresholds and resilience are closely interrelated, as system resilience plays a crucial role when a system approaches a threshold that is critical for regime shifts (Holling, 1973; Barrett & Conostas, 2014). Following the pioneering works by Scheffer et al (2001), Scheffer and Carpenter (2003) and Folke et al (2004), a regime shift is represented by an abrupt and persistent shift of the natural fluctuation of a phenomenon, or of the characteristic behaviour of a system, around a trend or stable average. Regime shifts can be caused either by internal dynamics or by external shocks and disturbances that trigger non-linear dynamics.

From a development perspective, the notion of resilience thresholds is closely related to the idea of stochastic poverty traps, since it concerns the likelihood that adverse outcomes actually persist for an extended period in a dynamic setting. The incorporation of the concepts of thresholds and non-linear

dynamics in resilience analysis stems from the theoretical work of Barrett and Constan (2014) who, building on the poverty traps literature on multiple equilibria (Azariadis & Drazen, 1990; Azariadis & Stachurski, 2005; Carter & Barrett, 2006; Carter et al., 2007; Barrett & Carter, 2013), highlight the presence of critical thresholds (the so-called ‘Micawber thresholds’) implying divergent longer-term prospects. They also suggest a division in three post-shock situations: humanitarian emergency; an area in which people only partially recover from shocks up to a poor standard wellbeing; a non-poor zone where people can recover adequately and relatively fast from the aftermath of negative shocks. In this respect, the identification of resilience thresholds also represents an important step towards an assessment of the presence of potential resilience traps, i.e. permanent low equilibria (Folke et al 2004).

Unfortunately, empirical efforts to investigate resilience thresholds have been hampered so far by a lack of readily available data (Walker & Meyers, 2004), by the inherent complexity of non-linear dynamics and by multiple factor controls that operate at diverse spatial and temporal scales (Groffman et al., 2006). As a result of these operative issues, most attempts have been limited to the investigation of exogenous thresholds unilaterally set up without any reference to real life or validity norms (Barrett & Constan, 2014; Upton et al., 2016).

Following the seminal work of Barret and Constan (2014), we identify the protective role of resilience in mediating possible deviations from positive consumption growth paths in the aftermath of temperature anomalies. This represents, to the best of our knowledge, the first empirical test for the existence of critical household resilience thresholds in response to exogenous disturbances. We show that in rural Tanzania a share between 25% and 47 % of sample households lie below the estimated resilience thresholds. Although these estimates are intrinsically relative and context-specific, the existence of regime shifts in food consumption growth induced by weather anomalies has important implications for policymaking aimed at fostering household adaptation to climate change in developing countries.

To explore crucial questions such as the relationship between weather disturbances, resilience and household growth, a long-run perspective is essential. Short-run analyses cannot provide full evidence on non-linear responses and regime shifts in the aftermath of a weather shock. Furthermore, it is also important to acknowledge the inherent inconsistency of the concept of “household” in a long-term perspective, since household splits are typically characterized by short-term frequencies. To overcome these limitations, we make use of pseudo-panels techniques to construct a synthetic longitudinal dataset and carry out a long-run empirical analysis. In particular, we match the Living Standard Measurement Survey (LSMS) – Integrated Survey on Agriculture (ISA) Tanzania National Panel Survey by the World Bank and the National Household Surveys by the Tanzanian Department of Statistics. In this way we are able to cover a thirteen-year time span. Note that the pseudo-panel approach should not only be seen as a workable solution to look at long-run phenomena, but also as an improvement on key aspects when compared with genuine panels (Deaton, 1985).

Our identification strategy is thus the following: i) by employing long-run pseudo-panels, we first test for resilience-driven heterogeneity in the effects of temperature shocks on food consumption growth, controlling for convergence as well as for household and geographical heterogeneity ii) we then test for the presence of “resilience thresholds” to check for regime shifts at a critical resilience level.¹

Figure 1 provides a graphical illustration of our empirical framework, showing two different (food consumption) growth trajectories of two different household clusters, cluster A above the resilience threshold and cluster B below it. As we can see from the picture, the growth rate of household cluster B is higher than the one of household cluster A (the slope of the food consumption path is steeper), suggesting the presence of a catch-up process over time. However, when a covariate weather shock strikes, this affects only the growth path of household cluster B, which at that point still lies below the resilience threshold, with no detrimental effects for the more resilient household cluster A. This,

¹Please note that regime shifts do not necessarily entail bifurcation of growth paths, i.e., a change of direction that translates into a permanent negative outcome for the household.

in turn, alters the slope of cluster B growth trajectory by making it less steep than it would have been in the absence of the weather shock (as represented by the dashed line), thus slowing their catch-up process towards the richer households of the unaffected cluster A. Due to heterogeneity in pre-shock resilience levels, therefore, the shock exogenously intervenes in the catch-up process by reducing the speed of convergence among households in the long-run. In other words, there is a regime shift in the convergence process determined by the heterogeneous impacts of weather anomalies, that in turn depend on the initial position with respect to the critical threshold. In this scenario, identifying the resilience thresholds that marks the regime shift is thus crucial to prevent such detrimental dynamics.

Figure 1: Resilience thresholds and well-being dynamics

Source: Authors' elaboration

Our focus on temperature shocks stands for many reasons: first, a recent and growing body of

empirical works shows that extreme weather may have damaging consequences on crop yields, especially in developing countries where agriculture is less modernized (Rowhani et al., 2011; Schlenker & Lobell, 2010). Second, several studies have provided theoretical underpinnings to explain how low crop yields and yield gaps could trap smallholder farmers in chronic poverty (Barrett & Swallow, 2006; Titttonell & Giller, 2013). Third, by assuming that weather variations are exogenously determined, we follow insights from the development literature on the impacts of uninsured risk on poverty via both *ex ante* (behavioural) and *ex post* channels (Dercon, 2004).

The remainder of this work is organized as follows: section 2 provides information on data and methods; section 3 describes the empirical strategy; section 4 presents the results; section 5 focuses on robustness checks; section 6 discusses and concludes.

2. Context, data and methods

2.1 Context and data

Tanzania is a poor Sub-Saharan African country which exhibits high average temperatures and a large climatic diversity. It is commonly classified as a country at high risk from the impacts of climate change: temperatures in the country are predicted to rise 2–4 °C by 2100 (Rowhani et al., 2011). Moreover, it is still a predominantly rural country where agriculture accounts for about half of gross production, employs about 80 percent of the labour force, and is primarily rainfed (Ahmed et al., 2011). Several empirical works documented a causal relationship between welfare dynamics and weather shocks in the country and particularly in rural areas (Ahmed et al., 2011; Bengtsson, 2010; Dercon, 1996; Hirvonen, 2016; Letta et al., 2018).

Our dataset of Tanzanian households consists of five rounds: two repeated cross-sections, namely the 2000-2001 and 2007 Tanzania Household Budget Surveys (HBS)² conducted by the Tanzanian National Bureau of Statistics (NBS); and the 2008-2009, 2010-2011 and 2012-2013 waves of the

²These surveys can be found at: <http://www.nbs.go.tz/>

National Panel Survey (NPS) by the World Bank, part of the Living Standards Measurement Study (LSMS) – Integrated Survey on Agriculture (ISA)³ collection. Household data were cleaned, aggregated and integrated with weather data. Our aggregated dataset consists of 16,190 original observations.

Data on food consumption are obtained from the food consumption module available in both the LSMS-ISA and HBS survey. The two surveys collect the information on the food consumed by the members of the households during the 7 days preceding the interview from three different sources: purchase, own production and gift/received for free. Food consumption variable is expressed as the monetary value of the per capita monthly (i) expenditure on food, (ii) auto-produced food, and (iii) received for free (as gift or part of a project) food. In order to express the own-produced and received for free food in monetary value, the prices are obtained from the expenditure on food, for which both quantity and expenditure are collected. The list of food items included in the two survey is different. Nevertheless, the list of food groups (cereals and products; starches, sugar and sweets; pulses; nuts and seeds; vegetables; fruits; meat, meat products and fish; milk and milk products; oil and fats; spices) considered is the same, thus allowing the variables obtained from the different surveys to be comparable. Finally, all monetary values were already spatially and temporally deflated in the single waves of both data sources. To make monetary values comparable *across* waves, we deflated all the nominal measures by using the Consumer Price Index by the World Bank. Food consumption is expressed in 2011 PPP US dollars.

Weather data include time series on precipitation and land surface temperature. Monthly time series (covering the period 1983 - 2016) of precipitation data (in millilitres) come from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015). Monthly time series (for the period 1983 - 2015) temperature data are from the Centre for Climatic Research (CRU) at the

³The complete LSMS-ISA dataset collection is available at the following link:
<http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,,contentMDK:23617057~pagePK:64168445~piPK:64168309~theSitePK:3358997,00.html>

University of East Anglia with a 0.5° latitude by 0.5° longitude spatial resolution. We aggregated both weather time series at the district-monthly level using geo-spatial software before merging them with household data.

2.2 The Resilience Capacity Index (RCI)

To measure household resilience to food insecurity we employ the Resilience Capacity Index (RCI) developed by FAO-RIMA (FAO, 2016), a methodology tested in more than twenty countries and scientifically validated in several peer-reviewed works (Brück et al, 2018; d’Errico et al., 2017; d’Errico & Pietrelli 2017; d’Errico & Di Giuseppe, 2018). In the RIMA approach, household resilience is defined as that capacity that ensures that shocks and stressors do not have long-lasting consequences on household food security (Constas et al., 2014). RIMA, as other multi-dimensional measurement methodologies (see, inter alia, Smith and Frankenberg, 2018), estimates a resilience capacity index that is a combination of many directly observable characteristics. Operationally, the RCI is measured using a two-step procedure. In the first step, four resilience pillars are estimated through a Factor Analysis (FA) from a set of observed variables. In the second step, the RCI is predicted using a Multiple Indicators Multiple Causes (MIMIC) model (Bollen & Davis, 2009). The four resilience pillars of the RIMA approach are the following: Access to Basic Services (ABS), Assets (AST), Social Safety Nets (SSN) and Adaptive Capacity (AC). ABS captures closeness to basic services, such as hospitals and schools, as well as housing conditions, such as type of roof, walls, floor, etc. AST proxies both productive (land, livestock, inputs) and non-productive (wealth) assets used by the household. SSN generally includes private and public transfers received or made by the household. AC expresses the capacity to adapt after a shock and is computed using variables such as the average education of household members and the main income-generating activity. The summary statistics of the observed variables employed to estimate the pillars is in Table A.1 in the Appendix, while the outcomes of FA employed in the estimation of the ABS, AST and AC pillars are

reported in Tables A.2-A.4.⁴

As for the MIMIC model, a system of equations is constructed, specifying the relationships between the unobservable latent variable (RCI), a set of outcome indicators (food security indicators), and a set of attributes (four resilience pillars). The food security indicators employed in the MIMIC model are food consumption and the Simpson index of dietary diversity. Table A.1 also reports the summary statistics of the food security indicators.

The MIMIC model is composed of two components, the measurement equation (1) – reflecting that the observed indicators of food security are imperfect indicators of resilience capacity – and the structural equation (2) which correlates the estimated attributes to resilience capacity:

$$\begin{bmatrix} \text{Food consumption} \\ \text{Simpson index} \end{bmatrix} = [\Lambda_1, \Lambda_2] \times [RCI] + [\varepsilon_1, \varepsilon_2] \quad (1)$$

$$[RCI] = [\beta_1, \beta_2, \beta_3, \beta_4] \times \begin{bmatrix} ABS \\ AST \\ SSN \\ AC \end{bmatrix} + [\varepsilon_3] \quad (2)$$

Therefore, the RCI is jointly estimated by its causes (the pillars), and its outcomes (the food security variables). This procedure ensures a proper link between the estimated resilience capacity and household food security. The MIMIC results present a good fit of the data, as shown in Table A.5 in the Appendix.⁵ All the pillar coefficients, except for Social Safety Nets, are positive and statistically significant. The RCI is not anchored to any scale of measurement. Therefore, a scale was defined setting the coefficient of the food consumption loading (Λ_1) as equal to 1, meaning that one standard deviation increase in RCI implies an increase of one standard deviation in food consumption. The final RCI is thus a scaled index which ranges from 0 to 100. This also defines the unit of measurement for the other outcome indicator (Λ_2) and for the variance of the two food security indicators. In

⁴Due to data constraints, FA could not be implemented for the SSN pillar, so a simple sum of public and private transfers was used. Cf. Annex 1 for more details.

⁵For sensitivity, the RCI was also estimated by employing alternative techniques for both the pillar estimation - FA, both with the iterated principal-factor method (ipf) and the principal-component factor (pcf). A validation index, which allows to compare the goodness of fit of the different models, shows that among the three MIMIC models, the use of FA in the first-step ensures smaller value of the index.

conclusion, the use of a MIMIC model guarantees the necessary linkage between the estimated resilience index and food insecurity. For more details on the estimation of the RCI conducted in this study, readers can consult Annex 1.

2.3 Pseudo-panels

In order to explore crucial questions such as the relationship between weather disturbances, resilience and household growth, a long-run perspective is essential. Short-run analyses cannot provide full evidence on non-linear responses and regime shifts in the aftermath of a weather shock. Furthermore, it is also important to stress the ephemeral nature of the concept of “household” in a long-term perspective, as household splits are typically characterized by short-term frequencies. To overcome these limitations, and since there are not long enough panel datasets, we make use of pseudo-panels techniques to construct a synthetic longitudinal dataset and carry out a long-run empirical analysis. In particular, we match the Living Standard Measurement Survey (LSMS) – Integrated Survey on Agriculture (ISA) Tanzania National Panel Survey by the World Bank and the National Household Surveys by the Tanzanian Department of Statistics. In this way we are able to cover a thirteen-year time span. Note that the pseudo-panel approach should not only be seen as a workable solution to look at long-run phenomena, but also as an improvement on key aspects when compared with genuine panels (Deaton, 1985).

Since the seminal work of Deaton (1985), the pseudo-panel approach has been used in several applications to estimate changes over time, including empirical studies in developing contexts (Antman & McKenzie, 2007a and 2007b; Warunsiri & McNown, 2010). It is essentially a hybrid between repeated cross-sections and genuine panel data, but presents some advantages with regard to the latter: i) attrition and non-response problems are minimized, and individuals’ response errors smoothed (Verbeek, 2008); ii) larger sample dimension (N) and time span (T) can be created by combining different sources; iii) longer-term dynamics can be studied (Antman & McKenzie, 2007a). The main drawback is that the same individuals cannot be followed over time (Verbeek, 2008).

The fundamental assumption of the pseudo-panel framework is that the mean cohort behaviour reproduces the form of an individual behaviour in that specific cohort. A ‘cohort’ is defined as a group with fixed membership with individuals who can be identified as they show up in the surveys (Deaton, 1985). Operationally, it means to group individuals sharing some common characteristics into cohorts, after which the averages within these cohorts are treated as observations in a pseudo panel (Verbeek, 2008). For the construction of our cohorts, we paid careful attention to the following recommendations underlined by the relevant literature: i) cohorts can be broadly defined, but on the basis of *time-invariant* variables that are observed for all individuals (Verbeek & Nijman, 1992). Possible choices include variables such as date of birth, race, gender, region, etc. (Verbeek, 2008) which may also be interacted to increase the number of cohorts C . McKenzie (2004) stresses the importance of allowing for inter-cohort parameter heterogeneity; ii) each individual must be a member of exactly one cohort for all T ; iii) in constructing cohort samples, there is a trade-off between n_c and C , that is between the accuracy of each cohort mean (n_c) and the number of observations (C) of the pseudo-panel. A large n_c minimizes measurement error but increases the efficiency loss. Hence, the challenge is to find a balance between these two dimensions where the optimal choice would be the one that minimizes the heterogeneity within each cohort but maximizes the heterogeneity among them. Verbeek and Nijman (1992) argue that with a sufficiently large cohort size, measurement error and the cohort nature of the data can safely be ignored, but this will come at the cost of reducing C ; iv) according to Verbeek & Vella (2005), the fixed effects estimator based on the pseudo-panel may provide an attractive choice.

Aggregating our five waves in a pseudo-panel allows us to expand the time span of our empirical analysis up to fourteen years, from 2000 to 2013. Such a thirteen-year panel ensures a sufficient temporal horizon to explore long-run phenomena such as growth convergence, post-shock recovery and resilience dynamics which would otherwise be unobservable in a short-run panel dataset.

Our baseline analysis is conducted on two different pseudo-panels (Versions 1 and 2) whose characteristics are shown in Table A.6. In Version 1 we use, as group variables - i.e. variables

interacted with each other to create cohorts - quintiles of long-run average temperature and year-of-birth of the household head quintiles. Similarly, the only difference in Version 2 is the use of long-run precipitation quintiles instead of long-run temperature quintiles as cohort variables. This alternative version is used to perform robustness checks (see Section 5). While the use of year-of-birth bands follows standard practice in pseudo-panel literature, the choice of interacting them with long-run temperature quintiles is an original contribution to this literature. Such choice is not arbitrary but based on a practical need: households aggregated in a cohort must be similar not only in terms of household characteristics but also, and perhaps more importantly, in terms of the magnitude of the weather shock they are exposed to. Weather anomalies, in turn, depend on the climate of the area in which households reside. Using only year-of-birth bands or another household feature as cohort variable would completely ignore this reasoning and put in the same cohort households living in completely different climatic areas (eg. plateaus and coasts). On top of that, such an approach also would gather in the same cohorts households with different expectations (based on their usual climate) on weather variability, thus confounding not only the shock but also the adaptive response to such shock by economic agents. The results of such a flawed approach would be meaningless. This is why we interact year-of-birth bands with long-run temperature and rainfall quintiles, which act as proxies for different climatic areas and ensure climatic variability between-cohorts while preserving within-cohort climatic homogeneity. Although not strictly time-invariant in absolute terms, long-run climatic averages move very slowly and can safely be considered as essentially fixed in our 13-year context. Finally, we are not the first to use geographic variables to build cohorts: Propper et al. (2001) used administrative regions of the United Kingdom to conduct their empirical exercise.

In both pseudo-panels, Versions 1 and 2, the number of cohorts C is 25 and the average number of observations per cohort, n_c , is 648.⁶ Given we study growth (not level) dynamics, we thus have 100 observations (25 cohorts x 4 waves) in our sample. Tables A.7 and A.8 shows descriptive statistics

⁶Note that our waves are different in terms of observations. HBS 2000 includes data on over 7000 households, HBS 2007 on about 3000 households and the three NPS waves on only approximately 2000 households. This implies that the average number of observations per cohort-wave differs across waves.

for Version 1 and Version 2 respectively: in both versions, food consumption growth is, on average, about 6% throughout the period and RCI also increased over time. The standard deviation is quite high for all the reported variables, pointing to a good degree of between-cohort variation and heterogeneity in their growth paths, resilience capacity and climatic conditions.

3. Empirical strategy

Our empirical strategy is derived from Dercon (2004), Carter et al. (2007), Jalan and Ravallion (2002), Letta et al. (2018). In particular, we augment the standard empirical growth model (Solow, 1965; Mankiw, Romer & Weil, 1992), with a set of explanatory variables as follows:

$$\Delta Y_{it} = \alpha + \beta_1 \ln Y_{it-1} + \beta_2 RCI_{it-1} + \beta_3 \Delta RCI_{it} + \beta_4 \Delta Temp_{dt} + \beta_5 \Delta Pre_{dt} + \beta_6 X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad [3]$$

In Equation (3), the dependent variable ΔY_{it} is the annualised growth rate in cohort monthly per capita food consumption and $\ln Y_{it-1}$ is lagged cohort monthly per capita consumption.⁷ All monetary variables are in real terms. $\ln Y_{it-1}$ represents the convergence term: a negative sign of the coefficient β_1 would indicate the presence of an ongoing convergence process, i.e. that poorest households tend to catch up over time with richer households.⁸ The use of consumption instead of income is motivated by the setting: in rural Tanzania most households depend on self-employed agriculture and measuring income is subject to large errors (Deaton, 1997). In such settings, consumption has been seen as a more reliable measure of welfare (Deaton & Grosh, 2000).

We then amend the standard empirical growth model by including additional variables which allow us to explicitly look at the role of resilience capacity, temperature shocks and their dynamic interactions. The role played by resilience capacity is identified by two distinct variables. RCI_{it-1}

⁷Given the fixed-effect setting, we could not include time-invariant initial consumption. We thus use lagged levels to test for convergence, following standard practice in micro literature.

⁸The concept of long-run convergence is at the heart of the literature on thresholds and poverty traps (see Barrett & Carter, 201). It has been addressed in previous empirical literature even in the framework of short panels (Jalan and Ravallion, 2002; Dercon, 2004). Here we make use of the notion of “convergence” with respect to regime shifts, trajectories or path dependence rather than to the (theoretical based) notion of bifurcation.

captures the impact of household resilience at time $t-1$, i.e. pre-‘treatment’, on food consumption growth. Hence, a positive sign of the coefficient β_2 would indicate that being more resilient to food insecurity, on average and *ceteris paribus*, boosts household food consumption growth. We then include ΔRCI_{it} , which stands for the annualized between-wave change in the RCI. This variable is added for two reasons: first, since the RCI is a catch-all index for a set of significant and relevant household characteristics which mimic the latent farmers’ resilience to food insecurity, its annualised change captures a wide range of time-varying variables; second, the sign of its coefficient β_3 can provide information on the role of such resilience factors in counterbalancing the impacts of shocks on consumption growth and highlight the presence of coping mechanisms.

We test for possible deviations from the assumed convergence path of consumption growth by including exogenous temperature and precipitation shocks, $\Delta Temp_{dt}$ and ΔPre_{dt} , observed at the district level (hence the subscript d). As for the functional form of temperature shocks, as in Dercon (2004), our weather variables are calculated as the difference in logarithms between their values at t and $t-1$, both scaled by long-run means. Thus, we assume that level changes matter not only in an absolute sense but also in proportion to an area’s usual variation (Dell, Jones & Olken, 2014). In line with the climate literature, although we are interested in temperature shocks, we include precipitation shocks as a control variable. As additional controls, we also add to our model biophysical variables, X_{it} , including elevation, plot slope and length of the growing period (LGP) for each household.

Given that we are interested in assessing whether there is heterogeneity in the impacts of temperature shocks with regard to pre-shock resilience capacity, we augment the baseline specification in Equation (3) by including several interactions between lagged or initial RCI level and weather variables. Finally, μ_i are cohort fixed effects, θ_t are wave fixed effects⁹ and ε_{it} are error terms clustered at the cohort level. This is the baseline specification to look for the aggregate impacts of the variables of interest on food consumption growth.

⁹This helps to control for possible factors that evolve over time but are constant across entities (included possible difference in aggregated trends between time series).

In a subsequent step, in line with the literature on poverty traps, we employ a fixed-effect panel threshold model to detect a critical RCI threshold or tipping point that entails a change of regime of temperature impacts. In doing so, we follow the approach used by Carter et al. (2007) and, more recently, Letta et al. (2018) and opt for the use of the Hansen (1999) panel fixed-effect threshold estimator, as implemented by Wang (2015). This model replicates Equation (3) but distinguishes two impact regimes conditional to a critical value of the RCI:

$$\Delta Y_{it} = \begin{cases} \alpha + \beta_1 \ln Y_{it-1} + \beta_2 RCI_{it-1} + \beta_3 \Delta RCI_{it} + \beta_4^l \Delta Temp_{dt} + \beta_5 \Delta Pre_{dt} + \beta_6 X_{it} + \mu_i + \theta_t + \varepsilon_{it} & \text{if } RCI_{it-1} \leq \omega \\ \alpha + \beta_1 \ln Y_{it-1} + \beta_2 RCI_{it-1} + \beta_3 \Delta RCI_{it} + \beta_4^u \Delta Temp_{dt} + \beta_5 \Delta Pre_{dt} + \beta_6 X_{it} + \mu_i + \theta_t + \varepsilon_{it} & \text{if } RCI_{it-1} > \omega \end{cases} \quad (4)$$

In Equation (4) the superscripts l and u on the coefficient indicate the lower and upper regime of temperature impacts, conditional on the RCI value at time $t-1$, i.e. the pre-shock resilience capacity. ω is the potential resilience threshold to temperature anomalies.

4. Results

Table A.9 in the Appendix reports the results of the preliminary estimation strategy of Equation (3). Lagged consumption level has a negative and significant effect on growth: this is consistent with the theoretical assumption of convergence among households. As expected, lagged RCI has a positive and strongly significant effect on growth: net of the convergence process, being more resilient to food insecurity enhances food consumption growth. Analogously, the coefficient of ΔRCI is positive, large and strongly significant: an increase in resilience capacity over time boosts growth. Both temperature and rainfall shocks do not have, on average, a significant effect on the growth rate of food consumption.¹⁰ But average effects hide substantial resilience-driven heterogeneity of impacts: using different dummies and interactions to capture least resilient households, we find that temperature shocks have a negative, larger and statistically significant effect only for the least resilient cohorts¹¹. Such sharp resilience-driven heterogeneity of temperature impacts raises the hypothesis of “resilience thresholds” or kink points that mark a regime shift in temperature impacts and, in turn, in

¹⁰Cf. Table A.9, Column 1.

¹¹See Table A.9, Columns 2-5.

the convergence process. To identify data-driven thresholds, we thus implement the fixed-effect panel threshold model described in Equation (4). Table 1 shows the results.

Table 1: Threshold model – Pseudo-panel Version 1

Dependent variable:	(1) ΔFood
L1.Food	-52.711*** (5.651)
L1.RCI	3.777*** (0.445)
ΔRCI	7.363*** (0.099)
ΔPre	-3.075* (1.496)
$\Delta\text{Temp_Lower regime}$	-61.361*** (20.920)
$\Delta\text{Temp_Upper regime}$	-5.661 (16.505)
Observations	100
Adjusted R-squared	0.994
Biophysical controls	Yes
<i>Notes:</i> All specifications include cohort and time fixed effects. 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. 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 t 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. Cluster-robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.	

There is a clear heterogeneity of impacts from temperature shocks: in the lower regime, i.e. below the threshold, the effect is large and strongly significant, and a one percent increase in temperature shocks reduces growth by about 0.6 percentage points. Above the threshold (in the upper regime) impacts are negligible. We test for the statistical significance of such thresholds using a bootstrap procedure with 1000 bootstrap replications. Table 2 shows the threshold value, confidence intervals and statistical tests.¹² The regime shift occurs at a pre-shock RCI value of 54.609, below the sample

¹²These include the residual sum of squares (RSS), the Root Mean Squared Errors (MSE), the F-Distribution and the p-value.

mean.¹³ This threshold is significant at the 1 % level according to the bootstrap test. A key question is whether there is more than one resilience threshold. We tested the hypothesis of multiple thresholds, which was always rejected in favour of the single threshold estimator, by far the one that suits better the pattern in our data.

Table 2: Threshold tests – Pseudo-panel Version 1

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 = 1000):

Threshold	RSS	MSE	Fstat	Prob
Single	13.5417	0.1411	21.08	0.008

5. Robustness

5.1 Out of sample validity

A pseudo-panel is made up of cohort data and not of ‘true’ households. Therefore, there may be a concern that our results are driven by the specific nature of this pseudo-panel and the selected cohort variables. Furthermore, estimates presented in Table 2 exhibit very high adjusted R-squared. While this is not surprising, given the inclusion in the model of both lagged consumption and a catch-all resilience index, one may be concerned that such a high in-sample fit may cause overfitting, with high variance and poor out-of-sample accuracy (Hastie et al., 2009). This is a valid point, which we acknowledge: it is important to show that our core findings are not altered when using alternative data and making different choices about the creation of the synthetic panel. Consequently, we implement a robustness check that consists in the repetition of the empirical analysis using a different pseudo-panel, Version 2. The unique but relevant difference with our benchmark version is that we employ, as a cohort-variable, long-run average precipitation quintiles in place of long-run average temperature

¹³Recall that the RCI is scaled from 0 to 100.

quintiles. Using a different proxy for climatic areas, in fact, leads to different groupings of households into cohorts, and could drastically change the results of the empirical analysis. By all accounts, this can be considered a different dataset with respect to the one employed in Version 1 which allows us to check for the out-of-sample validity of our findings.

Table 3 illustrates the results from the threshold model.¹⁴ Again, cohorts below the resilience thresholds are strongly and significantly affected by temperature shocks whereas the effect for cohorts above the threshold is slightly positive and insignificant.

Table 3: Threshold model – Pseudo-panel Version 2

Dependent variable:	(1) 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)
Observations	100
Adjusted R-squared	0.997
Biophysical controls	Yes
<i>Notes:</i> All specifications include cohort and time fixed effects. 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. 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 t 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.	

¹⁴Table A.10 shows the replicates the preliminary analysis of Table A.8. The pattern of sharp and significant heterogeneity of temperature impacts on growth conditional on pre-shock resilience capacity is confirmed in all cases, although physiologically different in magnitude. Again, temperature shocks slow the convergence process.

t-1, both scaled by long-run means. Standard errors are in parentheses and are clustered at the cohort level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4 shows the threshold value, confidence intervals and effect tests. The value of the threshold is higher compared with Table 2: the kink point in this panel occurs at a lagged RCI level of 60.796, and the threshold is significant at the 5% level. Again, the hypothesis of multiple thresholds was rejected.

Table 4: Threshold tests – Pseudo-panel Version 2

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 = 1000):

Threshold	RSS	MSE	Fstat	Prob
Single	16.528	0.1722	15.78	0.0270

Although the outcomes are of course different in detail (different methods of grouping households entail different average cohort values for all the variables, including the magnitude of weather anomalies¹⁵), these results confirm the existence of thresholds: on average and *ceteris paribus*, if temperature shocks are stronger, households must be more resilient to be immune to the impacts of these shocks. Therefore, our thresholds exhibit a good out-of-sample fit in the rural Tanzanian context, and this makes us confident that the high in-sample fit is not biasing the qualitative results.

5.2 Endogeneity

There are two reasons to be worried about endogeneity in our estimates. First, the inclusion of the lagged food consumption term to assess convergence. Second, two food security indicators are employed as latent variables in the estimation of the RCI, which is in turn included in our model both as (lagged) level and change. Both these features raise potential endogeneity issues when regressing food consumption growth on previous food consumption level and the resilience index. As a remedy for this concern, we use a different estimation strategy which directly tackles the endogeneity issue:

¹⁵Cf. summary statistics of weather variables in Tables A.7 and A.8 in the Appendix.

we repeat the baseline analysis reported in Tables A.9 and A.10 using the difference-GMM estimator by Arellano and Bond (1991). The Arellano-Bond estimator controls for the dynamic panel bias which derives from the inclusion of potentially endogenous variables by differencing all the regressors. In our model, we consider lagged food consumption and the RCI variables as endogenous regressors, and all the other variables included as exogenous. Results for this sensitivity test are presented in Table A.11 in the Appendix: the estimates are extremely similar to the baseline regressions, suggesting that potential endogeneity due to the inclusion of lagged food consumption or to the presence of two food security indicators in the construction of the RCI is not driving the outcomes of the empirical analysis.

6. Discussion and conclusions

Our analysis suggests sharp resilience-driven heterogeneity in the impacts of temperature fluctuations on food consumption growth. More specifically, we detect “resilience thresholds” that entail a regime shift in the effects of temperature anomalies on the convergence process: the growth rate of cohorts below such thresholds is strongly and significantly affected whereas cohorts above the threshold are immune to these negative effects. The estimated threshold is embodied by a value of the scaled RCI between 55 and 61. Going back to the original aggregate dataset, we compute that a share comprised between around 25% and 47% of households in our sample are below the value of the resilience threshold and consequently vulnerable to temperature shocks. Understanding what the key differences are between households below and above the critical thresholds is crucial for targeting and policymaking. Table 5 reports, for both threshold levels of pseudo-panels 1 and 2, a decomposition of key household characteristics by threshold regimes and a set of t-tests on the differences-in-means. Households below the resilience thresholds have a less educated household head, more members and children, own more land and are significantly poorer than households above the thresholds. Differences in key variables are strongly statistically significant, with the exception of the gender of the household head. Results are consistent between thresholds of the two alternative pseudo-panels employed, despite differences in the RCI threshold value and subsample sizes.

Table 5: Decomposition of key household characteristics by threshold regimes

Household characteristics	Below threshold	Above threshold	T-test p-values
	Mean	Mean	1 vs 2
Pseudo-panel Version 1			
Education of the household head	5.050	3.857	0.000
Gender of the household head (female = 1)	0.230	0.228	0.808
Household size	4.992	6.350	0.000
Number of children (< 15 year old)	2.172	3.263	0.000
Size of land owned (ha)	1.867	2.210	0.000
Per capita monthly total consumption	32.827	13.341	0.000
N	12143	4047	
RCI Threshold	54.609		
Pseudo-panel Version 2			
Education of the household head	5.313	4.131	0.000
Gender of the household head (female = 1)	0.232	0.227	0.426
Household size	4.697	6.034	0.000
Number of children (< 15 year old)	1.952	2.991	0.000
Size of land owned (ha)	1.796	2.126	0.000
Per capita monthly total consumption	37.876	16.956	0.000
N	8510	7680	
RCI Threshold	60.796		

This descriptive evidence shows the potential of resilience thresholds to support policymakers in targeting vulnerable people. However, several caveats are necessary. Although the identification of absolute thresholds would be the ideal tool for policymaking purposes, our resilience thresholds are intrinsically relative. First, in this case study they only apply to weather shocks and specifically to temperature shocks. Second, our thresholds are limited to the rural Tanzanian context whereas in other countries or settings, the picture may be different. Finally, our RCI is only one of the possible ways of measuring resilience, which remains an inherently latent and unobservable feature.

Still, the existence of resilience thresholds and regime shifts has significant consequences for

programme design. This approach should be replicated in order to predict, and consequently target, vulnerable people, regardless of the methodology adopted to measure resilience. As a tentative way forward, a generalized version of this methodology could be used to detect different thresholds assessed against multiple exogenous shocks in heterogeneous contexts for several resilience capacity levels. In such a flexible context, both the resilience capacity indicator and its component as well as the relative thresholds would vary depending on: i) the type and magnitude of the shock; ii) the context and characteristics of the case study; iii) the initial (i.e., pre-shock) resilience capacity level.

Ideally, this may lead to the creation of a vector of reference levels that could be employed in both programme design and emergency intervention. Such a framework would exploit the potential role of resilience as a bridge between humanitarian and development interventions: the identification of thresholds and regime shifts can enable the former to target in needs population and avoid the catastrophic consequences of disasters, and at the same time supporting the latter in identifying key drivers of growth and development for specific samples of the population.

Extrapolating from weather to climate, with the usual *caveat* about external validity (Dell, Jones & Olken, 2014), this conclusion is also relevant in view of the impacts of climate change in developing countries. Being above the critical resilience threshold neutralizes the diverging effect of temperature: the logical policy implication is that adaptation policies in developing countries will need to focus on boosting resilience capacity to empower households to cope with climate change.

This study provides the first empirical evidence on the existence of household resilience thresholds in response to exogenous weather anomalies. Despite the above-mentioned *caveats*, we reckon the methodological contribution is innovative and should be further refined by future research. In this respect, extensions of this pilot approach to other countries, measures of resilience and types of shocks, as well as disaggregated threshold tests with respect to crucial determinants or single drivers of resilience, all represent promising research avenues for the near future.

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