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Temperature shocks, growth and poverty thresholds: evidence from rural Tanzania

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Abstract: Using the LSMS-ISA Tanzania National Panel Survey by the World Bank, we study the relationship between rural household consumption growth and temperature shocks over the period 2008 – 2013. Temperature shocks have a negative and significant impact on household growth only if their initial consumption lies below a critical threshold. As such, temperature shocks slow income convergence among households. Agricultural yields and labour productivity are the main transmission channels. These findings support the Schelling Conjecture: economic development would allow poor farming households to cope with climate change, and closing the yield gap and modernizing agriculture is crucial for adaptation to the negative impacts of global warming.

JEL classification: I32; O12; Q12; Q54

Key words: weather shocks; climate change; household consumption growth; rural development

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1 Introduction

Poorer countries are generally found to be more vulnerable to climate change and weather variability, but research is concentrated in richer countries. Many would suspect that poorer people are more vulnerable too, but research is scarce. As Tol (2016) notes: "The pattern of vulnerability that is seen between countries, is likely to hold within countries as well. This would strengthen the worries about climate change, but there has hardly been any research on the quantification of the intra-country distributional implications of the impacts of climate change".

We shed light on the following questions: is a climate-induced poverty trap plausible? Can it describe the growth dynamics of farmer households in a developing context? To this end, we use the empirical tools and models of development economics to examine the link between short-term household welfare dynamics and temperature shocks in rural Tanzania. Specifically, we employ a micro-growth model borrowed from the macro-growth literature, and test for convergence among households and for the significance of weather shocks as determinants of growth, while controlling for heterogeneity. Then, we test for the presence of consumption thresholds with regard to the impacts of temperature shocks. Finally, guided by previous theoretical and empirical literature, we test potential transmission channels, viz. health expenditure, labour productivity, crop yields and asset growth, that may explain heterogeneity of impacts and the lack of consumption smoothing.

This paper thus speaks to two distinct strands of research: the development literature on poverty traps, that investigates the issues of poverty persistence, growth divergence and multiple equilibria; and the emerging climate-economy literature that studies short-run elasticities of weather shocks impacts on growth. Our identification strategy looks at short-run weather variations to infer changes over longer periods, exploiting the tight linkages between short-run weather shocks and climate change (Dell, Jones and Olken, 2014).

Tanzania is an appropriate setting for such a study for a number of reasons. It is commonly accepted that the future impacts of climate change will disproportionately affect poorer and hotter countries (Tol, 2015), and especially people living in rural, remote and scarcely populated areas, whose main source of income is agriculture. Sub-Saharan Africa, in particular, has been identified as one of the most vulnerable parts of the world to climate change (IPCC, 2014). Tanzania is a poor and hot Sub-

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Saharan country, where in 2015 68% of the population lived in rural areas[1]. It is typically classified as a country under high risk from the impacts of future climate change: temperatures in the country are predicted to rise 2-4°C by 2100, "with warming more concentrated during the dry season and in the interior regions of the country" (Rowhani, Lobell, Linderman & Ramankutty, 2011). Ahmed et al. (2011) underline the importance of agriculture for the Tanzanian economy: "The importance of agriculture to the poor is particularly true for Tanzania, where agriculture accounts for about half of gross production, and employs about 80 percent of the labour force. Agriculture in Tanzania is also primarily rain-fed, with only two percent of arable land having irrigation facilities—far below the potentially irrigable share". Tanzania is also a country which exhibits quite large climatic diversity, as noted by Rowhani, Lobell, Linderman, and Ramankutty (2011): "on the Indian Ocean, the United Republic of Tanzania possesses a complex landscape, formed by the western and eastern branches of the East African Rift, resulting in substantial spatial variability in climate within the nation. The country's climate varies from tropical at the coast to temperate in the highlands". Last but not least, data availability: we use the Living Standard Measurement Survey (LSMS) – Integrated Survey on Agriculture (ISA) Tanzania National Panel Survey by the World Bank, a three-wave household longitudinal dataset covering the period 2008 – 2013.

What emerges is a sharp and striking heterogeneity: temperature-induced consumption shocks only affect the poorest households. The observed growth of rural households suffers from a negative and significant contemporaneous impact of temperature shocks only if their initial consumption level lies below a critical threshold. In other words, positive temperature shocks slow convergence among households, and enhance inequalities. The main transmission channels responsible for this heterogeneity appear to be agricultural yields and labour productivity. Additionally, no impact on asset growth is found, suggesting that asset smoothing is taking place and that poorest households choose to destabilize their consumption in order not to have to sell their assets, or that they do not have enough assets to sell to cope with the income reduction caused by temperature shocks.

Obviously, given the short-run nature of this dataset, our capacity to assess convergence is limited, and we can only cautiously infer long-run trends. Also, we do not directly test for the presence of multiple equilibria and hence for the existence of a poverty trap. Under a classic 'poverty trap' threshold, households are trapped in an equilibrium with permanently low income, whereas here we only check whether there is a consumption threshold above which temperature impacts turn insignificant, i.e. whether impacts disappear as households grow richer. Deceleration is not

[1] http://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=TZ

bifurcation, as noted by Dercon (2004) and Jalan and Ravallion (2002). Finally, external validity with respect to climate change is an issue, given the intrinsic difference between short-run weather shocks and long-run changes in climate.

The contributions of this paper are the following. First, it complements aggregate growth - climate empirics with available micro panel data, by providing evidence on the (short-run) micro causal relationship between weather anomalies poverty and growth. Second, it links the weather-economic growth literature with the development literature on poverty traps, by applying the tools and models of the latter to the research questions of the former. Third, it contributes to the development literature, by testing for consumption *vs* asset smoothing, which has been rarely been done according to Carter and Lybbert (2012)[2]; and by showing that, when controlling for temperature shocks (often ignored in development literature), precipitation impacts are insignificant and close to zero.

The rest of this paper is arranged as follows. Section 2 reviews the relevant literature. Section 3 illustrates the empirical framework and the identification strategy. Section 4 describes data and provides introductory descriptive statistics. Section 5 shows and comments the results of the empirical analysis. Section 6 conducts a host of robustness checks. Section 7 investigates the channels of the heterogeneity of impacts. Section 8 wraps up, illustrates the policy implications of the analysis with regard to climate change, adds *caveats* and concludes.

2 Literature review

The recent and growing body of empirical works focusing on the climate-economy relationship and its channels stems from the interest to try to understand and quantify the future impacts of climate change on human welfare. Dell, Jones and Olken (2014) review this literature and notice how old cross-sectional works (Dell, Jones, & Olken, 2009; Gallup, Sachs, & Mellinger, 1999; Nordhaus, 2006), whose validity is challenged by the risk of endogeneity and omitted variable bias, have recently been replaced by more appropriate and robust panel methods, both at the macro (Bansal & Ochoa, 2011; Burke, Hsiang, & Miguel, 2015; Dell, Jones, & Olken, 2012; Hsiang, 2010; Hsiang & Jina, 2014) and micro (Cachon, Gallino, & Olivares, 2012; Cachon et al., 2012; Deschenes & Greenstone, 2011; Graff Zivin & Neidell, 2014; Heal & Park, 2015; Niemelä, Hannula, Rautio, Reijula, & Railio, 2002; Schlenker & Lobell, 2010; Sudarshan & Tewari, 2013) level, which isolate the exogenous effect of weather variables on the economic outcome of interest. The main findings of this emerging

[2] "Unfortunately, much of the empirical literature has not tested consumption smoothing against a theoretically well-defined alternative"

literature are that weather affects economic activity and growth through a wide range of channels and that these impacts are substantially bigger and significant in poor countries[3].

Agriculture, health and labour productivity are among the most important transmission channels of such impacts. Several studies have investigate the relationship between crop yields and weather variability, starting from the very plausible assumption that extreme temperatures and rainfall above or below a certain threshold may have damaging consequences on crop yields, especially in developing countries whose agriculture is less modernized (Challinor, Wheeler, Craufurd, & Slingo, 2005; Feng, Krueger, & Oppenheimer, 2010; Guiteras, 2009; Levine & Yang, 2006; Li et al., 2010; Porter & Semenov, 2005; Rowhani et al., 2011; Schlenker & Lobell, 2010; Welch et al., 2010). Other works have provided theoretical underpinnings to explain how low crop yields and yield gaps could be one of the reasons why smallholder farmers are trapped in chronic poverty (Barrett & Swallow, 2006; Sachs, 2008; Tittonell & Giller, 2013).

Both the economics and epidemiology literatures have examined the impact temperature can have on morbidity and mortality, which in turn affect labour productivity and income (and *vice versa*). Empirical works such as, among the others, Barreca (2012), Burgess, Deschenes, Donaldson, and Greenstone (2011), Deschênes and Greenstone, (2011) and Goldberg, Gasparrini, Armstrong, and Valois (2011) have documented the effects of temperature and heat waves on health, particularly mortality, using panel methods. From a theoretical point of view, instead, the long-run relationship between health and climate has been explored by Strulik (2008) and Tol (2011).

Finally, a recent but already large micro literature (Cachon, Gallino, & Olivares, 2012; Cachon et al., 2012; Graff Zivin & Neidell, 2014; Heal & Park, 2015; Niemelä, Hannula, Rautio, Reijula, & Railio, 2002; Park, 2017; Sudarshan & Tewari, 2013) has found vast and significant effects of temperature anomalies on the productivity of workers, especially on those who work outdoor.

In parallel, the development literature looks at the impacts of weather shocks on household welfare, vulnerability and poverty traps. This literature uses weather variation as an instrument to study non-climatic relationships (to the extent that climatic variables are exogenously determined). While, in her pioneering work, Paxson (1992) found that unexpected rainfall shocks did not have serious welfare consequences for Thai farm households, because they used savings and dissavings to buffer consumption from income shocks, the partial insurance strategies adopted by poor farmers against a temporary shock could indeed imply a reduction in crop yields with potentially negative impacts on

[3] These panel estimates have then been employed and calibrated *ad hoc* in simulation studies on the impacts of future climate change (Lemoine & Kapnick, 2015; Moore & Diaz, 2015) to provide empirically-grounded impact estimates to be used in Integrated Assessment Models (IAMs), and overcome the critiques about the arbitrary choice of crucial parameters like the damage function and climate sensitivity (Pindyck, 2012, 2013; Stern, 2013; Weitzman, 2009, 2010).

consumption growth (Morduch, 1995; Townsend, 1995). This because households might not be able to smooth their consumption in response to income fluctuations due to credit or liquidity constraints (Hirvonen, 2016; Morduch, 1995; Rosenzweig & Wolpin, 1993). In this respect, uninsured risk may be a cause of poverty due to two distinct mechanisms, one *ex ante* or behavioural and one *ex post* (Dercon, 2004). The first can be explained as follows: since poorer farmers are generally risk-averse, uninsured risk determines *ex-ante* changing in behaviour that implies precautionary saving and/or other optimal strategies to avoid profitable but risky opportunities at the expenses of mean returns (Dercon, 1996, 2004; Elbers, Gunning, & Kinsey, 2007). Dercon (1996), analysing, through a theoretical model of risk-taking behaviours, the relationship between risk, crop choice and savings in rural Tanzania, finds that wealthier households engage in more risky but higher return activities than households with a poor asset base. The *ex post* impact, instead, is the one that materializes after a 'bad' state (Dercon, 2004): in this respect weather shocks are shown to have an impact on *ex-post* poverty too. In such a context, several theoretical models underline the issues of persistence to highlight that temporary shocks can affect long-term outcomes such as the process of income convergence among households (Carter, Little, Mogues, & Negatu Little, Mogues, & Negatu, 2007; Reis, 2009). This permanent effect of temporary shocks has been typically explained by asset smoothing (Barrett & Carter, 2013; Carter & Barrett, 2006; Carter Little, Mogues, & Negatu, 2007) or by the conservative behaviour of risk-averse households that shy away from investing in profitable but risky technologies (Reis, 2009).

Indeed, this is what has emerged from many empirical studies on household welfare dynamics: Fafchamps, Udry and Czukas (1998), using panel data for farming households in Burkina Faso, test the hypothesis that households keep livestock as a buffer stock to insulate their consumption from income fluctuations, but only find evidence for very limited consumption smoothing. Dercon (2004) himself, using panel data from Ethiopia during the period 1989 – 1997, finds that rainfall shocks had a substantial contemporaneous impact on food consumption growth, and also shows persistence of impacts, suggesting that rainfall shocks may have a long-lasting effect which goes beyond the welfare cost of short-term consumption fluctuations. His subsequent works in the same setting confirmed these results (Dercon & Christiaensen, 2011; Dercon, Hoddinott, & Woldehanna, 2005; Dercon & Krishnan, 2000). Carter, Little, Mogues and Negatu (2007) explore the asset dynamics of Ethiopian and Honduran households in the wake of environmental shocks, and find that household growth can be hit not just in the immediate aftermaths but also in the long-run, and that coping strategies adopted are costly and can be a source of divergence among households. Hirvonen (2016), using the Kagera Health and Development Survey (KHDS), spanning the period 1991-2009, shows how household consumption co-moves with temperature, and then uses temperature shocks as a proxy for income shocks to study long-term migration decisions in Tanzania.

Other studies have instead focused on the possibility of long-run impacts on household welfare from weather shocks. Hoddinott and Kinsey (2001) first, reviewing literature on household responses to weather-related shocks, note how what emerges is that "[...] some, but not all households can smooth consumption. In particular, households facing liquidity constraints have limited smoothing ability. For these households, therefore, income fluctuations will generate a welfare loss". Then, drawing on a panel dataset in Zimbabwe, they try to determine whether these shocks have only transitory or also permanent effects, by examining growth in the heights of young children. They discover droughts have a long-lasting impact on child growth, and that this impact is heterogeneous, i.e. greatest amongst children living in poor households. They notice how this points to the possibility of the intergenerational transmission of poorer health status resulting from drought shocks. Alderman, Hoddinott and Kinsey (2006) follow this path and explore the long-term consequences of shocks on individuals, starting from the observation that where temporary shocks have long-lasting impacts, utility losses may be higher, and finding analogous results.

The amount of evidence of both short-run and long-run impacts of weather shocks on household welfare, and the contradictory evidence on consumption smoothing, has been the spark for the development of another strand of literature, based on the concept of "poverty traps".

The concept of poverty traps has been proposed both in macro- as well as in microeconomics and is closely related to the idea of convergence in neoclassical economics. The assumption of diminishing returns is a crucial one in neoclassical economic growth: essentially, it implies that the incomes of poorer countries (households) will eventually 'catch up' over time with those of richer countries (households). The following empirical evidence on macro growth contradicted the assumed convergence hypothesis between countries, as Carter and Barrett (2006) describe, "within the macro growth literature, two alternatives to the neoclassical growth model have emerged to account for the observed pattern of divergence", namely the idea of club convergence (Baumol, 1986; De Long, 1988; Quah, 1996, 1997) and the concepts of thresholds and multiple equilibria (Azariadis & Drazen, 1990; Hansen, 2000; Murphy, Shleifer, & Vishny, 1989).

At the micro level, as Carter and Barrett (2006) argue, it may be that "As with nations, individuals may also have intrinsic characteristics (skills, savings propensities, discount rates, and geographic locations) that condition their desired level of accumulation and ultimate equilibrium level of well-being. However, there may also be analogues to the locally increasing returns to scale that generate multiple equilibria and thwart the ability of initially poor households to catch up and converge with their wealthier neighbours".

Starting from this hypothesis, an empirical literature has developed to try and detect the presence of thresholds and multiple equilibria at the micro level. The task is hard, as noticed by Barrett and Carter (2013), Carter and Barrett (2006) and Jalan and Ravallion (2002), due to the lack of sufficiently long panels at the household level in developing countries, which contrasts with the fact that convergence among households, as well as post-shock recovery, are long-run processes.

While it is thus difficult to empirically detect the presence of multiple equilibria, several studies have attempted to do so, and have provided evidence of at least significant persistency of poverty. These works can be divided in two categories. The first has focused on income and consumption growth as indicators of household welfare (Dercon, 2004; Jalan & Ravallion, 2002, 2004). Dercon (2004) only tests for, and discovers, persistence of shocks, but he cannot assert the existence of a poverty trap, as he explicitly states: "This is not the same as testing for the existence of a 'poverty trap' in the sense of the investigation of the threshold, below which there is a tendency to be trapped in permanently low income, from which no escape is possible except for by large positive shocks. Persistence within the time period of the data does not exclude permanent effects, but does not imply them either". Jalan and Ravallion (2002; 2004) draw from the standard growth literature to derive micro-based growth models and explicitly test for divergence due to spatial factors and geographic externalities, finding evidence which supports the notion of "geographic poverty traps", i.e. the idea that, *ceteris paribus*, the welfare of a household living in a well-endowed area grows while the one of an otherwise identical household living in an unfavourable geographic area stagnates.

The other, the so-called 'asset-based' approach, taking cue from the theoretical underpinnings provided by Barrett and Carter (2006; 2013), focuses on asset growth as the dependent variable of interest, arguing that looking at assets makes it possible to distinguish persistent structural poverty from poverty that passes naturally with time thanks to the growth process. This second empirical current is mainly represented by the works of Carter, Little, Mogues and Negatu (2007), who show that the idea of asset-based poverty traps is consistent with the post-shock growth experience in Honduras after Hurricane Mitch, and in Ethiopia after the drought of the late 1990s, while also providing empirical support for the concept of "asset smoothing" (opposed to the hypothesis of consumption smoothing), according to which poorer households with very low assets (typically, livestock), choose to voluntarily destabilize consumption not to sell assets and be caught in a poverty trap from which it would be almost impossible to recover; Carter and Lybbert (2012), who test the two alternative hypothesis of consumption and asset smoothing, and using a panel dataset from West Africa they apply threshold estimation techniques which provide support for asset, and not consumption, smoothing in response to external shocks; Barrett et al. (2006), who examine welfare dynamics in rural Kenya and Madagascar and again, mixing quantitative and qualitative evidence, find that poor households defend their critical asset levels through asset smoothing, even if this comes at the cost of an immediate reduction in consumption. Finally, Barrett and Swallow (2006) try to unify macro and micro literature on poverty traps by providing the theoretical framework of “fractal poverty traps”, in which multiple dynamic equilibria, caused by endogenous and / or exogenous conditions, exist simultaneously at multiple scales (micro, meso and macro) and are self-reinforcing through feedback effects.

The idea of poverty traps has also been proposed and tested for in the context of the debate on the long-run determinants of growth and development. The two main currents in this literature are the geography hypothesis, which draws from the hypothesis of environmental determinism put forward in Diamond (1999) and Huntington (1922), namely that climate and geography are the fundamental drivers of development, and has found qualified empirical support in the works of Alsan (2014), Andersen, Dalgaard, and Selaya (2016), Gallup et al. (1999) and Olsson and Hibbs (2005); and the institution hypothesis (Acemoglu, Johnson, & Robinson, 2000, 2001; Easterly & Levine, 2003; Rodrik, Subramanian, & Trebbi, 2004), which conversely endorses institutional determinism and stresses the primacy of institutions over geography as a determinant of long-run growth. As Dell, Jones and Olken (2014) observe, the fact that geographic characteristics and institutional quality are highly correlated makes it challenging to definitely settle the debate. In this context, Bloom, Canning and Sevilla (2003), Bonds, Keenan, Rohani, and Sachs (2010), and Strulik (2008) provide both theoretical underpinnings and empirical evidence for the idea of ‘climate-induced’ poverty traps, while Tol (2011) explores the long-run mechanisms (diseases, infant mortality, fertility, education) through which climate and climate change could widen or deepen poverty traps or even cause intergenerational poverty traps. Finally, from a sustainable development perspective, Haider, Boonstra, Peterson and Schlüter (2017) review the conceptualizations of poverty traps in different disciplines, and call for a more integrated approach capable of accounting for social-ecological interactions and feedbacks that generate poverty traps.

This large body of literature notwithstanding, Tol (2015) notes: “The literature on the impact of climate (change) on development has yet to reach firm conclusions. Climate change could moderate the rate of economic growth, but estimates range from high to low. More people may be trapped in poverty because of climate, but this effect could be large or small.”

3 Empirical framework and identification strategy

Our empirical framework belongs to the strand of the literature that looks at growth in developing countries by using micro-level data, drawing in particular on the works of Carter, Little, Mogues and Negatu (2007); Dercon (2004); Jalan and Ravallion (2002). We assess convergence by using a standard empirical growth model, in a framework borrowed from the macro literature (Mankiw, Romer & Weil, 1992), where growth rates are assumed to be negatively related to the initial income levels:

$$(1) \quad ln\, Y_{it} - ln\, Y_{it-1} = \alpha ln\, Y_{it-1} + \beta \Delta Temp_{gt} + \gamma \Delta Pre_{gt} + \Omega Z_{it} + \omega X_{it} + \mu_i + q_{it} + w_t + \theta_{rt} + \varepsilon_{it}$$

In this equation, the left-hand side variable is the annualised growth rate in annual household per adult-equivalent[4] consumption between t and t-1, and $ln\, Y_{it-1}$ is household per adult-equivalent lagged consumption[5]. The coefficient α, if negative and statistically significant, would indicate, on average, convergence among households.

In all our specifications, Y_{it} either denotes food consumption or total consumption.
The reason why we use two different dependent variables is that looking only at food consumption growth one may confound the impact of weather shocks with the effects of relative price changes. In fact, due to changes in the ratio between food *vs* non-food prices, food consumption may follow a different growth path from total consumption. While Dercon (2004), due to lack of data availability for non-food expenditure, had to largely limit his analysis to food consumption growth, we employ both to address this concern.
The inclusion of lagged consumption level as an independent regressor may raise concerns about endogeneity. However, endogeneity tests, based on the difference of two Sargan-Hansen statistics – one for the equation with the smaller set of instruments, where lagged consumption is treated as endogenous and instrumented with asset and education levels at t-1, and one for the equation with the larger set of instruments, where lagged consumption is treated as exogenous – do not reject the assumption of exogeneity of this variable (see Table A.1). Furthermore, the core findings do not change when we use other estimation methods (see Section 6) which treat lagged consumption level as endogenous.

This basic empirical growth model is augmented to investigate the potential impacts of weather shocks. $\Delta Temp_{gt}$ and ΔPre_{gt} are temperature and precipitation shocks, where 'shocks' mean

[4] We use an adult-equivalent scale that was already included in the dataset instead of a per capita measure, since per capita measures would underestimate the welfare of households with children with respect to families with no children, and the welfare of large households with respect to small households, as stressed in the Basic Information Document of the original LSMS-ISA surveys. Basic Information Documents for the surveys are available at the following link: http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,,contentMDK:23635561~pagePK:64168445~piPK:64168309~theSitePK:3358997,00.html

[5] Given the household fixed-effects model, we could not include initial consumption levels because they are time-invariant. Hence the choice of including lagged levels, which in a panel with only three waves is in practice very similar.

‘anomalies’ in the sense defined by Dell, Jones and Olken (2014), i.e. our weather variables are calculated as the level difference between their average values in the period between interviews and the long-run means, divided by the long-run standard deviation[6]. This means we assume that level changes matter not only in an absolute sense but also, more importantly, in terms of deviation from their long-run averages. Given we have a short-run panel and only limited climatic variation, this choice of the weather functional form suits better the nature of our data.

A common practice in the development literature on the relationship between growth and shocks is the fact almost all these works only include rainfall shocks in the empirical analysis, neglecting the potential role of temperature as a determinant of household growth. Indeed, climate literature (Auffhammer, Hsiang, Schlenker, & Sobel, 2013; Dell, Jones, & Olken, 2014) has warned against the risk of omitted variable bias when dealing with the effects of weather regressors, and recommends to always include at least both temperature and precipitation as independent variables. Since the two are closely correlated, excluding temperature, as commonly done in many empirical development works, may mean attributing to precipitation shocks an impact which could be actually due to temperature. We avoid this risk by including both.

To capture potential heterogeneity of impacts, we also interact weather shocks with dummies for being “poor” and for living in “hot” areas, as well as with dummies for initial consumption quartiles, following Carter, Little, Mogues and Negatu (2007)[7].

Other than weather shocks, we include two sets of control variables. Z_{it} is a vegetation time series which includes variables providing data on the start of the wettest quarter, average changes in greenness, and onsets of greenness increase and decrease. These vegetation variables were already included in the original World Bank data as part of the Integrated Survey on Agriculture (ISA); we chose to add them in the regression following the advice in Auffhammer, Hsiang, Schlenker and Sobel (2013) and Dell, Jones and Olken (2014): it is important to include a rich set of climatic variables in the regression (when available), given the risk of omitted variable bias due to the fact climatic variables are always highly correlated.

X_{it} are household controls, which include household size, the square of household size, the age of the household head and its squared term, a dummy for the gender of the household head, average years

[6] The subscript g indicates temperature and precipitation variabes are observed at the grid level.

[7] Incidentally, we considered the possibility of a quantile regression model as an alternative and complementary specification, but we ruled out this option because when quantile regression is combined with panel data and a fixed-effect setting, identification and estimation become complicated, since the quantiles of the difference are not equal to the difference in quantiles (Ponomareva, 2010), and interpretation of the coefficient of the treatment variable is altered (Powell, 2016). Estimation gets even worse in case of dynamic models and a small number of time periods, which entail even greater bias (Galvao, 2011; Koenker, 2004). Although some estimators have been proposed to deal with these issues (Galvao, 2011; Powell, 2016), there is not yet an established consensus in literature and empirical applications are rare.

of education among adults, the number of infants (i.e. less than 5-year old) and dummies capturing a variety of self-reported shocks, both idiosyncratic (illness and deaths of household members) and covariate (e.g. market) shocks. The inclusion of control variables reduces the risk of omitted variable bias and provides smaller standard errors in the estimates.

As for the other elements in the equation, μ_i are household fixed effects; q_{it} are quarter of year dummies to capture when the interview took place; w_t are wave dummies; θ_{rt} are region-year fixed effects, to allow for differentiated time trends in different regions and capture idiosyncratic local shocks, as suggested by Dell, Jones and Olken (2012); ε_{it} are error terms clustered simultaneously at the Enumeration Areas (EAs) and wave levels, following the two-way clustering recommended by Cameron, Gelbach and Miller (2011). EAs are the main stratification level in the NPS surveys and also the closest unit to the grid level where temperature and precipitation are observed; furthermore, in most rural areas, EAs are defined by village boundaries[8].

After finding heterogeneity, we try to detect a critical consumption threshold for the significance of temperature impacts. In order to do so, we employed the Hansen (2000) threshold estimator following the approach by Carter, Little, Mogues and Newatu (2007). This model distinguishes two impact regimes conditional to a critical value of lagged (pre-shock) consumption level:

$$(2) \quad ln\, Y_{it} - ln\, Y_{it-1} = \begin{cases} \alpha ln\, Y_{it-1} + \beta^{l} \Delta Temp_{gt} + \gamma \Delta Pre_{gt} + \Omega Z_{it} + \omega X_{it} + \mu_i + q_{it} + w_t + \theta_{rt} + \varepsilon_{it} & if\ ln\, Y_{it-1} \leq \sigma \\ \alpha ln\, Y_{it-1} + \beta^{u} \Delta Temp_{gt} + \gamma \Delta Pre_{gt} + \Omega Z_{it} + \omega X_{it} + \mu_i + q_{it} + w_t + \theta_{rt} + \varepsilon_{it} & if\ ln\, Y_{it-1} > \sigma \end{cases}$$

Where the superscripts *l* and *u* on the coefficient β indicate, respectively, the lower and upper regime of temperature impacts, conditional on a given threshold σ of lagged consumption level.

4 Data and descriptive statistics

The data used in this work are taken from two different sources.

Household data

Household data come from the Tanzania National Panel Surveys, part of the World Bank collection of household surveys known as Living Standards Measurement Study – Integrated Survey on Agriculture (LSMS – ISA). In particular, this panel consists of three surveys: 2008 – 2009; 2010-

[8] In their works on Tanzania, Hirvonen (2016) clusters standard errors at the village level, Bengtsson (2010) at the "cluster"-level, i.e. the main stratification unit and the level at which rainfall is observed. Given the absence of village location data due to confidentiality reasons, EA coordinates were the most appropriate choice for the clustering level.

2011; 2012-2013[9]. These three surveys have been cleaned and aggregated using household identification numbers to build a three-round panel. All the monetary values in the surveys have been deflated, in order to convert nominal values in real/constant values, using the Consumer Price Index (CPI) for Tanzania by the World Bank[10], and they are expressed in Tanzanian shillings at 2013 monetary values. Importantly, we only selected rural households in building the panel, dropping urban households for which confounding factors would have been more likely. After cleaning the data, we are left with a balanced panel of 1,585 georeferenced households. This panel includes data on household and, as part of the ISA questionnaire, vegetation time series and geographic variables, as well as data on crops and agriculture.

Finally, data on the monetary value of total crop production and other agricultural characteristics used in Section 5 have been developed by the FAO Rural Income Generating Activities (RIGA) Team starting from the household data contained in the survey questionnaires.

Weather data

Weather data are taken from NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2), which is a global, gridded data set based on retrospective analysis of historical weather data obtained from satellite images and weather stations (Rienecker et al., 2011). The dataset provides daily temperature measures aggregated into grids that are 1/2° in latitude x 2/ 3° in longitude (which corresponds roughly to 55 km x 75 km at the equator). As with all re-analysis products, the data set is a combination of observed and imputed data points, using observation where and when available, and physics-based interpolation where and when needed.

We aggregated in two ways. First, we computed long-run averages over the period 1980 – 2015. Second, we built average measures of weather variability during the period between interviews for each household. However, to better catch the weather conditions during the growing season, as suggested by Hirvonen (2016), we chose to exclude the summer months from the computations of both averages (namely, June, July, August and September)[11].

Hence, temperature at time *t* is average monthly growing season temperature in the period between t and t-1, expressed in degree Celsius. Precipitation at time *t*, instead, is calculated as average monthly growing season precipitation (in millimetres) in the period between t and t-1. Long-run average

[9] These data are available at:
http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,,contentMDK:23635561~pagePK:64168445~piPK:64168309~theSitePK:3358997,00.html

[10] http://data.worldbank.org/indicator/FP.CPI.TOTL?page=1

[11] See http://www.geog.ox.ac.uk/research/climate/projects/undp-cp/UNDP_reports/TanzaniaTanzania.lowres.report.pdf, where it is stated that "the 'short' rains [take place] in October to December and the long rains in March to May, whilst the southern, western and central parts of the country experience one wet season that continues October through April or May". In this way, given the intrinsic difficulty in exactly identifying rainy seasons months for households scattered across the whole country, we excluded the summer months which are never part of any rainy season in Tanzania.

temperature and precipitation represent respectively long-run average monthly growing season temperature and long-run average monthly growing season precipitation. Finally, as already specified above, temperature and precipitation *shocks* (or anomalies) at time *t* are defined as the level difference between their values at *t* and their long-run averages, divided by the long-run standard deviation.

We used latitude and longitude coordinates to link these gridded weather data to household data. Unfortunately, for confidentiality reasons we did not have access to the exact location of households, but only to the average of household GPS coordinates in each enumeration area (EA), for which a random offset within a 5-km range was applied for rural households. Such an offset range, anyway, is not an issue of concern for us given the medium resolution of our weather data.

Furthermore, given the risk of incorrect inference when dealing with historical weather data, emphasized by Auffhammer et al. (2013), as a robustness check we also run a sensitivity analysis for our results by using a different source of weather data, where temperature data come from the *CRUCY Version 3.23* by the Climatic Research Unit (CRU) of the University of East Anglia (CRU, 2016), and have a resolution of 1/2° in latitude x 1/2° in longitude, and rainfall data come from the same NPS Dataset as part of the ISA module, and they contain data on total rainfall in the wettest quarter within 12-month periods starting in July previous to each round.

Descriptive statistics

Table 1 provides descriptive statistics for the main variables employed in the empirical analysis. Annualised average total and food consumption growth rates are both negative: they decreased on average by about 1.4 and 1.7 percentage points each year. However, the standard deviation is large for both variables, indicating heterogeneity in the growth paths experienced by rural households. Both temperature and precipitation anomalies were, on average, positive in the timespan considered, but for them as well it is worth noting the huge standard deviation, suggesting substantial heterogeneity in the weather conditions experienced by households living in different geographical areas.

5 Regression results

Tables 2 and 3 report the results from estimating Equation (1). First, the hypothesis of convergence among households is confirmed: growth rates are negatively related to ‘initial’ consumption levels, i.e. poorer household grow faster. As for the weather variables, Column 1 shows that, on average and *ceteris paribus*, temperature (precipitation) shocks have a slightly negative (positive) but not significant impact on growth.

Column 2 controls for heterogeneity of impacts, by interacting both temperature and precipitation with a dummy for being “poor”, i.e. a dummy with value 1 for households with below median initial food (in Table 2) or total consumption (in Table 3). Defining a household as “poor” is of course a relative concept in a context like rural Tanzania. We check for heterogeneity of impacts with respect to the poorest amongst the poor. Including these interactions qualitatively changes the results: temperature shocks now have a positive and weakly significant impact for the “non-poor” households, but a large, negative and significant (at the 5 percent level) impact on household growth for “poor” households, and this holds for both dependent variables (food and total consumption growth). Interpreting these results with respect to the within-standard deviation of temperature shocks (0.237), one standard deviation increase in temperature anomalies decreases household per-adult equivalent food consumption growth by about 2.76 %, and household per-adult equivalent total consumption growth by approximately 2.21 %, *ceteris paribus*, for households defined as “poor”. Rainfall impacts are insignificant. Given the presence of heterogeneity with respect to initial consumption, in Column 3 we also check for heterogeneity by interacting shocks with a dummy for living in “hot” areas, which takes value 1 for households living in an area with above mean long-run average monthly growing season temperature. Although the interaction between temperature shocks and the dummy for “poor” households stays unchanged in sign, magnitude and significance, the total effect of temperature shocks on poorest households is now slightly smaller and less significant. The interaction between temperature shocks and a dummy for households living in hotter areas is small and negligible, and so the total effect. Living in a hot area has a positive (and significant, but only in Table 3) impact on growth, but this is very likely due to the fact the hottest areas in Tanzania (coastal regions and Zanzibar) are also the richest ones. Temperature impacts on growth are always larger on food consumption growth than on total consumption growth, consistently with the fact that most households are subsistence farming households. This will be additionally addressed in Section 7, where the channels of the heterogeneity will be investigated.

Finally, Column 4 in both Tables 2 and 3 explores more in detail the relationship between consumption levels, temperature shocks and their impact on growth, by interacting the lagged consumption term (food consumption in Table 2, total consumption in Table 3) with temperature shocks. The results are consistent with the previous findings: the process of convergence is unaltered, the coefficient for temperature shocks is negative and statistically significant, the interaction between lagged consumption and temperature shocks is positive and statistically significant at the 1 percent level, suggesting that the impacts from temperature shocks tend to decrease as households grow richer. Figures 1 and 2 show the implications of the results in Column 4 for, respectively, Table 3 and 4. They show the marginal effect of temperature shocks at different lagged consumption levels. When households have a sufficiently high level of pre-shock consumption, impacts from temperature shocks turn first zero and then eventually positive.

Tables 4 and 5 take a closer look, by interacting weather shocks not with a dummy for being “poor”, but with dummies for initial consumption quartiles. The results, consistent between tables, reveal even further heterogeneity: as can be seen in Column 1 of both tables, households belonging to the poorest initial quartile suffer from a large, negative and statistically significant impact of temperature shocks, while the second and third quartiles do not, and growth for households in the upper initial quartile is positively and significantly affected, revealing heterogeneity in sign rather than size.

This core finding is not altered when including the interaction for living in an "hot" area, as shown in Column 2 of both tables. Finally, impacts due to precipitation shocks are always insignificant.

In sum, depending on initial conditions, the impacts of temperature shocks on household growth is sharply heterogeneous across quartiles, and poorest households are the only ones to be significantly and negatively affected.

This contrasts with the implications of the negative and significant coefficient of the lagged consumption term: while there seems to be an ongoing process of convergence among households, temperature shocks go in the opposite direction, slowing growth of the poorest households while bolstering growth for the richest ones.

However, we have not precisely identified thresholds of consumption that entail regime changes for temperature shocks. We just interacted shocks with arbitrary dummies that capture heterogeneity, but these choices are arbitrary. They are not driven by the data.

To overcome this drawback, following Carter, Little, Mogues and Negatu (2007), we present the results for a panel threshold model using the so-called Hansen (2000) estimator, as implemented in a fixed-effect setting by Wang (2015).

Threshold models identify structural breaks in the relationship between variables. In our context, we are looking for thresholds of pre-shock consumption above or below which there is a structural break in the impact of temperature shocks, as illustrated in Equation (2).

Temperature shocks are the regime-dependent variable.

Looking at the previous regressions, it appears there is not just one threshold, but two separate and distinct thresholds. The first is the threshold above which impacts turn negative but statistically insignificant; the second the one above which impacts turn positive and significant. We are therefore looking for two, and not just one, consumption level thresholds.

In Table 6 we present the results for this double threshold model using the Hansen estimator.

In Column 1 the dependent variable is food consumption growth, in Column 2 total consumption growth. As hypothesized, we find two thresholds and three regimes: a first threshold below which impacts of temperature shocks are negative and strongly significant, and above which they turn insignificant; and a second threshold from which impacts turn to being positive and strongly significant. Although the positive impact above the upper threshold is much bigger than the negative impact below the lower threshold, the percentage of observations falling below the lower threshold is much higher (47 % and 24 %, respectively, for food and total consumption) than the percentage of observations above the upper threshold (around 13 % in both cases), revealing it is a smaller group of better-off households that drives the significance of the positive impact for the upper quartile. Furthermore, the significance of this positive impact will prove to be sensitive to specification and not supported by evidence on the transmission channels (see Sections 6 and 7).

Both thresholds, for both dependent variables, are statistically significant at the 1 percent level, as reported in the threshold tests.

After re-converting logs into monetary values, for food consumption we find a lower threshold of approximately 483594 Tanzanian shillings or, expressed at 2013 Purchasing Power Parity (PPP) values[12], 803 dollars; and an upper threshold of approximately 917126 Tanzanian shillings, i.e. about 1523 dollars; for total consumption, instead, the two thresholds are approximately 2434956 Tanzanian shillings, approximately 723 dollars, and 1219559 Tanzanian shillings, or about 2026 dollars.

Temperature shocks, in sum, slow convergence, and may even cause divergence. This has strong distributional implications and raises the issue of which channels and transmission mechanisms could be responsible for such a sharp heterogeneity of impacts. These questions are addressed in Section 7 but, first, Section 6 conducts a number of tests to assess the robustness of our results to different sensitivity analyses, and make sure our findings are not driven by the chosen identification strategy or by properties of the data used.

6 Robustness checks

We explore the robustness of our results with respect to spatial autocorrelation, different weather data and different estimation strategies.

A. Conley (1999) standard errors

It is well known that both economic growth and temperature are spatially autocorrelated. One could thus argue that confidence in our results are inflated because we fail to take this into account. We therefore re-run the quartile regressions from Tables 4 and 5 correcting for Conley (1999) standard errors, which are robust to both spatial autocorrelation and heteroskedasticity. The computation of the Conley standard errors is based on a weighing matrix that places greater weight on observations that are closer to each other, and the weights decay to zero after a pre-specified distance cut-off is

[12] For the PPP conversion factor in 2013: https://data.worldbank.org/indicator/PA.NUS.PPP?locations=TZ .

met. We use the following cut-off points: 50, 75 and 100 km. These regressions are reported in Table A.2 in the Appendix: in Column 1 the dependent variable is food consumption growth, in Column 2 is total consumption growth. The core results are basically unchanged: our findings are not weakened when correcting for spatial autocorrelation and spatially-robust standard errors.

B. Different weather data

Results could be driven by properties of the weather data, the selection of weather stations, the homogenization of the data, and the imputation of missing observations. Auffhammer et al. (2013) highlight the risk of using reanalysis data, since reanalysis is conducted with models that, like economic models, are imperfect and contain systematic biases. Moreover, they recommend to always check that results also hold when using a different data source.

For temperature data, we use the *CRUCY Version 3.23* by the Climatic Research Unit (CRU) of the University of East Anglia (CRU, 2016), a gridded dataset which has a resolution of 1/2° in latitude x 1/2° in longitude. While the MERRA-2 Reanalysis data combine information from ground stations, satellites, and other sources with a physical climate model to create gridded weather data products, CRU data are gridded data, statistically interpolated from ground stations (Dell, Jones and Olken, 2014). Table A.3 in the Appendix provides descriptive statistics for the CRU temperature data. ΔTemp is on average almost 5 times bigger compared to average temperature shocks in Table 1. Despite this, the correlation between the two temperature series is more than 90 %.

As for rainfall, we use precipitation data that come from the NPS Dataset as part of the ISA module, and our variable is now average total rainfall in the wettest quarter before the interview. These data were taken from the NOAA datasets on African Rainfall Climatology (ARC) data. ARC data blend rain gauge measurements and InfraRed (IR) satellite information to render a daily, high resolution (0.1°x0.1°) gridded estimate covering the Africa continent.[13] Since data on the long-run standard deviation are not included, we simply define rainfall shocks as level differences from the long-run average. The results are reported in Table A.4 in the Appendix. The pattern of heterogeneity holds, and the effect size is similar, both for the negative impacts on households belonging to the poorest quartile and for the positive impacts for households belonging to the richest quartile. Precipitation shocks are now often significant, and seem to point to heterogeneity as well, but they are also quite sensitive to specification, and since we detect no significant precipitation impacts on crop yields using the same data source (see Section 7), we conclude their significance here is likely incidental.

In sum, our main findings hold when using a different source of weather data.

[13] Data can be found at: ftp://ftp.cpc.ncep.noaa.gov/fews/newalgo_est_dekad/ .

C. Hausman – Taylor regressions

Following Dercon (2004), we repeat our empirical analysis using the Hausman - Taylor (1981) model, which involves partitioning the time-invariant and time-varying vector of variables in two groups each, of which one group of variables is assumed to be uncorrelated with the fixed effect.

The Hausman-Taylor model, being a random-effect model for panel data allows us to include time-invariant variables in our regressions, thus extending identification beyond the within-household intertemporal variation. In particular, in addition to region dummies[14], we add distance to the nearest major road and long-run averages for our weather variables. Given the strong partitioning assumptions implied by this estimation strategy, we adopt a cautious approach, following Dercon (2004): lagged consumption terms and all household controls (with the exception of self-reported covariate shocks) are treated as time-varying endogenous variables; dummies for consumption quartiles are treated as time-invariant endogenous; all weather and geographic variables, both time-varying and time-invariant, are treated as exogenous.

Results can be found in Table A.5 for food consumption growth (Column 1) and total consumption growth (Column 2)[15]. Despite stark differences between estimation strategies, the overall picture is consistent with the results from the fixed-effect specification: the convergence process is confirmed, and temperature shocks only harm poorest households, although here also the second poorest quartile is negatively and significantly affected. Interestingly, while the coefficient for the upper quartile is still positive, its magnitude has decreased and its significance has disappeared in Column (1) and diminished in Column (2). This will be further addressed in the next robustness check. As above, there is no statistically discernible effect of rainfall shocks, while both long-run temperature and precipitation have a positive impact on both food and total consumption growth.

D. Two-Step Difference GMM

As a third, and last, estimation strategy we employ the two-step difference GMM, first proposed by Arellano and Bond (1991). This estimation method controls for the dynamic panel bias due to the presence of the lagged dependent variable and is especially recommended for dynamic panels which exhibit the following characteristics (Roodman, 2006): "1) "small *T*, large *N*" panels, meaning few time periods and many individuals; 2) a linear functional relationship; 3) one left-hand-side variable that is dynamic, depending on its own past realizations; 4) independent variables that are not strictly

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[14] Region dummies were included separately from year dummies because the estimation of Hausman-Taylor regressions requires the presence of time-invariant exogenous variables.

[15] Incidentally, although not reported in Table 7, distance from the nearest major road always has a large and significant effect on growth, consistently with what found by Dercon (2004) in rural Ethiopia, hinting at public infrastructure as another source of divergence among households.

exogenous, meaning they are correlated with past and possibly current realizations of the error; 5) fixed individual effects; and 6) heteroskedasticity and autocorrelation within individuals but not across them". Arellano–Bond estimation transforms all regressors by differencing, and uses the generalized method of moments (GMM) as the estimation method. Importantly, it adjusts for the potential bias caused by the inclusion of a lagged dependent variable as a regressor. The Hansen-J tests reported ensure the specification is valid, and the standard errors are corrected using Windmeijer (2005) adjustment procedure. In distinguishing between endogenous and exogenous variables, we followed Dercon (2004) and Jalan and Ravallion (2002): lagged consumption terms and all household controls are treated as endogenous, and weather shocks and vegetation time series as exogenous.

The results for the two-step Arellano-Bond GMM estimation are reported in Table A.6.

They are consistent with the fixed-effect and Hausman-Taylor regressions discussed above: heterogeneity of impacts from temperature shocks is confirmed, with a strong and significant impact only for households belonging to the poorest initial quartile. Similarly to the Hausman-Taylor model, temperature impacts for households in the richest quartiles are still positive, but much smaller and not significant anymore. This means that the significance of the positive impact detected using the fixed-effect model is not robust to different estimation strategies, and should be interpreted with extreme caution. Finally, precipitation is insignificant.

7 Transmission channels and mechanisms

Having demonstrated robustness, we now explore why there is such a sharp heterogeneity of impacts and perhaps even a *change in sign* of impacts on household growth depending on initial consumption. We shed light on this question by investigating four main channels: health expenditure, labour productivity, agricultural yields, and asset-smoothing.

A. Health expenditure

There is a large body of literature on the impacts of extreme temperature and heat waves on health and mortality (see Section 2). In our context, it could be temperature shocks on consumption growth appear, at least partially, through the health channel: temperature could affect health and hence productivity, and this in turns may affect income and subsequently consumption.

We test this mechanism by using the baseline specification set out in Equation (1) with a different dependent variable: instead of consumption growth, we now use as Y_{it} the ratio between health expenditure and total expenditure[16]. The expected sign of the relationship is the opposite: in response

[16] To calculate the growth rate of this ratio, we increased both per a.e. health and total expenditures by the same small increment (the equivalent of a US dollar) for all households.

to temperature shocks, the growth rate of the ratio should increase. Table 7, Column 1 partially supports our hypothesis: temperature shocks have a positive (but not significant) impact on the growth rate of the health expenditure / total expenditure ratio. Furthermore, to justify the pattern of heterogeneity, one would expect this ratio to increase significantly more for households belonging to the poorest quartile. As reported in Column 2, this is not the case: the impact is small and insignificant for all quartiles, and the sign is not the expected one. Hence, either the health channel is not responsible for the heterogeneity we find, or there is a transmission mechanism which is ongoing but cannot be caught given the limitations and short-run nature of our data. Column 3 shows that living in a hot area has a large, positive and significant effect on the growth rate of the ratio of health to total expenditure. In other words, if the weather is anomalously hot, people spend more on health care.

B. Labour productivity

As reviewed above, labour productivity is affected by weather anomalies.

In a context like rural Tanzania, a large share of workers is involved in outdoor work, primarily in farming. Outdoor work is more exposed to heat waves, and agriculture in Tanzania is still largely traditional and thus still involves a lot of manual labour. These characteristics make workers in rural areas vulnerable to stress from temperature shocks, but there could also be significant differences in farmers' characteristics that entail heterogeneity. Labour productivity may thus help explaining the heterogeneous impacts on consumption growth.

We created a rough measure of agricultural labour productivity by dividing the monetary value of household total crop production (taken from the FAO Rural Income Generating Activities (RIGA) Team Database[17]) in the 12 months before the interview by the number of family members engaged in agricultural activities in the 12 months before the interview. We are aware this measure represents a rough and only approximate proxy of (agricultural) labour productivity, stemming from one of the more general definitions of labour productivity as the ratio between total output and number of employed persons, but it is also the only one that we could get[18]. Consequently, our left-hand side variable is the growth rate of (agricultural) labour productivity between t and t-1[19]. Analogously to Equation (1), we regress this dependent variable on lagged agricultural labour productivity, temperature and precipitation shocks as well as controls and fixed effects. Since preliminary endogeneity tests (see Table A.7) did not reject the assumption of exogeneity of the lagged dependent variable, the model was estimated using two-step difference GMM.

[17] The FAO-RIGA Database can be found at: http://www.fao.org/economic/riga/riga-database/en/.

[18] Another shortcoming is that we only investigate the aggregate impact, without disentangling the impacts between labour supply and labour demand. Unfortunately, such refinements go beyond the limitations of our data.

[19] We added a small amount (the equivalent of a US dollar) to labour productivity values of all households not to lose observations with zeros when calculating growth rates.

Results are reported in Table 8. Column 1 shows average impacts. Temperature anomalies have a large and significant impact on the growth rate agricultural labour productivity. One within-standard deviation increase in temperature shocks decreases agricultural labour productivity growth by approximately 5.61 %, on average, *ceteris paribus*. Column 2 disentangles this aggregate impact across initial consumption quartiles: there is a large and significant negative effect on the poorest quartile, while impacts are negative but not significant for the other quartiles. Precipitation shocks are insignificant. This overall picture is consistent with the consumption growth regressions, and confirms labour productivity as one of the transmission channels responsible for the heterogeneity of impacts, but not for the sign change.

Why is there such a discrepancy of impacts on agricultural labour productivity growth across quartiles? Tables A.8 reports some descriptive statistics that can help clarifying this issue. It shows the average Agricultural Wealth Index for the four initial consumption quartiles. The Agricultural Wealth Index was again taken from the FAO-RIGA Database, and is a specific aggregated index based on a factor analysis of the agricultural assets and technologies used by rural households in the sample. In this context this is useful because it also proxies for the use of technologies that decrease the need for manual labour. The average index is more than three times higher for the upper quartile compared to the poorest quartile, although oddly very low for the third quartile .

Additionally, Table A.9 reports the percentage of households, across quartiles, for which farming was not the main source of income in at least two waves. According to our hypothesis above, the less households depend on farming activities, the less they work outdoors, and the lower the impact on labour productivity. Farming was the main source of income for about 81% of households in the poorest quartile. This share falls and, for the richest quartile, two-thirds of households depend on farming as the main source of income. This further enhances the influence of weather variability on the labour productivity of poorest households compared to that of the wealthier households.

Aware of the limitations of our labour productivity measure, we find an heterogenous impact on the growth rate agricultural labour productivity, which partially explains heterogeneity of impacts on consumption growth. This impact on labour productivity may have directly affected income or also entailed an indirect effect through crop yields, as Sudarshan & Tewari (2013) hypothesize: “Observed productivity losses in agriculture that have been attributed by default to plant growth responses to high temperatures may in fact be partly driven by lower labor productivity”. Of course, the opposite may also be true: impacts on agricultural labour productivity may be driven by losses in crop yields.

C. Crop yields

Following the vast literature on the impacts of temperature on crop productivity (see Section 2), we investigate the agricultural yield channel to explain heterogeneity of impacts on consumption growth.

Crop yields are defined as quantity produced (in kilograms) divided per hectare of cultivated land. Thanks to the ISA module in the original dataset, we had access to crop data for the two rainy seasons (long and short) preceding the interview month. In investigating the impacts of weather shocks on crops, we must also take into account the possibility of non-linear effects, given the apparent inverted-U and non-linear relationship between temperature and plant growth (Dell et al., 2014; Hirvonen, 2016; Schlenker & Roberts, 2009). In order to do so, we draw from Ahmed et al. (2011), Hirvonen (2016), and Rowhani et al. (2011) works on Tanzania and adopt a specific temperature measure, the number of growing degree days (GDDs) (Schlenker & Roberts, 2009) in the twelve months preceding the interview month. Following the procedure implemented by Hirvonen (2016), we took daily minimum and maximum temperatures from the MERRA-2 data and approximated the diurnal temperature distribution by interpolating between the minimum and maximum temperature values using a sinusoidal curve. Growing degree days are then measured by the time of exposure to a certain temperature range. As in Hirvonen (2016), we set the lower bound to 8°C and the upper bound to 34°C. Exposure to temperatures above 34°C is considered harmful for agricultural yields[20]. In our regressions we use a spline function of the GDD variable. The first part of this variable captures temperature exposure between 8-34°C and the second exposure to temperatures above 34°C. We included average total precipitation during the two wettest quarters before the interview and its squares, using the alternative ARC rainfall data (cf. Tables A.3 and A4), because they use the actual household plot location.

Table 9 reports the results for this specification. The dependent variable is average crop yield during the previous two rainy seasons. In Column 1 we only look at the aggregate impact. The estimates suggest that it is exposure to extreme temperatures (above 34°C) which is harmful for crop yields. , In Column 2 we check whether this negative effect mainly comes through maize and paddy, two of the most important crops in the country, as suggested by previous literature on the impacts of temperature on crop yields in Tanzania (Ahmed et al. 2011; Rowhani et al., 2011).

Therefore, we include interactions with a dummy for ‘Maize & paddy non-specializers’, a dummy with value 1 for households in which maize and paddy account for less than 50% of total crop production in a given wave[21]. As expected, negative effects on crop yields from extreme temperatures are driven by impacts on maize and paddy, and disappear if households are not specialized in the cultivation of these two crops. In Column 3 we decompose the aggregate impact of GDDs by looking at impacts across initial consumption quartiles. Rainfall impacts are close to zero and insignificant. Impacts of GDDs between 8-34°C is essentially zero for all four quartiles. Exposure to extreme temperatures (above 34°C) has negative and strongly significant impact on crop yields of households

[20] Descriptive statistics on GDDs can be found in the Appendix, Table A.10.
[21] See Table A.11 for descriptive statistics of this dummy.

in the poorest quartile, a negative and insignificant impact on crop yields of households in the second and third quartiles, and a positive but insignificant impact on crop yields of households in the upper quartile. These results are consistent with the pattern of heterogeneity of temperature shocks on consumption growth.

Why are there such big differences in the impacts from extreme temperatures on crop yields across quartiles? Table A.12 reveals that richer households produce more crops (Column 1) and have more productive plots (Column 2). The heterogeneity of impacts can thus be explained by the fact that richer households are advantaged by better agricultural assets, technologies and soil quality, which make them less vulnerable to the negative impacts entailed by temperature shocks, which conversely have serious welfare consequences for poorest households.

We have yet to explain the sign change for the upper quartile. The use of irrigation is still very limited (Table A.13) and so the use of inorganic fertilizers (Table A.14), but richer households show better conditions. Tables A.15-A.18 in the Appendix show data taken from the ISA module on the use of 'improved' seeds for maize and paddy. Improved seeds are more drought-resistant and can mitigate the negative impacts of extreme temperatures. Tables A.15 and A.16 show that the use of improved maize seeds sharply differ across consumption quartiles. Tables A.17 and A.18 reveal the same pattern with regard to the use of improved paddy seeds.

D. Asset smoothing

We have established that the main channels that account for the heterogeneity of impacts on consumption growth are agricultural yields and labour productivity. But we did not explain yet why households are not smoothing consumption by drawing on their assets. Drawing from previous theoretical and empirical literature (Barrett et al., 2006; Barrett & Carter, 2013; Carter & Barrett, 2006; Carter et al., 2007; Carter & Lybbert, 2012), we test the two alternative hypothesis of consumption *vs* asset smoothing by repeating the baseline specification but using, as an alternative dependent variable, asset growth instead of consumption growth. Our measure of assets is Tropical Livestock Units (TLUs), again taken from the FAO-RIGA Dataset. Descriptive statistics for TLUs is reported in Table A.19: the gap in TLUs per adult-equivalent across quartiles is evident.

The dependent variable, therefore, is now annualised percentage change in (ln) per a.e. household TLUs between t and t-1[22]. Table 10 reports the results. In Column 1 we can see that, while convergence among households is confirmed, temperature shocks have, on average, a negative but

[22] To calculate asset growth and use logarithms, since many households have no assets at all and this implied the presence of many zeroes in the data, we followed the method implemented in Carter, Little, Mogues, and Negatu (2007) and increase all livestock assets per adult-equivalent by the same small increment (namely the minimum value in the sample above zero).

not significant impact on asset growth. In Column 2, where we decompose the impacts by consumption quartiles, impacts are always negative but we do not find any significance.
These findings imply several considerations. First, it was a good choice to look at consumption growth instead of asset growth, following the reasoning in Carter, Little, Mogues and Negatu (2007), who argued that in the context of weather shocks such as droughts, characterized by a gradual onset and a prolonged effect (differently from the immediate disruption entailed by environmental shocks such as hurricanes or typhoons), impacts on welfare growth could appear through consumption and not through assets. Indeed, had we chosen asset growth as the dependent variable, we would have found no impacts at all. Second, poorest households in our sample could be performing asset-smoothing, i.e. they might be choosing of voluntarily destabilize consumption and hold on to their livestock, in order not to sell them and then fall in a poverty trap from which there could be no recovery. This is consistent with what Carter, Little, Mogues and Negatu (2007) find for Ethiopia, where they note that "poor households seek to defend their assets in the face of successive droughts rather than liquidate them and perhaps limit their subsequent chances of recovery.". Alternatively, selling livestock may entail a social stigma. In any case, we are prone to assert that, for the poorest households in our sample, asset smoothing is probably taking place, while the choice of using assets as buffer stocks, one of the main risk-coping strategy hypothesized in literature, was either not adopted or not effective during the survey period (Kazianga & Udry, 2006; Morduch, 1995).

8 Discussion and conclusion

Using the LSMS-ISA Tanzania Panel Surveys by the World Bank, we find a causal relationship between temperature shocks, household consumption growth and poverty in rural Tanzania. There is heterogeneity of impacts of temperature shocks: household consumption growth is affected only if initial consumption levels lie below a critical threshold. This is explained by the impacts of temperature anomalies on two interrelated transmission channels: labour productivity and, more importantly, crop yields. Richer and poorer households differ not only in that the former have more diversified incomes and are less engaged in outdoor farming activities, but also in yields and other differences in agricultural characteristics. Such differences among households may also be related to *ex-ante* risk-managing behaviours (Dercon, 2004), e.g. the conservative behaviour of the poorer risk-averse households that shy away from investing in profitable but risky technologies (such as modern agricultural inputs) and stick to low-risk, low-return activities, as indeed Dercon (1996) the case in rural Tanzania (Dercon, 1996). Or, poor households lack access to these technologies because of credit and liquidity constraints.

Importantly, while the negative effect for households below the lower threshold is robust, the positive impact above the second threshold is not, either in size or significance, across different estimation methods such as the Hausman-Taylor random-effect model and two-step difference GMM. Furthermore, the analysis of the transmission channels found no evidence of a significantly positive impact. While it may be that richest households take advantage from the negative impacts on poorest households by earning more from their crops, this explanation is not supported by sufficiently robust empirical evidence. In any case, temperature shocks have a heterogeneous *ex-post* impact which slows the process of convergence and enhances inequalities. These micro results are consistent with those found on the relationship between growth, temperature shocks and poverty by macro studies (Dell, Jones & Olken, 2012; Letta & Tol, 2016).

However, these findings must be interpreted with caution for a number of reasons, the first being the nature and limitations of the data. We use a six-year panel with only three rounds, so we can only estimate a short-run elasticity between temperature shocks and growth. The difference in mean between observed and long-run temperatures is small (cf. Table 1), so our period of study did not see, on average, large weather variability. This could explain the absence of a significant average impact. Severe droughts may well have much more pervasive consequences. However, even such extreme scenarios are unlikely to overturn the core finding that it is the poorest households who suffer more from the negative impacts of temperature shocks.

Second, convergence is a long-run process. Even though we observe convergence in this short-run panel, we can only infer about long-run convergence, but not directly test for it. In the future, the availability of longer household-level panels for developing countries could alleviate these issues, enabling further research to test whether these findings, emerged from short-run elasticities, also hold in the medium or long run. External validity is also an issue: weather variations are *not* climate variations: climate change is a long-run phenomenon in which other factors, as intensification of impacts, global non-linear effects and adaptation, could completely alter the nature and magnitude of the current elasticities (Dell, Jones and Olken 2014).

Third, the consumption thresholds we detected, other than being intrinsically relative and data-driven, are not thresholds in the sense of the existence ‘poverty traps’, below which households are permanently trapped in low income. Temperature shocks have a diverging effect which enhances inequalities and slows the convergence process, but does not reverse it. Making all households reach the critical threshold level above which impacts turn insignificant, would make this source of divergence disappear. There are no multiple equilibria, but rather different regimes of impacts separated by pre-shock consumption thresholds. Rather than a climate-induced poverty trap, whose potential existence was the research question at the heart of this work, if anything we could define this relationship a poverty-induced climate trap.

These *caveats* notwithstanding, we reckon that development and poverty reduction should be key and paramount elements of any climate policy, especially in vulnerable contexts like rural Tanzania, and that inequality of impacts will be, within countries other than between countries, the first and foremost challenge posed by climate change. Extrapolating from weather to climate, such a qualitative finding is particularly relevant to climate change policy. Sub-Saharan Africa is one of the most vulnerable parts of the world to the threats posed by climate change (IPCC, 2014). The so-called Schelling Conjecture (Schelling, 1992 & 1995), i.e. that economic development would reduce vulnerability to climate change, and Schelling's point that the need for greenhouse gas abatement cannot be separated from the developing world's need for immediate development (Schelling, 1997), find empirical support in the results of this work. More broadly, these results increase the concerns over the issue of the distributional implications of future impacts, because they show that inequalities of impacts hold at the micro level as they do at the macro level. If the impacts of temperature shocks decrease as households grow richer, growth is the key for rural Tanzanian households: diversifying income sources, reducing outdoor work, modernizing agriculture, closing the yield gap and using drought-resistant seeds would all make households less vulnerable to the negative impacts of weather shocks, and less dependent on climate.

Bibliography

Acemoglu, D., Johnson, S., & Robinson, J. A. (2000). The colonial origins of comparative development: An empirical investigation. *American Economic Review*, 91(5), 1369-1401.

Acemoglu, D., Johnson, S., & Robinson, J. A. (2001). Reversal of fortune: Geography and institutions in the making of the modern world income distribution. *The Quarterly Journal of Economics*, 117(4), 1231-1294.

Ahmed, S. A., Diffenbaugh, N. S., Hertel, T. W., Lobell, D. B., Ramankutty, N., Rios, A. R., & Rowhani, P. (2011). Climate volatility and poverty vulnerability in Tanzania. *Global Environmental Change*, *21*(1), 46–55.

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long term consequences of early childhood malnutrition. *Oxford economic papers*, *58*(3), 450–474.

Alsan, M. (2014). The effect of the tsetse fly on African development. *The American Economic Review*, *105*(1), 382–410.

Andersen, T. B., Dalgaard, C.-J., & Selaya, P. (2016). Climate and the Emergence of Global Income Differences. *The Review of Economic Studies*, rdw006.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), 277–297.

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, ret016.

Azariadis, C., & Drazen, A. (1990). Threshold externalities in economic development. *The Quarterly Journal of Economics*, *105*(2), 501–526.

Bansal, R., & Ochoa, M. (2011). *Temperature, aggregate risk, and expected returns*. National Bureau of Economic Research.

Barreca, A. I. (2012). Climate change, humidity, and mortality in the United States. *Journal of Environmental Economics and Management*, *63*(1), 19–34.

Barrett, C. B., & Carter, M. R. (2013). The economics of poverty traps and persistent poverty: empirical and policy implications. *The Journal of Development Studies, 49*(7), 976–990.

Barrett, C. B., Marenya, P. P., McPeak, J., Minten, B., Murithi, F., Oluoch-Kosura, W., … Wangila, J. (2006). Welfare dynamics in rural Kenya and Madagascar. *The Journal of Development Studies*, *42*(2), 248–277.

Barrett, C. B., & Swallow, B. M. (2006). Fractal poverty traps. *World development*, *34*(1), 1–15.

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: what the long-run data show. *The American Economic Review*, 1072–1085.

Bengtsson, N. (2010). How responsive is body weight to transitory income changes? Evidence from rural Tanzania. *Journal of Development Economics*, *92*(1), 53–61.

Bloom, D. E., Canning, D., & Sevilla, J. (2003). Geography and poverty traps. *Journal of Economic Growth*, *8*(4), 355–378.

Bonds, M. H., Keenan, D. C., Rohani, P., & Sachs, J. D. (2010). Poverty trap formed by the ecology of infectious diseases. *Proceedings of the Royal Society of London B: Biological Sciences*, *277*(1685), 1185–1192.

Burgess, R., Deschenes, O., Donaldson, D., & Greenstone, M. (2011). Weather and death in India. *Cambridge, United States: Massachusetts Institute of Technology, Department of Economics.*

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature* (527): 235-239.

Cachon, G., Gallino, S., & Olivares, M. (2012). Severe weather and automobile assembly productivity. *Columbia Business School Research Paper*, (12/37).

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, *29*(2), 238–249.

Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies*, *42*(2), 178–199.

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World development*, *35*(5), 835–856.

Carter, M. R., & Lybbert, T. J. (2012). Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics*, *99*(2), 255–264.

Challinor, A. J., Wheeler, T. R., Craufurd, P. Q., & Slingo, J. M. (2005). Simulation of the impact of high temperature stress on annual crop yields. *Agricultural and Forest Meteorology*, *135*(1), 180–189.

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of econometrics*, *92*(1), 1–45.

CRU (2016), Climatic Research Unit, University of East Anglia. Retrieved 9 July 2017, from: http://www.cru.uea.ac.uk/data

De Long, J. B. (1988). Productivity growth, convergence, and welfare: comment. *The American Economic Review*, *78*(5), 1138–1154.

Dell, M., Jones, B. F., & Olken, B. A. (2009). *Temperature and income: reconciling new cross-sectional and panel estimates*. National Bureau of Economic Research.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature*, *52*(3), 740–798.

Dercon, S. (1996). Risk, crop choice, and savings: Evidence from Tanzania. *Economic development and cultural change*, *44*(3), 485–513.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics*, *74*(2), 309–329.

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of development economics*, *96*(2), 159–173.

Dercon, S., Hoddinott, J., & Woldehanna, T. (2005). Shocks and consumption in 15 Ethiopian villages, 1999-2004. *Journal of African economies*.

Dercon, S., & Krishnan, P. (2000). Vulnerability, seasonality and poverty in Ethiopia. *The Journal of Development Studies*, *36*(6), 25–53.

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, *3*(4), 152–185.

Diamond, J. (1999). *Guns, germs, and steel: The fates of human societies*. WW Norton & Company.

Dorward, A., Kydd, J., Morrison, J., & Urey, I. (2004). A policy agenda for pro-poor agricultural growth. *World development*, *32*(1), 73–89.

Easterly, W., & Levine, R. (2003). Tropics, germs, and crops: how endowments influence economic development. *Journal of monetary economics*, *50*(1), 3–39.

Elbers, C., Gunning, J. W., & Kinsey, B. (2007). Growth and risk: Methodology and micro evidence. *The World Bank Economic Review*, *21*(1), 1–20.

Fafchamps, M., Udry, C., & Czukas, K. (1998). Drought and saving in West Africa: are livestock a buffer stock? *Journal of Development economics*, *55*(2), 273–305.

Field, C. B., Barros, V. R., Mastrandrea, M. D., Mach, K. J., Abdrabo, M.-K., Adger, N., … others. (2014). Summary for policymakers. In *Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1–32). Cambridge University Press.

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., … others. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–342.

Gallup, J. L., Sachs, J. D., & Mellinger, A. D. (1999). Geography and economic development. *International regional science review*, *22*(2), 179–232.

Galvao, Antonio F. 2011. «Quantile regression for dynamic panel data with fixed effects». *Journal of Econometrics* 164 (1):142–157.

Goldberg, M. S., Gasparrini, A., Armstrong, B., & Valois, M.-F. (2011). The short-term influence of temperature on daily mortality in the temperate climate of Montreal, Canada. *Environmental research*, *111*(6), 853–860.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, *32*(1), 1–26.

Haider, L. Jamila, Wiebren J. Boonstra, Garry D. Peterson, e Maja Schlüter. 2017. «Traps and Sustainable Development in Rural Areas: A Review». *World Development*.

Hansen, B. E. (2000). Sample splitting and threshold estimation. *Econometrica*, *68*(3), 575–603.

Hausman, J. A., & Taylor, W. E. (1981). Panel data and unobservable individual effects. *Econometrica: Journal of the Econometric Society*, 1377–1398.

Heal, G., & Park, J. (2015). *Goldilocks economies? temperature stress and the direct impacts of climate change*. National Bureau of Economic Research.

Hirvonen, K. (2016). Temperature Changes, Household Consumption, and Internal Migration: Evidence from Tanzania. *American Journal of Agricultural Economics*, aaw042.

Hoddinott, J., & Kinsey, B. (2001). Child growth in the time of drought. *Oxford Bulletin of Economics and statistics*, *63*(4), 409–436.

Howden, S. M., Soussana, J.-F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H. (2007). Adapting agriculture to climate change. *Proceedings of the national academy of sciences*, *104*(50), 19691–19696.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of sciences*, *107*(35), 15367–15372.

Hsiang, S. M., & Jina, A. S. (2014). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones*. National Bureau of Economic Research.

Huntington, E. (1922). *Civilization and climate*. Yale University Press.

Jalan, J., & Ravallion, M. (2002). Geographic poverty traps? A micro model of consumption growth in rural China. *Journal of applied econometrics*, *17*(4), 329–346.

Kazianga, H., & Udry, C. (2006). Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. *Journal of Development Economics*, *79*(2), 413–446.

Koenker, Roger. 2004. «Quantile regression for longitudinal data». *Journal of Multivariate Analysis*, Special Issue on Semiparametric and Nonparametric Mixed Models, 91 (1):74–89. https://doi.org/10.1016/j.jmva.2004.05.006.

Lemoine, D., & Kapnick, S. (2015). A top-down approach to projecting market impacts of climate change. *Nature Climate Change* 6(5):514-519.

Letta, M., Tol, R., (2016). Weather, climate and total factor productivity. *Working Paper Series No.102-2016, Department of Economics, University of Sussex*.

Li, S., Wheeler, T., Challinor, A., Lin, E., Ju, H., & Xu, Y. (2010). The observed relationships between wheat and climate in China. *Agricultural and Forest Meteorology*, *150*(11), 1412–1419.

Mankiw, N. G. & Romer D. & Weil, D.N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics* 107 (2):407–437.

Mendelsohn, R., & Dinar, A. (1999). Climate change, agriculture, and developing countries: does adaptation matter? *The World Bank Research Observer*, *14*(2), 277–293.

Moore, F. C., & Diaz, D. B. (2015). Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change*, *5*(2), 127–131.

Morduch, J. (1995). Income smoothing and consumption smoothing. *The journal of economic perspectives*, *9*(3), 103–114.

Mueller, N. D., Gerber, J. S., Johnston, M., Ray, D. K., Ramankutty, N., & Foley, J. A. (2012). Closing yield gaps through nutrient and water management. *Nature*, *490*(7419), 254–257.

Murphy, K. M., Shleifer, A., & Vishny, R. W. (1989). Industrialization and the big push. *Journal of political economy*, *97*(5), 1003–1026.

Niemelä, R., Hannula, M., Rautio, S., Reijula, K., & Railio, J. (2002). The effect of air temperature on labour productivity in call centres—a case study. *Energy and Buildings*, *34*(8), 759–764.

Nordhaus, W. D. (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(10), 3510–3517.

Olsson, O., & Hibbs, D. A. (2005). Biogeography and long-run economic development. *European Economic Review*, *49*(4), 909–938.

Park, J. (2017). *Will We Adapt? Labor Productivity and Adaptation to Climate Change*. Cambridge, Massachusetts, USA: Harvard Environmental Economics Program.

Paxson, C. H. (1992). Using weather variability to estimate the response of savings to transitory income in Thailand. *The American Economic Review*, 15–33.

Pindyck, R. S. (2012). Uncertain outcomes and climate change policy. *Journal of Environmental Economics and management*, *63*(3), 289–303.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? *Journal of Economic Literature*, *51*(3), 860–872.

Ponomareva, M. (2010). Quantile regression for panel data models with fixed effects and small T: Identification and estimation. *University of Western Ontario*.

Powell, David. 2016. «Quantile regression with nonadditive fixed effects». RAND Working Paper.

Porter, J. R., & Semenov, M. A. (2005). Crop responses to climatic variation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1463), 2021–2035.

Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., … Travasso, M. I. (2014). *Chapter 7: Food security and food production systems*. Cambridge University Press.

Quah, D. T. (1996). Twin peaks: growth and convergence in models of distribution dynamics. *The economic journal*, 1045–1055.

Quah, D. T. (1997). Empirics for growth and distribution: stratification, polarization, and convergence clubs. *Journal of economic growth*, *2*(1), 27–59.

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., … others. (2011). MERRA: NASA's modern-era retrospective analysis for research and applications. *Journal of climate*, *24*(14), 3624–3648.

Reis, R. (2009). The Time-Series Properties Of Aggregate Consumption: Implications For The Costs Of Fluctuations. *Journal of the European Economic Association*, *7*(4), 722–753.

Rodrik, D., Subramanian, A., & Trebbi, F. (2004). Institutions rule: the primacy of institutions over geography and integration in economic development. *Journal of economic growth*, *9*(2), 131–165.

Roodman, D. (2006). How to do xtabond2: An introduction to difference and system GMM in Stata. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=982943

Rosenzweig, M. R., & Wolpin, K. I. (1993). Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India. *Journal of political economy*, *101*(2), 223–244.

Rowhani, P., Lobell, D. B., Linderman, M., & Ramankutty, N. (2011). Climate variability and crop production in Tanzania. *Agricultural and Forest Meteorology*, *151*(4), 449–460.

Sachs, J. (2008). The end of poverty: economic possibilities for our time. *European Journal of Dental Education*, *12*(s1), 17–21.

Schelling, T. C. (1992). Some economics of global warming. *The American Economic Review*, *82*(1), 1–14.

Schelling, T. C. (1995). Intergenerational discounting. *Energy policy*, *23*(4–5), 395–401.

Schelling, T. C. (1997). The cost of combating global warming: Facing the tradeoffs. *Foreign Affairs*, 8–14.

Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*, *5*(1), 014010.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, *106*(37), 15594–15598.

Schmidhuber, J., & Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences*, *104*(50), 19703–19708.

Stern, N. (2013). The structure of economic modeling of the potential impacts of climate change: grafting gross underestimation of risk onto already narrow science models. *Journal of Economic Literature*, *51*(3), 838–859.

Strulik, H. (2008). Geography, health, and the pace of demo-economic development. *Journal of Development Economics*, *86*(1), 61–75.

Sudarshan, A., & Tewari, M. (2013). *The economic impacts of temperature on industrial productivity: Evidence from indian manufacturing*. Working Paper. http://icrier.org/pdf/working_paper_278.pdf

Tittonell, P., & Giller, K. E. (2013). When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. *Field Crops Research*, *143*, 76–90.

Tol, R. S. J. (2011). *Poverty Traps and Climate Change* (Paper No. WP413). Economic and Social Research Institute (ESRI).

Tol, R. S. J. (2015). *Economic impacts of climate change* (Working Paper Series No. 7515). Department of Economics, University of Sussex.

Tol, R. S. J. (2016). *Dangerous Interference With The Climate System: An Economic Assessment* (Working Paper Series No. 100-2016). Department of Economics, University of Sussex.

Townsend, R. M. (1995). Consumption insurance: An evaluation of risk-bearing systems in low-income economies. *The Journal of Economic Perspectives*, *9*(3), 83–102.

Wang, Q. (2015). Fixed-effect panel threshold model using Stata. *Stata Journal*, *15*(1), 121–134.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics*, *91*(1), 1–19.

Weitzman, M. L. (2010). What Is The" Damages Function" For Global Warming—And What Difference Might It Make? *Climate Change Economics*, *1*(01), 57–69.

Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A., & Dawe, D. (2010). Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*, *107*(33), 14562–14567.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of econometrics*, *126*(1), 25–51.

Zivin, J. G., & Shrader, J. (2016). Temperature extremes, health, and human capital. *The Future of Children*, *26*(1), 31–50.

Table 1

Descriptive statistics

	Mean	Var	sd	Obs
Food consumption growth rate	-1.696	992.409	31.503	3168
Total consumption growth rate	-1.441	901.549	30.026	3170
Food consumption	584138.1	1.37e+11	533314.7	4755
Total consumption	773108.5	2.84e+11	369904.3	4755
∆Temp	0.083	0.105	0.324	3170
∆Pre	0.051	0.023	0.153	3170
Temp	23.755	7.260	2.694	3170
Pre	117.998	589.714	24.284	3170
Long-run average temperature	23.658	6.924	2.631	4755
Long-run average precipitation	114.747	576.907	24.019	4755
Household size	5.659	10.029	3.167	4755
Number of infants (< 5 years)	0.918	1.147	1.071	4755
Adult education level	4.593	8.338	2.888	4750
Age of the household head	49.615	241.137	15.529	4755
Gender of the household head	0.239	0.182	0.426	4755
Tropical Livestock Units (TLUs)	0.436	1.328	1.152	3653
Total crop production	843322.4	8.32e+11	912363	3653

Notes:

Food consumption growth rate is the annualised percentage change in household per adult equivalent food consumption between t and t-1. Total consumption growth rate is the annualised percentage change in household per adult equivalent consumption between t and t-1. Food consumption is household per adult-equivalent food consumption, expressed in Tanzanian shillings. Total consumption is household per adult-equivalent total consumption, expressed in Tanzanian shillings. ∆Temp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ∆Pre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Temp is average monthly growing season temperature in the period between interviews. Pre is average monthly growing season precipitation in the period between interviews. Long-run average temperature is the average monthly growing season temperature over the period 1980-2015, expressed in degree Celsius. Long-run average precipitation represents average monthly growing season precipitation over the period 1980-2015, expressed in mm. Adult education level represents the average years of education among adults, where adult means > 15 year old. TLUs are per adult-equivalent. Total crop production is expressed in Tanzanian shillings.

Table 2

FE regressions – Food consumption

Dependent variable: food consumption growth rate	(1)	(2)	(3)	(4)
L1.Food	-72.965***	-75.796***	-75.808***	-74.281***
	(1.219)	(1.299)	(1.304)	(1.326)
ΔTemp	-1.895	9.925*	11.093**	-338.600***
	(4.750)	(5.332)	(5.449)	(44.868)
Poor x ΔTemp		-21.588***	-21.460***	
		(4.537)	(4.541)	
Hot x ΔTemp			-2.653	
			(3.718)	
ΔPre	0.839	3.259	2.113	-4.941
	(6.673)	(8.386)	(9.339)	(6.622)
Poor x ΔPre		-8.758	-8.482	
		(9.620)	(9.673)	
Hot x ΔPre			2.127	
			(10.264)	
Hot			4.032	
			(3.689	
L1.Food x ΔTemp				25.713***
				(3.438)
Obs	3,164	3,164	3,164	3,164
Adj. R^2	0.831	0.835	0.835	0.841
Vegetation time series	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Total temperature effect for poorest households		-11.663**	-10.366*	
		(5.091)	(5.308)	
Total temperature effect for households in hot areas			8.441	
			(5.748)	
Total temperature effect for poorest households in hot areas			-13.019**	
			(5.482)	
Total precipitation effect for poorest households		-5.499	-6.329	
		(7.742)	(8.387)	
Total precipitation effect for households in hot areas			4.240	
			(10.401)	

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks. Food consumption growth rate is the annualised percentage change in (ln) household per a.e. food consumption between t and t-1. L1.Food is lagged household per a.e. (ln) food consumption. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Poor is a dummy with value 1 for households with below median initial food consumption. Hot is a dummy with value 1 for households living in an area with an above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3

FE regressions – Total consumption

Dependent variable: total consumption growth rate	(1)	(2)	(3)	(4)
L1.Cons	-71.193***	-73.532***	-73.618***	-72.671***
	(1.299)	(1.380)	(1.387)	(1.338)
ΔTemp	-0.328	8.494*	9.199*	-319.134***
	(4.198)	(4.478)	(4.736)	(39.811)
Poor x ΔTemp		-17.813***	-17.565***	
		(3.748)	(3.739)	
Hot x ΔTemp			-1.645	
			(3.268)	
ΔPre	0.695	1.777	0.217	-6.080
	(5.848)	(7.452)	(8.279)	(5.597)
Poor x ΔPre		-5.771	-4.890	
		(8.412)	(8.495)	
Hot x ΔPre			2.370	
			(8.380)	
Hot			13.687***	
			(2.855)	
L1.Cons x ΔTemp				23.868***
				(2.988)
Obs	3,166	3,166	3,166	3,166
Adj. R^2	0.830	0.833	0.833	0.840
Vegetation time series	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Total temperature effect for poorest households		-9.319**	-8.366*	
		(4.694)	(4.897)	
Total temperature effect for households in hot areas			7.553	
			(4.846)	
Total temperature effect for poorest households in hot areas			-10.012**	
			(5.117)	
Total precipitation effect for poorest households		-3.994	-4.673	
		(6.747)	(7.235)	
Total precipitation effect for households in hot areas			2.587	
			(8.879)	

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks. Total consumption growth rate is the annualised percentage change in (ln) household per a.e. total consumption between t and t-1. L1.Cons is lagged household per a.e. (ln) food consumption. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Poor is a dummy with value 1 for households with below median initial consumption. Hot is a dummy with value 1 for households living in an area with an above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4

FE initial quartile regressions – Food consumption

Dependent variable: Food consumption growth rate	(1)	(2)
L1.Food	-77.172***	-77.224***
	(1.344)	(1.351)
q1 x ΔTemp	-19.847***	-19.157***
	(5.164)	(5.338)
q2 x ΔTemp	-5.693	-4.985
	(5.332)	(5.403)
q3 x ΔTemp	4.604	5.234
	(5.659)	(5.944)
q4 x ΔTemp	16.115***	16.784***
	(5.844)	(5.909)
Hot x ΔTemp		-1.386
		(3.677)
q1 x ΔPre	-6.451	-8.752
	(10.031)	(10.497)
q2 x ΔPre	-4.833	-7.239
	(8.634)	(9.354)
q3 x ΔPre	5.244	2.913
	(9.904)	(10.943)
q4 x ΔPre	-2.776	-5.841
	(10.418)	(11.452)
Hot x ΔPre		7.024
		(10.337)
Hot		3.525
		(3.702)
Obs	3,164	3,164
Adj. R^2	0.837	0.837
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks. Food consumption growth rate is the annualised percentage change in (ln) household per a.e. food consumption between t and t-1. L1.Food is lagged household per a.e. (ln) food consumption. q1, q2, q3, q4 are initial food consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5

FE initial quartile regressions – Total consumption

Dependent variable: Total consumption growth rate	(1)	(2)
L1.Cons	-75.155***	-75.297***
	(1.378)	(1.387)
q1 x ΔTemp	-14.965***	-15.279***
	(5.068)	(5.098)
q2 x ΔTemp	-3.732	-3.738
	(5.504)	(5.666)
q3 x ΔTemp	1.483	1.034
	(4.734)	(5.323)
q4 x ΔTemp	18.664***	18.436***
	(5.565)	(5.624)
Hot x ΔTemp		0.780
		(3.451)
q1 x ΔPre	-3.016	-5.158
	(9.118)	(9.555)
q2 x ΔPre	-6.526	-7.999
	(8.921)	(9.254)
q3 x ΔPre	3.671	0.846
	(8.803)	(9.925)
q4 x ΔPre	-5.478	-8.184
	(10.307)	(10.928)
Hot x ΔPre		6.415
		(8.563)
Hot		14.725***
		(2.894)
Obs	3,166	3,166
Adj. R^2	0.837	0.837
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. Total consumption growth rate is the annualised percentage change in (ln) household per a.e. consumption between t and t-1. L1.Cons is lagged household per a.e. (ln) consumption. q1, q2, q3, q4 are initial consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6

Double threshold model – Hansen Estimator

Dependent variable:	(1) ΔFood	(2) ΔCons
L1.Food	-74.698***	
	(1.256)	
L1.Cons		-72.326***
		(1.295)
ΔPre	-2.645	-5.367
	(6.709)	(5.809)
ΔTemp_Lower regime	-14.682***	-18.347***
	(4.878)	(4.863)
ΔTemp_Medium regime	5.340	1.383
	(4.846)	(4.386)
ΔTemp_Upper regime	29.135***	28.953***
	(6.811)	(6.638)
Obs	3,168	3,170
Adj. R^2	0.775	0.770
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t-1. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t-1. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at the EA and wave levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Threshold Confidence intervals and effect tests

<u>Column (1) – Food consumption</u>

1) Threshold estimator (level = 95):

Model	Threshold	Lower	Upper
Th-1	13.089	13.086	13.093
Th-21	13.089	13.084	13.093
Th-22	13.729	13.709	13.733

2) Threshold effect test (bootstrap = 300 300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	5.12e+05	161.770	141.92	0.000	17.715	22.171	27.298
Double	5.04e+05	159.234	50.43	0.000	20.140	22.664	26.723

3) Percentage of observations in each regime:

Lower regime:	47.16 %
Medium regime:	39.90 %
Upper regime:	12.94 %

Column (2) – Total consumption

1) Threshold estimator (level = 95):

Model	Threshold	Lower	Upper
Th-1	13.297	13.285	13.300
Th-21	12.983	12.979	12.991
Th-22	14.014	14.005	14.024

2) Threshold effect test (bootstrap = 300 300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	4.72e+05	148.891	113.50	0.000	16.957	19.678	26.294
Double	4.61e+05	145.622	73.09	0.000	18.415	22.431	29.031

3) Percentage of observations in each regime:

Lower regime:	23.56 %
Medium regime:	63.47 %
Upper regime:	12.97 %

Table 7

Health expenditure

Dependent variable: Share of health expenditure growth rate	(1)	(2)	(3)
L1.Share of health expenditure	-73.730***	-73.599***	-73.531***
	(1.235)	(1.232)	(1.274)
ΔTemp	0.869		
	(20.100)		
ΔPre	-0.248		
	(27.421)		
q1 x ΔTemp		-4.911	-8.074
		(20.097)	(21.462)
q2 x ΔTemp		0.789	-1.778
		(22.606)	(23.226)
q3 x ΔTemp		15.652	11.926
		(23.579)	(25.551)
q4 x ΔTemp		-6.589	-9.452
		(22.664)	(23.241)
Hot x ΔTemp			7.174
			(14.605)
q1 x ΔPre		8.047	6.092
		(36.340)	(38.827)
q2 x ΔPre		-15.644	-16.615
		(33.183)	(34.962)
q3 x ΔPre		7.444	3.828
		(36.515)	(40.909)
q4 x ΔPre		9.122	7.140
		(39.249)	(41.776)
Hot x ΔPre			7.824
			(43.651)
Hot			23.312**
			(2.153)
Obs.	2,952	2,952	2,952
Adj. R^2	0.820	0.820	0.821
Vegetation time series	Yes	Yes	Yes
Household controls	Yes	Yes	Yes

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. q1, q2, q3, q4 are initial consumption quartiles. Dependent variable is (ln) per a.e. between-wave percentage of the health expenditure / total expenditure ratio. L1.Share of health expenditure is lagged ln per a.e. health expenditure / total expenditure ratio. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8

Labour productivity – Two-step Difference GMM

Dependent variable:	(1) ΔALP	(2) ΔALP
L1.ALP	-70.206*** (4.677)	-70.657*** (4.785)
ΔTemp	-23.658** (11.942)	
ΔPre	-14.961 (14.656)	
q1 x ΔTemp		-32.790** (12.933)
q2 x ΔTemp		-20.770 (13.975)
q3 x ΔTemp		-18.107 (18.216)
q4 x ΔTemp		-17.618 (14.574)
q1 x ΔPre		-30.274 (27.740)
q2 x ΔPre		1.864 (20.903)
q3 x ΔPre		-18.424 (27.794)
q4 x ΔPre		-14.348 (26.282)
Obs	1,130	1,130
Vegetation time series	Yes	Yes
Household controls	Yes	Yes
Hansen – J test (p)	0.235	0.247

Notes: All specifications include households FE, wave dummies, year FE and quarter of year dummies. Region x time FE and month of interview dummies are used as additional instruments. All household controls are treated as endogenous with the exception of self-reported covariate shocks. ΔALP is agricultural labour productivity growth between t and t-1. L1.ALP is lagged (ln) agricultural labour productivity, instrumented using lagged assets and education levels at t-1. q1, q2, q3, q4 are initial total consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Weather variables and the vegetation time series variables are treated as exogenous. Robust standard errors are in parentheses and are corrected using Windmeijer's procedure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9

Crop yields

Dependent variable: Crop yield	(1)	(2)	(3)
Number of GDDs (8-34 °C)	0.000	0.000	
	(0.001)	(0.001)	
Number of GDDs (34 + °C)	-0.020**	-0.022**	
	(0.010)	(0.010)	
Precipitation	-0.000	-0.000	
	(0.002)	(0.002)	
$(\text{Precipitation})^2$	0.000	0.000	
	(0.000)	(0.000)	
Maize & paddy non-specializers x Number of GDDs (8-34 °C)	-0.000	-0.000	
	(0.000)	(0.000)	
Maize & paddy non-specializers x Number of GDDs (34 + °C)	0.026	0.026	
	(0.017)	(0.021)	
Maize & paddy non-specializers	0.460	0.460	
	(0.933)	(1.099)	
q1 x Number of GDDs (34 + °C)			-0.052***
			(0.016)
q2 x Number of GDDs (34 + °C)			-0.020
			(0.015)
q3 x Number of GDDs (34 + °C)			-0.017
			(0.011)
q4 x Number of GDDs (34 + °C)			0.011
			(0.021)
q1 x Precipitation			0.001
			(0.003)
q2 x Precipitation			-0.000
			(0.004)
q3 x Precipitation			-0.000
			(0.002)
q4 x Precipitation			-0.002
			(0.004)
q1 x $(\text{Precipitation})^2$			-0.000
			(0.000)
q2 x $(\text{Precipitation})^2$			-0.000
			(0.000)
q3 x $(\text{Precipitation})^2$			0.000
			(0.000)
q4 x $(\text{Precipitation})^2$			0.000
			(0.000)
Obs	3,537	3,537	3,537
Adj. R^2	0.595	0.599	0.599
Vegetation time series	Yes	Yes	Yes

Total effect of Number of GDDs (8-34 °C) for households not specialized in maize and paddy production	-0.000 (0.001)
Total effect of Number of GDDs (34 + °C) for households not specialized in maize and paddy production	0.005 (0.021)

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Crop yield is average crop yield (kg / ha) during the previous two rainy seasons. 'Maize & paddy non-specializers' is a dummy with value 1 for households in which maize and paddy account for less than 50% of total crop production in a given wave. q1, q2, q3, q4 are initial total consumption quartiles. Standard errors are in parentheses and are clustered at the EA and wave levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10

Asset smoothing

Dependent variable: Asset growth	(1)	(2)
L1.Assets	-74.762***	-75.053***
	(1.834)	(1.832)
ΔTemp	-5.823	
	(22.094)	
ΔPre	-27.314	
	(32.146)	
q1 x ΔTemp		-2.823
		(24.355)
q2 x ΔTemp		-3.731
		(25.099)
q3 x ΔTemp		-16.042
		(29.640)
q4 x ΔTemp		-4.402
		(28.642)
q1 x ΔPre		66.468
		(44.547)
q2 x ΔPre		-75.504*
		(42.217)
q3 x ΔPre		-80.426*
		(48.702)
q4 x ΔPre		-29.418
		(59.022)
Obs	2,223	2,223
Adj. R^2	0.800	0.804
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. Asset growth is the annualised percentage change in (ln) household per a.e. household Tropical Livestock Units (TLUs) between t and t-1. L1.Assets is lagged household per a.e. (ln) asset level (TLUs). q1, q2, q3, q4 are initial consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at the EA and wave levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1

Marginal effect of ΔTemp on food consumption growth

at different lagged food consumption levels

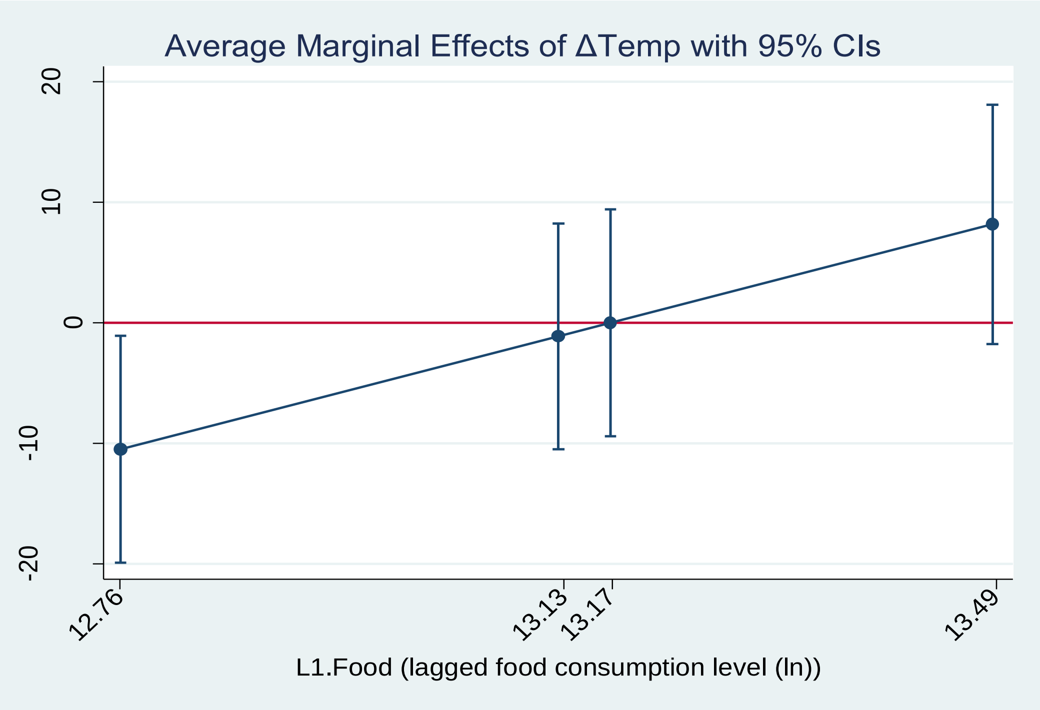
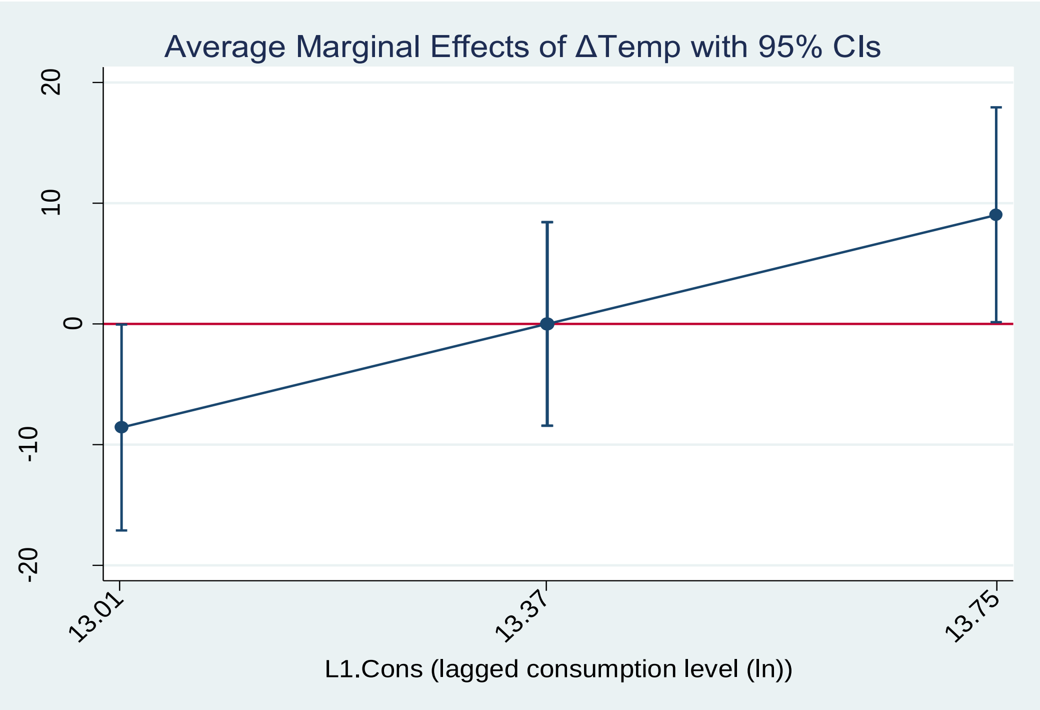


Figure 2

Marginal effect of ΔTemp on total consumption growth

at different lagged total consumption levels



Appendix

Table A.1

Instrumented FE regressions – Endogeneity tests

Dependent variable:	(1) ΔFood	(2) ΔCons
L1.Food	-98.481*	
	(51.761)	
L1.Cons		-91.758***
		(29.374)
ΔTemp	2.846	2.607
	(7.394)	(4.352)
ΔPre	2.440	-0.306
	(6.178)	(7.209)
Observations	3092	3094
Adjusted R-squared	0.304	0.342
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: L1.Food is lagged household per a.e. (ln) food consumption, instrumented using lagged assets and education levels at t-1. L1.Cons is lagged household per a.e. (ln) total consumption, instrumented using lagged assets and education levels at t-1. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm Standard errors are in parentheses and are clustered at the household and wave levels .
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Endogeneity tests:

Regressor	Test	p-value
L1.Food	0.074	0.786
L1.Cons	0.423	0.515

Table A.2

FE regressions with spatially-robust SEs

Dependent variable:	(1) ΔFood	(2) ΔCons
L1.Food	-77.224	
Conley(1999), 50 km cut-off	(0.911)***	
Conley(1999), 75 km cut-off	(0.914)***	
Conley(1999), 100 km cut-off	(0.943)***	
L1.Cons		-75.297
Conley(1999), 50 km cut-off		(1.007)***
Conley(1999), 75 km cut-off		(1.037)***
Conley(1999), 100 km cut-off		(1.087)***
q1 x ΔTemp	-19.157	-15.279
Conley(1999), 50 km cut-off	(3.679)***	(3.246)***
Conley(1999), 75 km cut-off	(3.744)***	(3.255)***
Conley(1999), 100 km cut-off	(3.823)***	(3.252)***
q2 x ΔTemp	-4.985	-3.738
Conley(1999), 50 km cut-off	(3.473)	(3.572)
Conley(1999), 75 km cut-off	(3.392)	(3.485)
Conley(1999), 100 km cut-off	(3.370)	(3.322)
q3 x ΔTemp	5.324	1.034
Conley(1999), 50 km cut-off	(3.704)	(3.466)
Conley(1999), 75 km cut-off	(3.658)	(3.427)
Conley(1999), 100 km cut-off	(3.632)	(3.390)
q4 x ΔTemp	16.784	18.436
Conley(1999), 50 km cut-off	(3.572)***	(3.539)***
Conley(1999), 75 km cut-off	(3.492)***	(3.501)***
Conley(1999), 100 km cut-off	(3.409)***	(3.454)***
Hot x ΔTemp	-1.386	0.780
Conley(1999), 50 km cut-off	(2.280)	(2.118)
Conley(1999), 75 km cut-off	(2.293)	(2.124)
Conley(1999), 100 km cut-off	(2.306)	(2.080)
q1 x ΔPre	-8.752	-5.158
Conley(1999), 50 km cut-off	(7.473)	(6.665)
Conley(1999), 75 km cut-off	(7.185)	(6.487)
Conley(1999), 100 km cut-off	(7.167)	(6.459)
q2 x ΔPre	-7.239	-7.999
Conley(1999), 50 km cut-off	(6.245)	(5.942)
Conley(1999), 75 km cut-off	(6.116)	(5.752)
Conley(1999), 100 km cut-off	(6.288)	(5.596)
q3 x ΔPre	2.913	0.846
Conley(1999), 50 km cut-off	(6.898)	(6.512)

Conley(1999), 75 km cut-off	(6.956)	(6.436)
Conley(1999), 100 km cut-off	(7.128)	(6.434)
q4 x ΔPre	-5.841	-8.184
Conley(1999), 50 km cut-off	(7.080)	(7.142)
Conley(1999), 75 km cut-off	(7.085)	(6.999)
Conley(1999), 100 km cut-off	(7.023)	(6.908)
Hot x ΔPre	7.024	6.415
Conley(1999), 50 km cut-off	(6.520)	(5.557)
Conley(1999), 75 km cut-off	(6.527)	(5.616)
Conley(1999), 100 km cut-off	(6.686)	(5.758)
Hot	3.525	14.725
Conley(1999), 50 km cut-off	(6.588)	(5.201)***
Conley(1999), 75 km cut-off	(6.586)	(5.207)***
Conley(1999), 100 km cut-off	(6.513)	(5.244)***
Obs	3,164	3.166
Adj. R^2	0.768	0.765
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks: ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t-1. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t-1.. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. q1, q2, q3, q4 are initial food consumption quartiles in Column (1) and initial consumption quartiles in Column(2). ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Conley (1999) standard errors are in parentheses and are robust to both spatial and temporal autocorrelation.

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

Table A.3

Descriptive statistics – Alternative weather data

	Mean	Var	sd	Obs
ΔTemp	0.405	0.131	0.363	3170
ΔPre	-21.565	8585.501	92.658	4755
Long-run average temperature	23.948	4.362	2.089	4755
Long-run average precipitation	502.203	19198.690	138.559	4755

Notes:

ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1983-2015) average monthly growing season temperature divided by long-run (1983-2013) standard deviation, and expressed in degree Celsius. ΔPre is the difference between total precipitation during the previous wettest quarter and long-run average (2001 - 2013) total precipitation during the wettest quarter divided by average decadal (2001 - 2013) standard deviation, expressed in mm. Long-run average temperature is the average monthly growing season temperature over the period 1983-2015, expressed in degree Celsius. Long-run average precipitation represents long-run average (2001 - 2013) total precipitation during the wettest quarter. Data source is the *CRUCY Version 3.23* by the University of East Anglia for temperature data, and the Tanzania LSMS-ISA NPS surveys for rainfall data.

Table A.4

FE initial quartile regressions - Alternative weather data

Dependent Variables:	(1) ΔFood	(2) ΔFood	(3) ΔCons	(4) ΔCons
L1.Food	-76.191***	-76.234***		
	(1.343)	(1.347)		
L1.Cons			-74.291***	-74.270***
			(1.392)	(1.396)
q1 x ΔTemp	-14.205***	-14.636***	-10.985**	-11.147**
	(4.602)	(4.736)	(4.622)	(4.786)
q2 x ΔTemp	-5.339	-5.963	-3.778	-3.964
	(5.507)	(5.559)	(5.031)	(5.073)
q3 x ΔTemp	-0.051	-0.649	-1.797	-2.111
	(5.768)	(5.838)	(4.809)	(4.931)
q4 x ΔTemp	15.130**	14.725**	19.063***	18.940***
	(5.897)	(5.906)	(5.058)	(5.155)
Hot x ΔTemp		2.090		2.623
		(2.453)		(2.342)
q1 x ΔPre	-0.009	-0.002	-3.819***	-0.004
	(0.011)	(0.012)	(1.295)	(0.011)
q2 x ΔPre	-0.001	0.007	1.124	0.003
	(0.010)	(0.010)	(0.763)	(0.011)
q3 x ΔPre	0.019**	0.027**	0.407	0.017
	(0.009)	(0.011)	(1.169)	(0.011)
q4 x ΔPre	0.025**	0.036***	5.007***	0.030**
	(0.010)	(0.013)	(1.250)	(0.014)
Hot x ΔPre		-0.021*		-0.018
		(0.012)		(0.011)
Hot		2.193		10.960***
		(3.445)		(3.198)
Obs	3,164	3,164	3,166	3,166
Adj. R^2	0.835	0.836	0.835	0.836
Vegetation time series	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes

Notes: All specifications include households FE, wave dummies, region x year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t-1. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t-1. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. q1, q2, q3, q4 are initial food consumption quartiles in Column (1) and initial consumption quartiles in Column (2). ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1983-2015) average monthly growing season temperature, divided by long-run (1983-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between total precipitation during the previous wettest quarter and long-run average (2001 − 2013) total precipitation during the wettest quarter, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels.

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

Table A.5

Hausman – Taylor regressions

Dependent variables:	(1) ΔFood	(2) ΔCons
L1.Food	-75.877***	
	(1.302)	
L1.Cons		-74.520***
		(1.277)
q1 x ΔTemp	-21.797***	-18.784***
	(3.888)	(3.625)
q2 x ΔTemp	-9.955***	-9.270**
	(3.818)	(4.064)
q3 x ΔTemp	-1.894	-4.931
	(4.615)	(3.942)
q4 x ΔTemp	6.179	10.206**
	(4.372)	(4.248)
q1 x ΔPre	-10.441	-7.986
	(7.424)	(7.642)
q2 x ΔPre	-3.261	-7.862
	(8.020)	(7.216)
q3 x ΔPre	2.289	-0.584
	(8.345)	(7.064)
q4 x ΔPre	-0.020	-1.665
	(8.364)	(8.918)
Long-run average temperature	1.049*	1.246**
	(0.557)	(0.588)
Long-run average precipitation	0.132**	0.129*
	(0.067)	(0.069)
Obs	3,164	3,166
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include wave, region, year and quarter of year dummies. All household controls are treated as time-varying endogenous variables with the exception of self-reported covariate shocks. Distance (in KMs) to nearest major road is included and treated as time-invariant exogenous. ΔFood is the between-wave percentage change in (ln) household per a.e. food consumption. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t-1. L1.Food is lagged household per a.e. (ln) food consumption and is treated as endogenous. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t-1. L1.Cons is lagged household per a.e. (ln) consumption and is treated as endogenous. q1, q2, q3, q4 are food consumption quartiles in Column (1) and total consumption quartiles in Column (2); they are all treated as time-invariant, endogenous variables. standard deviation, expressed in mm. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. All the weather variables are treated as exogenous. Standard errors are in parentheses and are clustered at the household level.

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

Table A.6

Two-step Difference GMM

Dependent variables:	(1) ΔFood	(2) ΔCons
L1.Food	-70.120***	
	(7.108)	
L1.Cons		-74.439***
		(5.701)
q1 x ΔTemp	-19.993***	-20.437***
	(6.929)	(6.065)
q2 x ΔTemp	-9.166	-7.303
	(5.769)	(5.928)
q3 x ΔTemp	-7.351	-1.323
	(6.051)	(6.254)
q4 x ΔTemp	4.081	10.417
	(8.389)	(7.461)
q1 x ΔPre	0.806	-2.193
	(9.327)	(9.242)
q2 x ΔPre	-3.949	-0.300
	(10.617)	(10.181)
q3 x ΔPre	8.584	12.033
	(12.051)	(10.431)
q4 x ΔPre	2.755	-3.414
	(12.770)	(12.652)
Obs	1,581	1.533
Vegetation time series	Yes	Yes
Household controls	Yes	Yes
Hansen – J test (p)	0.584	0.510

Notes: All specifications include households FE, wave dummies, year FE and quarter of year dummies. Region x time FE are used as additional instruments. All household controls are treated as endogenous. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t-1. L1.Food is lagged household per a.e. (ln) food consumption and is treated as endogenous. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t-1. L1.Cons is lagged household per a.e. (ln) consumption and is treated as endogenous. q1, q2, q3, q4 are initial food consumption quartiles in Column (1) and initial total consumption quartiles in Column (2). ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Weather variables and the vegetation time series variables are treated as exogenous. Robust standard errors are in parentheses and are corrected using Windmeijer's procedure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7

Labour productivity – Endogeneity test

Dependent variable:	(1) ΔALP
L1.ALP	-227.889 (220.885)
ΔTemp	-58.596 (92.139)
ΔPre	-15.059 (71.783)
Observations	2260
Vegetation time series	Yes
Household controls	Yes

Notes: ΔALP is agricultural labour productivity growth between t and t-1. L1.ALP is lagged (ln) agricultural labour productivity, instrumented using lagged assets and education levels at t-1. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980-2015) average monthly growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm Standard errors are in parentheses and are clustered at the household and wave levels .

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

Endogeneity test:

Regressor	**Test**	**p-value**
L1.ALP	7.611	0.0058

Table A.8

Descriptive statistics –Agricultural Wealth Index

Variable: Agricultural Wealth Index

	Mean	Var	sd	Obs
q1	0.066	1.151	1.073	905
q2	0.097	1.054	1.027	981
q3	0.018	0.841	0.917	931
q4	0.228	1.878	1.370	836

Notes: q1, q2, q3, q4 are initial consumption quartiles.
Agricultural Wealth Index is from the FAO Rural Income Generating Activities (RIGA) Team.

Table A.9

Descriptive statistics – Main source of income

Variable: Main source of income is not farming (in at least two periods) - % of households

	Yes	No
Whole sample	24.61	75.39
q1	19.40	80.60
q2	20	80
q3	25.25	74.75
q4	33.75	66.25

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.10

Descriptive statistics – Growing degree days

	Mean	Var	sd	Obs
Number of GDDs (8-34 °C)	3905.047	389495.400	624.096	4755
Number of GDDs (34 + °C)	3.280	46.273	6.802	4755

Table A.11

Descriptive statistics – Maize and paddy as a share of total crop production

	Maize and paddy account for 50% or more of total crop production - % of households	
	Yes	No
q1	50.59	49.41
q2	58.44	41.46
q3	51.60	48.40
q4	47.81	52.19

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.12

Descriptive statistics – Average crop yield and quantity produced

	(1) Mean quantity (kg)	(2) Mean crop yield (kg / ha)	Obs
q1	1268.625	715.602	876
q2	1452.362	1033.638	965
q3	1479.123	1225.526	903
q4	1762.087	1201.825	793

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.13

Descriptive statistics – Irrigation

	Use of irrigation in the previous long rainy season - % of households	
	Yes	No
q1	1.95	98.05
q2	3.30	96.70
q3	3.84	96.16
q4	6.05	93.95

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.14

Descriptive statistics – Inorganic fertilizers

	Use of inorganic fertilizers in the previous long rainy season - % of households	
	Yes	No
q1	17.65	82.35
q2	19.10	80.81
q3	25.25	74.75
q4	23.46	76.54

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.15

Descriptive statistics – Use of improved maize seeds on at least one plot

Variable: Use of improved maize seeds on at least one plot across waves - % of households		
	Yes	No
q1	34.16	65.84
q2	41.24	58.76
q3	46.48	53.52
q4	53.46	46.54

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.16

Descriptive statistics – Use of improved maize seeds on at least half plots

Variable: Use of improved maize seeds on at least half of the household plots across all waves - % of households		
	Yes	No
q1	8.77	91.23
q2	10.65	89.35
q3	18.79	81.21
q4	22.08	77.92

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.17

Descriptive statistics – Use of improved paddy seeds on at least one plot

Variable: Use of improved maize seeds on at least one plot across waves - % of households		
	Yes	No
q1	19.35	80.65
q2	24.76	75.24
q3	27.03	72.97
q4	27.15	72.85

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.18

Descriptive statistics – Use of improved paddy seeds on at least half plots

Variable: Use of improved paddy seeds on at least half of the household plots across all waves - % of households		
	Yes	No
q1	4.27	95.73
q2	6.27	93.73
q3	6.61	93.39
q4	16.49	83.51

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A.19

Descriptive statistics –Tropical Livestock Units per adult-equivalent

Variable: TLU level p.a.

	Mean	Var	sd	Obs
Whole sample	0.436	1.328	1.152	3653
q1	0.257	0.337	0.580	926
q2	0.424	1.031	1.016	963
q3	0.410	1.152	1.073	937
q4	0.680	2.890	1.700	827

Notes: q1, q2, q3, q4 are initial consumption quartiles.