**Temperature shocks, growth and poverty thresholds:**

**evidence from rural Tanzania**

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**Abstract** *Growing interest in the impacts of climate change in poor countries has sparked attention on the relationship between temperature and micro growth dynamics. 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. The main finding is a sharp heterogeneity: temperature shocks have a negative and significant impact on household growth only if their initial consumption lies below a critical threshold, i.e., they slow the convergence process among households. The main transmission channels appear to be agricultural yields and labour productivity. From a policy perspective, these findings support the Schelling Conjecture: development would be the best solution to cope with climate change for poor farming households in rural areas, and closing the yield gap and modernizing agriculture could substantially reduce the negative impacts of global warming in Sub-Saharan Africa.*

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

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**Introduction and literature review**

The recent and growing body of empirical works focusing on the weather-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1999; Nordhaus, 2006), whose validity is challenged by the risk of endogeneity and omitted variable bias, have recently been replaced by more appropriate and robust panel methods, both at the macro (Bansal & Ochoa, 2011; Burke, Hsiang, & Miguel, 2015; Dell, Jones, & Olken, 2012; Hsiang, 2010;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; Graff Zivin & Neidell, 2014; Heal & Park, 2015; Niemelä, Hannula, Rautio, Reijula, & Railio, 2002; Sudarshan & Tewari, 2013) level, which isolate the exogenous effect of weather variables on the economic outcome of interest.

The main findings of this emerging literature are that weather affects economic activity and growth through a wide range of channels (agriculture, health and mortality, labour productivity, energy, conflict and political stability, among the others) and that these impacts are substantially bigger and significant in poor countries.

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).

However, these panel studies only estimate short-run elasticities, whereas climate change is by definition a long-run phenomenon, which cannot be captured by empirical works because of the intrinsic difference between ‘climate’ and ‘weather’. As Dell, Jones and Olken (2014) explain: “The word climate is reserved for the distribution of outcomes, which may be summarized by averages over several decades, while weather describes a particular realization from that distribution and can provide substantial variability”. More simply, a 1°C shock in a given year and place is not the same of a permanent 1°C global increase.

Furthermore, short-run panels cannot capture neither the possibility of adaptation by economic agents, nor potential intensifying effects from phenomena which lie outside the range of historical experience (massive sea level rise, a thermohaline circulation slowdown, the release of methane from melting permafrost, etc.), both of which could eventually take place in the long-run and drastically change the nature and magnitude of the current short-run elasticities.

While assuming that this empirical literature can be informative about the structure of the damage function for climate change represents a leap in terms of external validity, the use of econometric techniques such as the inclusion of lags in the regressions, long differences (Dell, Jones and Olken, 2012), and the analysis of persistence of impacts of past shocks (Hornbeck, 2012), can alleviate these concerns, and partially fill the conceptual gap between short- and long-run impacts.

In development literature, however, the econometric identification of the impacts of weather shocks (especially rainfall) on human welfare is old practice.

Weather shocks, in fact, represent the exogenous shock *par excellence*, and many development studies have employed them both as independent regressors, in the context of the search for the determinants of growth, and as instruments for the estimation of impacts of other variables of interest.

In a pioneeristic work, Paxson (1992) used rainfall shocks to construct estimates of transitory income, and found that unexpected income shocks did not have serious welfare consequences for Thai farm households, because they used savings and dissavings to buffer consumption from income shocks.

Despite Paxson (1992), the lack of partial insurance strategies adopted by poor farmers against a temporary shock could indeed imply a reduction in crop yields with potentially negative impacts on consumption growth. Indeed, there is empirical evidence that self-insurance mechanisms only partially succeed (Morduch, 1995; Townsend, 1995), and that uninsured risk may well 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). To this end, Ligon and Schechter (2003) provide a micro-founded household level vulnerability measure by applying the so-called Jensen inequality.

Dercon (1996), analyzing, 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, and notes that “this evidence is to some extent disconcerting if one is interested in rural growth without exacerbating rural inequality, since it shows the existence and the mechanisms of a ‘poverty trap’”.

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. In a seminal work, 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 much higher”, and finding analogous results.

The amount of evidence of significant both short-run and long-run impacts of weather shocks on household welfare, and the limited evidence for precautionary saving and 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).

But, following empirical evidence on macro growth which 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 concept 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 and well known 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 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.

Despite this large body of literature, however, as 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.”

This work uses the empirical tools and models of development economics to examine the link between short-term household welfare dynamics and temperature shocks in rural Tanzania, in order to provide an empirical answer to the following questions: what is the micro relationship between temperature shocks and economic growth? Is the idea of a climate-induced poverty trap plausible to describe the growth dynamics of farmer households in a rural developing context?

We thus explore the short-run micro relationship between temperature, poverty and economic growth, similarly to what Letta and Tol (2016) do at the country level.

The justification for such an exercise stems from the lack of within-country works on the relationship between temperature and economic growth, as emphasized by Tol (2016): “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.”

From an academic point of view, thus, this article speaks to two well 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 weather-economy literature that studies short-run elasticities of weather shocks impacts on growth to infer about future impacts of climate change.

In doing so, we control for a set of potential transmission channels that can justify potential heterogeneity of impacts and explain the lack of consumption smoothing behaviours, namely: asset growth; labour productivity, following recent micro studies on temperature and labour productivity (Cachon, Gallino, & Olivares, 2012; Heal & Park, 2015; Niemelä, Hannula, Rautio, Reijula, & Railio, 2002; Sudarshan & Tewari, 2013); health expenditure; average crop yields, to understand whether or not poorer farmers shy away from investing in profitable but risky technologies (such as modern agricultural inputs) and keep conservative behaviours, or more simply they cannot use these technologies because of credit constraints; the role of micro institutions and insurance nets; finally, we test for the presence of consumption thresholds with regard to the impacts of temperature shocks. However, let us thus be clear at the outset. What we actually do is not the same as testing for the presence of multiple equilibria as a signal for the existence of a poverty trap. In fact, we only check whether or not there is a consumption threshold above which temperature impacts turn insignificant or even positive, i.e. whether impacts disappear as households grow richer. Under a classic ‘poverty trap’ threshold, households are trapped in an equilibrium with permanently low income, whereas here we simply show that temperature shocks only affect the poorest among the poor, and slow their consumption growth rate and the observed convergence process. Anyway, deceleration is not bifurcation, as noted by Dercon (2004) and Jalan and Ravallion (2002).

Tanzania is an appropriate setting for such a study.

It is by now commonly accepted that the future impacts of climate change will disproportionately affect poorer, hotter, and lower-lying 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 the threats posed by climate change (IPCC, 2014).

Tanzania is a poor, hot and lower-lying Sub-Saharan country, where in 2015 68% of the population lived in rural areas[[1]](#footnote-1). It is constantly 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 variability, 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”.

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.

We employ a micro-growth model borrowed from the standard growth literature, and test for convergence among households and for the significance of weather shocks as determinants of growth, while controlling for heterogeneity.

Obviously, given the short-run nature of this dataset, our capacity to assess convergence is limited, and we can only cautiously infer about long-run convergence.

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. Above that threshold impacts turn insignificant and, above a second upper threshold, they even turn positive. In other words, temperature shocks slow the observed convergence process among households, and entail distributional consequences by enhancing inequalities. The main transmission channels responsible for this heterogeneity appear to be agricultural yields and labour productivity, due to the fact that agricultural yields, technologies and assets, as well as income sources, differ significantly across consumption quartiles. Additionally, no impact on asset growth is found, suggesting asset smoothing is probably taking place and that poorest households choose to voluntarily destabilize their consumption in order not to sell their assets, or that more simply they do not have enough assets to sell to cope with the income reduction caused by temperature shocks.

We reckon 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 temperature, 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 geography *vs* institutions debate, by providing some micro evidence on the issue. Fourth, it provides minor contributions to the development literature, by testing for consumption *vs* asset smoothing, which has been rarely been done according to Carter and Lybbert (2012)[[2]](#footnote-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 1 illustrates the empirical framework and the identification strategy. Section 2 describes data and provides introductory descriptive statistics. Section 3 shows and comments the results from the main specification of the empirical analysis. Section 4 conducts a host of robustness checks as well as complementary empirical tests. Section 5 investigates the channels of the heterogeneity of impacts. Section 6 illustrates the thresholds and the method used to detect them. Section 7 discusses the main findings and limitations of the analysis, and illustrates the implications of the results with regard to climate change. Section 8 wraps up, derives policy guidelines, reminds some *caveats* and concludes.

**Section 1**

**Empirical framework and identification strategy**

Our empirical framework follows up the strand of the literature that looks at growth in developing countries by using micro-level data, drawing in particular from the works of Carter, Little, Mogues and Negatu (2007); Dercon (2004); Jalan and Ravallion (2002).

In particular, we assess convergence by using a standard empirical growth model, in a framework borrowed from the macro literature, and especially by the Solow (1956) and Mankiw, Romer and Weil (1992) models, where growth rates are assumed to be negatively related to the initial income levels:

1. $ ln Y\_{it}-ln Y\_{it-1}= αln Y\_{it-1}\_{}+μ\_{i}+m\_{it}+ θ\_{rt}+ε\_{it}$

In this equation, the left-side variable is the between-wave growth rate in annual household per adult-equivalent consumption, and $αln Y\_{it-1}$ is lagged household per adult-equivalent consumption, where the coefficient $α$, if negative and statistically significant, would indicate, on average, a process of conditional convergence among households. The next logical step would be to test whether convergence is occurring within or between villages, as investigated for Ethiopian households by Dercon (2004). Unfortunately, due to confidentiality reasons, data on village location for households are not released by the LSMS-ISA project.

In all our specifications, we alternatively use as *Yit*both total consumption and food consumption. Moreover, 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 families with a small number of members, as stressed in the Basic Information Document of the original LSMS-ISA surveys[[3]](#footnote-3).

The inclusion of lagged consumption level as an independent regressor may raise concerns about endogeneity. However, preliminary endogeneity tests, based on the difference of two Sargan-Hansen statistic (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) could never reject the assumption of exogeneity of this variable, as it is shown in Table A.1 for the baseline regressions. Furthermore, the core findings did not change when we used other estimation methods (see below) which treat lagged consumption level as endogenous, enhancing our confidence in the validity of the results.

As for the other elements in the equation, $μ\_{i} $are household fixed effects;$ m\_{it}$ are month of interview dummies to capture seasonality; $θ\_{rt}$ are region x 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 household-wave level, following the two-way clustering recommended by Cameron, Gelbach and Miller (2011).

This empirical growth model is then augmented to investigate the potential impacts of weather shocks, by adding temperature and precipitation shocks, as well as a vegetation time series and a number of household control variables:

(2)$ ln Y\_{it}-ln Y\_{it-1}= αln Y\_{it-1}+β∆Temp\_{it}+γ∆Pre\_{it}+ ΩZ\_{it}+ ωX\_{it} + μ\_{i}+m\_{it}+θ\_{rt}+ε\_{it} $

$β∆Temp\_{it} and γ∆Pre\_{it}$ are temperature and precipitation shocks, where ‘shocks’ mean ‘anomalies’ in the sense defined by Dell, Jones and Olken (2014), i.e. our weather variables are calculated as the level difference between their annual values and the long-run means, divided by the long-run standard deviation. 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 variability, this choice of the weather functional form suits better the nature of our data. One may be concerned for the fact we use the difference between *annual* levels and long-run means. This means we only take into account temperature and precipitation in the twelve months before the interview. However, waves are not annual, and in most cases the interval between interviews is close to two years. Considering only the year before the interview, thus, does not capture all the weather shocks that have taken place in the meantime. However, if anything such a choice represents a conservative estimate. In fact, we perform a robustness check in which we use weather data aggregated for the 24 months preceding the interview, which show, as expected, even bigger impacts (see Section 4).

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.

Importantly, 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 consumption quartiles.

Other than weather shocks, we include two sets of control variables.

$ΩZ\_{it}$ 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.

As for household controls, in all the specifications below we 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 of education among adults, the number of infants (i.e. less than five year old) and dummies capturing two idiosyncratic shocks, illness and death of a household member. The inclusion of control variables reduces the risk of omitted variable bias and provides smaller standard errors in the estimates.

We test the robustness of our results by using different estimation techniques. First, we use the Hausman - Taylor (1981) estimation 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. While the partitioning assumptions are strong, we treat all the household controls and the idiosyncratic shocks as endogenous time-varying variables. Additionally, we also estimate the model by using Two-Step Difference GMM following Arellano and Bond (1991).

After finding heterogeneity, we tried 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) consumption level:

(3)$ ln Y\_{it}-ln Y\_{it-1}=\left\{ \begin{array}{c}αln Y\_{it-1}+β^{l}∆Temp\_{it}+γ∆Pre\_{it}+ ΩZ\_{it}+ ωX\_{it} + μ\_{i}+m\_{it}+θ\_{rt}+ε\_{it} if \&ln Y\_{it-1}\leq σ\\αln Y\_{it-1}+β^{u}∆Temp\_{it}+γ∆Pre\_{it}+ ΩZ\_{it}+ ωX\_{it} + μ\_{i}+m\_{it}+θ\_{rt}+ε\_{it} if \&ln Y\_{it-1}>σ\end{array}\right.$

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

**Section 2**

**Data and descriptive statistics**

1. *Data*

The data used in this work are taken from three 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, as of today, of three surveys: 2008 – 2009; 2010-2011; 2012-2013[[4]](#footnote-4).

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 temporally deflated, in order to convert nominal values in real/constant values, using the Consumer Price Index (CPI) for Tanzania by the World Bank[[5]](#footnote-5), 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 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.

*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).

These weather data have been aggregated in two ways. First, long-run averages have been calculated over the period 1980 – 2015. Second, annual measures were carefully built for the period of twelve months before each interview date. 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).

This choice was made following a UNDP report on Tanzania, 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”[[6]](#footnote-6). 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.

Hence, temperature at time *t* is average monthly growing season temperature, expressed in degree Celsius. Precipitation at time *t*, instead, is calculated as total growing season precipitation (in millimetres). Long-run average temperature and precipitation represent respectively long-run average monthly growing season temperature and long-run average total monthly growing season precipitation. Finally, as already specified above, temperature and precipitation *shocks* 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.

*Income data*

Finally, income data 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.

*B. Descriptive statistics*

Table 1 provides some descriptive statistics for the main variables.

Interestingly, average total and food consumption growth rates are both negative: they decreased on average by about 3 percentage points between waves. However, standard deviation is very large for both variables, indicating heterogeneity in the growth paths experienced by rural households. As for the weather variables, both temperature and precipitation anomalies were, on average, negative 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.

**Section 3**

**Baseline results**

Tables 2 and 3 report, respectively, the results from the specification in Equation (2) for the two alternative dependent variables: food consumption growth and total consumption growth[[7]](#footnote-7).

A preliminary observation, confirmed in all the regressions in both tables, is that the assumed process of convergence among households is confirmed: the lagged (food and total, respectively, in Tables 2 and 3) consumption level is always negative and significant at the 1 percent level: growth rates are negatively related to ‘initial’ consumption levels[[8]](#footnote-8).

Our attention now shifts to the weather variables.

In Column 1 we only included weather shocks without checking for heterogeneity. This yields contrasting results depending on the choice of the dependent variable: in Table 2, in fact, on average temperature shocks have a negative and significant impact on *food* consumption growth, whereas in Table 3, the average impact on *total* consumption growth, although negative, is not statistically significant. Average precipitation shocks, instead, are insignificant in both cases.

Column 2 starts checking 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 (in Table 3) consumption. Defining household as “poor” is of course a relative concept in a context like rural Tanzania, and it essentially means we are checking 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 but insignificant impact for the “non-poor” households, but a large, negative and significant (at the 1 percent level) impact on household growth for “poor” households, and this is consistent regardless of the choice of the dependent variable (food or total consumption growth). Interpreting the results in Columns 2 with respect to the within-standard deviation of temperature shocks (0.096), one standard deviation increase in temperature anomalies decreases household per-adult equivalent food consumption growth by about 8 %, and household per-adult equivalent total consumption growth by approximately 5.85 %, *ceteris paribus*, for households defined as “poor”. Precipitation impacts instead, are positive and insignificant in Column 2 in both tables, negative and significant for “poor” households in Table 2 (food consumption growth), and negative and insignificant for “poor” households in Table 3. 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 median long-run average monthly growing season temperature. The inclusion of this additional interaction does not alter the previous findings: households living in a hot area do not experience significantly different impacts from neither temperature nor precipitation shocks, while the negative and significant impact from temperature shocks for “poor” households stays basically unchanged in magnitude, and only slightly diminished in significance in Table 3, where the dependent variable is total consumption growth.

It is worth noting, incidentally, that the temperature impacts on growth are always larger on food consumption growth than on total consumption growth, consistent with the fact that most households are subsistence farming households. This will be additionally addressed in Section 5, 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 vanish as households grow richer.

A visual representation of this poverty-temperature relationship can be helpful.

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 ‘initial’ 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 independently of the choice of the dependent variable, 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 quartile do not, and growth for households in the upper initial quartile is even positively and significantly affected, suggesting not only heterogeneity of impacts, but a reversal of impacts.

This core finding is not altered when including the interaction for living in an “hot” area, as shown in Column 2 in both tables. This interaction is positive and even significant at the 1 percent level in Table 5, i.e. for total consumption growth, which would point to the presence of adaptive behaviour, as explained in Dell, Jones and Olken (2014). However, we will argue below that this result should be interpreted with caution. Finally, impacts due to precipitation shocks are, as in the previous tables, almost always insignificant and sensitive to specifications.

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. Temperature shocks, in sum, slow the convergence process, and represent a source of 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 5 but, first, Section 4 conducts a host 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.

**Section 4**

**Robustness checks and complementary tests**

We explore the robustness of our results with respect to different estimation strategies, spatial autocorrelation, various subsamples of the main dataset, different weather data functional forms and sources.

1. *Use of Conley (1999) standard errors*

It is well known that both economic growth and temperature are spatially autocorrelated.

One could thus argue that our results are inflated because we fail to take into account spatial auto-correlation. To prevent this critique, we 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. As explained by Hirvonen (2016), 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 met. We use the following cut-off points: 25, 50, 75 and 100 km. These regressions are reported in Table 6: in Column 1 the dependent variable is food consumption growth, in Column 2 is total consumption growth. The results are basically unchanged: therefore, we can safely assert that our findings are not weakened when correcting for spatial autocorrelation and spatially-robust standard errors.

1. *Hausman – Taylor regressions*

Following Dercon (2004), we repeat the main specification of our empirical analysis but using the Hausman - Taylor (1981) model.

The Hausman-Taylor model, being a random-effect model for panel data, also allows us to include time-invariant variables in our regressions. In particular, we can now add a set of time-invariant geographic controls which include: population density and distances (in kilometres) to nearest major road, population centre, market, border crossing, headquarter of residence. Additionally, we can also include long-run averages for our weather variables. However, as argued above, given the strong assumptions implied by this estimation strategy, we adopted a cautious approach, following Dercon (2004): lagged consumption terms, all household controls and geographic controls are treated as time-varying endogenous variables; dummies for consumption quartiles are treated as time-invariant endogenous; all weather variables, both time-varying and time-invariant, are treated as exogenous.

Results can be found in Table 7. As usual, we report results for both our dependent variables, namely food consumption growth (Columns 1 and 2), and total consumption growth (Columns 3 and 4). 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 significantly affect households belonging to the poorest initial quartile; interestingly, though, while the coefficient for the upper quartile is positive here as well, it is not significant as in the baseline specification, which suggests it is sensitive to specification. This will be further addressed in the following robustness checks. As above, there is no statistically discernible effect of precipitation shocks, while both long-run temperature and precipitation have a positive and significant impact on both food and total consumption growth, temperature in particular. However, since hot areas in Tanzania are also the richest ones, this finding could be due to correlation and not to causality, and should be interpreted with caution.

On the whole, in sum, the sharp heterogeneity of impacts across initial consumption quartiles is confirmed by the Hausman-Taylor random-effect model.

1. *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).

The Arellano-Bond estimation method 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 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.

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 8: reassuringly, they are remarkably 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; again, temperature impacts for households in the upper quartile are positive, but not significant anymore. Precipitation keeps being insignificant. The Hansen-J tests reported in the bottom of the Table ensure the specification is valid, and the standard errors are corrected using Windmeijer (2005) adjustment procedure.

1. *Splitting the sample: coastal and inland areas*

Tanzania is a country with large climatic variability, where climate is temperate in the highlands and tropical on the coasts, as highlighted by Rowhani, Lobell, Linderman, & Ramankutty (2011).

One may be concerned that our results are driven by one of these two subsamples or rather that, while valid on average, they do not hold when splitting the sample.

In order to ensure this is not case, in Tables 9 and 10 we run the initial quartile regressions for, respectively, only coastal areas (included Zanzibar), and only inland areas.

While somewhat quantitatively different between each other, the results are consistent with the overall story: the pattern is confirmed, i.e. only the growth rates of the poorest households are significantly affected by temperature shocks, regardless whether they live in colder highlands or in hotter and wetter lowlands (either coastal regions or in Zanzibar).

1. *Splitting the sample: migrating and non-migrating households*

15.58 % of households in our rural sample migrated at least once across the panel. One could argue that the heterogeneity of temperature impacts is thus driven only by migrating, or non-migrating, households. On the other hand, we define weather shocks as level differences from their long-run averages. We thus assume the more current weather differs from the historical weather conditions a household is used to, the more its consumption growth is affected. Consequently, this implies we should find a bigger impact for migrating households since, moving across different geographic areas, they should in theory experience bigger weather anomalies and ‘climate changes’ compared to non-migrating ones. Tables 11 and 12 address these issues.

Table 11 explores impacts of weather shocks for non-migrating households. The heterogeneity pattern of temperature shocks is confirmed. Interestingly, there is no significance of positive impact for households belonging to the richest quartile.

Table 12 does the same with respect to migrating households. Heterogeneity of impacts across initial consumption quartile holds in this case as well. Apart from this, there are two main points that deserve to be stressed: first, as assumed above impacts in general are bigger for migrating households, as can be seen by looking at the size of the coefficients; second, temperature shocks have a positive and *significant* (at the 1 percent level) impact on household growth for the upper quartile.

The latter finding points to the fact that, since the positive impacts for the upper initial quartile are not significant for non-migrating households, for only coastal / only inland subsamples, and when using Hausman-Taylor and Arellano-Bond GMM estimation strategies, their significance we found in Tables 4 and 5 was either due to statistical flukes or being driven by the subsample of migrating households.

1. *Subsample of the poorest initial consumption quartile*

Table 13 explores the robustness of our findings by running the baseline specification only for the subsample of the households belonging to the poorest initial consumption quartile. As can be seen in Columns 1 and 2, temperature shocks have a negative and significant impact on (food and total) consumption growth of the initially poorest households. As always, precipitation impacts are not significant.

1. *Using annual weather anomalies*

We now present a host of tests that check the robustness of the results with regard to the choice of the weather functional forms and data sources. In fact, we acknowledge the remarks by Auffhammer et al. (2013) and Dell, Jones and Olken (2014) that economists should always be aware of the risks of getting spurious econometric inference when using weather data and should always check for the sensitivity of their findings.

Hence, we begin by showing in Table 14 the baseline regressions but using annual weather anomalies instead of growing season weather anomalies. We chose to use growing season weather data because we followed Hirvonen (2016) and thought this would be a better way to capture farming conditions during rainy seasons, on the assumption that the agricultural channel is the main one through which impacts affect consumption growth, but one could also make a point that annual weather anomalies, i.e. the difference in levels between weather data calculated over all the 12 months preceding the interviews (thus, without excluding the June-September period) and long-run averages, divided by the long run standard deviation, should instead be used.

As Columns 1 and 2 in Table 14 show, the use of annual weather anomalies does not qualitatively change our findings, although it somewhat weakens the significance of the coefficients (but not the magnitude), confirming our view that including off-season temperature and precipitation in the calculation of the weather averages does not make the estimates more precise but, on the contrary, more blurred, and that the impacts from weather shocks mainly appear through growing season conditions and the agricultural yield channel (see Section 5).

1. *Using weather levels*

Although Tanzania exhibits, comparatively speaking, substantial climatic variability for being a country, temperature in the country only varies to a limited extent, as the standard deviation for long-run average temperature in Table 1 illustrates. Hence we opted for a measure of weather anomalies, on the assumption that in such a within-country context level changes matter more in proportion to an area’s usual variation than in an absolute sense (Dell, Jones and Olken, 2014). But one could argue nonetheless that this choice of the weather functional form could be driving the results. To make sure this is not the case, in Table 15 we repeat the baseline quartile specification but using temperature and precipitation levels instead of anomalies.

The pattern of heterogeneity of temperature impacts across initial consumption quartiles is confirmed, although the significance of impacts for households in the poorest initial quartile is weakened, both for food and total consumption growth. However, in our view this is not something that alters the validity of our findings, but rather a hint that our choice of the functional form is more appropriate. Precipitation shocks, finally, are insignificant.

1. *Different weather data*

Results could be driven by properties of the weather data. 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.

We follow this advice, and use not only a different data source, but a different data product as well.

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 climate model to create gridded weather data products, CRU data are gridded data which interpolate from ground stations (Dell, Jones and Olken, 2014). The key difference between reanalysis and gridded data is that, rather than use a statistical procedure to interpo­late between observations, a climate model is used. Table A.2 in the Appendix provides descriptive statistics for the CRU temperature data: it is worth noting how, although annual growing season temperature and long-run average growing season temperature are very similar to their correspondent using MERRA-2 data (cf. Table 1), the average of the temperature anomaly, ∆Temp, is not only positive, while the one in Table 1 is negative, but twenty times bigger. Despite this stark difference in the average of temperature shocks, the two temperature datasets exhibit a correlation of about 85 %. Therefore, exploring the robustness of our findings using this alternative dataset is a crucial robustness check.

As for rainfall, we use precipitation data that come from the NPS Dataset as part of the ISA module, and our variable is now total rainfall in the wettest quarter (mm) within 12-month periods starting in July previous to each round. 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 degree) gridded estimate covering the Africa continent[[9]](#footnote-9). Therefore, this different kind of rainfall data is useful first, because they are readily available; second, because they have a better resolution and they are linked to the real, and not averaged, location of households; third, because they only take into account precipitation in the wettest quarter instead of the total growing season precipitation.

The results are illustrated in Table 15.

Reassuringly, the consistency is remarkable: not only the pattern of heterogeneity still holds, and significance of the coefficients is essentially analogous, but the magnitude of impacts is even bigger, both for the negative impacts on households belonging to the poorest quartile and for the positive impacts for households belonging to the richest quartile.

However, regarding the significance of the positive impact for the upper quartile we remind to be cautious in drawing inference given the high sensitivity to specification emerged above.

Even when using different data, there is not statistically discernible impact of precipitation shocks.

Therefore, we can safely conclude that using a different data source for both temperature and precipitation not only does not weaken the analysis, but it actually reinforces our findings.

This is further confirmed when we repeat the regressions with weather shocks defined as levels instead of anomalies using the alternative weather data. These results are reported in the Appendix (Table A.3).

1. *Persistence of weather shocks*

As already stressed in Section 2, waves are not annual, and on average the recall period between interviews is close to two years. We aggregated weather data using only the 12 months before the interview month because all the data in each separate survey are annualized, but this choice implies two things: first, we are ignoring potential persistence of weather shocks, and assuming that only weather shocks of the last 12 months before the interview affect annual consumption; second, we are not capturing all the weather shocks that took place in the interval between waves.

To investigate persistence, we therefore take cue from Dercon (2004) and re-run the baseline quartile regressions with just one difference: instead of using weather data aggregated in the 12 months before the interview month, we use weather shocks that have been aggregated in the 24 months before the survey. If there is persistence of shocks, one should then observe a bigger impact.

Indeed, as Table 15, Columns 1 and 2, show, this is the case: while the qualitative pattern is the same, the coefficients are all larger: this means that not only weather shocks that take place in the growing season immediately before the survey have an impact on the between-wave consumption growth, but also weather shocks in the year before the current interview. In sum, what these results imply is that, if anything, our results represent a conservative estimate of the impact of temperature shocks on food and total consumption growth.

Additionally, following the sensitivity analysis in Dercon (2004), in Columns 3 and 4 disentangle this two-year effect of weather shocks by aggregating weather data using only data which take place 24 to 12 months before the interview month, i.e. excluding the 12 months before the interview. This allows us to estimate the impacts of weather shocks during the growing season from the previous year. As can be observed, impacts are much smaller than when using the annualized weather data for households belonging to the poorest quartiles but, oddly, the positive impact is bigger for households belonging to the upper quartiles. However, given the significance of this positive impact has shown to be very sensitive to specifications, a note of caution is in order in interpreting them.

**Section 5**

**Transmission channels and mechanisms**

Having proved that our results are reasonably robust to a host of different checks, we must now address the issue of why is there such a sharp heterogeneity of impacts in our sample.

What are the reasons behind the fact that there is not only heterogeneity, but indeed a *reversal* of impacts on household growth depending on initial consumption?

We try to shed light on this question by investigating three main channels: health expenditure, labour productivity and agricultural yields. These three transmission channels find their theoretical and empirical grounding in previous literature.

Furthermore, to explain if and how households cope with impacts of temperature shocks, we investigate impacts on asset growth, to test for the potential presence of asset-smoothing in contrast to consumption smoothing behaviours (Carter et al., 2007; Carter & Lybbert, 2012; Schlenker & Lobell, 2010).

Finally, in the framework of the debate on the fundamental determinants of growth, we test whether the presence of micro, community-level institutions can dampen the negative impacts of temperature shocks.

1. *Health expenditure channel*

As summarized by Dell, Jones and Olken (2014) and Heal and Park (2015), several studies have documented the impact temperature can have on health and mortality, which in turn affect labour productivity and income (and *vice versa*). In our framework, it could be temperature shocks on consumption growth appear, at least partially, through this channel: temperature could affect health and hence productivity, and this in turns affects income and subsequently consumption.

We test this mechanism by regressing the baseline specification set out in Equation (2) on a different dependent variable: instead of consumption growth, we now use as $Y\_{it}$ the ratio between health expenditure and total expenditure[[10]](#footnote-10). The expected sign of the relationship is the opposite: in response to temperature shocks, the growth rate of the ratio should increase. Furthermore, to justify the pattern of heterogeneity, one would expect this ratio to increase significantly more for households belonging to the poorest quartile. The results for this specification can be found in Table 18, Column 2: although the regressions show that temperature shocks positively (but not significantly) affect this ratio for all the quartiles, the impact is quite homogeneous.

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.

Incidentally, looking at Column 3, living in a hot area has a large and strongly significant effect on the growth rate of the ratio between health and total expenditure.

1. *Labour productivity channel*

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; Sudarshan & Tewari, 2013) has found vast and significant effects of temperature increases on the productivity of workers, especially on those who work outdoor.

In a context like rural Tanzania, a large share of workers is involved in outdoor work, primarily in farming activities obviously. Outdoor work is notoriously more exposed to the impacts of temperature increases or hot waves. Furthermore, not only work is primarily performed outside, but additionally agriculture in Tanzania is still largely traditional and the lack of agricultural technologies, especially labour-saving technologies, remains widespread. Consequently, Tanzanian agriculture still involves significant 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.

In Table 19 we investigate whether this is the case. The dependent variable is ‘labour productivity growth’. We created a rough measure of labour productivity by dividing total household income by the numbers of worker in the household. The total income variable used was taken from the FAO Rural Income Generating Activities (RIGA) Team Database[[11]](#footnote-11), and expresses total annual net household income, built through a careful calculation of all the different income sources for each household. We are aware this measure represents a rough and only approximate proxy of 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.

Other than being an approximate measure, 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.

Having made these premises, we can now take a look at the results.

In Column 1 we do not look for heterogeneity of weather shocks, but only for average impacts, and find that temperature anomalies have a large and significant at the 5 percent level impact on labour productivity growth. More precisely, one within-standard deviation increase in temperature shocks decreases household labour productivity growth by approximately 8.7 %, on average, and *ceteris paribus*. Column 2 disentangles this aggregate impact by looking at heterogeneity across initial consumption quartiles: what emerges is that the negative impact is essentially concentrated in households belonging to the two poorest initial quartiles, becoming instead insignificant, although still negative, for households in the two upper quartiles.

Precipitation shocks, conversely, are always insignificant. This overall picture is remarkably consistent with the consumption growth regressions, and seems to confirm labour productivity as one of the transmission channels responsible for the heterogeneity of impacts (although not for the reversal, because here the sign is always negative).

One may then ask: what are the channels of this channel? Why is there such a discrepancy of impacts on labour productivity growth across quartiles? Tables 20 and 21 report some descriptive statistics that can help clarifying this issue. Table 20 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 labour-saving technologies in agriculture 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.

Table 21, instead, reports the percentage of households, across quartiles, for which farming was not the main source of income in at least two waves. This is relevant here because, according to our hypothesis above, the less households depend on farming activities, the less they work outdoor, and the lowest the impact on labour productivity. One can notice that while farming was not the main source of income for only about 19 % of households in the poorest quartile, this percentage goes progressively up and, for the richest quartile, one third of households do not depend on farming as the main source of income.

To investigate if these differences play a role in explaining the heterogenous impact on labour productivity growth, Columns 3 and 4 include interactions of weather shocks with, respectively, a dummy with value 1 for having an above average Agricultural Wealth Index and a dummy with value 1 if farming is not the main income source. Perhaps not surprisingly, looking at the bottom of the Columns, the total impact of temperature shocks on labour productivity growth substantially decreases, and becomes only weakly statistically significant, for households with an above average Agricultural Wealth Index (Column 3), and turns even insignificant for households who do not primarily depend on farming (Column 4).

Aware of the limitations of our labour productivity measure, as it stands, we find an heterogenous impact on labour productivity growth, which we reckon partially explains heterogeneity of impacts on consumption growth.

In particular, 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”.

1. *Agricultural yield channel*

The third and final transmission channel is the agricultural one.

It is very well known and documented in literature 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 (A. J. 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)

This is especially the case for rural Tanzania since, as Rowhani, Lobell, Linderman, & Ramankutty (2011) stress: “Not only is Tanzanian agriculture underdeveloped, it is also mostly rain-fed and low in intensity using very little chemical inputs. For maize, synthetic fertilizers were used only on 10% of cultivated land and represented 125 kg per fertilized cultivated hectare, around 60% less than in the USA (310 kg/ha) (FAO, 2007)”.

We therefore expect this to be the main transmission channel. Essentially, one would expect a significant aggregate impact of temperature shocks on crop yields and, to justify the pattern of heterogeneous impacts on consumption growth, a sharp heterogeneity as well.

In order to test these hypothesis, we investigate the impact on crops through two different ways. First, we repeat the baseline econometric specification of Equation (2) but using, as a dependent variable, total crop production growth. Total crop production growth is the between-wave percentage change in (ln) total crop production and, in turn, total crop production is the monetary value of all household own crop production in a given wave. Data for this variable were taken, again, from the FAO RIGA Database. Table 22 provides the results for this specification. In Column 1 we only regress total crop production growth on weather shocks, without interactions. While precipitation is again insignificant, there is a large, negative and significant impact from temperature shocks, namely one within-standard deviation increase in temperature anomalies entails a reduction in the growth rate of crop production of about 11.56 percentage points, on average. Column 2 checks for heterogeneity of impacts from weather shocks with respect to initial food consumption quartiles, Column 3 with respect to initial total consumption quartiles. Results are consistent between the two and show that, once again, households belonging to the poorest quartiles are more severely hit by temperature shocks: for comparison, one within-standard deviation increase in temperature shocks decreases household total crop production growth by approximately 15.85 %, *ceteris paribus*, for households belonging to the poorest initial food consumption quartile, compared to the reduction of about 9.25 % for households belonging to the richest initial food consumption quartile.

Second, we look directly at crop yields. 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). 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[[12]](#footnote-12). 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. As for precipitation instead, always to capture potential non-linearity in the relationship with plant growth, we included in the regressions precipitation levels and the square of precipitation levels, using, though, the alternative ARC rainfall data already used in the robustness checks (cf. Tables 16, A1 and A2), namely total precipitation during the wettest quarter, because being already included in the ISA module of the original dataset they are based on real household plot location, and hence more accurate in describing the impact of precipitation on crops, for which the higher the resolution, the more precise the estimate (Ahmed et al., 2011).

Table 23 reports the results for this specification.

The dependent variable is average crop yield during the previous two rainy seasons.

In Column 1, as usual, we only look at the aggregate impact.

The estimates here suggest that it is exposure to extreme temperatures (above 34°C) which is harmful for crop yields, and hence that it is the extreme temperatures that are driving the results in Table 22 on the impacts on total crop production.

Moving across the columns, in Column 2 we decompose the aggregate impact of GDDs by looking at impacts across initial consumption quartiles. What emerges is that precipitation impacts are close to zero and insignificant, that impacts from the number of GDDs between 8 and 34°C is essentially zero for all the four quartiles, while exposure to extreme temperatures (above + 34°C) has negative and strongly significant impact on crop yields of households in the poorest initial quartile, a negative and significant at the 5 percent level 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 remarkably consistent not just with Table 22 on total crop production, but with the pattern of heterogeneity of temperature shocks on consumption growth.

This leads us to think that, as hypothesized, this is the main transmission channel responsible for the heterogeneity / reversal of impacts conditional on initial consumption.

But the next question immediately arises: why are there such big differences in the impacts from extreme temperatures on crop yields?

We answer this question presenting both qualitative and quantitative evidence.

First, we check whether overall agricultural means and technologies can help explaining the heterogeneity. Hence, analogously to what we did with respect to the labour productivity channel[[13]](#footnote-13), in Table 24 we check heterogeneity with respect to the Agricultural Wealth Index (AWI). In Column 1 we just add a dummy with value 1 for having an above average AWI as an independent regressor in the baseline specification. As expected, this dummy has a positive and strongly significant (at the 1 percent level) impact on crop yields. Consequently, in Column 2 we interact it with our measure of weather shocks and, looking at the bottom of the table, it can be observed that the total effect of extreme temperatures (above + 34°C) for crop yields of households having an above average AWI is negative and slightly larger but not statistically significant, due to the largest standard errors. Recall households in the upper initial consumption quartile have on average higher values of the AWI[[14]](#footnote-14).

Next, in Table 25 we provide descriptive statistics which shows that maize and paddy are the two main staple crops cultivated by households in this sample, accounting on average for more than 50 % of the total quantity of crops produced for almost all households except for those in the upper initial consumption quartile, although for them as well their cumulative share is still very high (47 %).

Table 26, then, reveals how richer households not only produce more crops (Column 1), but they also have more productive plots (Column 2).

We therefore test for heterogeneity of impacts on crop yields due to these factors in Table 27.

In Column 1 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. In Column 2 we interact weather shocks with ‘Higher crop yield’, a dummy with value 1 for households having a higher than average crop yield in a given wave. In Column 3 we include interactions with ‘Higher crop production’, dummy with value 1 for households having a higher than average crop production (in kg) in a given wave.

Looking at the bottom of the Table, remarkably, the effect of the Number of GDDs above 34 °C turns statistically insignificant in all three cases, i.e. negative impacts on crop yields from extreme temperatures disappear if households are not specialized in the cultivation of maize and paddy, if they have a higher than average crop yield and if they produce a higher than average quantity of crops.

This tells us, first, that the negative impacts on crop yields mainly come through maize and paddy, consistently with the findings of previous literature on the impacts of temperature on crop yields in Tanzania (Ahmed et al. 2011; Rowhani et al., 2011). Second, the heterogeneity of impacts we find can overall be explained by the fact that richer households are advantaged by better agricultural assets, technologies and soil quality, which make them less vulnerable, or better immune, to the negative impacts entailed by temperature shocks, which conversely have serious welfare consequences for poorest households.

But one could still say: fine, the data and regressions presented partially account for heterogeneity of impacts, but this work actually finds a *reversal* of impacts, which turn even positive for the upper quartile. Can households be so different? After all, we are still talking about farming households in rural Tanzania, where no one really practices ‘modern’ agriculture. In fact, the use of irrigation is still very limited (Table A.5) and so the use of inorganic fertilizers (Table A.6), although in these cases too richer households show, on average, better conditions.

Furthermore, we showed above that even richer households do mainly cultivate maize and paddy, which are very sensitive to temperature shocks.

However, with regard to this we can also present interesting descriptive statistics that sheds further light on the differences between households.

Tables A.7-A.10 in the Appendix show data taken from the ISA module on the use ‘improved’ seeds for maize and paddy. Improved seeds, differently from traditional seeds, are more drought-resistant, and can strongly mitigate the negative impacts on crops from extreme temperatures.

Tables A.7 and A.8 show the use of improved maize seeds, and reveal how both the use of improved maize seeds on at least one plot, and the use of improved maize seeds on at least half plots, sharply differ across initial consumption quartiles. Tables A.9 and A.10 reveal the same pattern with regard to the use of improved paddy seeds.

On top of all the differences in agriculture illustrated above, in sum, richer households also make more use of drought-resistant seeds for crucial crops like maize and paddy.

Putting the pieces together, all this seems to point at the existence of a ‘yield gap’ among farming households in rural Tanzania, which accounts for the inequality of impacts of temperature shocks and slows the convergence process among households.

1. *Testing for asset smoothing*

We have showed that the main channels that account for the heterogeneity of impacts on consumption growth are agricultural yields and labour productivity.

But why poorest households do not smooth their consumption by drawing, for example, on assets?

Are they smoothing assets instead of consumption?

To answer this question we repeat 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 across quartiles is reported in Table 28.

The dependent variable, therefore, is now household per adult-equivalent between-wave percentage change in TLUs [[15]](#footnote-15). Table 29 reports the results.

In Column 1 we can see that temperature shocks have, on average, a negative but not significant impact on asset growth. In Column 2 we decompose the impacts by initial food consumption quartiles, but we do not find any significance, except for the impact on the richest quartile, which is positive but only weakly significant. Column 3 repeats the specification in Column 2 but using initial total consumption quartiles. Results do not change, except for the fact now even the weak significance of temperature impacts for the upper quartile disappears.

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 stubbornly 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 another Sub-Saharan country, 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.”.

In the context of the debate on consumption *vs* asset smoothing (Barrett et al., 2006; Barrett & Carter, 2013; Carter & Barrett, 2006; Carter et al., 2007; Carter & Lybbert, 2012), we are prone to assert that, for the poorest households in our sample, the latter is probably taking place, while conversely the use of assets as buffer stocks, one of the main risk-coping strategy hypothesized in literature, did not take place or was not effective during the survey period (Kazianga & Udry, 2006; Morduch, 1995).

But then, why do we find a positive and even weakly significant impact on asset growth of richer households? If they were performing consumption smoothing we would expect the opposite. Our answer is that they do not need to sell their assets because they essentially do not suffer from the negative impacts on temperature shocks on either crop yields or labour productivity, and consequently on consumption growth. If anything, they are indirectly taking advantage from the negative impacts on poorest households and earning more from their crop activities, which would explain both the positive impacts on consumption growth and on asset growth.

1. *The role of micro institutions and access to credit*

A vast literature has documented one of the reasons households might not be able to smooth their consumption over time in response to income fluctuations is the presence of credit or liquidity constraints (Hirvonen, 2016; Morduch, 1995; Rosenzweig & Wolpin, 1993).

As for Tanzania in particular, Dercon (1996) notes: “Tanzanian rural households cannot rely on credit for consumption smoothing since both formal and informal credit markets are very limited”. But since its study on rural Tanzania, things might have changed.

At the same time, in the context of the debate on the role of institutions and climate as the main determinants of growth (Acemoglu et al., 2000, 2001; Diamond, 1999; Easterly & Levine, 2003; Gallup et al., 1999; Rodrik et al., 2004), it is interesting to see whether the presence of micro, community-level institutions can alleviate the negative impacts of weather shocks on welfare.

To shed lights on these issues, we present a specification in which we interact weather shocks with a dummy for participation in a credit or saving group.

Table 29 illustrates first descriptive statistics which shows that the percentage of households participating in a credit / saving group is very low, although for the upper quartile is three times higher compared to the poorest quartile.

In Table 30, then, we present the results for this specification. ‘Part\_group’ is the dummy of interest, which takes value 1 for households participating in a credit / saving group in a given wave.

In Columns 1 and 2, we investigate the dependent variable is food consumption growth (respectively without and with the interaction between “hot” and temperature shocks), in Columns 3 and 4 total consumption growth (analogously, in Column 4 we also include the “hot” interaction).

Remarkably, Part\_group x ∆Temp has a positive and large sign in all the specifications and, when calculating the total effect of temperature shocks for households belonging to the poorest quartiles, the impact is negative but not statistically significant anymore.

In sum, access to credit and the presence of insurance nets seem to make households immune to weather shocks.

If we consider this measure as a proxy for micro, community-level institutions, then it stems from these findings that institutions might have an important role to play in rural Tanzania as determinants of growth and in alleviating the negative impacts of weather shocks and, more generally, the influence of climate on human welfare and development.

**Section 6**

**Thresholds**

After a thorough investigation of the channels and mechanisms behind the heterogeneity / reversal of impacts, we think we have found a credible story to justify our findings.

Poorest households have a larger share of income in farming activities (and hence they work more outdoor), worse agricultural means and technologies and less assets, worse crop yields, they produce less crops and, on top of all this, they also have a lower Non-Agricultural Wealth Index (cf. Table A.11) and less access to infrastructures (cf. Table A.12)[[16]](#footnote-16). Consequently, when temperature shocks occur, they are more severely hit.

Anyway, we have not precisely identified thresholds of consumption that entail regime changes for temperature shocks. By and large, all we have done has been to interact shocks with dummies for being “poor” (i.e. having a below median initial consumption) and with dummies for belonging to initial consumption quartiles, but these choices are arbitrary. They are not driven by the data.

To overcome this drawback and provide more precise inference about heterogeneity of impacts, on the wake of Carter, Little, Mogues and Negatu (2007), we here 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 the jumping character or structural break in the relationship between variables. In our context, we are looking for threshold (s) of initial consumption above or below which there is a structural break in the impact of temperature shocks, as illustrated in Equation (3).

Given we have a fixed-effect setting, we cannot use initial consumption as the threshold variable since it is a time-invariant variable; consequently, we use lagged consumption level.

Temperature shocks are, of course, the regime-dependent variable.

Looking at the impacts on quartiles in 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. We are therefore looking for two, and not just one, consumption level thresholds.

In Table 32 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 already 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 negative but statistically insignificant; and a second thresholds from which impacts turn from being negative and insignificant to being positive and strongly significant, although as usual we recommend caution in interpreting the significance of this positive impact which has proved to be sensitive to specifications.

Both thresholds, for both dependent variables, are statistically significant at the 1 percent level, as can be seen in the threshold tests (using 300 bootstrap replications) reported below the table, where thresholds values with the relative confidence intervals are also reported.

In particular, after re-converting logs into monetary values, for food consumption we find a lower threshold of approximately 226161 Tanzanian shillings or, in expressed at 2013 purchasing power parity (PPP), 376 dollars; and an upper threshold of approximately 821593 Tanzanian shillings, i.e. approximately 1365 dollars; for total consumption, instead, the two thresholds are approximately 233281 Tanzanian shillings, and 1148538 Tanzanian shillings, or about 1908 dollars [[17]](#footnote-17).

**Section 7**

**Implications of climate change**

In this work, we find a causal relationship between temperature shocks, household growth and poverty. In this penultimate section, we stress that this finding is especially 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). Climate change is a serious threat to crop productivity (Knox, Hess, Daccache, & Wheeler, 2012) and food security (A. Challinor, Wheeler, Garforth, Craufurd, & Kassam, 2007; Schmidhuber & Tubiello, 2007) in Africa, and Tanzania is no exception (Ahmed et al., 2011; Hirvonen, 2016; Rowhani et al., 2011) .

However, development could be a better solution than greenhouse gas emission reduction for developing countries, as originally hypothesized by Schelling (1992, 1995).

The so-called Schelling Conjecture, that is that economic development would reduce vulnerability to climate change, finds empirical support in the results of this work.

Tol (2015) illustrates the Schelling Conjecture with regard to Africa: “In the worst projections, climate change could cut crop yields in Africa by half (Porter et al., 2014). At present, subsistence farmers often get no more from their land than one-tenth what is achieved at model farms working the same soil in the same climate (Mueller et al., 2012). The immediate reason for the so-called yield gap is a lack of access to irrigation, high-quality seeds, pesticides, fertilizers, tools, and things like that. The underlying causes include a lack of access to capital and product markets due to poor roads and insecure land tenure (Dorward, Kydd, Morrison, & Urey, 2004; Foley et al., 2011). Closing the yield gap would do more good sooner than climate change would do harm later. If one really wants to spend money to help farmers in Africa, one should invest in the land registry rather than in solar power. Indeed, modernizing agriculture in Africa would also make it less *vulnerable* to climate change (Howden et al., 2007; Mendelsohn & Dinar, 1999). African farming is particularly vulnerable, because isolated, undercapitalized farmers struggle to cope with any change, climatic or otherwise.”

Extrapolating with regard to climate change, 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, as already guessed by Tol (2016). If the impacts of temperature shocks disappear 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, according to the results of this work, make households less vulnerable to the negative impacts of weather shocks, and less dependent on climate.

However, a note of caution is in order with regard to these considerations.

We are well aware that we only estimated a short-run elasticity, and that weather shocks are not equivalent to climate change. External validity is of course an issue, because 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). This is true for the Schelling Conjecture as well, as emphasized by Tol (2016), who actually finds an apparent overturning of the Schelling Conjecture which breaks down in the tail for high warming (above 3, °C), albeit due to a single study.

These *caveats* notwithstanding, we emphasize the role of development in alleviating, if not reversing, the negative impacts of weather shocks on household growth, and restate that poverty reduction should be a key and paramount element of any climate policy.

**Section 8**

**Discussion and conclusion**

Using the LSMS-ISA Tanzania Panel Surveys by the World Bank, we analyzed the relationship between weather shocks and household growth in rural Tanzania.

The most surprising result is the sharp heterogeneity of impacts from temperature shocks, which affect household consumption growth only if initial consumption levels lie below critical thresholds.

We think we provided a credible story to explain the reasons behind this heterogeneity of impacts: the main transmission channels are represented by impacts of temperature anomalies on labour productivity and, more importantly, on crop yields.

This is because the difference between richer and poorer households is not only due to the fact that the former have more diversified income sources and are less engaged in outdoor farming activities, but especially to the existence of a ‘yield gap’ and differences in crucial agricultural characteristics.

Such differences among households may also be related to *ex-ante* risk-managing behaviours (Dercon, 2004), such as the conservative behaviour of the poorer risk-averse households that shy away from investing in profitable but risky technologies and stick to low-risk, low-return activities, as indeed Dercon (1996) himself argues it is the case in the context of rural Tanzania.

In any case, due to these sharp differences among households, temperature shocks have an heterogeneous *ex-post* impact which slows the process of convergence, and enhances inequalities.

Given the lack of an impact on asset growth, we hypothesize poorer households are performing asset-smoothing, choosing to voluntarily destabilize consumption not to sell their livestock and risk to fall in a poverty trap from which there may be no recovery.

Finally, participating in a credit or a saving group apparently makes households immune to the impacts of temperature shocks, confirming that income risks such as weather risks result in consumption fluctuations if insurance and credit markets, which enable households to perform consumption smoothing, are absent (Dercon, 1996; Morduch, 1995; Rosenzweig & Wolpin, 1993; Townsend, 1995), and additionally showing that micro, community-level institutions such as insurance nets can eliminate the influence of climate on human welfare, as argued by Acemoglu et al., (2000, 2001), Easterly and Levine (2003), Rodrik et al. (2004).

In view of the future impacts of climate change, these findings do emphasize the importance of the Schelling Conjecture, i.e. development is a crucial and indispensable element of any climate policy, especially in vulnerable contexts like rural Tanzania, and inequality of impacts will be, within-country other than between countries, the first and foremost challenge posed by climate change.

These micro results are, in sum, surprisingly consistent with what found on the relationship between growth, temperature shocks and poverty by macro studies (Dell et al., 2012; Letta and Tol, 2016).

However, these findings must be interpreted with caution for a number of reasons.

First, the nature and limitations of the data. We use a six-year panel with only three rounds, so we are only estimating a short-run elasticity between temperature shocks and growth.

Second, and related, 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.

Third, external validity with regard to climate change. Again, weather variations are *not* climate variations: the first are random shorter-run temporal variations, the second are averages over several decades (Dell, Jones & Olken, 2014).

In the next future, the availability of longer household-level panels for developing countries could alleviate these issues, making future research able to test whether these findings, emerged from short-run elasticities, also hold in the medium or long run.

Finally, a reminder about the meaning of the thresholds.

The consumption thresholds we detected are not thresholds in the sense of the existence ‘poverty traps’, below which households are permanently trapped in low income. Rather, we found thresholds which bifurcate the significance and the sign of the temperature shocks conditional on initial consumption. 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 three different regimes of impacts separated by two initial consumption thresholds.

In conclusion, 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.

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**Table 1 – Descriptive statistics**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  |  |  |  |  |
|  | Mean | Var | sd |  Obs |
| Food consumption growth rate | -3.375 | 3855.9 | 62.096 | 3168 |
| Total consumption growth rate | -2.897 | 3508.9 | 59.236 | 3170 |
| Food consumption | 13.117 | 0.318 | 0.564 | 4754 |
|  |  |  |  |  |
| Total consumption | 13.384 | 0.334 | 0.578 | 4755 |
|  |  |  |  |  |
| △Temp | -0.006 | 0.0157 | 0.125 | 4755 |
| △Pre | -0.002 | 0.491 | 0.701 | 4755 |
| Temp | 23.645 | 7.207 | 2.685 | 4755 |
| Pre | 917.699 | 47631.330 | 218.246 | 4755 |
| Long-run average temperature  | 23.660 | 6.915 | 2.630 | 4755 |
| Long-run average precipitation | 917.978 | 36922.07 | 192.151 | 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 |

*Notes:*

Food consumption growth rate is the between-wave percentage change in household per adult equivalent food consumption, expressed in natural logarithm. Total consumption growth rate is the between-wave percentage change in household per adult equivalent consumption, expressed in natural logarithm. Food consumption is the natural logarithm of household per adult-equivalent food consumption, expressed in Tanzanian shillings. Total consumption is the natural logarithm of household per adult-equivalent total consumption, expressed in Tanzanian shillings. ∆Temp is the difference between average monthly growing season temperature in the twelve months preceding the interview 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 total growing season precipitation in the twelve months preceding the interview and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Temp is average monthly growing season temperature in the twelve months preceding the interview. Pre is total growing season precipitation in the twelve months preceding the interview. 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 total growing season precipitation over the period 1980-2015, expressed in units of mm per year. Adult education level represents the average years of education among adults, where adult means > 15 year old.

**Table 2**

**FE regressions – Food consumption[[18]](#footnote-18)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variable: food consumption growth rate | (1) | (2) | (3) | (4) |
|  |  |  |  |  |
| L1.Food |  -144.184\*\*\* |  -146.539\*\*\* |  -146.547\*\*\* | -144.337\*\*\* |
|  | (1.616) | (1.653) | (1.652) | (1.624) |
| ∆Temp |  -31.755\*\* | 16.425 | 32.328 |  -1,085.769\*\*\* |
|  | (16.066) | (18.580) | (21.484) | (142.192) |
| Poor x ∆Temp |  |  -83.308\*\*\* |  -84.293\*\*\* |  |
|  |  | (14.557) | (14.546) |  |
| Hot x ∆Temp |  |  |  -26.642 | -16.229 |
|  |  |  | (21.027) | (15.735) |
| ∆Pre | -2.427 | 2.371 | 4.315 | -1.909 |
|  | (2.587) | (2.992) | (3.660) | (2.567) |
| Poor x ∆Pre |  |  -8.330\*\*\* |  -8.413\*\*\* |  |
|  |  | (2.441) | (2.446) |  |
| Hot x ∆Pre |  |  | -2.836 |  |
|  |  |  | (3.950) |  |
| Hot  |  |  | 11.824 | 10.470 |
|  |  |  | (12.327) | (13.741) |
| L1.Food x ∆Temp |  |  |  |  81.862\*\*\* |
|  |  |  |  | (10.935) |
| Obs | 3,162 | 3,162 | 3,162 | 3,162 |
| Adj. R2 | 0.486 | 0.492 | 0.491 | 0.496 |
| Vegetation time series | Yes | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes | Yes |
| Total temperature effect for poorest householdsTotal temperature effect for households in hot areasTotal precipitation effect for poorest householdsTotal precipitation effect for households in hot areas |  |  -66.883\*\*\*(16.675) -5.959\*\*(2.744) |  -51.965\*\*\*(20.098)5.686(21.133)-4.099(3.384)1.478(3.514) |  |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Food consumption growth rate is the between-wave percentage change in (ln) household per a.e. food consumption. L1.Food is lagged household per a.e. (ln) food consumption. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 above median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table 3**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variable: total consumption growth rate | (1) | (2) | (3) | (4) |
|  |  |  |  |  |
| L1.Cons |  -140.493\*\*\* |  -142.385\*\*\* |  -142.441\*\*\* |  -141.073\*\*\* |
|  | (1.647) | (1.700) | (1.697) | (1.632) |
| ∆Temp | -23.817 | 10.246 | 10.217 |  -1,071.014\*\*\* |
|  | (15.730) | (17.700) | (19.780) | (138.886) |
| Poor x ∆Temp |  |  -60.921\*\*\* |  -59.916\*\*\* |  |
|  |  | (13.945) | (13.978) |  |
| Hot x ∆Temp |  |  |  37.042\*\*\* |  42.994\*\*\* |
|  |  |  | (10.789) | (10.820) |
| ∆Pre | -1.580 | 0.940 | 0.515 |  -0.574 |
|  | (2.448) | (2.752) | (3.279) | (2.367) |
| Poor x ∆Pre |  | -4.235\* | -4.112\* |  |
|  |  | (2.262) | (2.260) |  |
| Hot x ∆Pre |  |  | 1.379 |  |
|  |  |  | (3.697) |  |
| Hot  |  |  | 2.154 | -13.132 |
|  |  |  | (19.046) | (14.152) |
| L1.Cons x ∆Temp |  |  |  |  79.769\*\*\* |
|  |  |  |  | (10.410) |
|  |  |  |  |  |
| Obs | 3,164 | 3,164 | 3,164 | 3,164 |
| Adj. R2 | 0.482 | 0.485 | 0.485 | 0.492 |
| Vegetation time series | Yes | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes | Yes |
| Total temperature effect for poorest householdsTotal temperature effect for households in hot areasTotal precipitation effect for poorest householdsTotal precipitation effect for households in hot areas |  |  -50.675\*\*\*(16.589)-3.295(2.628) |  -49.699\*\*(19.536)12.371(20.277)-3.597(3.201)1.895(3.357) |  |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Total consumption growth rate is the between-wave percentage change in (ln) household per a.e. consumption. L1.Cons is lagged household per a.e. (ln) consumption. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 above median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household – wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**FE regressions – Total consumption**

**Table 4**

**FE initial quartile regressions – Food consumption**

|  |  |  |
| --- | --- | --- |
|  Dependent variable: | (1) | (2) |
| Food consumption growth rate |  |  |
|  |  |  |
| L1.Food |  -147.731\*\*\* |  -147.882\*\*\* |
|  | (1.663) | (1.655) |
| q1 x ∆Temp |  -87.375\*\*\* |  -76.773\*\*\* |
|  | (19.280) | (23.361) |
| q2 x ∆Temp |  -49.762\*\*\* | -37.605\* |
|  | (18.329) | (20.815) |
| q3 x ∆Temp | -12.648 | 0.578 |
|  | (20.257) | (23.349) |
| q4 x ∆Temp |  55.201\*\* |  67.563\*\*\* |
|  | (21.803) | (24.194) |
| Hot x ∆Temp |  | -19.814 |
|  |  | (21.099) |
| q1 x ∆Pre | -5.264 | -3.959 |
|  | (3.313) | (3.963) |
| q2 x ∆Pre |  -6.040\*\* | -4.356 |
|  | (3.026) | (3.573) |
| q3 x ∆Pre | 1.909 | 3.540 |
|  | (3.314) | (4.030) |
| q4 x ∆Pre | 3.718 | 5.043 |
|  | (3.411) | (3.984) |
| Hot x ∆Pre |  | -2.548 |
|  |  | (3.971) |
| Hot  |  | 10.688 |
|  |  | (12.303) |
| Obs | 3,162 | 3,168 |
| Adj. R2 | 0.494 | 0.492 |
| Vegetation time series | Yes | Yes |
| Household controls | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Food consumption growth rate is the between-wave percentage change in (ln) household per a.e. food consumption. L1.Food is lagged household per a.e. (ln) food consumption. q1, q2, q3, q4 are initial food consumption quartiles. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

|  |  |  |
| --- | --- | --- |
|  Dependent variable: | (1) | (2) |
| total consumption growth rate |  |  |
|  |  |  |
| L1.Cons |  -144.067\*\*\* |  -144.168\*\*\* |
|  | (1.726) | (1.724) |
| q1 x ∆Temp |  -87.801\*\*\* |  -88.002\*\*\* |
|  | (18.428) | (21.332) |
| q2 x ∆Temp | -21.604 | -18.933 |
|  | (18.253) | (20.713) |
| q3 x ∆Temp | -24.234 | -24.063 |
|  | (18.407) | (20.337) |
| q4 x ∆Temp |  63.373\*\*\* |  63.868\*\*\* |
|  | (22.267) | (24.214) |
| Hot x ∆Temp |  | 1.896 |
|  |  | (18.598) |
| q1 x ∆Pre |  -7.582\*\* |  -7.975\*\* |
|  | (3.074) | (3.592) |
| q2 x ∆Pre | 0.763 | 0.564 |
|  | (2.922) | (3.422) |
| q3 x ∆Pre | -1.335 | -1.773 |
|  | (3.024) | (3.498) |
| q4 x ∆Pre | 4.465 | 4.069 |
|  | (3.266) | (3.705) |
| Hot x ∆Pre |  | 1.441 |
|  |  | (3.655) |
| Hot  |  |  40.728\*\*\* |
|  |  | (10.576) |
| Obs | 3,164 | 3,164 |
| Adj. R2 | 0.490 | 0.490 |
| Vegetation time series | Yes | Yes |
| Household controls | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Total consumption growth rate is the between-wave percentage change in (ln) household per a.e. consumption. L1.Cons is lagged household per a.e. (ln) consumption. q1, q2, q3, q4 are initial total consumption quartiles. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table 5**

**FE initial quartile regressions – Total consumption**

**Table 6**

**FE regressions with spatially-robust SEs**

|  |  |  |
| --- | --- | --- |
|  |  (1) | (2) |
| Dependent variable: | ∆Food | ∆Cons |
|  |  |  |
| L1.Food |  -147.711 |  |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* |  (1.725)\*\*\* (1.725)\*\*\* (1.728)\*\*\* (1.822)\*\*\* |  |
| L1.Cons |  |  -144.168 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* |   |  (1.993)\*\*\* (1.993)\*\*\* (2.025)\*\*\* (2.139)\*\*\* |
| q1 x ∆Temp |   -76.050  |   -88.002  |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* |  (23.313)\*\*\* (23.313)\*\*\* (24.265)\*\*\* (24.717)\*\*\* |  (21.276)\*\*\* (21.276)\*\*\* (21.864)\*\*\* (22.440)\*\*\* |
| q2 x ∆Temp | -39.177 | -18.933 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* |  (16.497)\*\* (16.497)\*\* (16.177)\*\* (15.921)\*\* |  (16.956) (16.956) (16.623) (16.277) |
| q3 x ∆Temp | -0.172 | -24.063 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* |  (19.957) (19.957) (19.831) (19.467) |  (17.655) (17.655) (17.281) (16.792) |
| q4 x ∆Temp |  65.977 |  63.868 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* |  (21.618)\*\*\* (21.618)\*\*\* (21.736)\*\*\* (21.531)\*\*\* |  (20.285)\*\*\* (20.285)\*\*\* (20.615)\*\*\* (20.909)\*\*\* |
| Hot x ∆Temp | -19.593 | 1.896 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* | (20.017)(20.017)(20.483)(20.882) |  (17.105) (17.105) (17.584) (17.843) |
| q1 x ∆Pre | -3.776 | -7.975 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* | (3.487)(3.487)(3.549)(3.516) |  (3.389)\*\* (3.389)\*\* (3.442)\*\* (3.447)\*\* |
| q2 x ∆Pre | -4.567 | 0.564 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* | (2.845)(2.845)(2.860)(2.894) |  (2.807) (2.807) (2.810) (2.799) |
| q3 x ∆Pre | 3.557 | -1.773 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* | (3.378)(3.378)(3.410)(3.426) |  (3.147) (3.147) (3.154) (3.190) |
| q4 x ∆Pre | 5.170 |  4.069 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* | (3.544)(3.544)(3.554)(3.626) |  (3.347) (3.347) (3.424) (3.574) |
| Hot x ∆Pre | -2.346 |  1.441 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* | (3.509)(3.509)(3.614)(3.703) |  (3.222) (3.222) (3.317) (3.377) |
| Hot  | 11.530 |  40.728 |
|  *Conley(1999), 25 km cut-off* *Conley(1999), 50 km cut-off* *Conley(1999), 75 km cut-off* *Conley(1999), 100 km cut-off* | (14.146)(14.146)(14.179)(14.210) |  (11.379)\*\*\* (11.379)\*\*\* (11.471)\*\*\* (11.627)\*\*\* |
| Obs | 3,164 | 3.166 |
| Adj. R2 | 0.772 | 0.772 |
| Vegetation time series | Yes | Yes |
| Household controls | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 total consumption quartiles in Column(2). ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 median 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 7

**Hausman – Taylor regressions**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variables: | (1) | (2) | (3) | (4) |
|  | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -147.026\*\*\* |  -146.949\*\*\* |  |  |
|  | (2.614) | (2.610) |  |  |
| L1.Cons |  |  |  -143.404\*\*\* |  -143.385\*\*\* |
|  |  |  | (2.678) | (2.672) |
| q1 x ∆Temp |  -88.847\*\*\* |  -76.694\*\* |  -89.641\*\*\* |  -93.632\*\*\* |
|  | (30.013) | (36.235) | (29.110) | (33.384) |
| q2 x ∆Temp |  -60.656\*\* | -50.586 | -29.841 | -33.593 |
|  | (30.113) | (33.027) | (28.579) | (31.951) |
| q3 x ∆Temp | -42.313 | -30.990 | -55.959\* | -59.501\* |
|  | (33.579) | (37.535) | (30.045) | (32.465) |
| q4 x ∆Temp | 34.663 | 45.364 | 44.553 | 40.782 |
|  | (37.791) | (40.789) | (38.000) | (40.266) |
| Hot x ∆Temp |  | -19.048 |  | 6.329 |
|  |  | (33.360) |  | (28.488) |
| q1 x ∆Pre | -5.099 | -3.549 | -6.994 | -7.191 |
|  | (4.987) | (6.025) | (4.631) | (5.522) |
| q2 x ∆Pre | -6.512 | -5.127 | 1.280 | 1.099 |
|  | (4.600) | (5.497) | (4.304) | (5.196) |
| q3 x ∆Pre | -1.413 | 0.111 | -7.268 | -7.493 |
|  | (5.227) | (6.308) | (4.628) | (5.394) |
| q4 x ∆Pre | 1.965 | 3.441 | 4.482 | 4.249 |
|  | (5.348) | (6.261) | (4.993) | (5.742) |
| Hot x ∆Pre |  | -2.357 |  | 0.106 |
|  |  | (6.042) |  | (5.450) |
| Long-run average temperature |  4.867\*\*\* |  4.845\*\*\* |  4.536\*\*\* |  4.506\*\*\* |
|  | (1.724) | (1.715) | (1.650) | (1.655) |
| Long-run average precipitation |  0.059\*\* |  0.059\*\* |  0.051\*\* |  0.050\*\* |
|  | (0.025) | (0.025) | (0.023) | (0.024)  |
| Obs | 2,578 | 2,578 | 2,580 | 2,580 |
| Vegetation time series | Yes | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes | Yes |
| Geographic controls | Yes | Yes | Yes | Yes |

*Notes:* All specifications include wave dummies, region x year FE and month of interview dummies. All household controls are treated as time-varying endogenous variables. Geographic controls include population density and distances (in kms) to nearest major road, population centre, market, border crossing, headquarter of residence; they are treated as time-invariant exogenous variables. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. L1.Food is lagged household per a.e. (ln) food consumption and is treated as endogenous. L1.Cons is lagged household per a.e. (ln) consumption and is treated as endogenous. q1, q2, q3, q4 are food consumption quartiles in Columns (1) and (2) and total consumption quartiles in Columns (3) and (4); they are all treated as time-invariant, endogenous variables. standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above median long-run average monthly growing season temperature. All the weather variables, both time-varying and time-invariant, 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 8**

**Two-step Difference GMM**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variables: | (1) | (2) | (3) | (4) |
|  | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -152.716\*\*\* |  -153.733\*\*\* |  |  |
|  | (11.704) | (11.313) |  |  |
| L1.Cons |  |  |  -157.989\*\*\* |  -157.393\*\*\* |
|  |  |  | (10.280) | (10.121) |
| q1 x ∆Temp |  -88.441\*\* |  -84.788\*\* |  -98.758\*\*\* |  -108.715\*\*\* |
|  | (35.775) | (39.591) | (34.710) | (36.465) |
| q2 x ∆Temp |  -57.680\*\* | -50.563 | -25.903 | -35.094 |
|  | (27.843) | (33.025) | (26.424) | (30.788) |
| q3 x ∆Temp | -29.982 | -22.273 | -33.952 | -47.525 |
|  | (30.635) | (36.034) | (25.693) | (29.756) |
| q4 x ∆Temp | 21.015 | 27.329 | 39.872 | 24.869 |
|  | (39.033) | (40.966) | (35.674) | (38.896) |
| Hot ∆Temp |  | -8.900 |  | 23.121 |
|  |  | (28.847) |  | (26.608) |
| q1 x ∆Pre | -5.009 | -4.104 | -8.213\* |  -10.711\*\* |
|  | (4.478) | (5.329) | (4.234) | (4.868) |
| q2 x ∆Pre | -7.972\*\* | -7.097 | -0.228 | -2.372 |
|  | (3.993) | (4.617) | (3.450) | (4.238) |
| q3 x ∆Pre | -2.846 | -1.643 | -4.713 | -8.160\* |
|  | (4.664) | (5.902) | (3.649) | (4.725) |
| q4 x ∆Pre | 1.359 | 2.179 | 0.881 | -2.430 |
|  | (4.660) | (5.434) | (4.414) | (5.122) |
| Hot x ∆Pre |  | -1.150 |  | 4.701 |
|  |  | (4.482) |  | (4.050) |
| Hot  |  | 21.614 |  | 41.019 |
|  |  | (24.543) |  | (29.192) |
| Obs | 1,581 | 1,581 | 1,582 | 1,582 |
| Vegetation time series | Yes | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes | Yes |
| Hansen – J test (p) | 0.247 | 0.238 | 0.277 | 0.339 |
| *Notes:* All specifications include households FE, wave dummies, year FE and month of interview dummies. Region x time FE are used as additional instruments. 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 (all treated as endogenous) and two idiosyncratic shocks: illness and death of a household member, which are treated as exogenous. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. L1.Food is lagged household per a.e. (ln) food consumption and is treated as endogenous. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 median long-run average monthly growing season temperature. 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**

**FE initial quartile regressions – Only coastal areas**

|  |  |  |
| --- | --- | --- |
| Dependent variables: | (1) | (2) |
|  | ∆Food | ∆Cons |
|  |  |  |
| L1.Food |  -155.109\*\*\* |  |
|  | (2.946) |  |
| L1.Cons |  |  -152.871\*\*\* |
|  |  | (2.954) |
| q1 x ∆Temp |  -77.565\*\*\* | -50.576\*\* |
|  | (22.106) | (21.606) |
| q2 x ∆Temp | -46.518\*\* | -11.107 |
|  | (20.681) | (22.055) |
| q3 x ∆Temp | -54.882\*\* | -30.625 |
|  | (23.551) | (22.380) |
| q4 x ∆Temp | 16.281 | 36.734\*\* |
|  | (18.979) | (18.700) |
| q1 x ∆Pre |  -11.276\*\* |  -9.546\*\* |
|  | (5.172) | (4.744) |
| q2 x ∆Pre | -3.327 | 2.941 |
|  | (4.616) | (4.684) |
| q3 x ∆Pre | -3.423 | -2.164 |
|  | (4.763) | (4.817) |
| q4 x ∆Pre | 4.938 |  10.672\*\* |
|  | (4.956) | (4.910) |
| Obs | 1,022 | 1,024 |
| Adj. R2 | 0.572 | 0.547 |
| Vegetation time series | Yes | Yes |
| Household controls | Yes | Yes |
|  |  |  |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 total consumption quartiles in Column (2). ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.  |

**Table 10**

**FE quartile regressions – Only inlands**

|  |  |  |
| --- | --- | --- |
| Dependent variables: | (1) | (2) |
|  | ∆Food | ∆Cons |
|  |  |  |
| L1.Food |  -146.241\*\*\* |  |
|  | (2.085) |  |
| L1.Cons |  |  -141.988\*\*\* |
|  |  | (2.138) |
| q1 x ∆Temp |  -64.119\*\*\* |  -74.966\*\*\* |
|  | (18.117) | (17.501) |
| q2 x ∆Temp |  -52.961\*\*\* | -16.374 |
|  | (17.970) | (16.936) |
| q3 x ∆Temp | 13.224 | -24.068 |
|  | (19.561) | (17.376) |
| q4 x ∆Temp | 25.597 | 24.105 |
|  | (21.831) | (22.982) |
| q1 x ∆Pre | -1.518 | -6.207 |
|  | (4.568) | (4.378) |
| q2 x ∆Pre | -7.270 | 3.342 |
|  | (4.423) | (4.136) |
| q3 x ∆Pre |  9.750\*\*(4.947) | -0.743(4.406) |
| q4 x ∆Pre | -0.383 | -1.681 |
|  | (5.095) | (4.916) |
| Obs | 2,134 | 2,134 |
| Adj. R2 | 0.469 | 0.470 |
| Vegetation time series | Yes | Yes |
| Household controls | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 total consumption quartiles in Column (2). ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.  |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent | (1) | (2) | (3) | (4) |
| Variables: | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -145.142\*\*\* |  -145.192\*\*\* |  |  |
|  | (1.845) | (1.833) |  |  |
| L1.Cons |  |  |  -141.672\*\*\* |  -141.571\*\*\* |
|  |  |  | (1.957) | (1.957) |
| q1 x ∆Temp |  -98.826\*\*\* |  -85.474\*\*\* |  -103.434\*\*\* |  -101.263\*\*\* |
|  | (21.473) | (26.764) | (20.692) | (24.768) |
| q2 x ∆Temp |  -56.859\*\*\* | -43.159\* | -22.738 | -20.695 |
|  | (21.125) | (25.212) | (20.610) | (24.857) |
| q3 x ∆Temp | -17.640 | -1.535 |  -49.130\*\* |  -47.523\*\* |
|  | (22.583) | (26.926) | (21.357) | (24.176) |
| q4 x ∆Temp | 34.437 | 49.903\* | 30.038 | 31.840 |
|  | (24.296) | (28.051) | (24.448) | (27.767) |
| Hot x ∆Temp |  | -25.408 |  | -4.850 |
|  |  | (24.751) |  | (22.006) |
| q1 x ∆Pre |  -6.692\* | -3.430 |  -7.780\*\* | -6.287 |
|  | (3.498) | (4.486) | (3.424) | (4.263) |
| q2 x ∆Pre |  -6.571\* | -2.992 | 1.332 | 2.806 |
|  | (3.589) | (4.376) | (3.305) | (4.134) |
| q3 x ∆Pre | 2.856 | 6.666 | -3.257 | -1.875 |
|  | (3.670) | (4.608) | (3.461) | (4.177) |
| q4 x ∆Pre | 2.828 | 6.136 | 5.363 | 6.778 |
|  | (3.895) | (4.778) | (3.781) | (4.519) |
| Hot x ∆Pre |  | -6.505 |  | -2.940 |
|  |  | (4.486) |  | (4.216) |
| Obs | 2,670 | 2,674 | 2,672 | 2,672 |
| Adj. R2 | 0.471 | 0.469 | 0.465 | 0.464 |
| 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 month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). ∆Temp is the difference between average monthly growing season temperature and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, expressed in degree Celsius. ∆Pre is the difference between total growing season precipitation and long run (1980-2015) average total 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 median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table 11**

**FE quartile regressions - Non-migrating households**

**Table 12**

**FE quartile regressions - Migrating households**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent | (1) | (2) | (3) | (4) |
| variables | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -155.284\*\*\* |  -155.693\*\*\* |  |  |
|  |  (3.885) | (3.850) |  |  |
| L1.Cons |  |  |  -149.124\*\*\* |  -149.955\*\*\* |
|  |  |  | (3.720) | (3.654) |
| q1 x ∆Temp |  -132.753\*\*\* |  -135.968\*\*\* |  -92.378\*\*\* |  -105.141\*\*\* |
|  | (36.191) | (42.511) | (34.920) | (37.786) |
| q2 x ∆Temp | -64.609\* | -52.449 | -49.313 | -22.664 |
|  | (36.077) | (36.083) | (31.792) | (32.170) |
| q3 x ∆Temp | -42.115 | -28.101 | -15.321 | -18.572 |
|  | (35.135) | (41.161) | (30.518) | (32.325) |
| q4 x ∆Temp |  122.375\*\*\* |  132.824\*\*\* |  146.467\*\*\* |  147.932\*\*\* |
|  | (37.412) | (45.875) | (34.074) | (37.097) |
| Hot x ∆Temp |  | 1.490 |  | 17.498 |
|  |  | (32.219) |  | (25.643) |
| q1 x ∆Pre |  -15.284\*\* |  -18.220\*\* |  -13.447\*\* |  -19.700\*\*\* |
|  | (7.350) | (8.308) | (6.293) | (7.076) |
| q2 x ∆Pre | -2.937 | -5.328 |  -13.443\*\* |  -16.183\*\* |
|  | (6.961) | (8.044) | (6.630) | (7.457) |
| q3 x ∆Pre | -4.934 | -5.110 | 0.895 | -6.724 |
|  | (7.264) | (8.606) | (6.657) | (7.396) |
| q4 x ∆Pre | -10.681\* | -12.053 | -8.555 | -12.205\* |
|  | (7.285) | (7.885) | (6.078) | (6.403) |
| Hot x ∆Pre |  | 6.372 |  |  14.595\*\* |
|  |  | (7.895) |  | (6.956) |
| Hot  |  |  33.683\*\* |  |  52.547\*\*\* |
|  |  | (13.762) |  | (12.293) |
| Obs | 492 | 494 | 492 | 492 |
| Adj. R2 | 0.513 | 0.515 | 0.536 | 0.547 |
| 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 month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). ∆Temp is the difference between average monthly growing season temperature and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, expressed in degree Celsius. ∆Pre is the difference between total growing season precipitation and long run (1980-2015) average total 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 median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

|  |  |  |
| --- | --- | --- |
|   | (1) | (2) |
| Dependent variables: | ∆Food | ∆Cons |
|  |  |  |
| L1.Food |  -159.652\*\*\* |  |
|  | (2.601) |  |
| L1.Cons |  |  -157.432\*\*\* |
|  |  | (2.761) |
| ∆Temp |  -78.803\*\*\* |  -62.351\*\* |
|  | (30.530) | (30.642) |
| ∆Pre | -5.272 |  -4.146 |
|  | (4.523) | (4.333) |
| Obs | 918 | 920 |
| Adj. R2 | 0.538 | 0.513 |
| Vegetation time series | Yes | Yes |
| Household controls | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e. consumption. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. The subsample includes all households who are in the poorest quartile for either food consumption or total consumption. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table 13**

**FE regressions - Subsample of the poorest quartile**

**Table 14**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variables: | (1) | (2) | (3) | (4) |
|  | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -145.415\*\*\* |  -145.511\*\*\* |  |  |
|  | (1.641) | (1.632) |  |  |
| L1.Cons |  |  |  -141.642\*\*\* |  -141.628\*\*\* |
|  |  |  | (1.702) | (1.699) |
| q1 x ∆Temp |  -69.071\*\*\* | -56.215\* |  -72.398\*\*\* |  -71.408\*\* |
|  | (26.473) | (32.533) | (25.449) | (30.143) |
| q2 ∆Temp | -49.319\* | -35.545 | -25.644 | -19.787 |
|  | (25.296) | (29.854) | (24.473) | (28.455) |
| q3 x ∆Temp | -3.897 | 12.057 | -22.677 | -22.296 |
|  | (27.030) | (32.688) | (25.143) | (28.958) |
| q4 x ∆Temp |  51.769\* | 63.363\* | 48.219 | 50.184 |
|  | (30.798) | (34.490) | (30.295) | (33.863) |
| Hot x ∆Temp |  |  -22.940 |  |  -2.826 |
|  |  | (29.733) |  | (27.115) |
| q1 x ∆Pre | -3.851 | -1.596 |  -6.574\*\* | -6.435 |
|  | (3.444) | (4.292) | (3.318) | (4.115) |
| q2 x ∆Pre | -6.086\* | -3.609 | -0.108 | 0.692 |
|  | (3.308) | (4.087) | (3.073) | (3.799) |
| q3 x ∆Pre | 2.307 | 4.991 | -1.606 | -1.428 |
|  | (3.511) | (4.472) | (3.221) | (3.978) |
| q4 x ∆Pre | 4.090 | 5.986 | 3.706 | 3.907 |
|  | (3.705) | (4.458) | (3.535) | (4.257) |
| Hot x ∆Pre |  | -4.316 |  | -0.500 |
|  |  | (4.042) |  | (3.756) |
| Hot  |  | 10.039 |  |  35.224\*\*\* |
|  |  | (11.457) |  | (10.504) |
| Obs | 3,162 | 3,168 | 3,164 | 3,164 |
| Adj. R2 | 0.488 | 0.485 | 0.483 | 0.483 |
| 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 month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). ∆Temp is the difference between annual average temperature and long-run (1980-2015) annual average temperature, divided by long-run (1980-2015) standard deviation, and expressed in degree Celsius. ∆Pre is the difference between total annual precipitation and long run (1980-2015) average total annual precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

 **FE quartile regressions - Using annual weather anomalies**

**Table 15**

**FE quartile regressions - Using weather levels**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variables | (1) | (2) | (3) | (4) |
|  | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -146.837\*\*\* |  -146.790\*\*\* |  |  |
|  | (1.714) | (1.705) |  |  |
| L1.Cons |  |  |  -142.258\*\*\* | -142.404\*\*\* |
|  |  |  | (1.775) | (1.790) |
| q1 x Temp |  -17.192\*\* | -14.527\* | -14.668\* | -18.296\*\* |
|  | (7.844) | (8.611) | (7.585) | (8.729) |
| q2 x Temp | -8.360 | -7.303 | 2.288 | -1.762 |
|  | (5.892) | (6.302) | (5.487) | (6.198) |
| q3 x Temp | 3.731 | 5.500\* | 3.329 | -0.199 |
|  | (2.346) | (3.048) | (4.117) | (4.138) |
| q4 x Temp |  23.764\*\*\* |  25.972\*\*\* |  16.086\*\*\* |  14.069\*\* |
|  | (5.879) | (6.510) | (6.118) | (6.223) |
| Hot x Temp |  | -12.926\* |  | -3.399 |
|  |  | (6.945) |  | (6.561) |
| q1 x Pre | -0.006 | -0.001 | -0.016 | -0.026 |
|  | (0.017) | (0.020) | (0.016) | (0.019) |
| q2 x Pre | -0.016 | -0.012 | 0.019 | 0.009 |
|  | (0.015) | (0.017) | (0.014) | (0.017) |
| q3 x Pre | 0.023\* | 0.027 | 0.012 | 0.002 |
|  | (0.014) | (0.017) | (0.014) | (0.016) |
| q4 x Pre | 0.027\* | 0.032\* | 0.019 | 0.012 |
|  | (0.016) | (0.019) | (0.016) | (0.018) |
| Hot x Pre |  | -0.019 |  | 0.005 |
|  |  | (0.019) |  | (0.018) |
| Hot  |  |  335.563\* |  | 123.695 |
|  |  | (176.447) |  | (164.236) |
| Obs | 3,168 | 3,168 | 3,164 | 3,164 |
| Adj. R2 | 0.489 | 0.489 | 0.484 | 0.485 |
| 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 month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). Temp is average monthly growing season temperature, expressed in degree Celsius. Pre is total growing season precipitation, expressed in mm. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table 16**

**FE initial quartile regressions - Alternative weather data**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent  | (1) | (2) | (3) | (4) |
| Variables: | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -154.280\*\*\* |  -154.606\*\*\* |  |  |
|  | (1.749) | (1.741) |  |  |
| L1.Cons |  |  |  -150.158\*\*\* |  -150.286\*\*\* |
|  |  |  | (1.768) | (1.766) |
| q1 x ∆Temp |  -61.191\*\*\* |  -55.293\*\*\* |  -53.302\*\*\* |  -44.549\*\* |
|  | (18.705) | (20.464) | (18.399) | (20.030) |
| q2 x ∆Temp | -15.534 | -8.016 | 9.101 | 18.442 |
|  | (19.958) | (21.502) | (18.558) | (19.774) |
| q3 x ∆Temp | 31.666 |  37.568\* | 10.813 | 19.497 |
|  | (20.197) | (21.987) | (18.334) | (19.657) |
| q4 x ∆Temp |  116.904\*\*\*(21.235) |  125.695\*\*\*(22.904) |  120.671\*\*\*(20.366) |  129.886\*\*\* (21.921) |
| Hot x ∆Temp |  | -19.699 |  | -24.581 |
|  |  | (19.432) |  | (17.778) |
| q1 x ∆Pre |  -3.630\* | -0.674 | -2.295 | -1.211 |
|  | (2.128) | (2.843) | (2.012) | (2.848) |
| q2 x ∆Pre | -1.014 | 1.882 |  -3.711\*\* | -2.740 |
|  | (1.956) | (2.779) | (1.883) | (2.618) |
| q3 x ∆Pre | 3.248 |  6.735\*\* | 0.850 | 2.216 |
|  | (2.078) | (3.215) | (1.967) | (3.027) |
| q4 x ∆Pre |  4.171\* |  7.196\*\* |  4.551\*\* |  5.910\* |
|  | (2.188) | (3.197) | (2.279) | (3.214) |
| Hot x ∆Pre |  | -4.815 |  | -2.365 |
|  |  | (3.024) |  | (2.903) |
| Hot  |  | -11.115 |  | -2.526 |
|  |  | (10.113) |  | (9.826) |
| Obs | 3,162 | 3,168 | 3,164 | 3,164 |
| Adj. R2 | 0.510 | 0.509 | 0.507 | 0.507 |
| 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 month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). ∆Temp is the difference between average monthly growing season temperature and long-run (1983-2013) average monthly growing season temperature, divided by long-run (1983-2013) standard deviation, expressed in degree Celsius. ∆Pre is the difference between total precipitation during the wettest quarter and average decadal (2001 - 2013 ) total precipitation during the wettest quarter, divided by average decadal (2001 - 2013) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**Table 17**

**Persistence of weather shocks**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  Dependent variable: | (1)∆Food | (2)∆Cons | (3)∆Food | (3)∆Cons |
|  |  |  |  |  |
|  |  |  |  |
| L1.Food |  -152.462\*\*\* |  |  -148.398\*\*\* |  |
|  | (1.798) |  | (1.751) |  |
| L1.Cons |  |  -149.009\*\*\* |  |  -145.183\*\*\* |
|  |  | (1.807) |  | (1.742) |
| q1 x ∆Temp |  -109.739\*\*\* |  -85.061\*\*\* |  -30.430\*\* | -20.110 |
|  | (30.922) | (28.775) | (15.316) | (14.043) |
| q2 x ∆Temp | -37.945 | -1.246 | 4.380 | 8.425 |
|  | (29.523) | (28.662) | (13.230) | (13.707) |
| q3 x ∆Temp | 48.656 | 43.616 |  35.204\*\* |  35.874\*\*\* |
|  | (30.922) | (28.780) | (14.613) | (13.171) |
| q4 x ∆Temp |  146.964\*\*\* |  175.510\*\*\* |  70.906\*\*\* |  86.467\*\*\* |
|  | (29.779) | (28.174) | (14.076) | (13.707) |
| q1 x ∆Pre | -2.120 | -1.592 | 4.546 | 7.204\*\* |
|  | (4.714) | (4.461) | (2.980) | (2.820) |
| q2 x ∆Pre | -5.432 | -2.777 | 1.525 | -3.071 |
|  | (4.197) | (4.004) | (2.661) | (2.681) |
| q3 x ∆Pre |  9.237\*\* |  9.330\*\* | 4.271 |  8.489\*\*\* |
|  | (4.370) | (4.138) | (2.804) | (2.648) |
| q4 x ∆Pre |  10.170\*\* |  10.754\*\* | 4.462 | 4.296 |
|  | (4.657) | (4.688) | (3.162) | (3.160) |
| Obs | 3,162 | 3,164 | 3,162 | 3,164 |
| Adj. R2 | 0.503 | 0.502 | 0.493 | 0.495 |
| Vegetation time seriesHousehold controls  | YesYes | YesYes | YesYes | YesYes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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). ∆Temp in Columns (1) and (2) is the difference between the two-year average monthly growing season temperature and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, expressed in degree Celsius. ∆Pre in Columns (1) and (2) is the difference between the two-year average of total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. ∆Temp in Columns (3) and (4) is the difference between average monthly growing season temperature in the second year preceding the interview and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, expressed in degree Celsius. ∆Pre in Columns (4) and (4) is the difference between total growing season precipitation in the second year preceding the interview and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.  |

**Table 18**

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent variable: |  |  |  |
| (p.a. equivalent) Share of health expenditure growth rate | (1) | (2) | (3) |
|  |  |  |  |
| L1.Share of health expenditure |  -148.388\*\*\* |  -148.337\*\*\* |  -148.003\*\*\* |
|  | (1.596) | (1.592) | (1.590) |
| ∆Temp | 126.590 |  |  |
|  | (84.933) |  |  |
| ∆Pre | 9.181 |  |  |
|  | (13.298) |  |  |
|  |  |  |  |
| q1 x ∆Temp |  | 102.480 | -30.962 |
|  |  | (101.229) | (116.900) |
| q2 x ∆Temp |  | 101.279 | -12.333 |
|  |  | (97.534) | (112.011) |
| q3 x ∆Temp |  | 150.768 | 28.268 |
|  |  | (108.575) | (119.042) |
| q4 x ∆Temp |  | 142.361 | 15.636 |
|  |  | (105.600) | (119.440) |
| Hot x ∆Temp  |  |  |  236.244\*\* |
|  |  |  | (96.478) |
| q1 x ∆Pre |  | 19.303 | 2.546 |
|  |  | (16.714) | (19.394) |
| q2 x ∆Pre |  | -11.988 | -27.442 |
|  |  | (15.816) | (18.508) |
| q3 x ∆Pre |  | -4.597 | -21.835 |
|  |  | (17.483) | (19.963) |
| q4 x ∆Pre |  | 33.108\* | 16.482 |
|  |  | (17.163) | (19.339) |
| Hot x ∆Pre |  |  | 29.494 |
|  |  |  | (20.059) |
| Hot  |  |  |  215.366\*\*\* |
|  |  |  | (78.086) |
| Obs. | 3,164 | 3,164 | 3,164 |
| Adj. R2 | 0.448 | 0.448 | 0.449 |
| Vegetation time series | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. q1, q2, q3, q4 are initial total 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. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Health expenditure channel**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variable:**Table 19****Labour productivity channel** | (1) | (2) | (3) | (4) |
| Labour productivity growth rate |  |  |  |  |
|  |  |  |  |  |
| L1. Labour productivity |  -51.362\*\*\*(2.529) |  -51.538\*\*\*(2.493) |  -51.491\*\*\*(2.523) |  -51.833\*\*\*(2.546) |
| ∆Temp |  -90.565\*\* |  |  -95.920\*\* |  -101.402\*\*\* |
|  | (35.913) |  | (37.636) | (36.744) |
| ∆Pre | -5.496 |  | -2.637 | -9.239 |
|  | (5.643) |  | (6.085) | (5.784) |
| q1 x ∆Temp |  |  -171.087\*\*\* |  |  |
|  |  | (43.811) |  |  |
| q2 x ∆Temp |  |  -82.825\*\* |  |  |
|  |  | (39.977) |  |  |
| q3 x ∆Temp |  | -51.750 |  |  |
|  |  | (43.744) |  |  |
| q4 x ∆Temp |  | -10.155 |  |  |
|  |  | (50.357) |  |  |
| q1 x ∆Pre |  | -10.820 |  |  |
|  |  | (7.279) |  |  |
| q2 x ∆Pre |  | -4.845 |  |  |
|  |  | (6.705) |  |  |
| q3 x ∆Pre |  | -6.337 |  |  |
|  |  | (6.612) |  |  |
| q4 x ∆Pre |  | 6.248 |  |  |
|  |  | (7.447) |  |  |
| Agr\_wealthier x ∆Temp |  |  | 37.022 |  |
|  |  |  | (34.409) |  |
| Agr\_wealthier x ∆Pre |  |  | -10.367 |  |
|  |  |  | (6.519) |  |
| Agr\_wealthier |  |  | 4.267 |  |
|  |  |  | (5.407) |  |
| Non\_farming x ∆Temp |  |  |  | 63.733 |
|  |  |  |  | (38.868) |
| Non\_farming x Pre |  |  |  |  27.056\*\*\*(6.499) |
| Obs | 2,204 | 2,204 | 2,204 | 2,204 |
| Adj. R2 | -0.555 | -0.550 | -0.553 | -0.546 |
| Vegetation time series | Yes | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes | Yes |
| Total temperature effect for households with higher agricultural wealthTotal precipitation effect for households with higher agricultural wealthTotal temperature effect for households whose main source of income is not farmingTotal precipitation effect for households whose main source of income is not farming |  |   | -58.898(43.371)-13.004\*(6.973) |    -37.669(46.875)  17.817\*\*(7.471) |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Labour productivity growth rate is the between-wave percentage change in (ln) household (per worker) labour productivity. q1, q2, q3, q4 are initial total consumption quartiles. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Agr\_wealthier is a dummy with value 1 for households having an above average agricultural wealth index in a given wave. Non farming is a dummy with value one for households whose main source of income is not farming in at least two waves. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

|  |
| --- |
|  Variable: Agricultural Wealth Index |
|  |  |  |  |  |
|  |  Mean | Var | sd | Obs |
| q1q2q3q4 |  0.066 0.097 0.018 0.228 | 1.1511.0540.8411.878 | 1.0731.0270.9171.370 | 905981931836 |

**Table 20**

**Descriptive statistics –Agricultural Wealth Index**

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

 Agricultural Wealth Index is from the FAO Rural Income Generating Activities (RIGA) Team.

|  |
| --- |
| Variable: Main source of income is not farming(in at least two periods) - % of households |
|  |  |  |  |  |
|  | Yes24.6119.402025.2533.75 | No75.3980.608074.7566.25 |
| Whole sampleq1q2q3q4 |

**Table 21**

**Descriptive statistics – Main source of income**

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

**Table 22**

|  |  |  |  |
| --- | --- | --- | --- |
|  Dependent variable: total crop production | (1) | (2) | (3) |
|  |  |  |  |
|  |  |  |  |
| L1.Total crop production |  -136.957\*\*\* |  -137.540\*\*\* |  -137.402\*\*\* |
|  | (2.840) | (2.806) | (2.803) |
| ∆Temp |  -120.392\*\* |  |  |
|  | (50.065) |  |  |
| ∆Pre | -4.918 |  |  |
|  | (7.485) |  |  |
| q1 x ∆Temp |  |  -165.068\*\*\* |  -190.009\*\*\* |
|  |  |  (56.340) |  (57.240) |
| q2 x ∆Temp |  |  -173.692\*\*\* |  -155.400\*\*\* |
|  |  |  (62.317) |  (59.440) |
| q3 x ∆Temp |  | 18.278 | 5.370 |
|  |  | (59.768) | (60.263) |
| q4 x ∆Temp |  | -96.357 | -104.203\* |
|  |  | (58.646) | (61.229) |
| q1 x ∆Pre |  | 11.017 | -2.753 |
|  |  | (8.383) | (8.330) |
| q2 x ∆Pre |  |  -20.151\*\* | -13.311 |
|  |  | (9.459) | (9.149) |
| q3 x ∆Pre |  | 4.659 | 9.402 |
|  |  | (10.219) | (10.478) |
| q4 x ∆Pre |  | -5.657 | -8.746 |
|  |  | (10.167) | (10.683) |
| Obs | 2,418 | 2,418 | 2,418 |
| Adj. R2 | 0.316 | 0.322 | 0.318 |
| Vegetation time series | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Total crop production growth is the between-wave percentage change in (ln) total crop production. q1, q2, q3, q4 are initial food consumption quartiles in Column (2) and initial consumption quartiles in Column (3). ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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 median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Agricultural yield channel – Total crop production**

**Table 23**

**Agricultural yield channel - Crop yields**

|  |  |  |
| --- | --- | --- |
| Dependent variable: | (1) | (2) |
| Crop yield |  |  |
|  |  |  |
| Number of GDDs (8-34 °C) | 0.000 |  |
|  | (0.000) |  |
| Number of GDDs (34 + °C) |  -0.020\*\*\* |  |
|  | (0.007) |  |
|  Precipitation | 0.001 |  |
|  | (0.002) |  |
| (Precipitation)2 | -0.000 |  |
|  | (0.000) |  |
|  |  |  |
| q1 x Number of GDDs (8-34 °C) |  | 0.001 |
|  |  | (0.000) |
| q2 x Number of GDDs (8-34 °C) |  | -0.000 |
|  |  | (0.000) |
| q3 x Number of GDDs (8-34 °C) |  | -0.000(0.000) |
| q4 x Number of GDDs (8-34 °C) |  | -0.001(0.001) |
| q1 x Number of GDDs (34 + °C) |  |  -0.046\*\*\* |
|  |  | (0.010) |
| q2 x Number of GDDs (34 + °C) |  |  -0.022\*\* |
|  |  | (0.009) |
| q3 x Number of GDDs (34 + °C) |  |  -0.017\*\* |
|  |  | (0.007) |
| q4 x Number of GDDs (34 + °C) |  | 0.012 |
|  |  | (0.014) |
| q1 x Precipitation |  | 0.001 |
|  |  | (0.001) |
| q2 x Precipitation |  | 0.001 |
|  |  | (0.002) |
| q3 x Precipitation |  | 0.002 |
|  |  | (0.002) |
| q4 x Precipitation |  | -0.002 |
|  |  | (0.003) |
| q1 x (Precipitation)2 |  | -0.000 |
|  |  | (0.000) |
| q2 x (Precipitation)2 |  | -0.000 |
|  |  | (0.000) |
| q3 x (Precipitation)2 |  | -0.000 |
|  |  | (0.000) |
| q4 x (Precipitation)2 |  | 0.000 |
|  |  | (0.000) |
| Obs | 3,528 | 3,528 |
| R2Adj. R2 | 0.149-0.364 | 0.154-0.361 |
| Vegetation time series | Yes | Yes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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. q1, q2, q3, q4 are initial total consumption quartiles. R2 and Adjusted R2 are before partialling-out region x time FE. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

|  |  |  |
| --- | --- | --- |
| Dependent variable: | (1) | (2) |
| Crop yield |  |  |
|  |  |  |
| Number of GDDs (8-34 °C) | 0.000 | 0.000 |
|  | (0.000) | (0.000) |
| Number of GDDs (34 + °C) |  -0.020\*\*\* |  -0.020\*\*\* |
|  | (0.007) | (0.007) |
| Precipitation | 0.001 | 0.001 |
|  | (0.001) | (0.001) |
| (Precipitation)2 |  -0.000 | -0.000 |
|  | (0.000) | (0.000) |
| Agricultural Wealth Index |  0.095\*\*\*(0.022) |  |
| Agr\_Wealth x Number of GDDs (8-34 °C) |  | -0.000 |
|  |  | (0.000) |
| Agr\_Wealth x Number of GDDs (34 + °C) |  | -0.002 |
|  |  | (0.013) |
| Agr\_Wealth |  |  0.672\* |
|  |  | (0.346) |
| ObsR2 | 3,5170.149 | 3,528 0.151 |
| Adj. R2 |  -0.366 |  -0.361 |
| Vegetation time series | Yes | Yes |
| Total effect of Number of GDDs (8-34 °C)for households with an above average agricultural wealth indexTotal effect of Number of GDDs (34 + °C)for households with an above average agricultural wealth index |  | -0.000 (0.000)-0.022 (0.014) |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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. Agr\_wealth is a dummy with value 1 for households having a higher than average Agricultural Wealth Index in a given wave. R2 and Adjusted R2 are before partialling-out region x time FE. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table 24**

**Agricultural yield channel - Heterogeneity due to agricultural wealth**

|  |
| --- |
|  Maize and paddy account for 50% or more of total crop production - % of households |
|  |  |  |  |  |
|  | Yes 50.59 58.44 51.60 47.81 | No49.41 41.4648.4052.19 |
| q1q2q3q4 |

**Table 25**

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

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

**Table 26**

**Descriptive statistics – Average crop yield and quantity produced**

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) |  |
|  | Mean quantity (kg) | Mean crop yield(kg / ha) | Obs |
| q1q2q3q4 | 1268.6251452.3621479.1231762.087 | 715.6021033.6381225.5261201.825 | 876965903793 |

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

**Table 27**

**Agricultural yield channel – Other sources of heterogeneity**

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent variable: | (1) | (2) | (3) |
| Crop yield |  |  |  |
|  |  |  |  |
| Number of GDDs (8-34 °C) | 0.000 | 0.000 | 0.000 |
|  | (0.000) | (0.000) | (0.000) |
| Number of GDDs (34 + °C) |  -0.021\*\*\* |  -0.014\*\* |  -0.018\*\*\* |
|  | (0.007) | (0.006) | (0.007) |
| Precipitation | 0.001 | 0.000 | 0.001 |
|  | (0.001) | (0.001) | (0.001) |
| (Precipitation)2 | -0.000 | -0.000 | -0.000 |
|  | (0.000) | (0.000) | (0.000) |
| Maize & paddy non-specializers x Number of GDDs (8-34 °C) | -0.000 |  |  |
|  | (0.000) |  |  |
| Maize & paddy non-specializers x Number of GDDs (34 + °C) |  0.026\* |  |  |
|  | (0.014) |  |  |
| Maize & paddy non-specializers | 0.495 |  |  |
|  | (0.909) |  |  |
| Higher crop yield x Number of GDDs (8-34 °C) |  | 0.000 |  |
|  |  | (0.000) |  |
| Higher crop yield x Number of GDDs (34 + °C) |  | 0.004 |  |
|  |  | (0.006) |  |
| Higher crop yield |  |  1.356\*\*\* |  |
|  |  | (0.241) |  |
| Higher crop production x Number of GDDs (8-34 °C) |  |  | 0.000 |
|  |  |  | (0.000) |
| Higher crop production x Number of GDDs (34 + °C) |  |  | 0.008 |
|  |  |  | (0.006) |
| Higher crop production  |  |  | 0.417 |
|  |  |  | (0.540) |
| Obs | 3,528 | 3,528 | 3,528 |
| R2Adjusted R2 | 0.151-0.361 | 0.4510.120 | 0.253-0.198 |
| Vegetation time series | Yes | Yes | Yes |

|  |  |  |  |
| --- | --- | --- | --- |
| Total effect of Number of GDDs (8-34 °C)for households not specialized in maize and paddy productionTotal effect of Number of GDDs (34 + °C)for households not specialized in maize and paddy productionTotal effect of Number of GDDs (8-34 °C)for households with higher than average crop yieldTotal effect of Number of GDDs (34 + °C)for households with higher than average crop yieldTotal effect of Number of GDDs (8-34 °C)for households with higher than average crop productionTotal effect of Number of GDDs (34 + °C)for households with higher than average crop production |  -0.000(0.000)0.005(0.014) | 0.000(0.000)-0.010(0.007) | 0.000(0.000)-0.010(0.008) |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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. ‘Higher crop yield’ is a dummy with value 1 for households having a higher than average crop yield in a given wave. ‘Higher crop production’ is a dummy with value 1 for households having a higher than average crop production (kg) in a given wave. R2 and Adjusted R2 are before partialling-out region x time FE. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

|  |
| --- |
|  Variable: TLU level  |
|  |  |  |  |  |
|  | Mean | Var | sd | Obs |
| Whole sampleq1q2q3q4 | 2.4841.9602.5282.3703.157 | 32.17226.17426.02833.28644.427 | 5.6725.1165.1025.7696.665 | 3343845892863743 |

**Table 28**

**Descriptive statistics –Tropical Livestock Units**

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

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent variable: | (1) | (2) | (3) |
| Asset growth |  |  |  |
|  |  |  |  |
| L1.Assets |  -147.875\*\*\* |  -148.349\*\*\* | -148.279\*\*\* |
|  |  (2.424) | (2.402) | (2.397) |
| ∆Temp | -22.745 |  |  |
|  | (67.272) |  |  |
| ∆Pre | -12.745 |  |  |
|  | (10.569) |  |  |
| q1 x ∆Temp  |  | -91.481 | -43.634 |
|  |  | (75.103) | (79.663) |
| q2 x ∆Temp |  | -76.910 | -86.671 |
|  |  | (78.344) | (75.038) |
| q3 x ∆Temp |  | -26.619 | -35.847 |
|  |  | (81.239) | (80.327) |
| q4 x ∆Temp |  |  160.247\* | 114.557 |
|  |  | (95.111) | (87.781) |
| q1 x ∆Pre |  | 0.422 | 4.167 |
|  |  | (12.047) | (12.432) |
| q2 x ∆Pre |  |  -31.978\*\* |  -32.431\*\* |
|  |  | (12.801) | (12.613) |
| q3 x ∆Pre |  | -23.490\* | -35.847 |
|  |  | (13.436) | (80.327) |
| q4 x ∆Pre |  | 12.133 | 114.557 |
|  |  | (15.018) | (87.781) |
| Obs | 2,216 | 2,216 | 2,216 |
| Adj. R2 | 0.357 | 0.360 | 0.359 |
| Vegetation time series | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes |

 **Table 29**

**FE regressions – Asset growth as the dependent variable**

*Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Asset growth is the between-wave percentage change in household Tropical Livestock Units (TLUs). L1.Assets is lagged household. asset level (TLUs). q1, q2, q3, q4 are initial consumption quartiles in Column (2) and initial food consumption quartiles in Column (3). ∆Temp is the difference between average monthly growing season temperature and long-run (1980-2015) average monthly growing season temperature, divided by long-run (1980-2015) standard deviation, expressed in degree Celsius. ∆Pre is the difference between total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

|  |
| --- |
|  Participation in a credit / saving group- % of households |
|  |  |  |  |  |
|  | Yes3.303.435.649.70 | No96.7096.5794.3690.30 |
| q1q2q3q4 |

**Table 30**

**Descriptive statistics – Participation in a credit / saving group**

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

**Table 31**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent variables: | (1)∆Food | (2)∆Food | (3)∆Cons | (4)∆Cons |
|  |  |  |  |  |
| L1.Food |  -147.882\*\*\* |  -147.937\*\*\* |  |  |
|  | (1.729) | (1.720) |  |  |
| L1.Cons |  |  |  -143.856\*\*\* |  -143.959\*\*\* |
|  |  |  | (1.811) | (1.809) |
| q1 x ∆Temp |  -84.842\*\*\* |  -77.681\*\*\* |  -85.236\*\*\* |  -84.230\*\*\* |
|  | (20.230) | (24.394) | (19.242) | (22.315) |
| q2 x ∆Temp |  -39.678\*\* |  -30.367 | -11.973 | -7.976 |
|  | (18.710) | (21.803) | (18.654) | (21.632) |
| q3 x ∆Temp | -12.356 | -3.312 | -20.919 |  -19.638 |
|  | (21.138) | (24.435) | (19.102) | (21.293) |
| q4 x ∆Temp |  57.835\*\* |  65.501\*\*\* |  66.256\*\*\* |  67.966\*\*\* |
|  | (22.565) | (25.135) | (23.130) | (25.323) |
| Hot x ∆Temp |  | -14.285 |  | -0.253 |
|  |  | (22.377) |  | (19.847) |
| q1 x ∆Pre | -4.275 | -3.513 |  -7.124\*\* | -7.250\* |
|  | (3.544) | (4.249) | (3.244) | (3.809) |
| q2 x ∆Pre | -5.697\* | -4.476 | 1.368 | 1.413 |
|  | (3.222) | (3.945) | (3.103) | (3.746) |
| q3 x ∆Pre | 1.685 | 2.698 | -0.345 | -0.540 |
|  | (3.523) | (4.363) | (3.178) | (3.771) |
| q4 x ∆Pre | 5.425 | 6.243 | 6.110\* | 5.936 |
|  | (3.494) | (4.161) | (3.350) | (3.880) |
| Hot x ∆Pre |  | -1.463 |  | 0.967 |
|  |  | (4.256) |  | (3.922) |
| Hot  |  | 10.684 |  |  42.421\*\*\* |
|  |  | (12.607) |  | (10.640) |
| Part\_group x ∆Temp | 37.418 | 41.181 | 29.018 | 29.407 |
|  | (38.833) | (32.305) | (32.519) | (32.368) |
| Part\_group x ∆Pre | -5.825 | -5.217 | -6.194 | -5.920 |
|  | (4.672) | (4.631) | (4.215) | (4.211) |
| Part\_group | -2.226 | -2.705 | 1.482 | 1.981 |
|  | (3.974) | (3.880) | (3.654) | (3.653) |
| Obs | 2,974 | 2,980 | 2,976 | 2,976 |
| Adj. R2 | 0.493 | 0.491 | 0.489 | 0.490 |
| Vegetation time series | Yes | Yes | Yes | Yes |
| Household controls | Yes | Yes | Yes | Yes |

**Heterogeneity with respect to (micro) institutions**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Total temperature effect for q1 households participating in a saving/credit groupTotal temperature effect for q1 households participating in a saving/credit group in hot areas | -47.424(43.566) | -36.500 (40.701)-50.786 (38.012) | -56.217 (36.802) |  -54.822 (38.337) -55.076 (37.759) |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Part\_group is a dummy with value 1 for households participating in a credit / saving group in a given wave. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table 32**

|  |  |  |
| --- | --- | --- |
| Dependent | (1) | (2) |
| variable: | ∆Food | ∆Cons |
|  |  |  |
| L1.Food |  -144.957\*\*\* |  |
|  | (1.651) |  |
| L1.Cons |  |  -140.928\*\*\* |
|  |  | (1.674) |
| ∆Pre | -0.237 | -0.375 |
|  | (2.617) | (2.461) |
| ∆Temp\_Lower regime |  -109.684\*\*\*(21.575) |  -183.583\*\*\*(32.514) |
| ∆Temp\_Medium regime | -5.839 | -14.961 |
|  | (15.615) | (15.073) |
| ∆Temp\_Upper regime |  90.064\*\*\* |  85.753\*\*\* |
|  | (19.790) | (20.453) |
| Obs | 3,168 | 3,170 |
| Adj. R2 | 0.774 | 0.773 |
| Vegetation time seriesHousehold controls | YesYes | YesYes |
| *Notes:* All specifications include households FE, wave dummies, region x year FE and month of interview 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 two idiosyncratic shocks: illness and death of a household member. Food consumption growth rate is the between-wave percentage change in (ln) household per a.e. food consumption. Total consumption growth rate is the between-wave percentage change in (ln) household per a.e. total consumption. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) total consumption. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total growing season precipitation, divided by long-run (1980-2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at both household and wave levels. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Double threshold model – Hansen Estimator**

**Threshold Confidence intervals and effect tests**

**Column (1) – Food consumption**

1. Threshold estimator (level = 95):

Model Threshold Lower Upper

Th-1 13.619 13.606 13.624

Th-21 13.619 13.560 13.624

Th-22 12.360 12.332 12.369

1. Threshold effect test (bootstrap = 300 300):

Threshold RSS MSE Fstat Prob Crit10 Crit5 Crit1

Single 1.99e+06 627.192 54.62 0.000 16.864 20.110 25.514

Double 1.97e+06 621.125 30.93 0.003 17.022 20.242 26.065

**Column (2) – Total consumption**

1. Threshold estimator (level = 95):

Model Threshold Lower Upper

Th-1 13.954 13.940 13.959

Th-21 13.954 13.940 13.959

Th-22 12.329 12.281 12.345

1. Threshold effect test (bootstrap = 300 300):

Threshold RSS MSE Fstat Prob Crit10 Crit5 Crit1

Single 1.79e+06 563.948 55.67 0.000 15.955 18.802 23.964

Double 1.77e+06 558.408 31.43 0.010 19.079 20.854 31.182

**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**

|  |  |  |
| --- | --- | --- |
|  Dependent variable: | (1)∆Food | (2)∆Cons |
|  |  |  |
|  |  |  |
| L1.Food |  -179.604\*\*\* |  |
|  | (28.430) |  |
| L1.Cons |  |  -145.645\*\*\* |
|  |  | (37.304) |
| ∆Temp | 66.883 | 16.519 |
|  | (42.140) | (47.409) |
| Poor x ∆Temp |  -161.012\*\*\* | -75.821 |
|  | (60.117) | (75.015) |
| ∆Pre | 3.244 | -0.284 |
|  | (4.059) | (3.437) |
| Poor x ∆Pre |  -12.631\*\*\* | -7.602 |
|  | (3.886) | (4.830) |
| Observations | 2,426 | 2,426 |
| Adjusted R-squared | 0.436 | 0.479 |
| Vegetation time series | Yes | Yes |
| Household controls | Yes | Yes |
| Total temperature effect for poorest households |  -94.129\*\*\*(29.719) | -59.302\*(35.915) |
| *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. ∆Temp is the difference between average monthly growing season temperature 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 total growing season precipitation and long run (1980-2015) average total 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. Standard errors are in parentheses and are clustered at both household and wave levels. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. |

**Table A.1**

**Instrumented FE regressions – Endogeneity tests**

**Endogeneity tests:**

|  |  |  |
| --- | --- | --- |
| **Regressor** | **Test** | **p-value** |
| L1.Food | 0.720 | 0.396 |
| L1.Cons | 0.011 | 0.916 |

**Table A.2**

**Descriptive statistics – Alternative weather data**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Mean | Var | sd | Obs |
| ∆Temp |  0.122 |  0.021 | 0.145 | 4755 |
| ∆Pre | -0.136 | 0.393 | 0.627 | 4755 |
| Temp | 24.220 | 4.379 | 2.093 | 4755 |
|  |  |  |  |  |
| Pre | 483.357 | 23226.09 | 152.401 | 4755 |
| Long-run average temperature | 23.97 | 4.368 | 2.090 | 4755 |
| Long-run average precipitation | 502.2 | 19198.69 | 138.559 | 4755 |
| *Notes:* |  |  |  |  |
| ∆Temp is the difference between average monthly growing season temperature in the twelve months preceding the interview and long-run (1983-2013) average monthly growing season temperature divided by long-run (1983-2013) standard deviation, and expressed in degree Celsius. ∆Pre is the difference between total precipitation during the wettest quarter and average decadal (2001 - 2013) total precipitation during the wettest quarter divided by average decadal (2001 - 2013) standard deviation, expressed in mm. Temp is average monthly growing season temperature in the twelve months preceding the interview. Pre is total precipitation during the wettest quarter. 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 and average decadal (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.3**

**Alternative weather data – Using weather levels**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent | (1) | (2) | (3) | (4) |
| variables: | ∆Food | ∆Food | ∆Cons | ∆Cons |
|  |  |  |  |  |
| L1.Food |  -153.753\*\*\* |  -153.872\*\*\* |  |  |
|  | (1.722) | (1.732) |  |  |
| L1.Cons |  |  |  -149.713\*\*\* |  -149.796\*\*\* |
|  |  |  | (1.752) | (1.759) |
| q1 x Temp |  -27.880\*\*\* |  -22.708\*\* |  -27.361\*\*\* |  -19.843\*\* |
|  | (8.479) | (9.661) | (8.222) | (9.407) |
| q2 x Temp | -7.648 | -1.827 | 3.357 | 10.833 |
|  | (8.776) | (9.850) | (8.899) | (9.696) |
| q3 x Temp | 14.779 | 19.306\* | 1.140 | 8.439 |
|  | (10.021) | (10.984) | (8.279) | (9.209) |
| q4 x Temp |  52.346\*\*\* |  57.607\*\*\* |  51.676\*\*\* |  59.187\*\*\* |
|  | (9.628) | (10.607) | (8.920) | (9.865) |
| Hot x Temp |  | -9.171 |  | -14.897\* |
|  |  |  (8.631) |  | (7.831) |
| q1 x Pre |  -0.027\* | -0.010 |  -0.018 | -0.012 |
|  | (0.014) | (0.020) | (0.014) | (0.020) |
| q2 x Pre | -0.000 | 0.015 | -0.023\* | -0.019 |
|  | (0.014) | (0.020) | (0.013) | (0.018) |
| q3 x Pre | 0.022 |  0.044\*\* | 0.007 | 0.014 |
|  | (0.014) | (0.023) | (0.014) | (0.022) |
| q4 x Pre | 0.022 |  0.042\* | 0.026 | 0.033 |
|  | (0.016) | (0.024) | (0.016) | (0.023) |
| Hot x Pre |  | -0.030 |  | -0.014 |
|  |  | (0.021) |  | (0.020) |
| Hot  |  | 210.252 |  |  346.936\* |
|  |  | (208.821) |  | (189.076) |
| Obs | 3,168 | 3,168 | 3,164 | 3,164 |
| Adjusted R2 | 0.508 | 0.508 | 0.507 | 0.507 |
| 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 month of interview 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 two idiosyncratic shocks: illness and death of a household member. ∆Food is the between-wave percentage change in (ln) household per a.e. food consumption. ∆Cons is the between-wave percentage change in (ln) household per a.e consumption. 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 Columns (1) and (2) and initial total consumption quartiles in Columns (3) and (4). Temp is average monthly growing season temperature, expressed in degree Celsius. Pre is total precipitation during the wettest quarter, expressed in mm. Hot is a dummy with value 1 for households living in an area with above median long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at both household - wave level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |
|  | Mean | Var | sd | Obs |
| Number of GDDs (8-34 °C) | 3905.0 | 389495.4 | 624.1 | 4755 |
| Number of GDDs (34 + °C) | 3.280 | 46.27 | 6.802 | 4755 |

**Table A.4**

**Descriptive statistics – Growing degree days**

**Table A.5**

**Descriptive statistics – Irrigation**

|  |
| --- |
|  Use of irrigation in the previous long rainy season - % of households |
|  |  |  |  |  |
|  | Yes1.953.303.846.05 | No98.05 96.7096.1693.95 |
| q1q2q3q4 |

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

|  |
| --- |
|  Use of inorganic fertilizers in the previous long rainy season - % of households |
|  |  |  |  |  |
|  | Yes17.6519.1025.2523.46 | No82.3580.8174.7576.54 |
| q1q2q3q4 |

**Table A.6**

**Descriptive statistics – Inorganic fertilizers**

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

|  |
| --- |
|  Variable: Use of improved maize seeds on at least one plot across waves - % of households |
|  |  |  |  |  |
|  |  Yes34.1641.24 46.4853.46 |  No65.8458.7653.5246.54 |
| q1q2q3q4 |

**Table A.7**

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

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

|  |
| --- |
|  Variable: Use of improved maize seeds on at least half of the household plots across all waves - % of households |
|  |  |  |  |  |
|  | Yes8.7710.65 18.7922.08 | No91.2389.3581.2177.92 |
| q1q2q3q4 |

**Table A.8**

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

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

|  |
| --- |
|  Variable: Use of improved maize seeds on at least one plot across waves - % of households |
|  |  |  |  |  |
|  | Yes19.3524.76 27.0327.15 | No80.6575.2472.9772.85 |
| q1q2q3q4 |

**Table A.9**

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

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

|  |
| --- |
|  Variable: Use of improved paddy seeds on at least half of the household plots across all waves - % of households |
|  |  |  |  |  |
|  | Yes4.276.27 6.6116.49 | No95.7393.7393.3983.51 |
| q1q2q3q4 |

**Table A.10**

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

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

**Table A.11**

**Descriptive statistics – Non-Agricultural Wealth Index**

|  |
| --- |
|  Variable: Non-Agricultural Wealth Index |
|  |  |  |  |  |
|  | Mean | Var | sd | Obs |
| q1q2q3q4 | -0.229-0.0740.0140.155 | 0.3310.5710.7411.158 | 0.5750.7560.8611.076 | 905981931836 |

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

**Table A.12**

**Descriptive statistics – Index of Access to Infrastructure**

|  |
| --- |
|  Variable: Index of Access to Infrastructure |
|  |  |  |  |  |
|  | Mean | Var | sd | Obs |
| q1q2q3q4 | -0.378-0.339-0.182-0.114 | 0.299 0.3510.6360.662 | 0.5470.5920.7970.814 | 905981931836 |

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

1. <http://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=TZ> [↑](#footnote-ref-1)
2. “Unfortunately, much of the empirical literature has not tested consumption smoothing against a theoretically well-defined alternative” [↑](#footnote-ref-2)
3. 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](http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0%2C%2CcontentMDK%3A23635561~pagePK%3A64168445~piPK%3A64168309~theSitePK%3A3358997%2C00.html) [↑](#footnote-ref-3)
4. 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](http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0%2C%2CcontentMDK%3A23635561~pagePK%3A64168445~piPK%3A64168309~theSitePK%3A3358997%2C00.html) [↑](#footnote-ref-4)
5. [http://data.worldbank.org/indicator/FP.CPI.TOTL?page=1](%20http%3A/data.worldbank.org/indicator/FP.CPI.TOTL?page=1) [↑](#footnote-ref-5)
6. <http://www.geog.ox.ac.uk/research/climate/projects/undp-cp/UNDP_reports/Tanzania/Tanzania.lowres.report.pdf> . [↑](#footnote-ref-6)
7. As already anticipated above, in these and all the following specifications, the lagged dependent terms are treated as exogenous, since endogeneity tests could never reject the assumption of exogeneity of the lagged consumption levels (see Table A.1 in the Appendix). [↑](#footnote-ref-7)
8. Given the fixed-effect 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. [↑](#footnote-ref-8)
9. Data can be found at: ftp://ftp.cpc.ncep.noaa.gov/fews/newalgo\_est\_dekad/ [↑](#footnote-ref-9)
10. Moreover, we also include a lagged dependent term in the regressions (see Table 18). [↑](#footnote-ref-10)
11. The FAO-RIGA Database can be found at: <http://www.fao.org/economic/riga/riga-database/en/>. [↑](#footnote-ref-11)
12. Descriptive statistics on GDDs can be found in the Appendix, Table A.4. [↑](#footnote-ref-12)
13. Cf. Table 19, Column 3. [↑](#footnote-ref-13)
14. Cf. Table 20. [↑](#footnote-ref-14)
15. 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 by the same small increment (namely minimum value in the sample above zero) for all the households owning livestock in at least one wave. [↑](#footnote-ref-15)
16. The Non-Agricultural Wealth Index and the Index of Access to Infrastructure (Tables A.9 and A.10) were taken from the FAO – RIGA database. [↑](#footnote-ref-16)
17. For the PPP Conversion Factor: <http://data.worldbank.org/indicator/PA.NUS.PPP?locations=TZ> . [↑](#footnote-ref-17)
18. All the regressions in this and the following tables below report, except where specified in the Notes, the Adjusted R-Squared after partialling-out region x time fixed effects (to ensure appropriate estimation with the *xtivreg2* command in Stata). [↑](#footnote-ref-18)