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Hydro-climatic thresholds and economic growth reversals in developing countries: an empirical investigation

Cécile Couharde* Rémi Generoso †

Abstract: In this paper, we exploit the Global Standardized Precipitation and Evapotranspiration Index database to search for a nonlinear relationship between hydro-climatic conditions and economic growth on a sample of developing countries over the period 1980-2011. We evidence a nonlinear link between hydro-climatic conditions and economic growth only in developing agricultural-dependant countries, the impact of hydro-climatic variations being more easily absorbed in more diversified economies. Furthermore, threshold values reached by hydro-climatic conditions that drive changes in the pattern of economic growth are lower than to those corresponding to extreme weather conditions, suggesting a high sensitivity of economic growth in developing agricultural-dependent countries to small fluctuations in weather.

JEL Classification: C33; 040; Q54

Keywords: Developing countries; Economic growth; Hydro-climatic conditions; Panel Smooth Transtion Regression (PSTR) model

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1. Introduction

Extreme weather conditions[1] have been found to be prominent in African countries by exerting an important negative shock on their economic growth. A number of explanations for this observed pattern have been forwarded: the tropical climate (Nicholson, 1994; Sachs and Warmer, 1997; Bloom and Sachs, 1998), the low level of development [2] which prevents African countries to fully implementing precautionary measures designed to reduce the impacts of extreme climate events and the prevalence in those countries of the agricultural sector which heavily depends on climatic conditions (Barrios *et al.*, 2010). Incidence of adverse weather conditions is however not only confined to Africa. Asian countries have also been challenged by the double hazard of both drought and flooding. For instance, Bangladesh is generally known to be vulnerable to flooding while up to 15 percent of its cultivable land experiences drought every two years (Ahmed *et al.*, 2005). India is also known for being a drought prone country (Prabhakar and Shaw, 2008).

In recent decades, the global awareness of more frequent and severe extreme weather events related to climate change (and in particular the global warming) has led to a renewed interest for studying their impact on economic growth. In particular, a growing concern is that, according the predictions of the Intergovernmental Panel on Climate Change (IPCC, 2007), during the next decades, billions of people, particularly those in developing countries, will face changes in rainfall patterns that will contribute to severe water shortages or flooding, and rising temperatures that will cause shifts in crop growing seasons. This has led to a wide literature which aims to understand how economic growth of developing countries is affected by extreme weather events in order to advance knowledge of the impact of climate change.

A large part of this literature has focused on the economic impacts of natural disasters

1. Extreme events occur when weather or climate variable reach a threshold value near the upper (or lower) tails of the range of observed values of the variable.

2. Several studies have evidenced that the impact of natural disasters varies according the macroeconomic policy environment and other structural characteristics of countries. In particular, a consistent finding of these studies is that better institutions - for instance, as more stable democratic regimes or greater security of property rights - reduce disaster impact (Kahn, 2005; Skidmore and Toya, 2007; Noy, 2009; Aurenqzeb and Stengos, 2012).

–which are known to occur when extreme weather events affect a vulnerable area (see Cavallo and Noy, 2010 for a review of the literature)– to identify extreme events' economic effects. Almost of this empirical literature has relied on the Emergency Events Database (EM-DAT) maintained by the Center for Research on the Epidemiology of Disasters (CRED) which provides the number of people killed, the number of people affected, and the dollar amount of direct damages for each disaster.

Nevertheless, by exploiting information from this database, these studies cannot causatively identify effects of extreme weather events on economic growth. Indeed data on damages, number of people affected and deaths have several limitations as they are likely to be endogenously determined by the level of income (Skidmore and Toya, 2002). To the extent that those variables are endogenously determined, reverse causality is likely to be a major concern in those empirical studies. Moreover, if some studies overcome this causality problem by using instead the number of natural events which can be considered as the best exogenous measures of disaster risk available, they cannot capture the size and the intensity of the extreme event. In recent years, in line with the improvement of weather indexes, a new literature qualified by Dell *et al.* (2014) as the New Climate Economy Literature has overcome this identification problem and derived more accurate shocks' indicators by using precipitation and/or temperature data (Dell *et al.*, 2008; Barrios *et al.*, 2010; Jones and Olken, 2010; Lanzafame, 2014). Assessments made in this area usually focus on the effects of the temporal variability in a weather variable on economic growth. If these estimates provide more rigorous econometric evidence that weather has manifold effects on economic activity, they are not however able to indicate whether these weather conditions refer or not to extreme events.

This article tries to overcome this drawback by estimating thresholds values from which weather conditions can alter economic growth and which determinants of economic growth are the most affected. More specifically, this article improves upon the existing literature on two major accounts. First we avoid the implicit bias of some of the literature that use rainfall and temperature data. Indeed, those data cannot be compared from one country to another or even inside a country given the diversity of climates. Moreover, hydro-climatic conditions refer to a combination of temperature and precipitation so that it is not appropriate to separate the two types of data. As a result, in this paper, we use the Standardized Precipitation and Evapotranspiration Index (SPEI) recently developed by Vicente-Serrano *et al.* (2010). This indicator has the advantage of reflecting multiple hydro-climatic conditions –relevant both in agriculture (short-term) and in hydrology (medium-term)– and of allowing comparison across countries characterized by different climatic regimes. Secondly, we adopt panel error correction methodology and test a potential threshold effect exerted by hydro-climatic conditions in the relationship between economic growth and its short-term determinants. This approach has several advantages compared to earlier studies. The error correction model allows us to estimate short-run effects of climatic conditions on economic growth and on the convergence towards the steady state within one regression framework, which to our knowledge has not previously been done. Moreover, unlike many assessments of the economic impacts of weather events focus on meteorological trends, we rather assess impacts resulting from threshold values reached by hydro-climatic conditions which induce shifts in growth dynamics. Our aim is then to identify the nature of changes in weather conditions which can affect growth dynamics. Accordingly, we rely on a Panel Smooth Transition Regression (PSTR) specification (González *et al.*, 2005) which allows economic growth to switch from one to another regime, depending on thresholds reached by hydro-climatic conditions. Those thresholds being interpretable in terms of intensities reached by hydro-climatic events, it is therefore possible to measure the sensibility of economic growth to the intensity of weather events.

Our analysis focuses on 37 developing countries characterized by a large variety of climate features over the period 1980-2011. To investigate whether economic growth in agricultural-dependent countries is more sensible to hydro-climatic variations, we split our sample into two sets: (a) 19 consisting of agricultural-dependent countries and (b) 18 other countries which have a more diversified production basket.

Our analysis yields three main findings. The estimation results in both the full sample of 37 developing countries and the first subsample (a) of developing agricultural-dependent countries show that the level of hydro-climatic conditions exerts a significant nonlinear effect on economic growth. This is in contrast to the experience of the 18 other developing countries, subsample (b), for which this nonlinear effect doesn't hold. We attribute this asymmetric pattern to the diversified nature of the latter group's production. Our second main finding is that the pattern of economic growth significantly varies, depending on hydro-climatic conditions. But the most outstanding point is that threshold values reached by hydro-climatic conditions that drive changes in the pattern of economic growth are lower than those corresponding to extreme weather conditions, suggesting a high sensitivity of economic growth to small fluctuations in weather. In particular, we evidence that mechanisms through which smaller fluctuations in hydro-climatic conditions cause economic growth reversals are the same as the ones found for extreme weather events. Indeed, under abnormal hydro-climatic conditions, the return to long-run equilibrium is significantly hampered as well as the positive effect that structural factors (investment and trade openness) exert on economic growth, reflecting a lack of adaptive capacities to wetter and drier conditions. In contrast, the positive effect of public spending and remittances on economic growth is strengthened, suggesting their important role as coping mechanisms in order to overcome the adverse effect exerted by abnormal hydro-climatic conditions in developing agricultural-dependent countries.

The rest of this paper is structured as follows. Section 2 describes our empirical framework. Section 3 presents data and some stylized facts. The results and related comments are displayed in Section 4. Section 5 is devoted to robustness analysis. Finally, Section 6 concludes.

2. The empirical framework

The starting point of our empirical analysis is that, beyond a certain level, hydro-climatic conditions can lead to a transitory income shock which may involve a different pattern of economic growth in the short-run. Thus our empirical framework relies on the behavior of the Solow (1956) neo-classical growth model that is augmented to include human capital (Mankiw *et al.*, 1992) in the long term, but allows for different short-run growth patterns depending on hydro-climatic conditions.

We assume that output is determined in the long run by a Cobb Douglas production function of the form:

$$Y_{it} = A_{it} K_{it}^{\alpha} H_{it}^{\beta} L_{it}^{1-\alpha-\beta} U_{it} \tag{1}$$

Where Y is total output, A is total factor productivity, K is physical capital, H is human capital, L is labor and U is an error tern. i and t stand for respectively index countries and index time. We assume constant returns to scale, so that the sum of the exponents is one. This seems reasonable since there is little evidence of a pure size effect on a country's output level. In addition, we assume that total factor productivity takes the form $logA_{it} = a_i + b_t$ which we can regard as a country fixed effect, indexed by i and worldwide growth of productivity, indexed by t. Dividing through by L, and taking logs, we can derive:

$$y_{it} = a_i + b_t + \alpha k_{it} + \beta h_{it} + u_{it} \tag{2}$$

Where capital stock, human capital and output are now in log per worker terms (respectively k,h,y) and $u_{it} = logU_{it}$

Consistent with this approach, output per capita converges to its steady state given by Equation 3 with a speed of adjustment measured by the coefficient δ ($0 < \delta < 1$):

$$\Delta y_{it} = \varphi \Delta k_{it} + \rho \Delta h_{it} + \sigma \left(w_{it} \right) - \delta \left[y_{it-1} - \alpha k_{it-1} - \beta h_{it-1} \right] + \varepsilon_{it} \tag{3}$$

With w_{it}, other exogenous variables that also can affect economic growth in the short run.

As described by Equation 3, the convergence process of output per capita to its steady state can be adequately estimated by a vector error-correction model (VECM): the long-run output per capita corresponding to the hypothesized cointegrating equation, short-run dynamics reflecting the adjustment of output per capita towards its long-run equilibrium level and the error correction term measuring the speed at which prior deviations of output per capita from its long-run equilibrium are corrected. Nevertheless, in the framework defined by the classical VECM, the growth process is assumed to be linear. As mentioned before, this assumption does not necessarily hold, as abnormal hydro-climatic conditions are likely to exert detrimental impacts on economic growth compared to normal ones. In order to take into account those potential nonlinearities, we estimate a regime-specific model allowing for switching effects driven by hydro-climatic conditions in the short-run dynamics of output per capita.

Accordingly, we rely on the Panel Smooth Transition Regime (PSTR) methodology proposed by González *et al.* (2005) in which the observations can be divided into different regimes, with estimated coefficients that vary depending on the considered regime. The change in the estimated value of coefficients is smooth and gradual, since PSTR models are regime-switching processes in which the transition from one state to the other is smooth rather than discrete. We justify this choice by the potential transitory nature of the income shock induced by changes in weather conditions, contrary to abrupt changes in the capital stock that could be the consequence of natural disasters or wars.

We then consider the following PSTR specification with fixed effects:

$$\Delta y_{it} = \mu_{it} + \theta_0 \eta_{it-1} + \beta\prime_0 x_{it} + \Sigma_{j=1}^{r} \left(\theta_1 \eta_{it-1} + \beta\prime_1 x_{it}\right) g_j \left(s_{it}; \gamma_j, c_j\right) + u_{it} \tag{4}$$

Where the dependent variable, Δy_{it}, is the first difference of output per capita; s_{it} is a climate index considered here as the transition variable and x_{it} is a vector of short-term determinants of economic growth. The transition function $g\left(s_{it}; \gamma, c\right)$ is a continuous function of the observable transition variable s_{it}. γ is the transition or slope parameter, measuring the slope of the transition function. c is the location parameter

The variable η_{it-1} is the error correction term, i.e. the difference between the observed output per capita and its estimated value from the cointegration relationship. It is then obtained by estimating the long-term relationship between the log of output per capita and its long-term determinants depicted by Equation 2:

$$\eta_{it} = y_{it} - \hat{y}_{it} \tag{5}$$

$$\hat{y}_{it} = \hat{a}_i + \hat{b}_t + \hat{\alpha} k_{it} + \hat{\beta} h_{it} \tag{6}$$

With $\hat{y}_{it}$ the long-run output per capita defined by the augmented Solow model and $\hat{\alpha}$, $\hat{\beta}$ the estimated long-run coefficients.

The inclusion of the error correction term η_{it-1} in the PSTR model has the advantage of linking the short-run dynamics of economic growth to its long-run path. The coefficient of the error correction term in the PSTR model then reflects the adjustment speed with which economic growth converges towards to its steady state.

The relationship between economic growth and its short-run determinants, i.e., the coefficients of the variables included in the x_{it} vector as well as the coefficient of the error correction term η_{it-1} are allowed to vary according to the value taken by the climate index (s). Assuming a two regime PSTR specification, let us denote the sum of coefficients $\phi_1 = \xi_{01} + \xi_{11} g_j\left(s_{it}; \gamma_j, c_j\right)$ with $\xi_{01} = \theta_0, \beta\prime_{01}, ..., \beta\prime_{0p}$ and $\xi_{11} = \theta_1, \beta\prime_{11}, ..., \beta\prime_{1p}$. In the first regime, when $g(.) = 0$, the estimates coefficients are given by $\phi_1 = \xi_{01}$. In the second regime, when $g(.) = 1$, the estimates coefficients are given by $\phi_1 = \xi_{01} + \xi_{11}$. Between those two extremes, ϕ_1 takes a continuum of values depending on the realization of the transition variable.

The transition function is normalized to be bounded between 0 and 1 and is defined following Gonzales *et al.*(2005) as follows:

$$g\left(s_{it}; \gamma_j; c_j\right) = \left(1 + exp\left(-\gamma \Pi_{j=1}^{m}\left(s_{it} - c_j\right)\right)\right)^{-1} \tag{7}$$

$c = (c_1, ..., c_m)$ is a vector of location parameters and γ is a parameter which determines the smoothness of the transition with the condition $\gamma > 0$ and $c_1 \leq c_2 \leq ... \leq c_m$. When $m = 1$, the transition function $g\left(s_{it}; \gamma, c\right)$ is a logistic function and γ determines the speed of the transition from one regime to another. When $m = 2$, $g\left(s_{it}; \gamma, c\right)$ is a quadratic logistic function. The model becomes a three-regime threshold model where the intermediate regime follows a different pattern compared to that in the extremes. We also consider the case of a doubled threshold model ($r = 2$). By setting $r = 2$, we allow for three regimes where each one has its own slope and location parameters.

The model (4) can be rewritten as:

$$\Delta y_{it} = \mu_{it} + \psi\prime_0 \Omega_{it} + \Sigma_{j=1}^{r} \psi\prime_j \Omega_{it} g_j \left(s_{it}; \gamma_j; c_j\right) + u_{it} \qquad (8)$$

where $\psi\prime_0 = (\theta_0, \beta_0)\prime$ and $\psi\prime_j = \left(\theta_j, \beta_j\right)\prime$ for $j = 1, .., r$; $\Omega_{it} = (\eta_{it-1}, x_{it})\prime$

3. Data and stylized facts

Since our main goal is to analyze the short-run effects of hydro-climatic variations, we are interested in econometrically modelling short-run output deviations. We therefore use original annual data instead of five-year averages. Our sample consists of yearly data from 1980 to 2011 for a panel of 37 developing countries characterized by a large variety of climate features.[3] This heterogeneity is not systematically related to differences between countries but refers also to differences within each country. It is therefore important to account for this diversity by using data that make accurate comparisons of different climate regimes.

3.1. Long and short-run determinants of growth

The dependent variable is the growth rate of output per worker (y) measured by the first difference (in logarithm) of the GDP per capita in $US and in 2005 prices. Data are taken from the World Bank's World Development Indicators (WDI) database. The stock of physical capital per worker (k) is also expressed in $US and in 2005 prices. Following Barro and Lee (1993), the stock of human capital per worker (h) is proxied by the average years of schooling.[4] The long-run explanatory variables are both taken from the Penn World Tables (version 8.0).

Four types of short-run explanatory variables are used to capture different short-run determinants of economic growth in line with the existing literature (Aghion and Durlauf,

3. The list of countries is given in Table A.1 in the Appendix

4. Rates of return to education are used in order to complete different sets of years of education (Psacharopoulos, 1994).

2005, 2014): structural factors, policy variables, factors that are likely to provide additional sources of revenues and indicators of political stability.

Structural factors include the first difference of the capital stock per worker at constant \$US 2005 prices and the openness degree to international trade, measured as the ratio of the sum of exports and imports of goods and services to GDP ($Trade/GDP$). As indicators of macroeconomic policies we include the following variables. First, following Fischer (1993), we take inflation as a measure of monetary policy. Inflation is calculated as $infl = log\left(1 + \pi/100\right)$ with π the annual percentage change in consumer prices. We also consider one of the two fiscal variables suggested by Easterly and Rebelo (1993), the first difference of the government consumption in \$US 2005 prices (G). We also take into account additional sources of revenues which may affect economic growth: the first difference of remittances per worker ($Remit$, in current \$US), the first difference of overseas development aid per worker (ODA, in constant \$US 2005 prices) and the ratio of broad money (M2) to GDP which proxies for the level of financial development (King and Levine, 1993). All data are extracted from the World Development Indicators database (WDI, The World Bank) except capital stock data that are coming from the Penn World Tables (version 8.0). Finally, we control for the occurrence of armed conflicts as extreme weather events are likely to increase armed conflicts and political instability (see Dell *et al.*, 2014 for a survey). Accordingly, we use the UCDP/PRIO Armed Conflicts Dataset[5] and we create a dummy variable taking the value of 1 for years characterized by the occurrence of a conflict in a given country and 0 otherwise.

3.2. The Standardized Precipitation and Evapotranspiration Index (SPEI)

This article uses the Global Standardized Precipitation and Evapotranspiration Index (SPEI) database developed by Vicente-Serrano *et al.* (2010). The Global SPEI database provides long-time and robust information about climatic conditions at the global scale, with a 0.5 degrees spatial resolution and a monthly time resolution between January 1901

5. The database is maintained by the Uppsala Conflict Data Program (UCDP) at the department of Peace and Conflict Research, Uppsala University and the Centre for the Study of Civil War at the International Peace Research Institute Sweden. Cf. https://www.prio.org/Data/Armed-Conflict/UCDP-PRIO/.

and December 2011.[6]

The SPEI is now one of the most widely used indicators in climatology because of the advantages it offers. First, the SPEI is fairly easy to compute since it is based on the original Standardized Precipitation Index (SPI) developed by McKee *et al.* (1993). However, the major difference between the two indexes is that the SPI focus only on precipitation while the SPEI is a water balance index that considers the difference between precipitation and potential evapotranspiration. Therefore, the SPEI has the advantage of combining the impact of temperature and precipitation which is expected to be important for agricultural regions facing rising temperatures resulting from climate change. Another advantage of this indicator is to allow for the identification of the beginning and the end of droughts and for the comparison of changes in droughts severity across time and space. This is particularly important since droughts are complex and dynamic phenomena. A real strength of the SPEI is its ability to be calculated for many timescales, which makes it possible to deal with many types of droughts or humid conditions. For instance, timescales ranging from one to three months usually reflect short-term onsets. Medium-term onsets such as agricultural drought are associated with a 6-month time scale while longer term onsets such as hydrological events can be approximated by time scales from 12 to 24 months. In this respect, the SPEI is able to describe a wider range of relevant hydro-climatic conditions than the Palmer Drought Severity Index (PDSI), which although based on water conditions (supply and demand of water), can only consider droughts on relatively long time scales (between 9 and 12 months). In this article, we use the 6-month time scale SPEI as a benchmark indicator. This time scale is more suited for capturing any climatic water deficiency and excess in agricultural seasons such as agricultural droughts. Finally, the SPEI, as it is a standardized indicator, allows the comparison between climates different from each other, by defining different hydro-climatic conditions.

The SPEI is based on the monthly water balance which is defined as the difference be-

6. We use the Global SPEI database v2.2. Monthly precipitation and potential evapotranspiration data used for the calculation of the SPEI are from the Climatic Research Unit of the University of East Anglia.

tween precipitation (P_i) and evapotranspiration (PET_i) during the month i:

$$D_i = P_i - PET_i \tag{9}$$

Where PET_i is based on the Penman-Monteith equation of water balance (Allen *et al.*, 1998) and D_i reflects the water surplus or deficit for the current month. The calculated values of D_i are then aggregated at various time scales k (i.e., over one month, two months, three months, etc...). The aggregated water surplus or deficits values D_n^k are obtained by the sum of the D_i values from $k-1$ months before the n^{th} current month:

$$D_n^k = \Sigma_{l=0}^{k-1} \left(P_{n-l} - PET_{n-l}\right) \tag{10}$$

Given the strong differences in climatic regimes inside and between countries, the D_n^k series are fitted to a probability distribution to transform the original values to standardized units that are comparable in space and time and at different time scales. A density function of log-logistic probability is adjusted to the distribution of the variable D_n^k since it allows a better behavior of the SPEI to extreme (Vicente-Serrano *et al.*, 2010).

The probability density function of a three parameter Log-logistic distributed variable is expressed as:

$$f(x) = \frac{\omega}{v}\left(\frac{x-\mu}{v}\right)^{\omega-1}\left[1+\left(\frac{x-\mu}{v}\right)^{\omega}\right]^{-2} \tag{11}$$

where v, ω and μ are parameters of scale, shape and origin for D_n^k values in the range ($\mu > D < \infty$). The three parameters are estimated using the L-moments procedure. $f(x)$ is then transformed into a random variable with mean zero and a variance equals to one according the conversion method of Abramowitz and Stegun (1965). The SPEI calculated for each month at a spatial resolution of 0.5 degrees are then aggregated by calculating the annual average for each country between 1980 and 2011.[7] Thus, the value of the SPEI is, as the SPI, bounded between -3 and 3. Between these two values, different intensities in hydro-climatic conditions can be identified, according threshold values reached by the

7. We use the ArcGIS software to assign each SPEI to the limits of our countries sample. SPEI calculated with a 6 month time scale are plotted in Ffigure A.1 in the Appendix.

SPEI, as detailed by Table 1.

Table 1. *Hydro-climatic conditions according to threshold values of the SPEI*

Values of SPEI	Hydro-climatic conditions
$SPEI > 2$	Exceptionally moist
$1.60 < SPEI < 1.99$	Extremely moist
$1.30 < SPEI < 1.59$	Very moist
$0.80 < SPEI < 1.29$	Moderately moist
$0.51 < SPEI < 0.79$	Slightly moist
$-0.50 < SPEI < 0.50$	Near normal conditions
$-0.79 < SPEI < -0.51$	Slightly dry
$-1.29 < SPEI < -0.80$	Moderately dry
$-1.59 < SPEI < -1.30$	Very dry
$-1.99 < SPEI < -1.60$	Extremely dry
$SPEI < -2$	Exceptionally dry

Source: NOAA's National Centers for Environmental Information, 2015

3.3. Stylized facts

We present here some stylized empirical facts emerging from the statistical analysis of hydro-climatic conditions and economic growth for our sample of countries, according to the importance of the agricultural sector. We split our initial sample of 37 developing countries into two sub-samples: countries with a higher share of agriculture in GDP and countries with a lower share of agriculture in GDP. Accordingly, we calculate the average share of agriculture in GDP for each country over the period and we divide the sample according to the median value of these average shares which corresponds to 18.6% to GDP.[8]

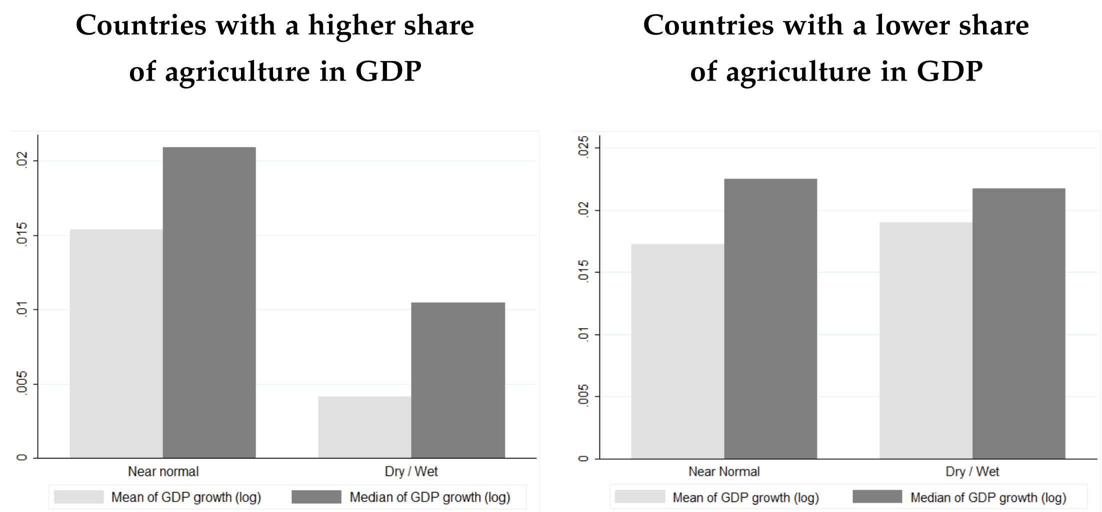
We first check the distribution of climatic conditions across the two sub-samples of countries in order to ensure that our decomposition will not lead to biased results. Indeed, the widespread finding that countries with a higher share of agriculture in total GDP are most affected by abnormal hydro-climatic conditions may simply due to higher frequency and magnitude of abnormal weather patterns in these countries. We then perform a two

8. Data on agricultural GDP are extracted from the World Bank Development indicators (WDI, World Bank). The list of countries and all descriptive statistics are given in tables A.1 and A.2 in the Appendix.

sample t-test (mean comparison test) in order to assess whether the means of the SPEI are different or not between our two sub-samples of countries. Using Bartlett's test suggests strong evidence to accept the null hypothesis of equality of means across the two groups of countries (cf. Table A.3 in the Appendix).

To illustrate now the potential impact of hydro-climatic conditions on economic growth in developing countries, we create a dummy variable taking the value of 0 for years characterized by near normal climate conditions ($-0.50 < SPEI < 0.50$) and 1 for years characterized by drier and wetter conditions ($SPEI < -0.50$ and $SPEI > 0.50$). The bars in Figure 1 show average and median GDP growth per capita according to the value taken by the dummy variable. From the figure, it is evident that there is an obvious link between hydro-climatic conditions and economic growth for developing agricultural-dependent countries. Indeed, observations during wetter and drier years have median growth and mean levels of growth lower than the values corresponding to years when normal hydro-climatic conditions prevail. Regressing the growth rate of GDP per capita on the dummy

Figure 1. *GDP growth per capita according to hydro-climatic conditions*



Notes: dry and wet conditions correspond to SPEI values strictly lower than -0.5 and strictly higher than 0.5. Near normal conditions correspond to SPEI values of -0.5 to 0.5.

variable yields remarkably similar conclusions. Indeed, results from panel regressions (cf.

Table A.4 in the Appendix) using Feasible Generalized Least Squares (FGLS)[9] indicate that switching from near normal hydro-climatic conditions to abnormal ones results in a decline in the growth rate of GDP only for developing countries whith a higher share of agriculture in GDP.

4. Results

4.1. Estimating the long-run relationship

In order to estimate the long-run relationship, we implement the conditional pooled mean group (CPMG) panel model[10] because of its appealing features. Indeed, as the PMG estimator of Pesaran *et al.* (1999), it does not impose untenable exogeneity restrictions on the considered series, restricts the long-run coefficients to be homogenous over the cross-sections, but allows for heterogeneity in intercepts and in short-run coefficients (including the speed of adjustment) and error variances.[11] Moreover, the CPMG is valid in the presence of cross-section dependencies. This hypothesis is likely to hold for our sample as weather shocks usually lead to potential correlation between macroeconomic performances on a regional scale.

The CPMG estimator is based on an Autoregressive Distributive Lag (ARDL) model. The main requirements for the validity of this methodology are that the dynamic specification of the model is sufficiently augmented so that the regressors become weakly exogenous and the resulting residual is serially uncorrelated.

We first test for the order of integration of our variables, by using the panel unit root test

9. We use the FGLS estimator to correct for heteroscedasticity, serial correlation and dependence among panels' units. Indeed, we find strong rejection of homoscedasticity and independence using the modified Wald test and the Breusch Pagan LM test respectively. We also correct for first order autocorrelation based on the Wooldridge test in countries with a lower share of agriculture in GDP.

10. For more details, see de V. Cavalcanti *et al.* (2012).

11. It can be argued that country heterogeneity is particularly relevant in short-run relationships, given that countries can be affected by several constraints in short-time horizons, albeit to different degrees. On the other hand, there are often good reasons to expect that long-run relationships between variables are homogeneous across countries.

of Pesaran (2007) that allows for cross-sectional dependence.[12] The results in table B.2 in the Appendix provide strong evidence that our three variables of interest y, k and h are I(1) variables. We then run the cointegration tests proposed by Westerlund and Edgerton (2008) to test for panel cointegration, that is, the existence of an I(0) relation between y, k and h. This test has the advantage of taking into account the presence of structural breaks and cross-sectional dependance in series. Results reported in Table B.3 in the Appendix show that we can reject the null hypothesis of the absence of cointegration regarding the Westerlund and Edgerton test.

We can thus turn to estimation results for the panel ARDL model (1,1,1).[13] Table 2 reports CPMG estimation results. In addition to these CPMG results we also report the mean group estimates (CMG), which are averages of the individual country coefficients. The CMG approach provides consistent estimates of the averages of long-run coefficients, although they are inefficient if homogeneity is present. On the contrary, under long-run slope homogeneity, CPMG estimates are consistent and efficient. We test for long-run homogeneity using the Hausman test statistics for the coefficients on each of the explanatory variables and for all of them jointly based on the null of equivalence between the CPMG and CMG estimations. If we reject the null hypothesis (i.e. a probability value lower than 0.05), the homogeneity assumption on long-run coefficients across countries is invalid.

12. The presence of a similar pattern across our sample of countries has been tested by the cross-sectional dependence (CD) statistic of Pesaran (2004). Results reported in Table B.1 in the Appendix reject the null hypothesis of cross-sectional independence between countries for the three variables.

13. The lag structure of the panel ARDL is based on the minimization of the AIC and BIC criteria.

According to the Hausman statistics, the long-run homogeneity restriction is not rejected for individual parameters and jointly in all regressions. Thus, we focus on the results obtained using the CPMG estimator, which, given its gains in consistency and efficiency over the alternative CMG estimator, is more appropriate. The CPMG results indicate that the error correction coefficient η_{it-1} is statistically significant and negative, confirming therefore that the null hypothesis of no long-run relation is rejected. In the long run, the output per worker is, as expected, positively related to capital stock and human capital stock per worker. Moreover, only the CPMG estimate of the capital stock per worker is statistically significant in the short run, which means that human capital stock per worker influences GDP per capita only in the long run. Overall there results show that the augmented Solow's growth model is appropriate for describing the long run growth of our sample of developing countries over the period under study.

4.2. Estimating the PSTR growth model

We estimate our nonlinear growth model following the methodology proposed by Gonzales *et al.* (2005). In a first step, we test for homogeneity against the PSTR alternative. If homogeneity is rejected, we test the appropriate form of the transition functions by choosing between the logistic ($m = 1$) and the logistic quadratic specification ($m = 2$). Following Eggoh (2010), we use the Akaike Information criterion (AIC) and the Bayesian Information Criterion (BIC) to assess the correct order of the transition function. In a second step, data are demeaned and parameters are estimated using nonlinear least squares. In a third and final stage, we test the validity of the model and relevance of the transition variable through various robustness tests.

The first step before estimating the PSTR model involves testing if the response of economic growth to the explanatory variables is different whether facing abnormal or near normal hydro-climatic conditions. We then test for the null hypothesis of linearity in Equation 8 by replacing the transition variable s_{it} by the SPEI and by imposing $H_0 : \gamma = 0$ or $H_0^1 : \psi\prime_1 = 0$ against the PSTR specification. However, the associated tests are not standard tests because of the presence of nuisance parameters which are unidentified (like

Table 2. *Common correlation effect Pooled Mean Group (CPMG) and Mean Group (CMG)*

	CPMG	**CMG**
η_{it-1}	-0.294^{***}	-0.614^{***}
	(0.045)	(0.048)
Long-run coefficients		
k	0.494^{***}	-0.031
	(0.015)	(0.210)
h	0.156^{***}	-0.201
	(0.023)	(0.329)
$\bar{y}$	0.074	0.727^{**}
	(0.191)	(0.319)
$\bar{k}$	0.050	-0.084
	(0.160)	(0.318)
$\bar{h}$	-0.064	0.333
	(0.047)	(0.369)
Short-run coefficients		
Δk	0.976^{***}	1.500^{***}
	(0.135)	(0.197)
Δh	0.073	0.138
	(0.103)	(0.127)
$\Delta \bar{y}$	0.758^{***}	0.392^{***}
	(0.122)	(0.116)
$\Delta \bar{k}$	-0.351	-1.039^{*}
	(0.238)	(0.542)
$\Delta \bar{h}$	-0.151	-0.181
	(0.108)	(0.115)
Constant	0.529^{***}	0.951
	(0.092)	(0.725)
Hausman test	$\chi^2(5) = 3.91$	
	$Prob > \chi^2 = 0.562$	
Number of observations	1147	

*Notes: all estimations include a constant country specific term. Standard errors are presented below the corresponding coefficients in brackets. Symbols ***, ** and * denote significance at 1%, 5% and 10% respectively. The bars over the variables indicate the cross-sectional averages of these variables. Null hypothesis of the Hausman test indicates no systematic difference in coefficients.*

the parameter c) under both null hypothesis. Hence, Gonzalez *et al.* (2005) proposed to test the null hypothesis of $H_0 : \gamma = 0$ by replacing the transition function $g\left(SPEI_{it}; \gamma, c\right)$ by its first-order Taylor expansion around $\gamma = 0$, in order to overcome the problem of nuisance parameters. After reparameterization, this leads to consider the following regression:

$$\Delta y_{it} = \mu_{it} + \psi\prime_0 \Omega_{it} + \Gamma\prime_1 \Omega_{it} SPEI_{it} + \Gamma\prime_2 \Omega_{it} SPEI_{it}^2 + ... + \Gamma\prime_m \Omega_{it} SPEI_{it}^m + \varepsilon_{it} \tag{12}$$

Where $\psi_0 = (\theta_0, \beta_0)\prime$, $\Omega_{it} = (\eta_{it-1}, x_{it})\prime$ and the parameters $\Gamma\prime_k$ are a multiple of the slope parameter γ. Thus testing the linearity against the PSTR model consists in testing $\Gamma_1 = \Gamma_2 = ... = \Gamma_m = 0$ in the linear panel model described by Equation 12.

The test of linearity consists in applying the Lagrange Multiplier (LM) test developed by Gonzalez *et al.* (2005): $LM = TN\left(SSR_0 - SSR_1\right)/SSR_0$ with SSR_0, the sum of squared residuals of the model with fixed effects and SSR_1, the sum of squared residuals of the alternative equation (PSTR model with two regimes). For robustness check, we also compute a pseudo-LRT statistic defined as: $LRT = -2\left[log\left(SSR_1\right) - log\left(SSR_0\right)\right]$.

The results of the LM and LRT tests are displayed in Table 3 for the whole sample as well as for the two sub-samples of countries. The null hypothesis is that of linearity against the alternative of a PSTR specification with a logistic ($m = 1$) and a logistic quadratic specification ($m = 2$). Results for the whole sample test indicate a strong rejection of the null hypothesis of linearity especially for the logistic quadratic specification ($m = 2$) with a significance level far beyond the usual 5%. The same observation is found for agricultural-dependent countries, while it does not hold for the group of countries characterized by a lower share of agriculture in GDP. Thus there is strong evidence that hydro-climatic conditions exert a nonlinear impact on economic growth in developing agricultural-dependent countries. In other words, economic growth in those countries is more sensible to climate variations, while impacts of hydro-climatic variations seem to be more easily absorbed in more diversified economies, in part reflecting the typically smaller contribution of the agricultural sector to GDP. Therefore, those findings support strongly the stylized facts of the previous section.

Table 3. *Nonlinearity tests*

Whole sample				
	$H_0 : r = 0$ vs $H_1 : r = 1$		$H_0 : r = 1$ vs $H_1 : r = 2$	
	$m = 1$	$m = 2$	$m = 1$	$m = 2$
LM test	30.93	56.23	16.24	24.03
	($3.04.10^{-4}$)	($8.02.10^{-4}$)	(0.062)	(0.153)
Pseudo *LRT* test	31.41	57.85	16.98	26.80
	($2.51.10^{-4}$)	($5.00.10^{-4}$)	(0.048)	(0.082)
Countries with a higher share of agriculture in total GDP				
	$H_0 : r = 0$ vs $H_1 : r = 1$		$H_0 : r = 1$ vs $H_1 : r = 2$	
	$m = 1$	$m = 2$	$m = 1$	$m = 2$
LM test	20.46	39.58	12.83	16.27
	(0.0152)	(0.0023)	(0.170)	(0.328)
Pseudo *LRT* test	20.88	41.18	5.80	15.76
	(0.0132)	(0.0014)	(0.571)	(0.322)
Countries with a lower share of agriculture in total GDP				
	$H_0 : r = 0$ vs $H_1 : r = 1$		$H_0 : r = 1$ vs $H_1 : r = 2$	
	$m = 1$	$m = 2$	$m = 1$	$m = 2$
LM test	13.91	28.02	–	–
	(0.125)	(0.062)		
Pseudo *LRT* test	14.12	28.89	–	–
	(0.118)	(0.050)		

Notes: the testing procedure works as follows. First, test a linear model ($r = 0$) against a model with one threshold ($r = 1$). If the null hypothesis is rejected, test the single threshold model against a double threshold model ($r = 2$). The procedure is continued until the hypothesis of no additional threshold is not rejected. The corresponding p-values are reported in parentheses.

Table 3 also reports the test of no remaining linearity. The null hypothesis of PSTR with one regime ($r = 1$) against a PSTR with two regime i.e., a double threshold variable model ($r = 2$) cannot be rejected for $m = 1$ and $m = 2$. Thus, the linearity and no remaining linearity tests indicate an optimal number of regime $r^* = 1$ in the PSTR specification.

Finally, in the PSTR model, it is necessary to choose the number of location parameters used in the transition functions, i.e. the value of m. We report, in Table C in the Appendix, the optimal number of transition functions derived from the Lagrange Multiplier (LM) and pseudo-LRT tests of remaining nonlinearity for each value of m. We estimate the PSTR models for each potential specification and report the Residual Sum of Squares (RSS), the AIC and the BIC. Statistic tests and model selection criteria are reported only for developing agricultural-dependent countries for which linearity is strongly rejected. The various indicators reported in Table C indicate a better performance of the quadratic logistic specification. In other words, hydro-climatic conditions lead to a three-regime threshold model, in which the pattern of economic growth is different in the intermediate regime (near normal hydro-climatic conditions) compared to that in the two other extremes regimes (wetter and drier conditions).

Table 4 reports the parameter estimates of the final PSTR model.[14] The effect of the SPEI on growth dynamics appears to be clearly nonlinear. As shown in Table 4, the two estimated cut points are respectively $c_1 = -0.82$ and $c_2 = 0.71$. They represent thresholds which delineate the two following regimes. A first one, the intermediate regime, is characterized by values of the SPEI ranging between -0.83 and 0.71 which correspond according to threshold values defined for the SPEI (see Table 1) to slightly moist and wet conditions including near normal hydro-climatic conditions.[15] The second one prevails when hydro climatic conditions reach either moderate wet (value of the SPEI greater than 0.71), either moderate dry (value of the SPEI greater than -0.83) conditions. The most outstanding point here is that threshold values of hydro-climatic conditions that drive changes in the pattern of growth are reached when moderate moist and wet conditions are exceeded. These thresholds are then lower than those corresponding to extreme weather conditions. The estimated slope parameter (1607.74) indicates a high speed adjustment between the intermediate regime and the extreme ones, meaning that the transition between these different regimes is abrupt. Thus our findings evidence a strong sensitivity of economic growth to small fluctuations in hydro-climatic conditions in developing agricultural-dependent countries: indeed, the pattern of economic growth changes sharply in those countries and well before hydro-climatic conditions become extreme.

14. Considering endogeneity issues, we have replaced explanatory variables that could be potentially endogenous (remittances per worker, overseas development aid per worker, armed conflicts) by their lagged values. Results remain unchanged, putting forward the robustness of our results to endogeneity issues. To save space, we do not report here all the estimations, but complete results are available upon request to the authors.

15. The extreme value of this regime is given by $(c_1 + c_2)/2 = -0.055$.

Table 4. *Estimation of the PSTR model ($m = 2$; $r^* = 1$)*

Variables	ξ_{0l} (1)	$\xi_{1l} \times g(.)$ (2)
η_{it-1}	-0.0902^{***}	-0.0046
	(0.0154)	(0.0093)
G	0.0432^{***}	0.0925^{**}
	(0.0148)	(0.0448)
$Infl$	-0.0065	-0.1958^{***}
	(0.0163)	(0.0489)
$Trade/GDP$	0.0712^{***}	0.0135
	(0.0152)	(0.0193)
Δk	0.2266^{***}	0.0134
	(0.0658)	(0.1230)
$M2/GDP$	-0.0141	-0.0078
	(0.0205)	(0.0110)
ΔODA	0.0028	0.0481
	(0.0043)	(0.0128)
$\Delta Remit$	0.0056^{*}	0.0481^{***}
	(0.0033)	(0.0128)
Armed conflicts	-0.0056	-0.0119
	(0.0042)	(0.0104)
Slope parameter $\hat{\gamma}$	1320.85	
Cut points $\hat{c}$	$[-0.82; 0.71]$	
N	516	

*Notes: countries with a higher share of agriculture in total GDP. The SPEI with 6 month time scale is considered as the transition variable. Coefficients θ_0 (θ_1) and β_0 (β_0) reported in columns (1) and (2) stand for near normal hydro-climatic and abnormal hydro-climatic regimes respectively. Standard errors are in parentheses. * (resp. **, ***) stands for a significant coefficient at the 10% (resp. 5%, 1%) statistical level.*

Effects of explanatory variables on economic growth according to hydro-climatic conditions are reported in columns (1) and (2). Column 1 reports estimated coefficients in the intermediate regime (ξ_{0l}), corresponding to near normal hydro-climatic conditions while column (2) shows the estimated coefficients of deviation from the intermediate regime to the other ones, i.e., $\xi_{1l} \times g(.)$, when dry and wet conditions reach a moderate level corresponding to abnormal hydro-climatic conditions.

The regression corresponding to near normal hydro-climatic conditions (column 1) shows results consistent with the previous empirical literature. The proxies of capital investment, trade openness, public spending and remittances have positive and significant coefficients, denoting their beneficial impact on economic growth in the short-run. On the other hand, other variables (inflation, financial development, overseas development aid and the civil liberties index) carry a nonsignificant coefficient. Finally, under near normal hydro-climatic conditions, economic growth tends to return to its steady state as the coefficient associated to the error correction term is significant with the expected negative sign.

Column 2 reports the regression results that correspond to abnormal hydro-climatic conditions. An interesting pattern emerges as the impact of explanatory variables differs substantially from that observed in near normal conditions. Firstly, when abnormal climate conditions prevail, the coefficient of the error correction term is no more significant. Thus, when hydro-climatic conditions are near normal, there is a convergence process of economic growth towards its steady state. However, this adjustment process is no more effective under drier or wetter conditions. This first result shows that small fluctuations in hydro-climatic conditions can make economic growth easily departing from its long-run trajectory.

Secondly, regarding structural factors, the positive impact exerted by the investment ratio as well as the trade openness ratio tends to disappear when abnormal hydro-climatic conditions prevail, their respective coefficient being no more significant. Thus, if economic growth in developing countries is driven, in the short-run, by investment and trade, it is no longer the case under abnormal hydro-climatic events. Indeed, such events can typically result in reductions in agricultural output, related productive activity, and employment. In turn, this is likely to lead to lower agricultural export earnings (Jones and Olken, 2010) and other losses associated with a decline in rural income, reduced consumption and investment, and destocking. Furthermore, abnormal hydro-climatic conditions may have a direct adverse impact not only on irrigated agriculture but also on nonagricultural production, including hydroelectric power generation (Barrios *et al.*, 2010) and certain industrial processes, as well as human water supply.

Thirdly, abnormal hydro-climatic conditions have additional potential multiplier effects on economic policies (fiscal and stabilization policies). Indeed, public spending exerts a stronger role when countries face abnormal hydro-climatic conditions, while the negative effect of inflation on economic growth becomes significant. This result suggests a higher response of economic growth to economic policies in abnormal hydro-climatic conditions. Inflationary pressures might exert a stronger impact due to declines in supply of goods and in aggregate productivity (IMF, 2008) but also by monetary expansion in order to finance the increase in public spending. Indeed, the higher coefficient of public spending tends to support that budget balances are less resilient to weather events; a result that has been confirmed on a larger sample of developing countries (Lis and Nickel, 2009). This result also suggests that governments are more prone to use ex-post financing rather than ex-ante insurance. Indeed, there are barriers in developing countries to the introduction of insurance mechanisms such as paucity of markets, political resistance and inadequate institutional framework. Thus governments may be confronted to the financing of public response to hydro-climatic variations.

We also evidence some interesting results on the role played by alternative source of revenue under abnormal hydro-climatic conditions. We find no evidence that the impact of overseas development aid on economic growth increases when hydro-climatic conditions become drier or wetter. This result is consistent with those of the literature on the response of international financial flows to natural disasters. For example, David (2011) shows that the response of aid flows to natural disaster shocks in general tends to be no statistically significant. Moreover, when significant, the aid surge seems to cover only a small fraction of estimated direct damages caused by the disasters (Becerra *et al.*, 2012). This result is also consistent with the evidence that governments seem to meet a larger share of the costs related with a lower income, rather than relying on international assistance. Moreover, we find that the level of financial development doesn't impact economic growth[16] while the effect of remittances becomes more significant, under abnormal hydro-climatic conditions. One possible interpretation of this finding is the role of domestic credit markets in shaping the response of remittance flows to country-specific

16. This finding is robust to the choice of the proxy retained for financial development. The use of the private credit to GDP ratio leads to the same result. Results are available upon request from the authors.

income shocks. For example, Arezki and Brückner (2012) evidence on a sample of 41 Sub-Saharan African countries that at low levels of credit to GDP the effect of rainfall on remittances is significantly positive. This result is also in line with those of Giuliano and Ruiz-Arranz (2009) who find that remittances play a key role in supporting growth by acting as a substitute for a lack of financial development especially when economies face negative shocks. In this case, remittances provide an alternative way to finance investment and help overcome liquidity constraints in developing countries.

Finally, the impact of civil liberties on economic growth remains no significant, suggesting that climate variations don't exacerbate conflict or political instability that could hamper economic growth.[17]

5. Robustness check

To analyze the nonlinear impact of hydro-climatic on economic growth, we have used the 6-month SPEI which is usually considered as the most appropriate index when addressing events occurring at the agricultural season level (Törnros and Menzel, 2014; Vicente-Serrano *et al.*, 2010). But, as drought is a multiscale phenomenon, the time scale over which water deficits accumulate becomes extremely important. As a result, climatologists usually separate agricultural droughts happening when crops become affected from hydrological droughts occurring at longer time scales when low water supply becomes evident, especially in streams, reservoirs, and groundwater levels, usually after many months of meteorological droughts. It is then important to control for time scales over which water deficits or surplus accumulate since the response of economic growth to hydro-climatic conditions can also vary as a function of time.

We then use the 12 month-SPEI reflecting droughts and wet conditions at a higher time scale to test the robustness of our results. The 12 month-SPEI has been shown to be highly correlated to the Palmer Drought Severity Index (PDSI). According to Wang *et al.*

17. This finding is robust to the choice of the proxy retained for political stability. The use of the civil liberties index from the Freedom House database leads to the same result. Results are available upon request from the authors.

(2014), when the time scale is greater than 10 months, the correlation coefficient between the SPEI and the PDSI reaches a value of between 0.7 and 0.9.[18] Then, using such an indicator allows us taking into account the dynamics of hydrological conditions - such as soil moisture, streamflow, groundwater and reservoir levels - and identifying shifts in countries' growth according to these hydrological events. Accounting for such hydrological events is particularly important since human activities heavily rely on available water in hydrologic storage systems. These are often used for competing purposes and conflicts between water users might rise in case of drought.

We then re-estimate our PSTR growth model using the SPEI calculated with a 12 month time scale. Table 5 shows estimates for countries with a higher share of agriculture in total GDP with the SPEI calculated over 6 month and 12 month time scales.[19]

Considering the SPEI with a 12 month timescale as a transition variable instead of a 6 month time scale makes any difference to the result. In particular, the estimated thresholds triggering the regime switch, while being higher (respectively -1.15 and 0.91), correspond according to threshold values defined for the SPEI (see table 1) to moderate moist and wet conditions. These thresholds are then again lower than those corresponding to extreme weather conditions. This result confirms the high sensitivity of economic growth of developing agricultural-dependent countries to small fluctuations in hydrological conditions. It also reveals the lack of ex-ante adaptive capacities in those countries to drier or wetter conditions.

The regression results corresponding to near normal hydrological conditions (table 5, column 3) lead to similar findings to those prevailing under near normal hydro-climatic conditions (table 5, column 1). Moreover, when developing agriculture-dependent countries face wetter and drier conditions, results reported in column 4 show that economic growth is no more driven by investment and trade, and tends to deviate persistently from

18. We use the SPEI calculated over 12 months rather than the PDSI since the latter has several deficiencies including the strong influence of calibration period, its limited utility in areas other than that used for calibration, problems in spatial comparability, and subjectivity in relating drought conditions to the values of the index (Wu *et al.*, 2005).

19. We show the results obtained from the benchmark indicator among those from robustness tests for the sake of readability.

Table 5. *Estimation of the PSTR model ($m = 2$; $r^* = 1$) using SPEI with multiple timescales*

Variables	SPEI - 6 months		SPEI - 12 months	
	ξ_{0l}	$\xi_{1l} \times g(.)$	ξ_{0l}	$\xi_{1l} \times g(.)$
	(1)	(2)	(3)	(4)
η_{it-1}	-0.0902^{***}	-0.0046	-0.0906^{***}	0.0143
	(0.0154)	(0.0093)	(0.0149)	(0.0110)
G	0.0432^{***}	0.0925^{**}	0.0391^{***}	0.1587^{**}
	(0.0148)	(0.0448)	(0.0144)	(0.0580)
$Infl$	-0.0065	-0.1958^{***}	-0.0051	-0.3223^{***}
	(0.0163)	(0.0489)	(0.0161)	(0.0620)
$Trade/GDP$	0.0712^{***}	0.0135	0.0712^{***}	0.0010
	(0.0152)	(0.0193)	(0.0145)	(0.0233)
Δk	0.2266^{***}	0.0134	0.2408^{***}	-0.1080
	(0.0658)	(0.1230)	(0.0634)	(0.1563)
$M2/GDP$	-0.0141	-0.0078	-0.0071	-0.0213
	(0.0205)	(0.0110)	(0.0198)	(0.0330)
ΔODA	0.0028	0.0481	0.0002	0.0271
	(0.0043)	(0.0128)	(0.0040)	(0.0181
$\Delta Remit$	0.0056^{*}	0.0481^{***}	0.0071^{**}	0.0306^{*}
	(0.0033)	(0.0128)	(0.0032)	(0.0181
Armed conflicts	-0.0056	-0.0119	-0.0048	-0.0063
	(0.0042)	(0.0104)	(0.0040)	(0.0132)
Slope parameter $\hat{\gamma}$	1320.85		79.66	
Cut points $\hat{c}$	$[-0.82; 0.71]$		$[-1.15; 0.91]$	
N	516			

*Notes: standard errors are in parentheses. * (resp. **, ***) stands for a significant coefficient at the 10% (resp. 5%, 1%) statistical level.*

its steady state. However the positive coefficient of public spending and remittances increases in the regime of abnormal hydrological conditions, highlighting the role played by those additional revenue as coping mechanisms in order to overcome the adverse effect exerted by drier or wetter conditions.

Finally, it is interesting to see that the slope parameter of the transition function is smoother when the 12-month SPEI is used as transition variable.[20] The switch from the growth regime prevailing under near normal hydrological conditions to the ones prevailing under wetter and drier conditions is then smoother and more gradual than the

20. See Figures A.2 and A.3 in the Appendix for graphical representations of the transition functions with the 6 and the 12-month SPEI.

one found with the 6 month-SPEI. One explanation for this might be that the frequency of abnormal hydrological conditions decreases with time scale, while their duration increases. Then it can be reasonably expected that the response of economic growth to abnormal hydrological events will be more gradual over longer time scale.

6. Conclusion

More frequent and severe extreme weather events related to climate change will be certainly a major challenge that developing countries will have in the future to deal with. In order to assess the sensibility of the economies of those countries to changes in climatic conditions, we examine the relationship between hydro-climatic conditions, measured by the Standardized Precipitation and Evapotranspiration Index (SPEI), and economic growth on a sample 37 developing countries spanning the period 1980-2011.

In particular we seek to estimate threshold values reached by the SPEI which induce shifts in growth dynamics of those countries. Accordingly, we rely on a Panel Smooth Transition Regression (PSTR) specification which allows economic growth to switch from one to another regime, depending on thresholds reached by the SPEI that can be identified as particular hydro-climatic events.

Our first finding is that across our sample of developing countries, agricultural-dependent countries (with a share of agriculture in GDP of 18.6 and above) are more vulnerable to fluctuations in weather by experiencing a notably reversal in their growth pattern when abnormal hydro-climatic conditions prevail. Secondly, small fluctuations in weather are associated with adverse outcomes for growth in those countries. Indeed, the nonlinear response of economic growth to hydro-climatic conditions is reached for values that are well below the threshold corresponding to extreme weather events, suggesting a high sensitivity of economic growth in those countries to small fluctuations in hydro-climatic conditions. Thirdly, while our results evidence a lack of adaptive capacities to wetter and drier conditions, they highlight the role played by public spending and remittances as coping mechanisms in order to overcome the adverse effect exerted by abnormal hydrological conditions. Finally, those results are robust to the use of the SPEI on a longer time scale (12 months).

Our findings have some policy implications. In particular, economists and policy analysts studying economic growth in developing countries facing hydro-climatic variations should also pay closer attention to continuous weather fluctuations of lesser amplitude than extreme natural events as an explanatory and conditioning factor of economic growth. Indeed, if extreme natural events can result in economic disasters with much larger welfare costs, continuous weather fluctuations of lesser amplitude have also harmful consequences for economic growth particularly in developing agricultural-dependent countries. Thus, while attention is usually focused on disaster risk management, it might be also important to consider how capacity to adapt to weather fluctuations can be enhanced in those countries.

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Appendix

Table A.1. *List of countries by sub-samples*

Countries with a higher share of agriculture in total GDP	Countries with a lower share of agriculture in total GDP
Bangladesh	Bolivia
Benin	Botswana
Cameroon	Costa Rica
Côte d'Ivoire	Dominican Rep.
Ghana	Ecuador
Guatemala	Egypt
India	El Salvador
Indonesia	Gabon
Kenya	Honduras
Mali	Jordan
Morocco	Mexico
Mozambique	Panama
Niger	Peru
Pakistan	Philippines
Paraguay	Sri Lanka
Rwanda	Swaziland
Senegal	Thailand
Sudan	Tunisia
Togo	
$N = 19$	$N = 18$

Figure A.1. *SPEI 6 month time scales by countries*

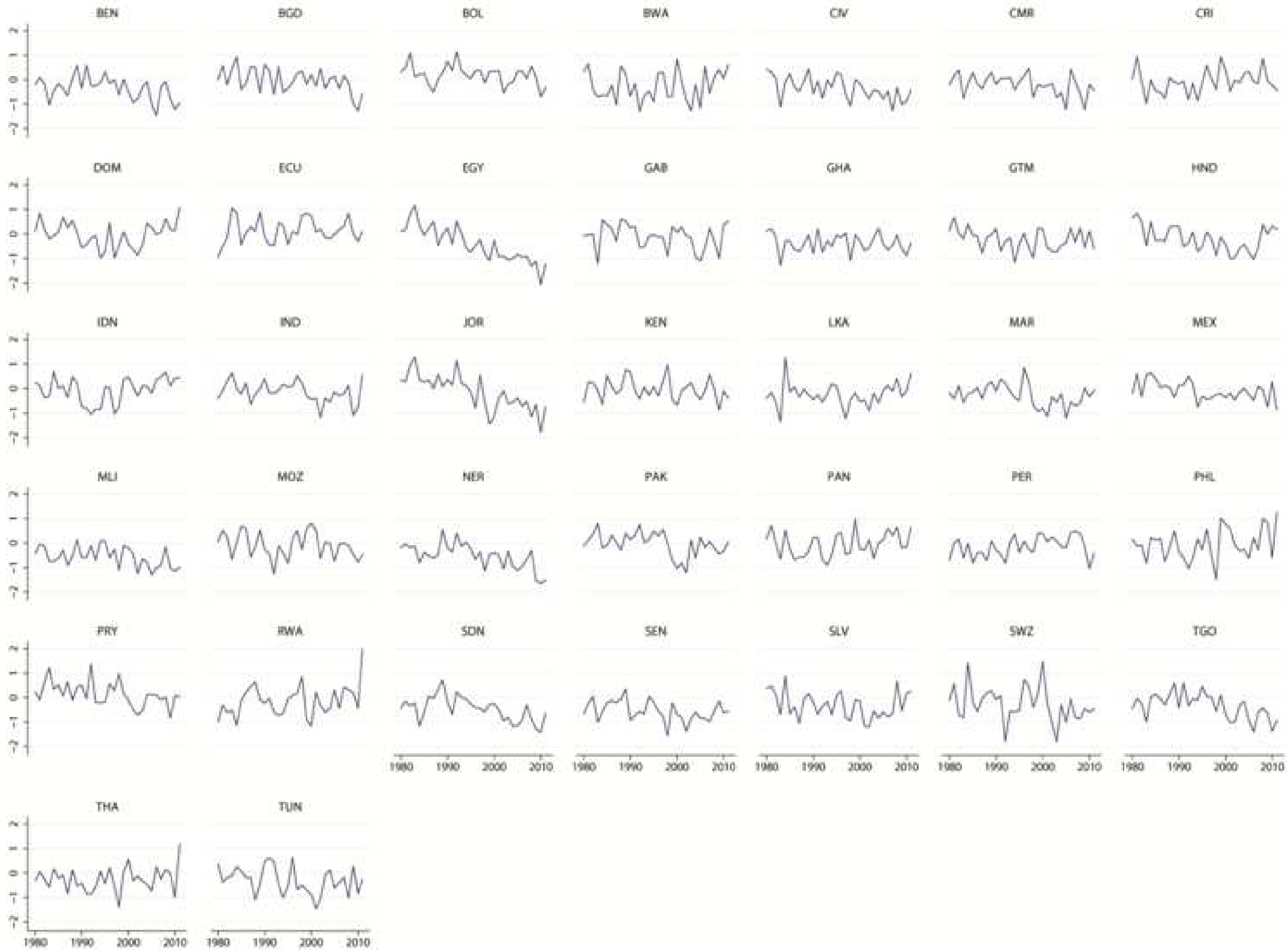


Table A.2. *Descriptive statistics*

Whole sample					
Variables	Mean	Median	S.D.	Min.	Max.
Variables	Mean	Median	S.D.	Min.	Max.
SPEI-6 month	-0.193	-0.174	0.539	-2.057	1.978
SPEI-12 month	-0.233	-0.228	0.626	-2.172	1.906
$y(log)$	7.039	7.032	0.935	4.943	9.024
$\Delta y(log)$	0.014	0.019	0.046	-0.640	0.313
h	1.958	1.936	0.471	1.086	3.161
η_{it-1}	1.642	1.596	0.560	0.364	3.158
$\Delta G(log)$	0.034	0.033	0.099	-0.843	0.782
$infl$	0.123	0.073	0.272	-0.124	4.774
$trade/GDP$	0.674	0.601	0.342	0.063	2.028
$k(log)$	6.431	6.410	1.054	3.565	8.783
$\Delta k(log)$	0.0169	0.015	0.032	-0.078	0.236
$M2/GDP$	0.381	0.304	0.237	0.065	1.399
$\Delta ODA(log)$	-0.018	-0.025	0.446	-3.697	3.535
$\Delta Remit(log)$	0.080	0.061	0.412	-1.975	6.101
Agriculture in % of GDP	20.724	18.564	10.912	4.688	43.07
Countries with a higher share of agriculture in total GDP					
Variables	Mean	Median	S.D.	Min.	Max.
SPEI-6 month	-0.241	-0.203	0.511	-1.836	1.978
SPEI-12 month	-0.290	-0.276	0.587	-1.950	1.661
$y(log)$	6.385	6.274	0.646	4.943	7.797
$\Delta y(log)$	0.011	0.016	0.051	-0.641	0.313
h	1.638	1.635	0.331	1.086	2.651
η_{it-1}	1.380	1.280	0.451	0.364	2.355
$\Delta G(log)$	0.035	0.036	0.120	-0.843	0.782
$infl$	0.097	0.070	0.121	-0.081	0.845
$trade/GDP$	0.528	0.512	0.225	0.063	1.231
$k(log)$	8.059	8.205	0.765	5.868	9.509
$\Delta k(log)$	0.012	0.010	0.036	-0.078	0.236
$M2/GDP$	0.311	0.268	0.158	0.065	1.127
$\Delta ODA(log)$	-0.014	-0.021	0.360	-2.355	2.632
$\Delta Remit(log)$	0.070	0.062	0.456	-1.976	6.102
Agriculture in % of GDP	28.941	26.102	8.431	17.042	43.07

Countries with a lower share of agriculture in total GDP					
Variables	Mean	Median	S.D.	Min.	Max.
SPEI-6 month	-0.143	-0.132	0.563	-2.057	1.483
SPEI-12 month	-0.198	-0.193	0.564	-2.172	1.906
$y(log)$	7.731	7.740	0.654	6.298	9.025
$\Delta y(log)$	0.018	0.022	0.041	-0.215	0.157
h	2.285	2.301	0.344	1.425	3.161
η_{it-1}	1.966	1.860	0.514	0.928	3.158
$\Delta G(log)$	0.034	0.033	0.072	-0.312	0.633
$infl$	0.148	0.076	0.364	-0.124	4.775
$trade/GDP$	0.827	0.770	0.376	0.192	2.028
$k(log)$	9.446	9.627	0.824	6.981	11.08
$\Delta k(log)$	0.022	0.020	0.028	-0.056	0.123
$M2/GDP$	0.455	0.355	0.280	0.102	1.399
$\Delta ODA(log)$	-0.023	-0.031	0.526	-3.698	3.536
$\Delta Remit(log)$	0.093	0.062	0.359	-1.175	3.908
Agriculture in % of GDP	12.051	12.805	4.849	4.688	20.95

Table A.3. *Two-sample t test with equal variances*

	Group 0	Group 1
Mean	-0.143	-0.241
Standard Errors	0.036	0.046
N	18	19
t	1.6471	
χ^2 (1)	1.246	
$Prob > \chi^2$	0.264	
Two-tailed p-value	0.108	

Notes: we assume equal variances between the groups since the Bartlett's chi squared statistic test indicates no violation of the assumption of equal variances. Group 0 (1) includes countries with a lower (higher) share of agriculture in total GDP.

Table A.4. *Feasible Generalized Least Squares regression results*

	Countries with a lower share of agriculture in total GDP	Countries with a higher share of agriculture in total GDP
SPEI dummy	-0.0023	-0.0110^{***}
	(0.0015)	(0.0013)
Constant	0.0201^{***}	0.0153^{***}
	(0.0024)	(0.0014)
χ^2 (1)	2.22	70.62
p-value	0.1358	0.000
N	558	589

*Notes: standard errors are in parentheses. *** indicates significance at the 1% level.*

Table B.1. *Pesaran CD test*

	CD test	ρ	$\lvert\rho\rvert$
y	66.81***	0.458	0.704
k	39.87***	0.273	0.730
h	139.67***	0.957	0.957

*Notes: under the null hypothesis, the cross-sectional dependence test is no dependence between cross-section units. *** indicates significance at the 1% level.*

Table B.2. *Pesaran (2007) Panel Unit Root test (CIPS)*

		Without trend		With trend	
y	Lags	Level	First difference	Level	First difference
	0	1.123	−12.754***	−1.139	−11.897***
	1	1.142	−9.406***	−1.293*	−7.877***
	2	1.706	−5.555***	0.049	−3.169***
	3	2.110	−3.450***	0.878	−0.295
k	Lags	Level	First difference	Level	First difference
	0	5.318	−4.378***	4.929	−1.715**
	1	2.769	−3.966***	−1.915**	−2.036**
	2	2.209	−1.974**	0.976	−1.811**
	3	1.227	−2.148**	−0.264	−0.761
h	Lags	Level	First difference	Level	First difference
	0	2.758	−15.503***	5.204	−16.225***
	1	3.316	−6.414***	5.471	−7.213***
	2	3.100	−2.829***	4.894	−4.654***
	3	2.605	−3.687***	4.263	−9.712***

*Notes: *** indicates significance at the 1% level and ** at the 5% level.*

Table B.3. *Panel cointegration test*

	τ_N		ϕ_N	
Model	Value	p-value	Value	p-value
No break	−5.344	0.000	−9.149	0.000
Level break	−2.315	0.010	−4.055	0.000
Regime shift	−0.855	0.196	−1.810	0.035

Notes: the number of common factors is determined by using the information criterion proposed by Bai and Ng (2004) and the maximum number is set to 5.

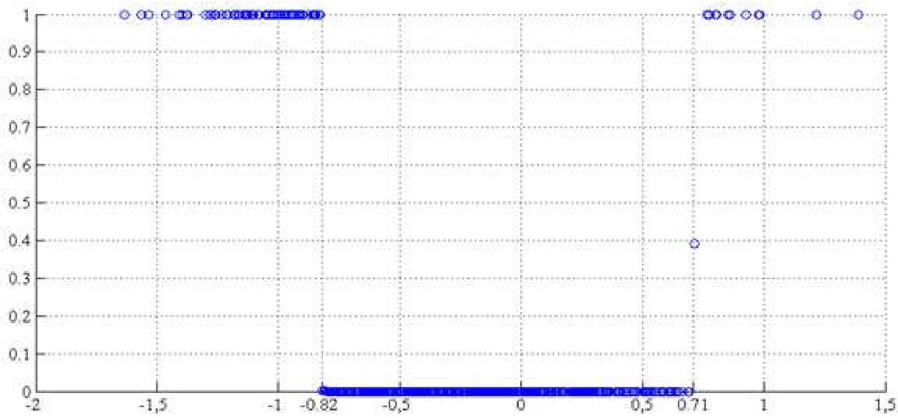
Table C. *Determination of the Number of Location Parameters*

Countries with a higher share of agriculture in total GDP

Location Parameter	$m = 1$	$m = 2$
Optimal Number of Threshold (r^*)	1	1
RSS	0.548	0.532
Centered R^2	0.210	0.234
AIC	−6.768	−6.794
BIC	−6.603	−6.622
N	516	

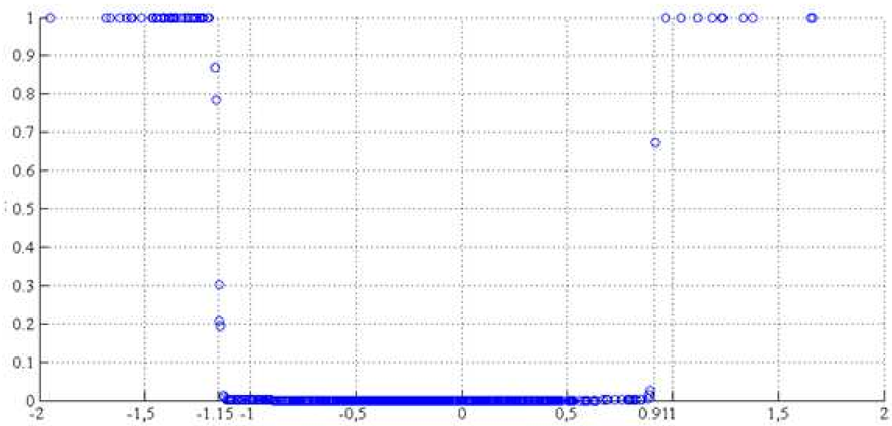
Notes: for each specification, the optimal number of locations parameters used in the transition function can be determined as follows. For each value of m, the corresponding optimal number of thresholds, denoted r^*, is determined according to a sequential procedure based on the LM statistics of the hypothesis of non remaining nonlinearity. Thus, for each couple $(m; r^*)$, the value of the Residual Sum of Squares (RSS) of the model is reported. The total number of parameters is determined by the formula $K\,(r^* + 1) + r^*\,(m + 1)$ where K denotes the number of explanatory variables.

Figure A.2. *Transition function(6-Month SPEI)*



Notes: the two estimated cut points are respectively $c_1 = -0.82$ *and* $c_2 = 0.71$*; The estimated slope parameter is* $\gamma = 1320.85$*.*

Figure A.3. *Transition function(12-Month SPEI)*



Notes: the two estimated cut points are respectively $c_1 = -1.15$ *and* $c_2 = 0.91$*; The estimated slope parameter is* $\gamma = 79.66$*.*