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Reexamining the growth effects of ENSO: the role of local weather conditions[1]

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Abstract

This paper examines the growth effects of ENSO events through their interactions with local weather conditions using the Standardized Precipitation and Evapotranspiration Index (SPEI) from 1975 to 2014 and over a sample of 74 countries. The inclusion of SPEI in panel estimation makes it possible to control for time-varying country-specific effects of ENSO events, therefore outlining their heterogeneous effects on growth and eliminating a potential source of omitted-variable bias. By better identifying the persistence of ENSO effects on local weather conditions, we evidence that ENSO events generate heterogeneous and local effects depending not only on countries' climate regime but also on their weather patterns. Our results suggest that examining the growth effects of ENSO events should thus explicitly account for their interaction with weather patterns to capture more precisely the heterogeneity across countries.

Keywords: Economic growth, ENSO events, Weather conditions

JEL codes: C33 O13 Q54

[1] A preliminary version of this paper has already been presented at the Sustainability and Development Conference, University of Michigan, Ann Arbor, MI, 2018 November 9-11, at the GDRI-IDE Symposium, Clermont-Ferrand, France, 2018 November 15-16, at the CREATE seminar of the Laval University (Canada) in January 2019. This updated version has been presented in June 2019 at the 2019 AFSE Annual Meeting in Orléans, France and at the International Association for Applied Econometrics in Nicosia, Cyprus.

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1. Introduction

The pressure for new research on climate change issues has never looked stronger. Recent research by Hsiang and Kopp (2018) put forward the central role that economists might play in the quest for tackling climate warming and helping climate science advance. In this context, a recent climate-macroeconomy literature focuses on the challenges that global climate cycles are posing for economic activities. Such cycles are characterized by simultaneous physical variations in climate over distant parts of the globe and are commonly referred to as teleconnections in the meteorological literature. Among these teleconnection patterns, El Niño Southern Oscillation (ENSO) is the most important coupled ocean-atmosphere phenomena. The warm phase of ENSO, called El Niño, is associated with a band of warm ocean water that develops in the central and east-central equatorial Pacific while the cool phase of ENSO, known as La Niña, is characterized by below-average Sea Surface Temperatures (SST) in the eastern Pacific. The ENSO cycle, including both El Niño and La Niña, causes global changes in temperature and rainfall on average every two to seven years.
Despite ENSO events have been identified as having profound impacts on almost every aspect of human life, the literature focusing on their economic impacts is still developing. Some studies examine whether ENSO influences economies around the world,[1] with the evidence generally suggesting that it does.[2] Estimating several vector autoregressive (VAR) models, Brunner (2002) found evidence of ENSO effects on growth and inflation in the G7 countries. Since this seminal paper, only two studies have explored the relationship between ENSO and economic performances from a multi-country perspective (Cashin et al., 2017; Smith and Ubilava, 2017). Cashin et al. (2017) estimate a Global VAR covering 21 countries/regions over the period 1979Q2 to 2013Q1 and show that El Niño events have a direct effect on economic activity for those countries that are at the epicenter of an El Niño event (Australia, Chile, Indonesia, New Zealand, and Peru). The study also highlights important indirect effects on economic growth, inflation and price commodities channeled through trade for countries that are geographically more distant from the phenomenon. Smith and Ubilava (2017) analyze the effect of this atmospheric phenomenon in 69 developing countries on growth rate and agricultural value added using both linear and threshold panel regressions. They show that El Niño events have negative impacts on economic growth while the effect of La Niña events are much less apparent. Their results also indicate that important regional heterogeneities exist in the impact of ENSO shocks with stronger evidence of El Niño growth effect in tropical countries.
Yet, this literature has identified several transmission channels through which ENSO can influence economic growth, such as real prices of primary commodities (Brunner, 2002), trade (Cashin et al.,

[1]Most research has been conducted using data from a single country. See for example Berry and Okulicz-Kozaryn (2008) who analyze the relationships between ENSO, U.S. inflation and economic growth over a long time span and studies focusing on ENSO effects on domestic agricultural sector (Dilley, 1997; Naylor et al., 2001).

[2]By contrast, Laosuthi and Selover (2007) find weak evidence that ENSO has an important effect on the business cycles of most of the countries that they study.

2017), or agriculture share in total output (Smith and Ubilava, 2017). However, while the climate literature has put forward that ENSO events have large scale and regional impacts on weather patterns and seasonal climate averages (Poveda and Mesa, 1997; Vicente-Serrano et al., 2011), no study has so far considered the ENSO impact on economic performances through its effects on countries' weather conditions. There are, however, a number of potential reasons why weather variables should be considered in order to identify the true causal relationship between ENSO and economic performances. First, ENSO influences climate variability at the global scale with large differences in spatial patterns while countries' weather conditions have important effects on economic performances (Dell et al., 2014). It is then likely that the most vulnerable countries to climate hazards will also be more affected by an ENSO event. Second, ENSO signals may have too localized impacts that cannot be reflected in economic growth without explicitly taking into account their impacts on countries' weather conditions. A third issue is that each ENSO event is different and occurs in conjunction with other climatic events (Davey et al., 2014). The corollary is that distinct ENSO episodes recording identical SST anomalies may be different in intensity at the regional or country level. Such temporal asymmetries may then mask macroeconomic implications of ENSO shocks (Smith and Ubilava, 2017).

In the light of these developments, we assess in this paper the effects of ENSO on economic growth taking into account its heterogeneous and delayed effects on countries' climatic conditions. Moreover, given that ENSO shocks are only slowly absorbed by the economy, we supplement our analysis by considering their role in affecting Total Factor Productivity (TFP).

For our investigation, we use the usual ENSO regime categorization that defines El Niño and La Niña regimes by respectively positive and negative values of SST anomalies together with a finer classification that differentiates three states of ENSO according the duration of SST anomalies (El Niño, La Niña, neutral). To assess weather conditions, we use the Standardized Precipitation and Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2010). This indicator incorporates both precipitation and temperatures data of current weather conditions, plus their cumulative patterns of previous months. This multi-scalar feature allows us to consider the intensification process of climate effects addressed by Dell et al. (2014) and therefore the economic impacts of ENSO through the present and past weather conditions of each country.

As the weather response, and thus economic growth, to ENSO events typically depends on countries' climatic zones, we estimate our different empirical models by allowing for a differential effect of ENSO shocks according to the type of climate regime that prevails in each country of our sample. To deal with the issue of spatial correlation inherent to climatic phenomena (Auffhammer et al., 2013), we use panel-corrected standard error (PCSE) estimates for panel models (Beck and Katz, 1995). As an alternative to mitigate cross-sectional correlation problems, we also use the Driscoll-Kraay estimator (DK), developed by Driscoll and Kraay (1998).

Using an unbalanced panel of annual data on 74 countries spanning the 1975-2014 period, we find that ENSO events have a differentiated impact on economic activity depending on the type of climate. We also highlight important delayed effects on economic growth, through local weather conditions. In particular, El Niño phases have a persistent negative effect through drier conditions in already dry areas located in the tropical sphere. In contrast, arid and temperate countries with already wet conditions are negatively affected by La Niña events through increased pluvial periods. These findings are highly robust to the use of an alternative categorization of ENSO regimes and across estimation methodologies.

Our paper contributes to the existing literature in several respects. First, existing studies assess the relationship between economic growth and ENSO events, by focusing on the global effect of ENSO events as common shocks, paying less attention to their specific effects channeled through modifications in countries' weather conditions. By contrast, we systematically analyze the role of weather patterns in influencing the transmission of global climate cycles to economic growth. This allows us to identify the growth effect of an ENSO event given the great cross-country heterogeneity in weather patterns and to evidence a significant effect exerted by La Niña (at least in temperate/arid areas), contrary to what is usually found in the climate-economy literature. Second, in addition to the usual two-way ENSO regime categorization, we consider a finer classification that allows us to assess the growth effect differential of El Niño and La Niña relative to neutral episodes. The results suggest that not only humid/tropical countries but also arid/temperate countries are negatively, albeit differently, impacted by a El Niño event. Third, in addition to output growth, our analysis focuses on TFP growth, that helps to shed light on the long-lasting effects of ENSO events. Our findings evidence that the sensitivity of economic growth to global climate shocks through local weather conditions is associated with a similar sensitivity in TFP growth, suggesting long-lasting adverse effect of ENSO on economic growth.

The rest of the paper is organized as follows. To set the stage, section 2 begins by describing the data set and presenting some stylized facts. Section 3 lays out the empirical methodology and benchmark results. Section 4 conducts a sensitivity analysis of our central results by using another measure of ENSO events. Finally, section 5 concludes.

2. Data and summary statistics

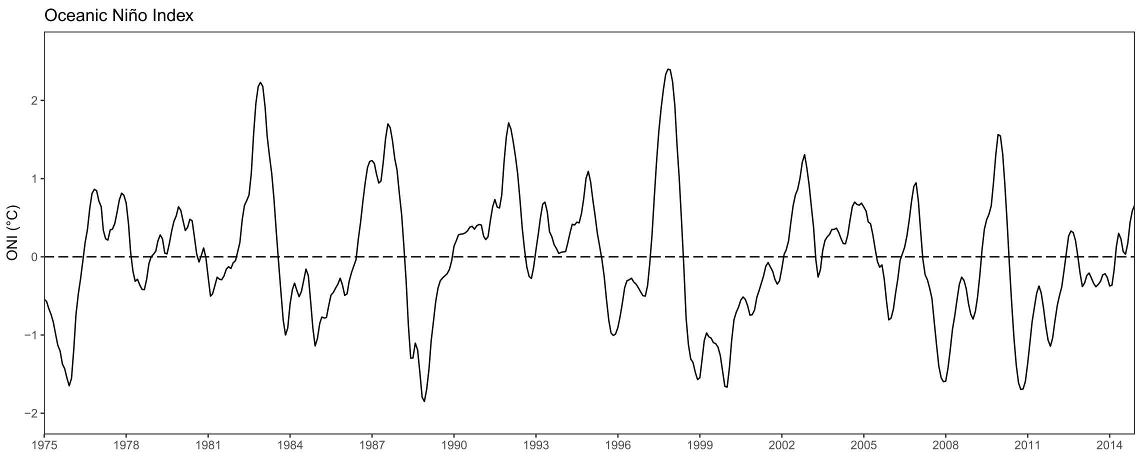
Our sample comprises the 74 countries listed in Appendix Table A1, and is an unbalanced panel with data spanning from 1975[3] to 2014. The sample includes low-income, lower-middle-income and upper-middle-income economies as classified by the World Bank.

[3]The year 1975 is used as the starting date since the ENSO properties and dynamics have changed over time (Aiken et al., 2013) with lower frequency and stronger amplitude since the late 1970s (An and Wang, 2000).

2.1. ENSO phases and weather conditions

One of our main variables of interest, the measure of ENSO events, is taken from the National Oceanic and Atmospheric Administration (NOAA) of the United States dataset, which provides monthly data on the Oceanic Niño Index (ONI) from 1950 to 2018.[4] The underlying methodology used to derive these series consists essentially of three steps. The average SST is calculated for each month in the Niño 3.4 region, spanning from 170°W - 120°W longitude and 5°N - 5°S latitude, and then averaged with values from the previous and following months. This running 3-month average is compared to a 30-year average of the three most recent complete decades, updated in each new decade. The observed difference from the average SST in that region corresponds to the ONI value for that 3-month season. Following Hsiang et al. (2011) and Sarachik and Cane (2010), ENSO phases are identified by averaging ONI values between the month of May of a given year and the month of February of the following year, i.e. between the months in which the El Niño and La Niña events are typically most active. Positive (negative) values of the ONI reflects warming (cooling) SSTs prevailing during El Niño (La Niña) phases (Figure 1).[5]

Figure 1: *Evolution of the Oceanic Niño Index (1975-2014)*



The other variable of interest, the measure of weather conditions, is taken from the Global SPEI database[6] which provides monthly values of the Standardised Precipitation-Evapotranspiration Index (SPEI) at the global scale, with a 0.5 degrees spatial resolution and for the period between

[4]We use this index, instead of other ones because it has the stronger correlation with the surface atmospheric pressure-based Southern Oscillation index (SOI) (Bamston et al., 1997), which explains its widespread use in the literature.

[5]ONI series are taken from the R 'rsoi' package : `https://github.com/boshek/rsoi`

[6]We use the version 2.5 of the Global SPEI database : `http://spei.csic.es/database.html`

January 1901 and December 2015. The main advantage of this index is that it combines the sensitivity of the Palmer Drought Severity Index (PDSI) to changes in evaporation demand (caused by temperature fluctuations and trends) with the multi-scalar nature of the Standardized Precipitation Index (SPI). By capturing the joint impact of precipitations and temperatures variability and extremes on water demand, the SPEI therefore is particularly suited to detecting dry and wet conditions in the context of global warming (Beguería et al., 2014).

Another advantage of the SPEI is that it can be calculated at various time scales (between 1 and 48 months) over which water deficits / surplus accumulate reflecting times of response to weather conditions of multiple natural and economic systems.[7] This multi-scalar feature allows us to address the intensification process of climate effects by taking into account the time structure of weather shocks in the economic response to ENSO signals (Dell et al., 2014). As shown by Penalba and Rivera (2016), El Niño and La Niña phases exert differing impacts depending on the hydrological cycle. Thus, the economic impact of an ENSO shock could be reinforced by the climatic conditions prevailing in previous months. We use as a benchmark indicator the 6-month SPEI given its ability to capture seasonal to medium-term trends in weather conditions that mainly affect agricultural systems.

A key challenge of using weather indicators is to aggregate gridded weather observations in order to obtain indexes consistent with economic data and which must adequately reflect the climate variability experienced by each country. The procedure consisting in averaging weather data at the country scale could make SPEI losing their relevance for two main reasons. First, as changes in temperature, precipitation, and other climate parameters usually vary within countries, resulting in differential exposure and uneven consequences, ignoring this scale-dependency issue can be problematic in terms of understanding and addressing weather conditions, particularly if conclusions are derived from coarse scale assessments. Indeed, in this case, extreme conditions at the local level are likely to be obscured, and a biased assessment of weather conditions at the country level will result. Secondly, this approach could fail to identify climate shocks affecting human activities especially if large areas where little economic activity and sparse populations dominate, such as deserts or rain forests (Dell et al., 2014). To deal with this problem and to derive consistent country-level series, we assign individual gridded SPEI values over cropland areas to individual countries to arrive at country-wide time series. As the main channel linking weather shocks and economic growth operates through shocks to agricultural incomes, restricting weather conditions to cropland areas allows us to isolate the component of climate variability which is relevant for agriculture. Another advantage of this measure is that it provides a consistent measure of climate variability within a country as land areas within a country broadly share the same weather conditions. To retrieve the climate variability in cropland areas we rely on the Global Land Cover SHARE (GLC-SHARE) prepared by

[7]For further details on this indicator, see Vicente-Serrano et al. (2010).

FAO's Land and Water Division (NRL). This database provides information on main land use and land cover shares, on each 1 by 1 kilometer plot of land covering the entire globe.[8] We construct monthly SPEI values at country level by overlaying grid cells of SPEI over cropland distribution in each country and averaging the SPEI values over each country's arable and permanent crop land.

2.2. Identifying climatic groups

To capture the variability across countries in the magnitude of ENSO impacts, with some regions considered more "teleconnected" to ENSO (continental tropics) than others (mid-latitudes regions), we partition the globe into two groups –tropical/humid and temperate/arid countries– based on how coupled their climates are to ENSO, according to the Köppen-Geiger Climate Classification updated by Kottek et al. (2006). However, in order to have country groups consistent with SPEI values calculated at country level, we identify climatic conditions which only prevail in cropland areas within each country. Specifically, we define tropical/humid countries as those characterized by 50% or more of their total cropland areas that fall into the four subtypes of tropical climates: tropical rain forest, tropical monsoon, tropical savannah with dry summer, tropical savannah with dry winter. Countries having a temperate/arid climate refer to those with 50% or more of their total cropland area characterized by one type of arid or mild temperate climates. Classes of arid climates refer to desert, steppe-hot arid and steppe-cold arid while subtypes of mild temperate climates include mild temperate with dry summer, mild temperate with dry winter, mild temperate fully humid warm summer, mild temperate fully humid cool summer. The list of countries included in each group is provided in Appendix A (Table A.1).[9]

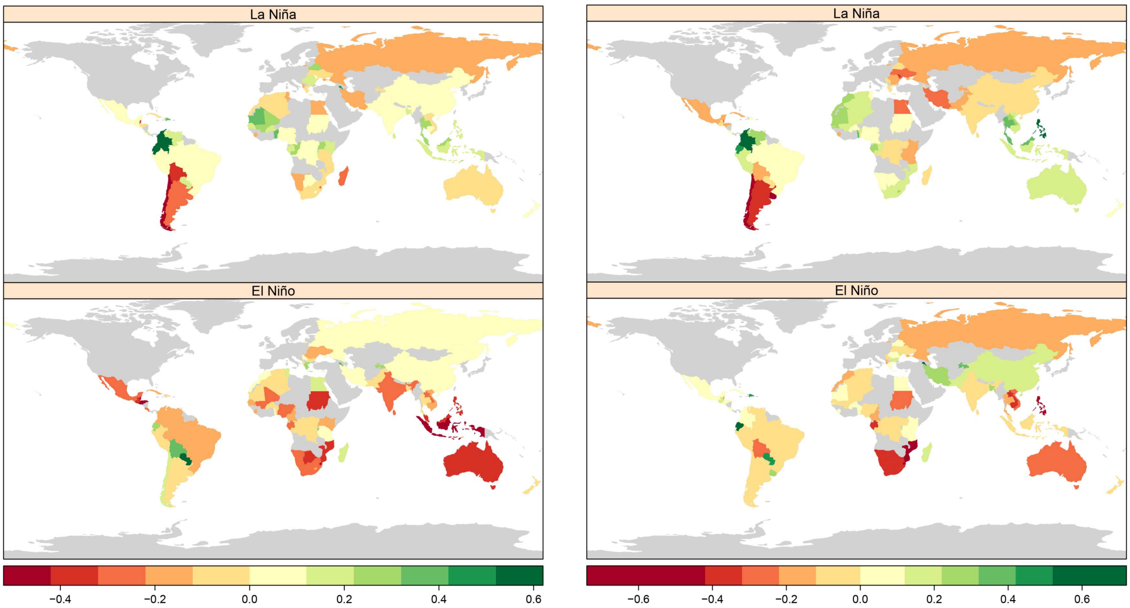
The widespread influence of ENSO events on local weather patterns is provided by Figure 2 which reports SPEI anomalies, defined as the difference between the SPEI values prevailing during normal conditions and those prevailing during an ENSO episode (illustration on the left). To illustrate the persistent impact of El Niño and La Niña on weather patterns, we also report SPEI anomalies during the year following an ENSO episode (illustration on the right).

This figure shows that globally most countries receive less precipitation during a El Niño episode. In Central America, El Niño is associated with serious drought in Mexico, Guatemala, Honduras, and El Salvador. Some Caribbean countries seem also suffer drought. El Niño effect is also present in Africa, as countries such Mali, Soudan, Nigeria tend to see drier SPEI during an El Niño event while droughts occur in the south of the continent already very dry (Mozambique, Botswana). In addition, dryness is seen throughout Indonesia, South and South-East Asia, and Australia.

[8]The 11 aggregated land cover classes identified by this database are: artificial surfaces (01), cropland (02), grassland (03), tree covered areas (04), shrubs covered areas (05), herbaceous vegetation, aquatic or regularly flooded (06), mangroves (07), sparse vegetation (08), bare soil (09), snow and glaciers (10), and water bodies (11).

[9]The classification is close to the one used in the literature except for large countries as India, Mexico.

Figure 2: *Difference between the SPEI average during El Niño (La Niña) years and neutral years (1975 - 2014)*



(a) *Immediate effect* ***(b)*** *Persistent effect*

Note: Map (a) shows the difference between the average of countries SPEIs during the El Niño (La Niña) years and the average of the countries SPEIs during years characterized by a neutral ENSO regime. The persistent effect (map b) is calculated as the average difference between the SPEIs the year following an El Niño (La Niña) shock and the years characterized by a neutral regime.

La Niña effects on weather patterns are the opposite of those induced by El Niño resulting in wetter-than-normal conditions in Southern Africa and in the central Andes. Very heavy rains and flooding reported in the Philippines, Malaysia, Indonesia and Australia are also largely determined by the La Niña events. In contrast, many droughts are reported in Argentina, Chile and over East Africa following La Niña events.

Finally, the surface extent and duration of the SPEI anomalies show that large areas of the world have SPEI anomalies lasting several months, confirming that the effects of El Niño and La Niña events on weather patterns can last over many seasons (Vicente-Serrano et al., 2011). One year after the occurrence of ENSO events, El Niño still affect most of Indonesia, the Indochina Peninsula, parts of Africa and Australia whereas La Niña causes significant positive SPEI anomalies in Africa and South East Asia.

2.3. Real income

As the main purpose of this paper is to link ENSO events to growth of real incomes through trends in weather conditions, we use real GDP (in 2011 constant US$) per capita as a measure of real income in a country, and for this, we take data directly from the recent version of the Penn World Table (PWT 9.0, 2018).

In Table 1, we report the final data set, with means, standard deviations, and ranges for the 6-month SPEI and the real GDP per capita growth by climate areas (tropical/humid and temperate/arid).[10]. According to the mean value of SPEI and real GDP per capita growth, few differences are apparent between the two climatic areas.

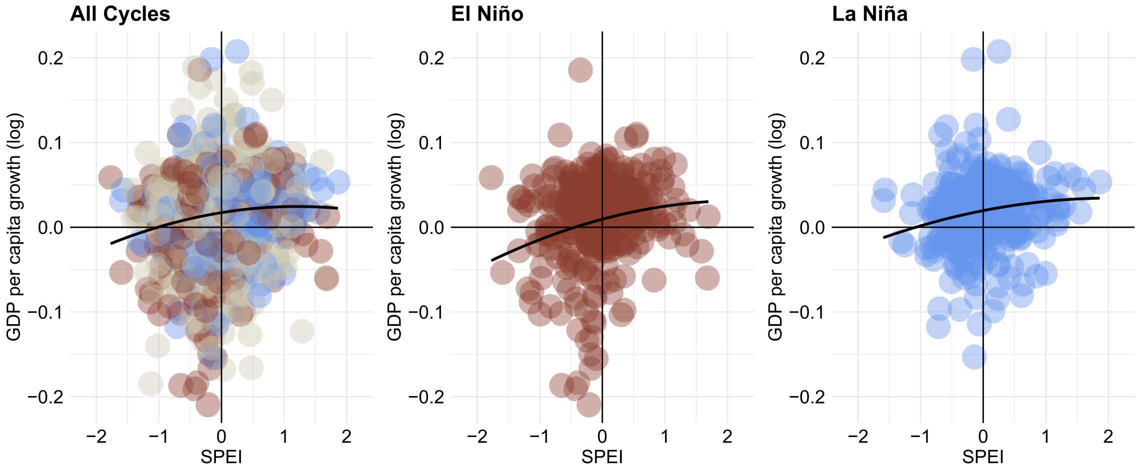
Table 1: *Summary statistics by geographical and climate areas*

Countries		SPEI - 6 month				Growth rate			
	n	mean	min	max	sd.	mean	min	max	sd.
All	74	-0.0307	-1.772	2.348	0.5248	0.0166	-0.5226	0.2833	0.0521
Tropical & Humid	39	-0.0110	-1.772	2.348	0.5197	0.0165	-0.2983	0.2833	0.0165
Temperate & Arid	35	-0.0537	-1.559	1.957	0.5299	0.0167	-0.5226	0.2571	0.0583

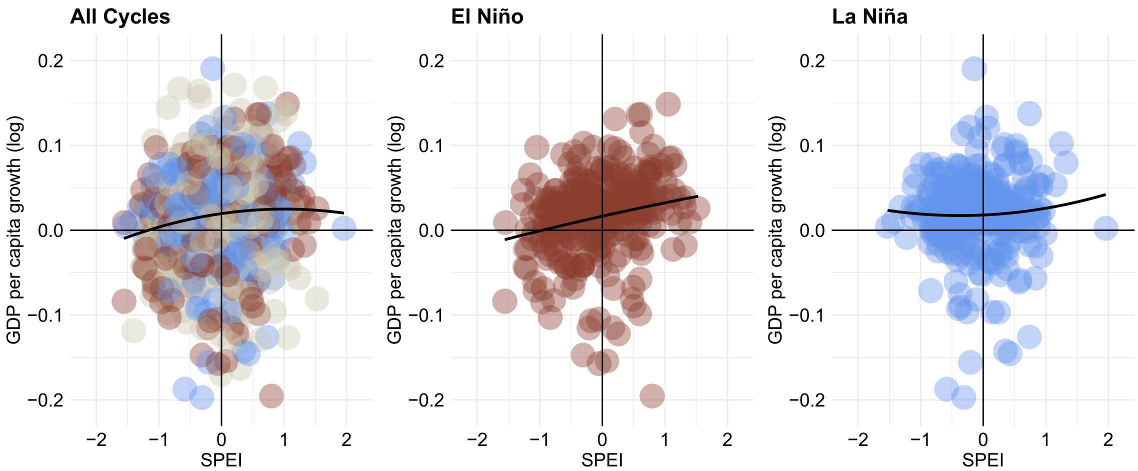
To take a closer look at the ENSO growth effects through weather conditions, Figure 3 plots the logarithm of real GDP growth against the values of the SPEI for any ENSO cycle and during the year following a El Niño and a La Niña events for both tropical/humid and temperate/arid countries.

[10]Table A.2 in Appendix A provides a detailed overview of the variables included in our data set. For the panel unit root tests for annual GDP growth and SPEI, see Appendix B

Figure 3: *Real GDP per capita growth and the SPEI*



(a) Tropical & Humid countries



(b) Arid & Temperate countries

Note: Figures (All Cycles) show the association between the SPEI and the growth rate for any ENSO cycle. Figures (El Niño) and (La Niña) represent the values of the SPEI and the growth rate the year following El Niño and La Niña events respectively. Positive (negative) SPEI values mean wet (dry) conditions. Normal weather conditions are defined when the SPEI reaches a value between "−0.5" and "+0.5".

Figure 3 exhibits two remarkable features. The picture that first emerges is one that is well known in the climatology literature: local weather conditions exert non-linear impacts on economic outcomes (Schlenker and Roberts, 2009; Burke et al., 2015). Indeed, Figure 3 shows that, for any ENSO cycle, country-level real GDP per capita growth is smooth, non-linear, and concave in weather conditions: economic growth initially increases as weather conditions become wetter but after reaching its maximum it subsequently falls at higher wetter conditions. The other key feature is that the nonlinear effects are less pronounced during El Niño and La Niña episodes. As can be seen, El Niño phases are characterized, on average, by a lower growth in tropical/humid countries with dry conditions while La Niña episodes generate opposed weather patterns compared to any ENSO cycle in arid/temperate countries: economic growth initially decreases as weather conditions become wetter but after reaching its minimum it subsequently increases at higher wetter conditions. Overall, these patterns reveal an important cross-country dispersion, showing a great heterogeneity in countries' responses to ENSO shocks due to their weather conditions. The assessment of ENSO growth impacts implies therefore to control for country-specific weather conditions.

3. Benchmark specifications and outcomes

3.1. Methodology and estimation strategy

Since ENSO impacts can extend beyond a calendar year and may also be temporally displaced, we estimate the contemporaneous as well as the lagged growth effects of ENSO events. Moreover, in order to obtain unbiased estimates of the effects of ENSO events, which are correlated with weather patterns, we include both variables in the regression equation. Finally, as our central hypothesis is that ENSO events are associated with varying impacts on economic growth through their delayed incidence on local weather conditions, we also assess how ENSO growth effects interact with weather conditions, following this basic specification:

$$\begin{aligned}\Delta y_{i,t} =& \alpha_0 + \underbrace{\alpha_1 ONI_t + \beta_1 SPEI_{i,t} + \beta_2 SPEI_{i,t}^2}_{\text{contemporaneous effect}} \\ &+ \underbrace{\alpha_2 ONI_{t-1} + \gamma_1 ONI_{t-1} \times SPEI_{i,t} + \gamma_2 ONI_{t-1} \times SPEI_{i,t}^2}_{\text{lagged effect}} + \mu_i + \varepsilon_{i,t}\end{aligned} \tag{1}$$

Where i represents each country and t represents each time period. The dependent variable, $\Delta y_{i,t}$, is the first difference of the real GDP per capita in constant 2011 US dollars (in logarithm) for country i between years t and $t-1$. ONI_t (ONI_{t-1}) is a vector of variables depicting the effects of ENSO events captured by annualized ONI values in year t ($t-1$). $SPEI_{i,t}$ is a vector of weather conditions for country i during period t measured by the 6-month SPEI. Following Burke et al. (2015), the estimated regression has a quadratic specification in the weather variable to allow for the expected non-linear effect of weather conditions on economic growth. Country-specific fixed effect, μ_i, are included to control for time-invariant omitted-variable bias and $\varepsilon_{i,t}$ is the error term. To assess the delayed impacts of ENSO events through local weather conditions, we interact the variable ONI_{t-1} with the country-specific weather variable, the latter being either the value of the 6-month SPEI or its squared value. If the coefficients on the interaction terms between the SPEI value and ENSO events are significant (and possibly, the coefficient on ENSO insignificant), this will imply that ENSO events act as common shocks with country-specific incidence on economic growth through local weather conditions.

Equation (1) imposes a monotonic relationship between ENSO events and economic growth by assuming that climate anomalies related to La Niña events can be regarded as a mirror image of those associated to El Niño events. However, the climatology literature has produced considerable evidence on the asymmetry between El Niño and La Niña events (Burgers and Stephenson, 1999; Jin et al., 2003b; An and Jin, 2004; An et al., 2005; Zhang et al., 2015) mainly due to nonlinear responses in the atmosphere to the underlying SST anomalies (Hoerling et al., 1997; Jin et al., 2003a). Thus, La Niña events may not necessarily lead to opposite effects to those associated with El Niño events. To address this asymmetry issue, we follow Smith and Ubilava (2017) and interact the variable ONI with an Heaviside indicator that partitions the variable ONI into positive and negative values. Then equation (1) becomes:

$$\begin{aligned}\Delta y_{i,t} &= \alpha_0 + \alpha_1^{\text{Niño}} ONI_t I(ONI_t \geq 0) + \alpha_1^{\text{Niña}} ONI_t I(ONI_t < 0) + \beta_1 SPEI_{i,t} \\ &+ \beta_2 SPEI_{i,t}^2 + \alpha_2 ONI_{t-1} + \gamma_1^{\text{Niño}} ONI_{t-1} I(ONI_{t-1} \geq 0) \times SPEI_{i,t} \\ &+ \gamma_1^{\text{Niña}} ONI_{t-1} I(ONI_{t-1} < 0) \times SPEI_{i,t} + \gamma_2^{\text{Niño}} ONI_{t-1} I(ONI_{t-1} \geq 0) \times SPEI_{i,t}^2 \\ &+ \gamma_2^{\text{Niña}} ONI_{t-1} I(ONI_{t-1} < 0) \times SPEI_{i,t}^2 + \mu_i + \varepsilon_{i,t}\end{aligned} \tag{2}$$

Where the Heaviside indicator I is such that $I(\cdot) = 1$ if the condition inside the parentheses is satisfied and 0 otherwise.

The standard methods of estimating ENSO events with panel data rely usually on fixed effects models. The major drawback with these models is that they not directly address the important question of the spatial and temporal correlation of climate and weather conditions across countries. As noted by Beck and Katz (1995), coefficient estimates from standard panel estimators can be severely biased if cross section dependence is present alongside heteroskedasticity and serial correlation (Beck and Katz, 1995). A preliminary analysis of the data using OLS reveals evidence of serial correlation and heteroscedasticity among the residuals.[11] This finding is not surprising given that economic activity may spill over into contiguous or economically related countries. This scenario is especially pertinent in the case of climate events, such as ENSO, which cross countries borders (Auffhammer et al., 2013).

To address these problems, we use Prais-Winsten estimates with panel-corrected standard errors (PCSE) developed by Beck and Katz (1995) and fixed effects (within) regression models with

[11] Results of this preliminary analysis are reported in Appendix B.

Driscoll and Kraay (DK) standard errors (Driscoll and Kraay, 1998). Both methodologies are robust to very general forms of cross-sectional as well as temporal dependence and perform better than the Parks-Kmenta Feasible Generalized Least Squares estimator (Parks, 1967) that tends to produce unacceptably small standard error estimates (Beck and Katz, 1995).[12]

3.2. Results

Tables 2 and 3 present the results of the regression analyses for respectively tropical/humid and arid/temperate countries. Each table includes two sets of results from PCSE and DK estimations. We first estimate equation (2) without any weather variable or interaction term between ONI and SPEI, as shown in columns (1) and (4) of Tables 2 and 3. We find that increasing positive values of the ONI - reflecting El Niño conditions - has a negative contemporaneous effect on growth in countries located in both areas, indicating that El Niño regime leads on average to lower growth rates, whereas the coefficient on La Niña regimes is insignificant. This result is consistent with the literature evidencing that the overall effect of a La Niña regime is the result of more localized tropical convection anomalies than those observed during El Niño phases(Mason and Goddard, 2001).

When including weather variables, the negative growth effect of El Niño phases becomes not or less significant while the coefficient attached to the main effect of SPEI is positive and significant in both climate areas (the opposite result is observed with DK estimates). In order to determine whether the lack of significance of the ONI variable may be due to contemporaneous opposing effects between global climate cycles and weather variables, we include a lagged effect of ENSO events and an interaction term of the ONI variable and the SPEI variables. Columns (3) and (6) depict the results of this general specification that includes both contemporaneous and lagged effects of ENSO events.

As can be seen, in tropical/humid areas, the contemporaneous negative effect of El Niño becomes significant while the coefficient on La Niña remains no significant. Moreover, one finds a significant coefficient on the interaction term between the positive lagged value of ONI and the SPEI. This lagged impact through weather conditions can be explained by the role played by El Niño events on the occurrence of tropical droughts. Unlike other natural hazards, droughts tend to develop very slowly over time and preferentially during El Niño events in this part of the world with a linear relationship to the strength of El Niño (Vicente-Serrano et al., 2011; Lyon, 2004; Mason and Goddard, 2001). The delayed effect of El Niño events on economic growth in tropical/humid countries is thus channeled through a higher probability of drier than normal weather conditions.

[12]The Parks-Kmenta Feasible Generalized Least Squares estimator (FGLS) cannot be estimated when the time period (T) is less than the number of cross-sectional units (N) since the associated Error Variance Covariance Matrix cannot be inverted. Even when $T \geq N$, the FGLS approach of Parks produces standard errors that lead to overconfidence rendering hypothesis testing useless.

Table 2: *Contemporaneous and lagged impacts of ENSO events*
Tropical & Humid Countries

	PCSE estimates			DK estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ONI}_t \geq 0$	-0.0132**	-0.0113*	-0.0152**	-0.0222**	-0.0206**	-0.0224***
	(0.00594)	(0.00586)	(0.00609)	(0.00875)	(0.00812)	(0.00800)
$\text{ONI}_t < 0$	-0.00228	-0.00221	-0.00456	-0.00719	-0.00706	-0.00773
	(0.00605)	(0.00592)	(0.00590)	(0.00645)	(0.00688)	(0.00653)
$\text{ONI}_{t-1} \geq 0$			-0.00858			-0.0137*
			(0.00620)			(0.00701)
$\text{ONI}_{t-1} < 0$			-0.00630			-0.00726
			(0.00590)			(0.00811)
SPEI_t		0.00479**	-0.00274		0.00392	-0.00369
		(0.00215)	(0.00379)		(0.00241)	(0.00487)
SPEI_t^2		-0.00369	-0.00222		-0.00299	-0.00116
		(0.00241)	(0.00381)		(0.00201)	(0.00291)
$\text{ONI}_{t-1} \geq 0 \times SPEI_t$			0.0188***			0.0167***
			(0.00698)			(0.00595)
$\text{ONI}_{t-1} < 0 \times SPEI_t$			0.00892			0.0122*
			(0.00751)			(0.00671)
$\text{ONI}_{t-1} \geq 0 \times SPEI_t^2$			-0.00421			-0.00302
			(0.00723)			(0.00498)
$\text{ONI}_{t-1} < 0 \times SPEI_t^2$			0.00230			-0.000171
			(0.00931)			(0.00689)
Constant	0.0163	0.0161	0.0213*	0.0233***	0.0238***	0.0292***
	(0.0126)	(0.0125)	(0.0129)	(0.00433)	(0.00339)	(0.00632)
N	1521	1521	1521	1521	1521	1521
Groups	39	39	39	39	39	39
$R^2[within]$	0.0778	0.0814	0.0904	[0.0200]	[0.0226]	[0.0335]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
PSAR(1)	Yes	Yes	Yes	No	No	No
MA(3)	No	No	No	Yes	Yes	Yes

Note: Prais-Winsten (PSCE) estimates and fixed effects (within) regression models with Driscoll and Kraay (DK) standard errors. $ONI \geq 0$ and $ONI < 0$ stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation. MA(3) denotes autocorrelation of the moving average type with automatic lag length.

Table 3: *Contemporaneous and lagged impacts of ENSO events*
Arid & Temperate Countries

	PCSE estimates			DK estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ONI}_t \geq 0$	-0.0152**	-0.0121	-0.0135*	-0.0222**	-0.0206**	-0.0214*
	(0.00772)	(0.00773)	(0.00737)	(0.00875)	(0.00812)	(0.0120)
$\text{ONI}_t < 0$	0.00100	0.00308	0.000700	-0.00719	-0.00706	0.000930
	(0.00867)	(0.00852)	(0.00774)	(0.00645)	(0.00688)	(0.00818)
$\text{ONI}_{t-1} \geq 0$			-0.00805			-0.0145
			(0.00772)			(0.0124)
$\text{ONI}_{t-1} < 0$			-0.0120			-0.00895
			(0.00767)			(0.0145)
SPEI_t		0.0121***	0.0147***		0.00392	0.0155***
		(0.00322)	(0.00569)		(0.00241)	(0.00530)
SPEI_t^2		-0.00565	-0.00798		-0.00299	-0.0104
		(0.00411)	(0.00892)		(0.00201)	(0.00789)
$\text{ONI}_{t-1} \geq 0 \times SPEI_t$			0.00971			0.00926
			(0.00962)			(0.00629)
$\text{ONI}_{t-1} < 0 \times SPEI_t$			-0.0198**			-0.0221**
			(0.00851)			(0.00941)
$\text{ONI}_{t-1} \geq 0 \times SPEI_t^2$			-0.00290			0.00101
			(0.0132)			(0.0165)
$\text{ONI}_{t-1} < 0 \times SPEI_t^2$			0.0135			0.00917
			(0.0110)			(0.0132)
Constant	0.0203***	0.0236***	0.0289***	0.0233***	0.0238***	0.0297***
	(0.00541)	(0.00529)	(0.00633)	(0.00433)	(0.00339)	(0.00984)
N	1260	1260	1260	1260	1260	1260
Groups	35	35	35	35	35	35
$R^2[within]$	0.0656	0.0846	0.0960	[0.0193]	[0.0361]	[0.0510]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
PSAR(1)	Yes	Yes	Yes	No	No	No
MA(3)	No	No	No	Yes	Yes	Yes

*Note: Prais-Winsten (PSCE) estimates and fixed effects (within) regression models with Driscoll and Kraay (DK) standard errors. ONI ≥ 0 and ONI < 0 stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation. MA(3) denotes autocorrelation of the moving average type with automatic lag length.*

Accordingly, taking account of contemporaneous ENSO effects and their lagged effects through weather conditions suggests that El Niño regimes have a negative growth effect in tropical/humid countries and that this effect is likely to be persistent by increasing the sensibility of those countries to wet conditions. As shown in the sixth column of Table 2, these results for tropical/humid countries – a significant contemporaneous of El Niño regimes and a lagged effect through weather conditions but no growth effect of La Niña events – are robust to DK estimates.

El Niño events have only a significant and contemporaneous impact in tropical/humid countries. Indeed, as shown in column (6) of Table 3, estimates for arid/temperate countries leads to a not significant coefficient on contemporaneous El Niño events. However, the effect of SPEI remains positive and significant, indicating a high vulnerability of these countries to droughts. Only La Niña events have a lagged effect on weather patterns which is essentially the reverse of the El Niño effect in tropical/humid countries. Indeed, by bringing higher than average precipitation, La Niña causes wet areas in arid/temperate countries to become wetter and rainfall to become more intense, which adversely affect economic growth. Again, this result is robust to the choice of estimator confirming that ENSO events also affect in a significant way economic growth of arid/temperate areas through their weather conditions.

3.3. Additional results

How much of the ENSO growth effects are associated with impacts on growth in total factor productivity (TFP)? This paragraph aims to investigate this question. As ENSO events have persistent effects through weather patterns, ENSO shocks are only slowly absorbed by the economy and should therefore have long-lasting effects. We thus examine whether the previous results on economic growth are driven through TFP growth.

In order to accomplish this aim, we repeat a similar process from the previous paragraph, except that we replace in equation (2) the GDP per capita growth with TFP per capita growth, calculated from data provided by the PWT database.[13] We estimate the contemporaneous effects of ENSO events, then augment this basic specification with weather variables, and then incorporate the lagged effects of ENSO events.

The results in Table 4 indicate strong evidence that the ENSO events affect TFP per capita growth through their interaction with weather patterns. The predominance of TFP growth for explaining the delayed ENSO effects on output growth is in line with other panel studies that find strong evidence of weather effects on TFP growth (Letta and Tol, 2018).

[13] for the definition of TFP see Table A.2 in Appendix A and for the panel unit root tests for annual TFP growth, see Table B.1 in Appendix B.

Table 4: *Contemporaneous and lagged impacts of ENSO events*
TFP growth

	Tropical & Humid Countries			Arid & Temperate Countries		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{ONI}_t \geq 0$	-0.0178***	-0.0154***	-0.0194*	-0.00941	-0.00759	-0.00796
	(0.00594)	(0.00578)	(0.0106)	(0.00741)	(0.00723)	(0.00708)
$\mathrm{ONI}_t < 0$	-0.00963	-0.00979*	-0.0128	-0.00260	-0.00148	-0.00349
	(0.00590)	(0.00576)	(0.0103)	(0.00806)	(0.00781)	(0.00735)
$\mathrm{ONI}_{t-1} \geq 0$			-0.0171			-0.00678
			(0.0111)			(0.00774)
$\mathrm{ONI}_{t-1} < 0$			-0.00189			-0.00910
			(0.0108)			(0.00748)
SPEI_t		0.00705***	-0.00458		0.0104***	0.0148**
		(0.00224)	(0.00675)		(0.00336)	(0.00581)
SPEI_t^2		-0.00390*	-0.00643		-0.000796	-0.00208
		(0.00219)	(0.00564)		(0.00467)	(0.00953)
$\mathrm{ONI}_{t-1} \geq 0 \times SPEI_t$			0.0289**			0.00626
			(0.0122)			(0.00951)
$\mathrm{ONI}_{t-1} < 0 \times SPEI_t$			0.0210			-0.0227**
			(0.0138)			(0.0115)
$\mathrm{ONI}_{t-1} \geq 0 \times SPEI_t^2$			0.00418			-0.00795
			(0.0107)			(0.0143)
$\mathrm{ONI}_{t-1} < 0 \times SPEI_t^2$			0.00181			0.0134
			(0.0158)			(0.0128)
Constant	0.0133	0.0129	0.0226	0.00594	0.00813	0.0123*
	(0.0122)	(0.0119)	(0.0178)	(0.00595)	(0.00598)	(0.00681)
N	1135	1135	1135	1019	1019	1019
Groups	39	39	39	35	35	35
R^2	0.0464	0.0556	0.0459	0.0250	0.0369	0.0529
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
PSAR(1)	Yes	Yes	Yes	Yes	Yes	Yes

*Note: Prais-Winsten (PSCE) estimates. $ONI \geq 0$ and $ONI < 0$ stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.*

Columns (1) and (4) show a still pronounced immediate impact of El Niño on TFP growth in tropical/humid countries while being not significant in arid/temperate countries. Moreover, adding lagged effects of ENSO yields very similar effects as the interaction terms with SPEI are still significant in both areas (columns (3) and (6)). As for economic growth the analysis by climate regions

reveals different ENSO effects through weather conditions, with a predominance of negative lagged effects of El Niño events in tropical/humid countries and of La Niña episodes in arid/temperate countries.
This main finding yields an important conclusion. Indeed, as productivity growth is reduced due to the delayed effects of ENSO on weather patterns, this fall is likely to have a persistent negative impact on output growth in subsequent periods and possibly alter income trajectories in a permanent way.

4. Sensitivity analysis

This section tests the robustness of our results, in particular the significance of the interaction term between ENSO events and weather conditions.

4.1. Variables measures

First, we examine how variable measures affect results. We reestimate Equation (2) for different measures of income and ENSO. For example, as an alternate measure of income, we use GDP per capita series from the World Bank's World Development Indicators. As other measure of ENSO, we use the Southern Oscillation Index (SOI), calculated by the difference between the atmospheric pressure at sea level at Tahiti and at Darwin. Results[14] show that no matter which measure is utilized, the interaction term between ENSO events and weather conditions remains significant and has the same sign with the same order of magnitude for both climate areas.[15]

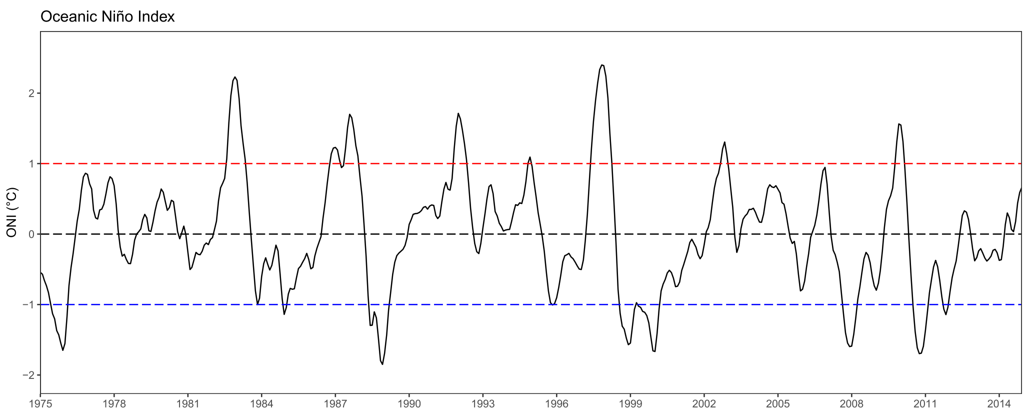
4.2. Accounting for extreme events

In addition to variables measures, another concern with this paper is that definitions of extreme events such as El Niño and El Niña events could affect results. In particular, it is not clear whether the analysis of the asymmetric effects of the ENSO phases through the introduction of an Heaviside indicator fully captures the occurrence of extreme events. Recent studies have shown that the duration of the ENSO events is crucial to its teleconnection patterns.[16] As El Niño and El Niña events events are defined according to the duration during which they are significantly different from the neutral regime, they thus cannot not be detected adequately through SST anomalies captured by positive and negative values of the ONI variable.
We then defined a categorical variable reflecting each state of ENSO following the standard decision process in determining moderate to strong ENSO events as proposed by the Climate Prediction

[14]The results of these robustness checks are not reported for the sake of brevity but are available from the authors upon request.
[15]This finding is not surprising as GDP per capita growth rates from the two sources as well as the SOI and ONI are highly correlated.
[16]See Trenberth (1997) for a detailed discussion of the different definitions of ENSO.

Center (CPC). El Niño episodes are defined by a Oceanic Niño index 1°C warmer than normal for at least five consecutive overlapping 3-month seasons. La Niña episodes arise when the Oceanic Niño index is 1°C cooler than normal for at least five consecutive overlapping 3-month seasons. Episodes that not fall in these two categories are considered as neutral. Neutral, El Niño and La Niña episodes identified by these definitions are reported back to 1975 in Figure 4 and Table 5. For example, years 1988 and 2010 show average values of ONI equal to -0.56°C and -0.19°C, respectively. Despite these low average negative values, these years are nevertheless characterized by the occurrence of La Niña events since during these two years ONI values lower than -1°C were observed during at least five consecutive months. By contrast, other years may exhibit larger but negative anomalies of ONI but due the short duration of these anomalies, they are characterized by neutral ENSO conditions.

Figure 4: *Evolution of the Oceanic Niño Index since 1975 (°C) and ENSO episodes*



Note: the red (blue) line indicates the threshold SST of +1°C (−1°C) that categorizes the ENSO phase as El Niño (La Niña).

Table 5: *Years characterized by moderate and strong ENSO events*

El Niño		La Niña	
Moderate	Strong	Moderate	Strong
1994^a	1982-1983	1995^a	1975
2002^a-2003^a	1987		1988
2009	1991		1998-1999
	1992		2007
	1997		2010-2011

Note: ^{a} Years characterized by events of lower amplitude but reported by NOAA as having significant repercussions.

Therefore to account more adequately for the different phases associated to ENSO (El Niño, La Niña or neutral phases) we run a specification which includes categorical variables, as depicted by Equation (3):[17]

$$\begin{aligned}\Delta y_{i,t} =& \alpha_0 + \alpha_1 ENSO_t + \beta_1 SPEI_{i,t} + \beta_2 SPEI^2_{i,t} \\ &+ \alpha_2 ENSO_{t-1} + \gamma_1 ENSO_{t-1} \times SPEI_{i,t} + \gamma_2 ENSO_{t-1} \times SPEI^2_{i,t} + \mu_i + \varepsilon_{i,t}\end{aligned} \tag{3}$$

Where $ENSO_t$ is a categorical variable defined by annualized ONI values in year t and scoring 1 for a La Niña event in year t, 2 for a El Niño event in year t and 0 otherwise. Neutral episodes are then the excluded episodes, so that the coefficients on La Niña and El Niño events must be interpreted differently than those in Equation (2). Indeed, the coefficients now measure the growth effect differential of La Niña and/or El Niño relative to neutral episodes, instead of analyzing differences in growth according to the positive or the negative values taken by the variable ONI. In Equation (3), if La Niña and/or El Niño events are associated with a lower growth rate compared to neutral episodes, then their respective coefficient (α_1 and α_2) should be negative and statistically significant.

The estimation results of Equation (3) are reported in Table 6.

We first notice that taking account the duration and magnitude in the definition of ENSO events does significantly change the estimated contemporaneous impact of El Niño events. Of particular importance is strong evidence of a less pronounced impact in tropical/humid countries while growth in arid/temperate countries seems more impacted. Thus, compared to normal episodes, El Niño events seem to be now associated with lower growth rates in temperate/arid areas. In contrast, and consistent with our previous results, La Niña events are not significantly different from normal ones for both climatic areas.

As can be seen, adding the delayed effects of ENSO does not significantly change the coefficient of the interaction term in tropical and humid countries (column (3)). Indeed estimates for this climate area show similar results to previous ones. El Niño events are growth limiting by bringing unusual warmth in tropical/humid countries already experiencing dry conditions.

[17] We calculate the polychoric correlation coefficient between the ONI variable and dummy variables taking the value 1 in case of El Niño / La Niña events and 0 otherwise (ρ_{nino} and ρ_{nina}). The correlation between ONI and the dummy variable that captures El Niño is high ($\rho_{nino} = 0.91$) while the correlation with La Niña events is smaller as $\rho_{nina} = -0.76$.

Table 6: *Contemporaneous and lagged impacts of ENSO events*
Dummy variables

	Tropical & Humid Countries			Arid & Temperate Countries		
	(1)	(2)	(3)	(4)	(5)	(6)
El Niño$_t$	-0.00678*	-0.00582	-0.00757*	-0.0122**	-0.0141**	-0.0127***
	(0.00386)	(0.00377)	(0.00395)	(0.00524)	(0.00578)	(0.00469)
La Niña$_t$	0.00186	0.00177	0.00180	0.00560	0.00374	0.00694
	(0.00428)	(0.00415)	(0.00415)	(0.00557)	(0.00633)	(0.00502)
El Niño$_{t-1}$			-0.00271			-0.00947*
			(0.00423)			(0.00567)
La Niña$_{t-1}$			-0.00277			-0.0128**
			(0.00417)			(0.00524)
SPEI$_t$		0.00499**	0.000240		0.0126***	0.0123**
		(0.00215)	(0.00300)		(0.00371)	(0.00483)
SPEI$_t^2$		-0.00429*	-0.000716		-0.00806*	-0.0161***
		(0.00240)	(0.00352)		(0.00454)	(0.00580)
El Niño$_{t-1}$ $\times SPEI_t$			0.0118**			0.00974
			(0.00491)			(0.00740)
La Niña$_{t-1}$ $\times SPEI_t$			0.00438			-0.0146**
			(0.00526)			(0.00693)
El Niño$_{t-1}$ $\times SPEI_t^2$			-0.00549			0.0108
			(0.00571)			(0.00942)
La Niña$_{t-1}$ $\times SPEI_t^2$			-0.00552			0.0254***
			(0.00517)			(0.00706)
Constant	0.0141	0.0144	0.0163	0.0188***	0.0245***	0.0293***
	(0.0131)	(0.0129)	(0.0130)	(0.00465)	(0.00596)	(0.00512)
N	1521	1521	1521	1260	1260	1260
Groups	39	39	39	35	35	35
R^2	0.0717	0.0766	0.0839	0.0753	0.0864	0.116
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
PSAR(1)	Yes	Yes	Yes	Yes	Yes	Yes

*Note: Prais-Winsten (PSCE) estimates. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.*

In contrast, the growth effects of ENSO in arid/temperate countries are more sensitive to the definition of these climate events. Globally the use of dummy variables makes patterns of weather extremes more significant in those countries. Indeed, the coefficient estimates in column (6) indicate a more pronounced nonlinear effect of weather conditions on growth: economic growth increases as weather conditions become wetter, and then declines when wet conditions reach a critical threshold. However, these effects are completely reversed after the occurrence of a La Niña event. La Niña by causing increased rainfall has a negative growth effect in arid/temperate countries with already wet conditions while its effect instead becomes positive in areas with already dry conditions. This last result indicates a lower exposure to dry conditions during La Niña years. By bringing more water in some economies characterized by an arid climate, La Niña could bring relief to areas impacted by droughts and enhance restoration of pasture and crop production. Overall, those findings support our main hypothesis related to the importance of local weather conditions when assessing the growth effects of ENSO cycles.

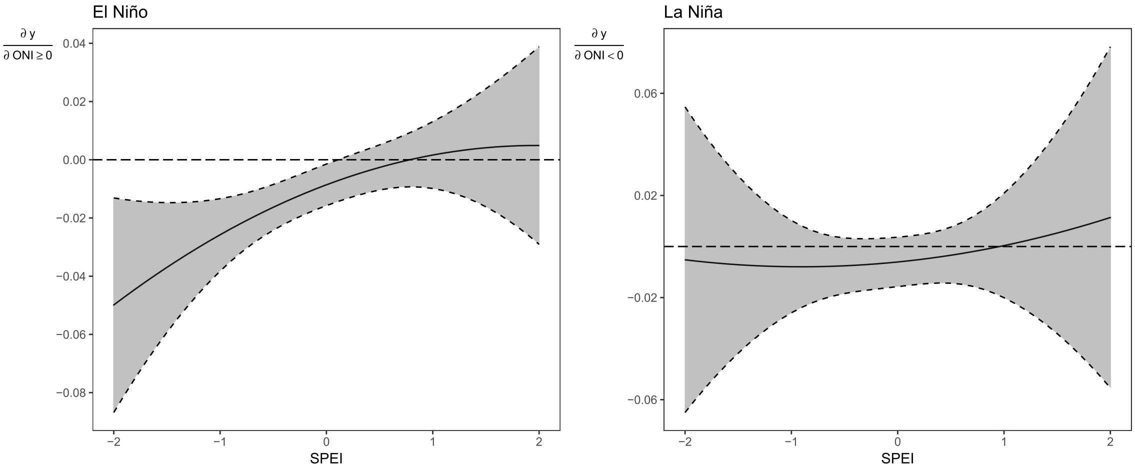
4.3. Illustration: marginal effects

In order to better explain the significance of the coefficients on the interaction terms between ENSO cycles and weather variables (e.g. coefficients γ_1 and γ_2), we finally estimate the marginal effects of these climate events at different levels of SPEI and for each measure of ENSO events. Figures 5 and 6 depict the estimated marginal effect of ENSO phases at time $t-1$ on GDP growth as estimated from respectively regressions (2) and (3) and at different levels of weather conditions.

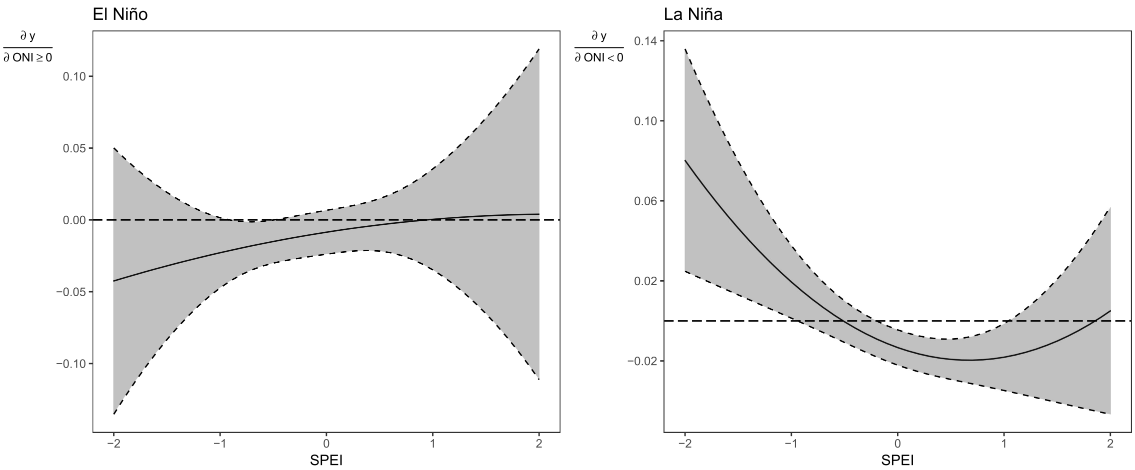
As can be seen, in tropical and humid countries, the derivative of El Niño variables is clearly different from zero at all negative SPEI (dry conditions) while for positive SPEI (wet conditions), the derivative is close to zero. When wet conditions prevail, El Niño has no effect on growth, while at dryer temperatures, by inducing, with some delay, deficits in rainfalls, it leads to significant lower growth rates. In contrast, the derivative of La Niña is clearly not significant for all SPEI values. These findings hold for both specifications using the Heaviside indicator or the dummy variable.

For arid and temperate countries, as it apparent, the marginal growth effect of El Niño is no significant. The marginal effect of La Niña on economic growth is instead significant: it is positive when dry conditions prevail (for negative values of the SPEI) and decreases as SPEIs increase. This last finding confirms that La Niña, by bringing heavier precipitation in arid/temperate countries, leads to significant lower growth when wet weather conditions prevail and higher growth in areas with already dry conditions.

Figure 5: *Marginal effect of ONI according to SPEI values*



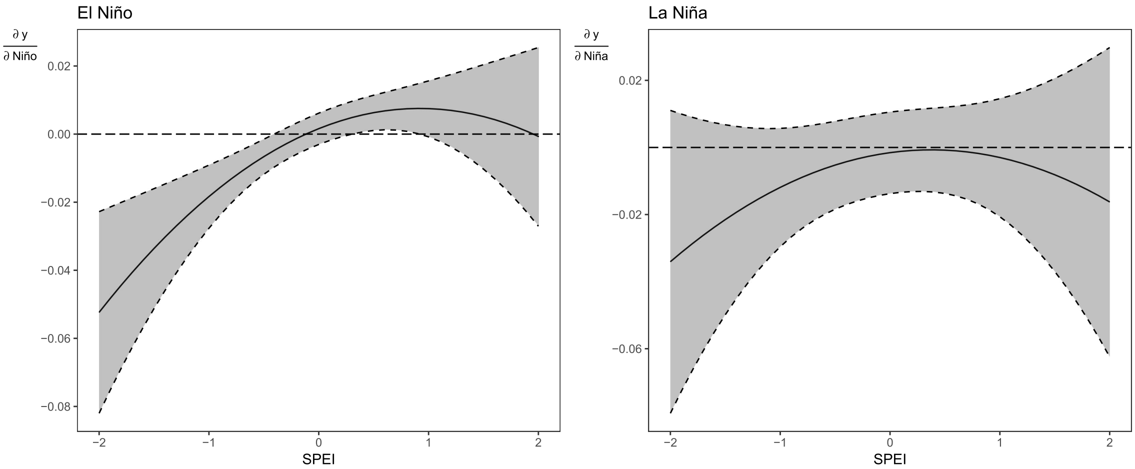
(a) *Tropical & Humid countries*



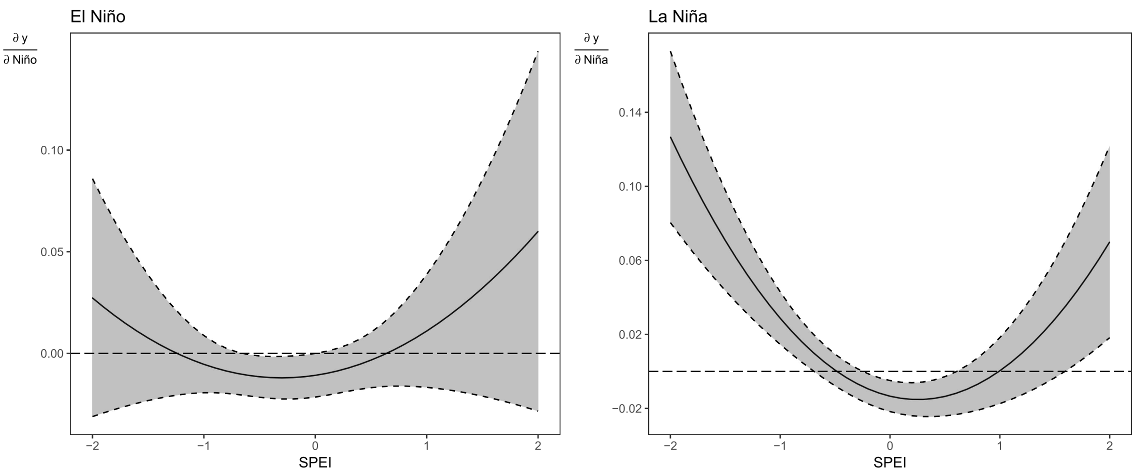
(b) *Arid & Temperate countries*

Note: Solid lines report derivatives of the growth response with respect to changes in $ONI_{t-1}I(ONI_{t-1} \geq 0)$ *(El Niño phases) and* $ONI_{t-1}I(ONI_{t-1} < 0)$ *(La Niña phases). Shaded areas represent 95% confidence intervals.*

Figure 6: *Marginal effect of ENSO shocks according to SPEI values*



(a) *Tropical & Humid countries*



(b) *Arid & Temperate countries*

Note: Solid lines report derivatives of the growth response with respect to discrete change from neutral regime to El Niño (La Niña) regime. Shaded areas represent 95% confidence intervals.

5. Conclusion

In this paper, we conduct an analysis of the effects exerted by ENSO events on a sample of 74 countries over the period 1975-2014. Compared to the existing literature, we exploit time-varying and country-specific weather variables, to detect the heterogeneours effects of ENSO events through their interactions with local weather conditions.

We find that ENSO events have sizeable and persistent economic effect in both tropical/humid and arid/temperate countries. In particular, El Niño regimes impact the economic growth of tropical / humid countries with some delay by increasing the sensibility of those countries to wet conditions through a higher probability of drier than normal weather conditions. This lagged impact of El Niño on economic growth can be explained by its role on the occurrence of tropical droughts. On the contrary, arid and temperate countries are particularly vulnerable to La Niña events. Teleconnection patterns between La Niña phases of ENSO and arid/temperate countries favors higher than average precipitation that adversely affect economic growth in wet parts of this climate area.

This finding is independent of the way in which asymmetric effects of ENSO are taken into account. Indeed, this result holds if we consider two phases of the ENSO cycle measured by positive (El Niño) or negative (La Niña) SSTs anomalies or if we consider a neutral regime and two extreme regimes (El Niño or La Niña) characterized by both their magnitude and their duration. We also bring strong evidence that ENSO events affect TFP per capita growth through their interaction with weather patterns. This last finding has important implications. As productivity growth is reduced due to the delayed effects of ENSO on weather patterns, this fall is likely to have a persistent negative impact on output growth in subsequent periods and possibly alter income trajectories in a permanent way.

Overall, our results indicate that caution should be exerted when interpreting results of studies analyzing the growth effect of such climate events and which do not control for the observed heterogeneity in countries' sensitivity to climate shocks. Not only the type of climate seems to explain the relationship between ENSO events and economic growth; local weather variables do also matter.

In this respect, this paper, by analyzing the weather channel through which ENSO events impact economic growth, can contribute to a better understanding of ENSO effects. By showing the consequences over time of El Niño and La Niña episodes on weather patterns, it can also improve management risks in countries most exposed to those global climate cycles.

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Appendix

Appendix A: Data and statistical information

Table A.1: *ENSO country assignment*

Country	ISO3	Region	Climate	% of croplands		
				Trop.	Arid	Temp.
Albania	ALB	Europe & Central Asia	Arid & Temperate	0.00	0.00	1.00
Argentina	ARG	Latin America & Caribbean	Arid & Temperate	0.00	0.02	0.98
Armenia	ARM	Europe & Central Asia	Arid & Temperate	0.00	0.33	0.67
Australia	AUS	East Asia & Pacific	Arid & Temperate	0.00	0.57	0.43
Burundi	BDI	Sub-Saharan Africa	Tropical & Humid	0.80	0.00	0.20
Benin	BEN	Sub-Saharan Africa	Tropical & Humid	0.75	0.25	0.00
Burkina Faso	BFA	Sub-Saharan Africa	Arid & Temperate	0.25	0.75	0.00
Bangladesh	BGD	South Asia	Tropical & Humid	0.87	0.00	0.13
Bulgaria	BGR	Europe & Central Asia	Tropical & Humid	0.00	0.00	1.00
Belarus	BLR	Europe & Central Asia	Arid & Temperate	0.00	0.00	1.00
Belize	BLZ	Latin America & Caribbean	Tropical & Humid	1.00	0.00	0.00
Bolivia	BOL	Latin America & Caribbean	Tropical & Humid	0.82	0.12	0.05
Brazil	BRA	Latin America & Caribbean	Tropical & Humid	0.75	0.10	0.16
Botswana	BWA	Sub-Saharan Africa	Arid & Temperate	0.00	1.00	0.00
Chile	CHL	Latin America & Caribbean	Arid & Temperate	0.00	0.01	0.99
China	CHN	East Asia & Pacific	Arid & Temperate	0.00	0.32	0.68
Cameroon	CMR	Sub-Saharan Africa	Tropical & Humid	0.67	0.33	0.00
Congo, Democratic Republic	COD	Sub-Saharan Africa	Tropical & Humid	0.95	0.00	0.05
Congo	COG	Sub-Saharan Africa	Tropical & Humid	1.00	0.00	0.00
Colombia	COL	Latin America & Caribbean	Tropical & Humid	0.85	0.00	0.15
Costa Rica	CRI	Latin America & Caribbean	Tropical & Humid	0.99	0.00	0.01
Cyprus	CYP	Europe & Central Asia	Arid & Temperate	0.00	0.52	0.48
Dominican Republic	DOM	Latin America & Caribbean	Tropical & Humid	0.97	0.00	0.03
Algeria	DZA	Middle East & North Africa	Arid & Temperate	0.00	0.31	0.69
Ecuador	ECU	Latin America & Caribbean	Tropical & Humid	0.73	0.07	0.20
Egypt	EGY	Middle East & North Africa	Arid & Temperate	0.00	1.00	0.00
Gabon	GAB	Sub-Saharan Africa	Tropical & Humid	1.00	0.00	0.00
Gambia	GMB	Sub-Saharan Africa	Arid & Temperate	0.10	0.90	0.00
Greece	GRC	Europe & Central Asia	Arid & Temperate	0.00	0.11	0.89
Guatemala	GTM	Latin America & Caribbean	Tropical & Humid	0.85	0.00	0.15
Honduras	HND	Latin America & Caribbean	Tropical & Humid	0.90	0.00	0.10
Indonesia	IDN	East Asia & Pacific	Tropical & Humid	1.00	0.00	0.00
India	IND	South Asia	Tropical & Humid	0.36	0.36	0.28
Iran	IRN	Middle East & North Africa	Arid & Temperate	0.00	0.61	0.39
Kenya	KEN	Sub-Saharan Africa	Tropical & Humid	0.57	0.20	0.23
Cambodia	KHM	East Asia & Pacific	Tropical & Humid	1.00	0.00	0.00

Lao People's Democratic Republic	LAO	East Asia & Pacific	Tropical & Humid	0.87	0.00	0.13
Sri Lanka	LKA	South Asia	Tropical & Humid	1.00	0.00	0.00
Lesotho	LSO	Sub-Saharan Africa	Arid & Temperate	0.00	0.00	1.00
Morocco	MAR	Middle East & North Africa	Arid & Temperate	0.00	0.33	0.67
Moldova, Republic of	MDA	Europe & Central Asia	Arid & Temperate	0.00	0.00	1.00
Madagascar	MDG	Sub-Saharan Africa	Tropical & Humid	0.82	0.00	0.18
Mexico	MEX	Latin America & Caribbean	Tropical & Humid	0.70	0.10	0.20
Mali	MLI	Sub-Saharan Africa	Arid & Temperate	0.20	0.80	0.00
Mozambique	MOZ	Sub-Saharan Africa	Arid & Temperate	0.33	0.57	0.10
Mauritania	MRT	Sub-Saharan Africa	Arid & Temperate	0.00	1.00	0.00
Mauritius	MUS	Sub-Saharan Africa	Tropical & Humid	1.00	0.00	0.00
Malaysia	MYS	East Asia & Pacific	Tropical & Humid	1.00	0.00	0.00
Namibia	NAM	Sub-Saharan Africa	Arid & Temperate	0.00	1.00	0.00
Nigeria	NGA	Sub-Saharan Africa	Tropical & Humid	0.72	0.28	0.00
New Zealand	NZL	East Asia & Pacific	Arid & Temperate	0.00	0.00	1.00
Pakistan	PAK	South Asia	Arid & Temperate	0.00	0.83	0.17
Peru	PER	Latin America & Caribbean	Tropical & Humid	0.48	0.24	0.28
Philippines	PHL	East Asia & Pacific	Tropical & Humid	0.99	0.00	0.01
Paraguay	PRY	Latin America & Caribbean	Arid & Temperate	0.34	0.07	0.59
Romania	ROU	Europe & Central Asia	Arid & Temperate	0.00	0.00	1.00
Russian Federation	RUS	Europe & Central Asia	Arid & Temperate	0.00	0.19	0.81
Sudan	SDN	Sub-Saharan Africa	Arid & Temperate	0.07	0.93	0.00
Senegal	SEN	Sub-Saharan Africa	Arid & Temperate	0.02	0.98	0.00
Sierra Leone	SLE	Sub-Saharan Africa	Tropical & Humid	1.00	0.00	0.00
El Salvador	SLV	Latin America & Caribbean	Tropical & Humid	1.00	0.00	0.00
Serbia	SRB	Europe & Central Asia	Arid & Temperate	0.00	0.00	1.00
Swaziland	SWZ	Sub-Saharan Africa	Tropical & Humid	1.00	0.00	0.00
Togo	TGO	Sub-Saharan Africa	Tropical & Humid	1.00	0.00	0.00
Thailand	THA	East Asia & Pacific	Tropical & Humid	1.00	0.00	0.00
Tajikistan	TJK	Europe & Central Asia	Arid & Temperate	0.00	0.68	0.32
Tunisia	TUN	Middle East & North Africa	Arid & Temperate	0.00	0.04	0.96
Tanzania	TZA	Sub-Saharan Africa	Tropical & Humid	0.72	0.20	0.08
Uganda	UGA	Sub-Saharan Africa	Tropical & Humid	0.94	0.04	0.02
Ukraine	UKR	Europe & Central Asia	Arid & Temperate	0.00	0.00	1.00
Uruguay	URY	Latin America & Caribbean	Arid & Temperate	0.00	0.00	1.00
Venezuela, Bolivarian Republic of	VEN	Latin America & Caribbean	Tropical & Humid	1.00	0.00	0.00
Viet Nam	VNM	East Asia & Pacific	Tropical & Humid	0.67	0.00	0.33
South Africa	ZAF	Sub-Saharan Africa	Arid & Temperate	0.02	0.58	0.40

Table A.2: Variables and data sources

Mnemonic	Source	Variable description
ONI	NOAA database	Oceanic Niño Index
$SPEI$	Global SPEI database	Standardised Precipitation-Evapotranspiration Index
y	Penn World Table database (PWT 9.0)	Real GDP per capita at Constant National Prices (in 2011 US dollars)
TFP	Penn World Table database (PWT 9.0)	Real Total Factor Productivity per capita (Index 2011=1, Annual)

Appendix B: Analysis of the data

***Table B.1**: Cross-sectionally augmented Im, Pesaran and Shin (IPS) test for unit roots*

		Without Trend $\bar{Z}_t$		With Trend $\bar{Z}_t$	
Variable	lags	Level	1st Diff	Level	1st Diff
Δy	0	-1.303*	-22.172***	1.582	-20.611***
	1	-4.597***	-16.116***	-1.006*	-13.775***
	2	-1.862*	-9.484***	0.029	-6.503***
	3	-0.043	-7.642***	1.193	-4.647***
ΔTFP	0	0.551	-25.898***	-0.616	-23.710***
	1	-1.117	-18.277***	-3.622***	-15.081***
	2	0.319	-11.668***	-1.342	-7.921***
	3	0.596	-8.316***	-0.457	-4.695***
SPEI	0	-27.432***	.	-25.218***	.
	1	-19.007***	.	-16.925***	.
	2	-12.899***	.	-10.686***	.
	3	-8.541***	.	-6.387***	.

*Note: ***, **, and * denote the rejection of the null hypothesis at the 10%, 5% and 1% level. The null hypothesis is the presence of unit root in panel data with cross-sectional dependence in the form of common factor dependence.*

***Table B.2**: Pesaran CD test for cross-section independence*

Variable	CD-test	Correlation	abs(correlation)
Δy	32.52***	0.100	0.189
ΔTFP	18.84***	0.074	0.176
SPEI	16.91***	0.049	0.190

*Note: The CD test of Pesaran (2004) is defined under the null hypothesis of no cross-sectional dependence. ***, **, and * indicate 1%, 5%, and 10% significance levels.*