**Environmental Research Letters**

**LETTER**

The El Niño impact on maize yields is amplified in lower income teleconnected countries

David Ubilava and Maryam Abdolrahimi

1 School of Economics, University of Sydney, Australia
2 School of Economics, University of Sydney, Australia

E-mail: david.ubilava@sydney.edu.au

Keywords: climate econometrics, El Niño Southern oscillation, global maize yields, panel smooth transition regression

Supplementary material for this article is available online

Original content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Abstract

We use a multiple-regime panel smooth transition regression to examine the economic and climatic sources of the nonuniform relationship between El Niño Southern Oscillation (ENSO) and maize yields around the globe. While the yield effect is predominantly observed in strongly teleconnected countries, it is amplified in lower income countries, which we attribute to possible lack of resilience to ENSO-induced weather shocks. Both El Niño-like and La Niña-like conditions result in maize yield reduction, but it is during El Niño events when maize yields drop by up to 20% in most affected countries. Because in many of these countries maize is an important agricultural crop, the presented results are of interest to researchers and policy makers in the areas of world nutrition and international aid. Moreover, because larger share of maize is produced by high income weakly teleconnected countries, the observed geographic heterogeneity of the El Niño impact offers possible benefits from global risk sharing. These findings also offer insights to climate change economics, as possible increased frequency of the ENSO cycle may negatively impact maize production in strongly teleconnected low income countries.

1. Introduction

The impact of the El Niño Southern Oscillation (ENSO) events on global weather and crop yields can be nonuniform (e.g. Iizumi et al. 2014, Hsiang and Meng 2015, Anderson et al. 2017). The reasons for this are heterogeneity in the ENSO–weather linkages, as well as heterogeneity in countries’ responses to weather shocks (e.g. Cashin et al. 2017). Weather anomalies—e.g. excessive heat, droughts, floods—are more frequent in the tropics, where the majority of low income countries are located (Masters and McMillan 2001, Hsiang 2010). Moreover, the agricultural sector, which is inherently linked with weather, constitutes a larger share of these economies (Schlenker and Lobell 2010). Finally, the climate resilience of these countries is not at par with that of high income countries (Dell et al. 2012, Hertel and Lobell 2014). This study aims to disentangle and examine climatic and economic sources of the aforementioned heterogeneity of the ENSO impact on maize yields.

A typical ENSO event forms during the boreal summer, and reaches its peak at the end of that year. It usually vanishes during the subsequent spring, although an ENSO event may span a two–year period as well. Immediate impacts of ENSO are felt in countries adjacent to the Pacific Ocean, where this event occurs. For example, its warm phase—El Niño—results in increased rainfall across the western tier of the American continent and droughts in the Asia-Pacific region. Its cool phase—La Niña—manifests in weather conditions opposite those described above. ENSO events also affect other regions—including the US (e.g. Barlow et al. 2001) and Europe (e.g. Pozo-Vázquez et al. 2005, Bulić and Kucharski 2012, Ionita et al. 2012)—via the teleconnections, which link the

3 The term El Niño, which translates as The Little Boy or Christ Child from Spanish, originates from Peruvian fishermen who, in some years, observed unusual warming of ocean waters just before and during the Christmas period. Subsequently, an event characterized by unusual cooling of ocean waters was named La Niña, which translates as The Little Girl.
realized ENSO conditions in the equatorial Pacific to temporal changes in weather conditions around the globe (Ropelewski and Halpert 1987, Rasmusson 1991, Stone et al 1996, Richter et al 2013).

We focus on maize because of the direct effect of extreme weather on field crops, as well as the importance of maize as food and feed, and more recently as a source of renewable energy. Our interest in the ENSO phenomenon is twofold. First, we present the year-to-year variability of maize yields due to the ENSO cycle within the current climate. This allows us to envisage transitory effects of the ENSO events. Second, as extreme ENSO events (i.e. El Niño-like and La Niña-like conditions) may become more frequent (Cai et al 2014, 2015), we offer a snap-shot of the possible yield impact of climate change.

Empirical investigation of the relationship between ENSO and agricultural production can be traced back to the mid-1980s (e.g. Handler 1984, Nicholls 1985), but the turning point in the economic assessment of this climate phenomenon was the 1997/1998 El Niño event, which caused several billion US dollars worth of damage in the US alone (Adams et al 1999). Since the late 1990s, a large body of literature has addressed the ENSO impact on cereal production in different regions of the world, including the Americas, Australasia, and Africa (Phillips et al 1998, 1999, Naylor et al 2001, Amisah-Arthur et al 2002, Adams et al 2003, Stige et al 2006, Roberts et al 2009, Anderson et al 2017).

A considerable portion of the existing studies rely on simulated, rather than observed, yield data (e.g. Phillips et al 1998, 1999, Adams et al 2003). While simulated observations offer some benefits, such as availability over a longer time span and for smaller geographic areas, their main drawback is that such data largely ignore any adaptive actions that crop producers may have taken in response or in anticipation of climatic shocks (Miao et al 2016). A relatively smaller group of studies, which rely on observational data, focus on a subset of countries, often just a single country (e.g. Cane et al 1994, Podestá et al 1999, Naylor et al 2001, Selvaraju 2003, Anderson et al 2017). Moreover, most studies consider ENSO as a categorical variable and use basic statistical methods to compare yield distributions during the event years with those during neutral years (e.g. Legler et al 1999, Podestá et al 1999, Selvaraju 2003, Iizumi et al 2014). As in the foregoing instance, studies that rely on a regression-based framework, or a continuous proxy variable for ENSO, are scarce and often focus on small group of countries or regions within a country (e.g. Tack and Ubilava 2013, Anderson et al 2017). Finally, while recent research has addressed the climatic heterogeneity of the ENSO effect (Hsiang and Meng 2015), none of the existing studies assess the heterogeneous impacts of ENSO conditional on the economic development of the affected countries, which is the focus of this research.

We contribute to the literature in several directions. First, we present a global regression-based analysis using observational data on sea surface temperature anomalies in the Niño3.4 region (SST), a continuous series that proxies ENSO, and country-level maize yields. Second, we allow for asymmetries in yield responses to SST, and geographical heterogeneity of these effects. Third, in examining the heterogeneity, we allow a continuum of the effects ranging across distinct regimes, based on climatic and, importantly, economic characteristics of countries in consideration. We do so by adopting a panel smooth transition regression (PSTR) framework of González et al (2017)—a modeling approach that nests commonly applied linear and discrete specifications as its special cases and offers a parsimonious framework for examining potentially complex relationships between the variables of interest.

We find that SST anomalies, indeed, considerably affect maize yields in the lower income, strongly tele-connected countries. This finding is consistent with Hsiang and Meng (2015), who examined cereal grain yield responses to SST anomalies. In addition, we also find that the effect is particularly strong, both statistically and economically, during positive SST deviations, i.e. in El Niño-like conditions, and is negligible during negative SST deviations, i.e. in La Niña-like conditions. This finding is consistent with Cashin et al (2017), who employ a dynamic multi-country framework to find the asymmetric international macro-economic transmission of El Niño and La Niña related weather shocks. Thus, not only the ENSO cycle has geographically heterogeneous effects on maize yields, but these effects are also asymmetric.

Several implications follow from these findings. First, because in many affected low-income countries maize is one of the most important crops, the local adverse effects of ENSO shocks, particularly as they relate to household incomes, can be substantial. Second, because a larger share of maize is produced in the high income countries that are hardly impacted by ENSO shocks, their global effect on the maize yield can be seen as economically negligible, which implies little pressure on the world prices of this commodity. This is consistent with Ubilava (2018), who examined commodity price responses to ENSO shocks. Third, the asymmetry of maize yield responses to positive and negative sea surface temperature deviations—a finding that echoes existing studies (e.g. Iizumi et al 2014, Cashin et al 2017)—indicates that, for example, a negative impact of an El Niño event in the tele-connected countries is not subsequently balanced out by a positive impact of a La Niña event. It then follows that in the short term, proactive global risk sharing—e.g. international aid to low income countries—is particularly crucial during El Niño years. In the long term, in the absence of adaptation, if ENSO cycles were to become more frequent, we can expect an increase in the incidence of bad crops and reduction of
the unconditional mean of maize yields, particularly in the lower income countries that are directly affected by ENSO events.

2. Data description

Data on country-specific maize yields, area harvested, production, and area allocated to agricultural land, were sourced from the online platform of FAOSTAT. The series span the 1961–2017 period. After discarding problematic countries (i.e. those with missing observations or those displaying constant yields for more than three consecutive years), we retained 67 countries representing 91% (93%) of global maize production (area harvested). Figure 1 illustrates the geographical distribution of the expected yields⁴ in the sample of countries.

We obtained data on country-specific growing seasons from Villoria and Delgado (2017), who use the global information on the pixel-level planting and harvesting dates of Sacks et al (2010) to construct monthly growing season weights for each country. Thus, a weight of zero, in a given month, implies that the month is not part of the growing season; a positive weight denotes the share of pixels in a country for which the month is part of the growing season. We define the growing season as an uninterrupted sequence of months for which the weights exceed 0.5.

We sourced the sea surface temperature (SST) series from the online portal of National Oceanic and Atmospheric Administration (NOAA). The SST anomalies are measured as deviations (°C) from the 1980–2010 base period in the Nino3.4 region, a rectangular area bounded by 120°W–170°W and 5°S–5°N, and are reported at monthly frequency. To obtain a measure of the relevant SST anomalies for country i in period t, we averaged these observations over the maize growing season of that country.

Following Hsiang et al (2011), we use ENSO teleconnections as a potential source of geographical heterogeneity in the effect of the SST anomalies on maize yields. However, the approach that we use here is slightly different from that of the aforementioned study. For each country i, first we calculate correlations between the growing season average temperature and growing season average SST anomaly, denoted by \( \rho^t_i \), and the growing season average precipitation and growing season average SST anomaly, denoted by \( \rho^p_i \). Then we obtain the measure of teleconnection, denoted by \( \tau^p_i \) as the geometric average of the absolute values of the two correlation coefficients, \( \tau^p_i = \sqrt{|\rho^t_i| \times |\rho^p_i|} \). The temperature and precipitation series are obtained from Villoria and Delgado (2017), who use the online database of the University of East Anglia Climatic Research Unit (Harris et al 2014) to construct crop-specific average growing season temperature and precipitation variables for each crop-producing country.

Another potential source of geographical heterogeneity in the ENSO-yield relationship is the level of economic development of a country. The reasoning here is similar to that put forward by Dell et al (2012), albeit in the context of ENSO-related year-to-year weather variation. Thus, for each country, we first calculate the average GDP per capita (in terms of 2010 US dollars) over the 2001–2015 period. We then obtain the measure of economic development, denoted by \( \lambda_i \), as the natural logarithm of this average. That is, \( \lambda_i = \ln \{ \bar{G}_i \} \), where \( \bar{G}_i \) is the average real GDP per capita of that country. The economic data were collected from the World Development Indicators—the World Bank’s online database.

![Figure 1. Geographical distribution of expected maize yields (in metric tonnes per hectare). For each country, the expected yield is obtained by fitting a quadratic trend to the natural logarithm of the yield series and subsequently exponentiating the fitted values for year 2010.](image-url)

---

⁴ Expected yields are obtained by fitting a quadratic trend to the natural logarithm of the yield series and subsequently exponentiating the fitted values for year 2010.
Figure 2 offers insights on the associations among key variables of interest: high maize yields in higher income temperate countries that tend to be weakly teleconnected with ENSO; low maize yields in lower income tropical countries, which may be strongly or weakly teleconnected with ENSO. Put differently, while there is a strong positive correlation between country income levels and their latitudinal distance from the equator, there appears to be negative, albeit weak, relationship between the measures of economic development and teleconnection.

3. The econometric model

We estimate the relationship between the annualized measure of the SST anomaly, $s_{it}$, and the natural log of a crop yield in country $i$ at time $t$, $y_{it}$, in a fixed effects setting. A basic representation of this model is given by:

$$ y_{it} = \beta s_{it} + \mu_i + \delta_i(t) + \varepsilon_{it}, $$

where $\varepsilon_{it}$ is an error term with zero mean and constant variance; $\beta$ represents a semi-elasticity measure of yield with respect to a 1°C change in $s_{it}$; $\mu_i$ is a fixed effect that controls for country-specific time invariant factors; $\delta_i(t)$ denotes country-specific trend, which here is modeled as a quadratic trend.

The foregoing specification assumes a linear, i.e. symmetric, relationship between the SST anomaly and maize yields. But empirical evidence indicates that this relationship is likely asymmetric (e.g. Iizumi et al 2014, Anderson et al 2017). To allow for asymmetries, we interact $s_{it}$ with a Heaviside indicator function, $d_{it} \equiv I(s_{it} \geq 0)$, that takes the value one when $s_{it} \geq 0$, and zero otherwise. In addition to asymmetries, it is plausible that yield responses to ENSO shocks vary across countries. We consider two sources of such geographical heterogeneity. One, motivated by Hsiang and Meng (2015), is based on the association of a given country’s weather with the SST anomalies in the Niño3.4 region. That is, ENSO shocks are likely to have greater impact on strongly teleconnected rather than weakly teleconnected countries. The other, motivated by Dell et al (2012), is based on the economic development of a country. That is, not only high income countries are less prone to ENSO-related weather shocks, but they are also more resilient to (i.e. better equipped to deal with) these shocks, compared to lower income countries. Unlike the aforementioned studies, we do not assign countries to the different groups, however. Instead, we introduce nonlinear (smooth transition) functions of the economic development and the teleconnection measures—i.e. $\lambda_i$ and $\tau_i$—given by $g(\lambda_i; \gamma, c)$ and $g(\tau_i; \gamma, c)$, respectively, and as such, allow for a continuum of effects across different possible regimes. Finally, to account for possible lag dependence in yields, we add lagged dependent variable to the regression. This results in the following heterogeneous panel specification:

$$ y_{it} = \beta'_0 s_{it} + \beta'_1 s_{it} g(\lambda_i; \gamma_1, \epsilon_1) + \beta'_2 s_{it} g(\tau_i; \gamma_2, \epsilon_2) + \phi y_{i,t-1} + \mu_i + \delta_i(t) + \varepsilon_{it}, $$

where $s_{it} = [s_{it} (1 - d_{it}), s_{it} d_{it}]'$, and $\beta_j$, $j = 0, 1, 2$, is the associated vector of the parameters, and where the heterogeneity stems from the interaction of location-specific transition functions with the regime-specific effects. These transition functions are designed
Table 1. Estimated effects of the SST anomalies.

|               | Weakly teleconnected | Strongly teleconnected |
|---------------|----------------------|------------------------|
| Low income    |                      |                        |
| El Niño       | -0.061 (0.030)       | -0.209 (0.078)         |
| La Niña       | -0.002 (0.025)       | -0.049 (0.040)         |
| High income   |                      |                        |
| El Niño       | 0.036 (0.029)        | -0.113 (0.057)         |
| La Niña       | -0.003 (0.025)       | -0.050 (0.040)         |

Note: The table entries are estimated long-term effects associated with positive (El Niño) and negative (La Niña) SST deviations in each of the four extreme regimes; the values in parentheses are heteroskedasticity consistent standard errors, adjusted for spatial (2000 km) and temporal (one year) correlation (Conley 1999).

to be bounded by zero and one, wherein \( \gamma \) and \( \epsilon \) are smoothness and centrality parameters that govern the shape of these functions. A notable distinction of the present study from the previous studies is that the threshold (i.e. the inflection point) that divides countries into poor versus rich countries (as in Dell et al 2012), or teleconnected versus weakly affected countries (as in Hsiang and Meng 2015), is not predetermined, but rather it is estimated in the nonlinear regression setting. As a final note, SST anomalies are mediated to the crop yield variability primarily via the weather variables (i.e. temperature and precipitation), but possibly also via other channels (e.g. extreme climatic events not captured by the conventional weather variables, expected prices that affect crop producers’ decision making, etc.). Therefore, the estimated parameters here capture all channels through which SST anomalies manifest in crop yield variability (refer to Technical appendix for further discussion on this matter).

4. Results and discussion

Table 1 presents the estimated effects of SST anomalies associated with each of the four regimes, while the estimated transition functions are illustrated in figure 3.

Several key findings emerge here. First, the relationship between SST anomalies and maize yields is most evident in the strongly teleconnected countries, but is largely absent in the weakly teleconnected countries. A positive 1 °C SST deviation may result in 11%–21% yield reduction in the strongly teleconnected countries. This finding is expected and, in effect, it validates the weather link between SST anomalies and maize yields.

Second, the relationship between SST anomalies and maize yields is amplified in lower income countries. The difference in yield reduction, due to a positive 1 °C SST deviation, is 10% between the lowest income and highest income countries in the sample. Because we account for the teleconnection in the regression setting, this finding suggests that there may be additional ENSO-related factors (e.g. extreme weather events not measured by temperature and precipitation that we applied to obtain the teleconnection measure) that result in yield reduction in lower income countries, and that these countries are less resilient (or unable to effectively adapt in the short term) to El Niño-like conditions, compared to high income countries.

Third, while it is a positive deviation in SST (i.e. the El Niño-like conditions), rather than a negative deviation in SST (i.e. the La Niña-like conditions), that strongly impacts yields, both these events are potentially damaging in the teleconnected countries. Notably, the effect of a negative SST deviation is qualitatively and quantitatively similar in countries from both income groups. In the teleconnected countries, a negative 1 °C SST deviation results in 5% (statistically insignificant) yield reduction. That yield reduction during El Niño conditions is not balanced out by yield increase during La Niña conditions is an important finding, as it implies that on average ENSO cycles are yield-reducing in the affected countries.

Fourth, the transition between the low income and high income regimes is smooth. That is, majority of the countries in consideration fall between the estimated extreme regimes. On the other hand, a switch between weakly teleconnected and strongly teleconnected countries happens almost instantaneously, at approximately 0.4. The effect of these results are illustrated in figures 4 and 5. A positive 1 °C deviation in SST results in 10%–15% yield reduction in the affected higher income countries, and as much as 20% yield reduction in the affected low income countries that are predominantly located in southeastern tier of Sub-Saharan Africa, as well as Central America, South Asia, and Australia. A complete list of countries is presented in the appendix table D1.

Several implications follow from these results. First, on a local scale, we find clear indication that El Niño-like conditions are most detrimental to maize yields in low income countries. In these countries maize is an important element of the agricultural sector (as measured by its share of area harvested relative to the total agricultural land). Thus, adverse effects of El Niño shocks on household incomes are likely to be substantial. Indeed, majority of recent famines in Sub-Saharan Africa have been in some way associated with ENSO events.

Second, because maize is mostly supplied by the countries that are hardly affected by ENSO shocks (see

---

\(^5\) Equation (2) represents the modeling framework, put forward by González et al (2017), that can be seen as an extension of univariate smooth transition regressions in the time series setting Luukkonen et al (1988), Eitrheim and Terasvirta (1996) or as a generalization of the panel threshold model of Hansen (1999) with potentially gradual, rather than instantaneous, switches between two (or more) regimes. See Technical appendix for more details on the transition functions, as well as the model selection, estimation, and evaluation specificities.
appendix figure D1), the global effect on maize yields is small, suggesting little pressure on the prices. This finding is consistent with Ubilava (2018), who found little evidence for cereal grain price responses to ENSO shocks. Thus, because a considerable share of major maize exporters are largely unaffected by ENSO shocks, there is an opportunity for global risk sharing, be that via trade or international aid, from higher income/weakly teleconnected countries to lower income/strongly teleconnected countries.
Third, the asymmetry of maize yield responses to positive and negative SST deviations suggests that, for example, a negative yield impact of an El Niño event in the strongly teleconnected countries is not subsequently balanced out by the positive yield impact of a La Niña event. To the extent that extreme ENSO events are anticipated to become more frequent due to climate change (Cai et al 2014, 2015), this finding suggests that, in the absence of adaptation, ENSO cycles can become more damaging for the strongly teleconnected countries in the future. To that end, the aforementioned international involvement in mitigating the negative impacts of ENSO shocks is to become more crucial with time.

This study is not without caveats and limitations. These are primarily related to the ‘data issues.’ In the presented analysis, we rely on the national yield data. While these data give us sufficient information to conduct an econometric analysis and answer the key question of interest—does economic development of a country play a role in the climate-production nexus?—more detailed yield data could possibly unveil additional intricacies of this relationship, which may be camouflaged in the national aggregates. We retain this as one of the interesting and important directions for future research.

5. Conclusion

We find that the effect of ENSO events, as measured by SST anomalies, is most pronounced in lower income strongly teleconnected countries. We also find that the ENSO effect is asymmetric: it is evident during El Niño–like conditions, and virtually nonexistent during La Niña–like conditions. These findings point to potential benefits of risk sharing—over time and across space—particularly as it relates to food programs directed to low income countries. In absence of adaptation, the issue is likely to become more crucial with climate change, due to a possibility of more frequent ENSO cycles.

Acknowledgments

We would like to thank Weston Anderson, Jesse Tack, and Nelson Villoria for their valuable suggestions on the earlier version of the manuscript. We are also grateful to the editor and the anonymous reviewers for their helpful comments on the manuscript.

Appendix A. Smooth transition functions and estimated effects

Consider a PSTR (equation (2) in the main text):

\[
y_{it} = \beta_0 s_{it} + \beta_1 s_{it} g(\gamma_1, \varepsilon_i) + \beta_2 s_{it} g(\gamma_2, \varepsilon_i) + \mu_i + \delta_i(t) + \epsilon_{it},
\]

where \( y_{it} \) is the dependent variable, \( s_{it} \) is a vector of independent variables, \( \mu_i \) is a country fixed effect, and \( \delta_i(t) \) is a trend component, and \( \beta_j, j = \{0, 1, 2\}, \) are set of parameters to be estimated; \( \epsilon_{it} \) is an idiosyncratic error term. Of interest here are transition functions, \( g(\gamma_i; \gamma, \sigma), \gamma_i = [\lambda_i, \tau_i], \) which are bounded by zero and one, by construction. While several possible functional forms can satisfy such a requirement, here we consider a logistic functional form, given by:

\[
g(\gamma_i; \gamma, \sigma, \gamma) = \left\{1 + \exp\left(-\gamma \prod_{j=1}^{m} \left(\frac{\pi_j - c_m}{\sigma_j}\right)\right)\right\}^{-1},
\]

where \( \pi_i \) is a transition variable and \( \sigma_j \) is its standard deviation, the role of which is to make the smoothness parameter, \( \gamma \), unit-free. In practice, it is sufficient to consider the \( m = 1 \) and \( m = 2 \) cases of this transition function (González et al 2017). When \( m = 1 \), we have a single centrality parameter, \( c \), and for relatively low

![Figure 5. The distribution of the effects (in percentage terms) of positive (El Niño) and negative (La Niña) 1°C SST deviations on maize yields in (a) lower income countries and (b) higher income countries. The grouping here is based on the estimated transition function, wherein countries associated with g(\( \lambda_i, \gamma_i, \varepsilon_i \)) < 0.5 fall into the lower income category.](image)
values of $\gamma$, $g(\pi; \gamma, c)$ is a monotonically increasing function, which takes the value 0.5 when $\pi = c$. It converges to a constant when $\gamma \to 0$, and it becomes a Heaviside indicator function of $\pi - c$ that mimics a discrete jump across regimes as $\gamma \to \infty$, $g(\pi; \gamma, c)$. When $m = 2$, we have two centrality parameters, $c_1$ and $c_2$, and for relatively low values of $\gamma$, $g(\pi; \gamma, c)$ is an inverse bell-shaped function, which reaches the minimum at $(c_1 + c_2)/2$ and attains its maximum at both the low and high values of $s_y$. As in the previous instance, $g(\pi; \gamma, c)$ converges to a constant when $\gamma \to 0$, while as $\gamma \to \infty$, it becomes a Heaviside indicator function with three regimes, of which the outer regimes are identical to each other and different from the ‘inner’ regime.

The foregoing modeling setup offers a number of possible effects to be estimated. More specifically, at the extreme, four possible effects can be identified as illustrated below. In addition, a wide range of effects can also be available, for instance, when $0 < g(\lambda_i; \gamma, c_1) < 1$ and $0 < g(\tau_i; \gamma, c_2) < 1$.

\[
\begin{align*}
g(\tau_i; \gamma, c_1) = 0 & \quad \beta_0 \\
g(\tau_i; \gamma, c_1) = 1 & \quad \beta_0 + \beta_1 \\
g(\lambda_i; \gamma, c_2) = 0 & \quad \beta_2 \\
g(\lambda_i; \gamma, c_2) = 1 & \quad \beta_0 + \beta_2 \\
\end{align*}
\]

**Table B1.** Homogeneity and misspecification tests.

| Transition variable: $\lambda_i$ | Transition variable: $\tau_i$ |
|---------------------------------|--------------------------------|
| $m = 1$ | $0.007$ | $0.001$ |
| $m = 2$ | $0.030$ | $0.001$ |
| $m = 2$ | $0.196$ | $0.128$ |

**Note:** The entries are probability values of LM-type (F-version) tests for hypotheses under consideration; the entries in the brackets are probability values of the heteroskedasticity and autocorrelation consistent variant of the tests.

The superscript ‘a’ next to an entry indicates that the actual probability value is less than that reported here.

**Appendix B. Linearity (homogeneity) testing**

Because PSTR is nonlinear in parameters, we cannot directly test restrictions in the model. This issue, better known as the Davies’ problem (Davies 1977, 1987), is due to the unidentified nuisance parameters. Put simply, the PSTR is not identified if the true model is homogeneous (González et al. 2017). As a workaround, we can test the homogeneity hypothesis in an auxiliary regression framework, which involves Taylor series expansion, initially put forward for nonlinear time series models (Luukkonen et al. 1988, Terasvirta and Anderson 1992) and subsequently adopted for the PSTR (González et al. 2017).

To obtain the auxiliary regression, we set up a linear fixed effects model, and interact the independent variables with polynomials of the candidate transition variables (i.e. $\lambda_i$ and $\tau_i$). This results in a auxiliary regression of the following form:

\[ y_{it} = \phi_0 s_{it} + \sum_{m=1}^{2} \phi_m s_{it} \pi_i^m + \mu_i + \epsilon_{it}^a, \]

where $\pi_i$ is one of the two transition variables of interest. The parameter vectors $\phi_0$, $\phi_1$ and $\phi_2$ are functions of the parameters, including those of the transition function; the error term combines the original error of the PSTR model and the remainder term due to the approximation. Under the null hypothesis, $\epsilon_{it}^a = \epsilon_{it}$. Therefore, the Taylor series expansion does not affect the asymptotic distribution theory, and thus, Lagrange multiplier (LM)-type tests can be applied for hypotheses testing (González et al. 2017). The two null hypotheses of interest are: $H_0^\lambda$: $\phi_1 = \phi_2 = 0$, and $H_0^\tau$: $\phi_1 = 0|\phi_2 = 0$. If we fail to reject both of these hypothesis, the homogeneous model is then considered to be consistent with the underlying data. Otherwise, if the rejection of $H_0^\lambda$ is the strongest, we set $m = 1$, and if the rejection of $H_0^\tau$ is the strongest, we set $m = 2$ in the transition function.

The results of the homogeneity test are presented in panel (a) of table B1. As shown, homogeneity is strongly rejected when either $\lambda_i$ or $\tau_i$ are used as transition variables. In both instances, the heteroskedasticity and autocorrelation consistent variant of the test favor $m = 1$ in the transition function. Therefore, we sequentially picked each of the transition variables and set $m = 1$ to estimate the two-regime PSTR model. That is, we first estimated a PSTR using either $\lambda_i$ or $\tau_i$ as a transition variable. We then tested the estimated PSTR for no remaining heterogeneity related to each of the two transition variables. The results of these tests show evidence of remaining heterogeneity with regard to the other transition variable, as shown in panel (b) of table B1. That is, when the two-regime PSTR model uses $\lambda_i$ as the transition variable, there is evidence of remaining heterogeneity with regard to $\tau_i$, and vice versa. Therefore, both tests indicate that a four-regime PSTR may be a suitable model. Indeed, after estimating a four-regime PSTR, there remains no further evidence of unaccounted heterogeneity, as shown in panel (c) of table B1. Therefore, we rely on...
the specification given by equation (2) to generate the main results of this study.

Appendix C. Remarks on the use of mediators and controls

In the applied regression, the parameters are total effects of SST anomalies maize yield variability. The potential channels through which SST impacts yields include the key weather variables, i.e. temperature and precipitation, but may also include additional links through which ENSO can influence crop yield variability. These could be extreme climatic events not captured by the conventional weather variables, as well as non-weather variables, e.g. expected prices, that affect crop producers’ decision making. To the extent that these variables are influenced by ENSO, they are the outcome of the natural experiment, and represent mediators in the ENSO-yield relationship. That is, they are post-treatment variables, whereby treatment is an ENSO event. By not including them in the regression setting, we are not inducing the omitted variable bias (Hsiang and Burke 2013, Smith and Ubilava 2017). Quite the contrary, if we were to include these variables in the regression setting, they would serve as ‘bad controls’ and would introduce the so-called ’post-treatment bias’ to the estimated coefficients (Angrist and Pischke 2008, Acharya et al 2016, Montgomery et al 2018).

Notably, in the regression setting, we could ‘safely’ use other controls, i.e. variables that are uncorrelated with SST anomalies but are known to affect yields. By doing so, however, we would merely improve the efficiency of the estimated coefficient. To that end, we can think of the currently reported standard errors as their upper bound. In summary, because the goal here is to estimate the total effect of SST anomalies on maize yields, there would be little benefit (i.e. efficiency gains) and possibly more harm (i.e. post-treatment bias) if we were to control for additional factors in the model. On the other hand, because there are no known phenomena or events that simultaneously cause ENSO cycle and crop yields (as well as factors affecting crop yields), the currently specified model does not suffer from the omitted variable bias.

Appendix D. Heterogeneity of El Niño impacts across countries
The scatterplots illustrate yield effects in the context of income (measured as the natural logarithm of average real GDP per capita over the 2001–2015 period), teleconnection (measured as the geometric average of the correlation between SST anomalies and temperature and precipitation over the 1961–2014 period), and (a) share of maize area harvested (measured as a ratio of the average maize area harvested and average area of agricultural land over the 2001–2015 period), (b) average production (measured in million metric tones over the 2001–2015 period), (c) average area harvested (measured in million hectares over the 2001–2015 period), (d) average exports (measured in thousand metric tones over the 2001–2015 period). The data on exports are obtained from USDA/FAS Production, Supply and Distribution online database. The other data sources are presented in the Data Description section.
| Country     | Export | Area | Country     | Export | Area | Country     | Export | Area | Country     | Export | Area |
|-------------|--------|------|-------------|--------|------|-------------|--------|------|-------------|--------|------|
| Greece      | 0.0    | 2.9  | Thailand    | 0.5    | 5.4  | Egypt       | 0.0    | 25.5 | El Salvador | 0.0    | 17.0 |
| Romania     | 0.0    | 18.6 | South Africa| 1.5    | 2.9  | Nepal       | 0.0    | 20.7 | India       | 2.1    | 4.5  |
| Albania     | 0.0    | 4.4  | Australia   | 0.0    | 0.0  | Madagascar  | 0.0    | 0.6  | Zambia      | 0.2    | 3.4  |
| Poland      | 0.0    | 2.6  | Colombia    | 0.0    | 1.3  | Nigeria     | 0.1    | 6.2  | Malawi      | 0.1    | 29.7 |
| Italy       | 0.0    | 7.1  | Botswana    | 0.0    | 0.2  | Burkina Faso| 0.0    | 5.2  | Zimbabwe    | 0.0    | 9.3  |
| Bulgaria    | 0.0    | 7.0  | Costa Rica  | 0.0    | 0.4  | Sri Lanka   | 0.0    | 1.7  | Mozambique  | 0.0    | 3.3  |
| Austria     | 0.0    | 7.2  | Vietnam     | 0.1    | 10.3 | Tanzania    | 0.1    | 8.5  |            |        |      |
| Hungary     | 0.0    | 21.0 | Philippines | 0.0    | 21.5 | Benin       | 0.0    | 23.3 |            |        |      |
| Portugal    | 0.0    | 3.0  | Morocco     | 0.0    | 0.7  | Pakistan    | 0.1    | 2.9  |            |        |      |
| South Korea | 0.0    | 0.9  | Indonesia   | 0.1    | 6.9  | Ethiopia    | 0.0    | 5.4  |            |        |      |
| Chile       | 0.1    | 0.8  | Kenya       | 0.0    | 6.8  |            |        |      |            |        |      |
| Germany     | 0.0    | 2.7  | Cambodia    | 0.2    | 2.5  | Laos        | 0.2    | 7.3  |            |        |      |
| Switzerland | 0.0    | 1.2  |            |        |      | Cameroon    | 0.0    | 7.6  |            |        |      |
| Spain       | 0.0    | 1.5  |            |        |      |            |        |      |            |        |      |
| France      | 0.0    | 5.9  |            |        |      |            |        |      |            |        |      |
| Turkey      | 0.1    | 1.3  |            |        |      |            |        |      |            |        |      |
| Argentina   | 15.4   | 2.3  |            |        |      |            |        |      |            |        |      |
| New Zealand | 0.0    | 0.2  |            |        |      |            |        |      |            |        |      |
| Uruguay     | 0.1    | 0.5  |            |        |      |            |        |      |            |        |      |
| United States| 49.9 | 7.7  |            |        |      |            |        |      |            |        |      |
| Panama      | 0.0    | 2.4  |            |        |      |            |        |      |            |        |      |
| Canada      | 0.7    | 1.9  |            |        |      |            |        |      |            |        |      |
| Ecuador     | 0.0    | 5.9  |            |        |      |            |        |      |            |        |      |
| Paraguay    | 1.6    | 3.4  |            |        |      |            |        |      |            |        |      |
| Mexico      | 0.3    | 6.6  |            |        |      |            |        |      |            |        |      |
| Peru        | 0.0    | 2.1  |            |        |      |            |        |      |            |        |      |
| Brazil      | 11.3   | 4.9  |            |        |      |            |        |      |            |        |      |

**Note:** The table entries are in percentage terms. The columns headed by *Export* include the share of maize exports relative to the world exports (measured as the average of the shares over the 2001–2015 period); the columns headed by *Area* include the share of maize area harvested relative to the area of agricultural land in a given country (measured as the share of averages over the 2001–2015 period). The values underneath the *Export* and the *Area* headings indicate the sum and the average of the entries in these columns. The data on exports are obtained from USDA/FAS Production, Supply and Distribution online database. The other data sources are presented in the Data Description section.
Hsiau S M 2010 Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America Proc. Natl Acad. Sci. 107 15367–72
Hsiau S M, Burke M and Miguel E 2013 Quantifying the influence of climate on human conflict Science 341
Hsiau S M and Meng K C 2015 Tropical economics Am. Econ. Rev.: Papers Proc. 105 257–61
Iizumi T, Luo J J, Challinor A J, Sakurai G, Yokozawa M, Sakuma H, Brown M E and Yamagata T 2014 Impacts of El Niño southern oscillation on the global yields of major crops Nat. Commun. 5 3712
Iotii M, Lohmann G, Rimbu N, Chekka S and Dima M 2012 Interannual to decadal summer drought variability over europe and its relationship to global sea surface temperature Clim. Dyn. 38 363–77
Legler D, Bryant K and O’Brien J 1999 Impact of ENSO-related climate anomalies on crop yields in the US Clim. Change 42 351–75
Luukkonen R, Saikkonen P and Terasvirta T 1988 Testing linearity against smooth transition autoregressive models Biometrika 75 491–9

References

Acharya A, Blackwell M and Sen M 2016 Explaining causal findings without bias: detecting and assessing direct effects Am. Political Sci. Rev. 110 512–29
Adams R, Chen C, McCrall B and Weiher R 1999 The economic consequences of enso events for agriculture Clim. Res. 13 165–72
Adams R M, Houston I L, McCrall B A, M Tiscareño L M, Matus G J and Weiher R F 2003 The benefits to mexican agriculture of an El Niño-Southern Oscillation (ENSO) early warning system Agric. Forest Meteorol. 115 183–94
Amissah-Arthur A, Jagtap S and Rosenzweig C 2002 Spatio-temporal effects of El Niño events on rainfall and maize yield in Kenya Int. J. Climatol. 22 1849–60
Anderson W, Seager R, Baethgen W and Cane M 2017 Crop production variability in north and south america forced by life-cycles of the El Niño southern oscillation Agric. Forest Meteorol. 239 151–65
Angrist J D and Pischke J S 2008 Mostly Harmless Econometrics: An Empiricist’s Companion (Princeton, NJ: Princeton University Press)
Barlow M, Nigam S and Berbery E 2001 ENSO, pacific decadal variability, and US summertime precipitation, drought, and stream flow J. Clim. 14 2105–28
Bulíč H and Kucharski F 2012 Delayed ENSO impact on spring precipitation over North/Atlantic european region Clim. Dyn. 38 2593–612
Cai W et al 2014 Increasing frequency of extreme El Niño events due to greenhouse warming Nat. Clim. Change 4 111–6
Cai W et al 2015 Increased frequency of extreme La Niña events under greenhouse warming Nat. Clim. Change 5 132–7
Cane M A, Eshel G and Buckland R W 1994 Forecasting zimbabwean maize yield using eastern equatorial pacific sea surface temperature Nature 370 204–5
Cashin P, Mohaddes K and Raisi M 2017 Fair weather or foul? The macroeconomic effects of El Niño J. Int. Econ. 196 37–54
Conley T G 1999 GNM estimation with cross sectional dependence J. Econometrics 92 1–45
Davies R 1977 Hypothesis testing when a nuisance parameter is present only under the alternative Biometrika 64 247–54
Davies R 1987 Hypothesis testing when a nuisance parameter is present only under the alternative Biometrika 74 43–43
Dell M, Jones B F and Olken B A 2012 Temperature shocks and economic growth: evidence from the last half century Am. Econ. J.: Macroecon. 4 66–95
Eitzenhem O and Terasvirta T 1996 Testing the adequacy of smooth transition autoregressive models J. Econometrics 74 59–75
González A, Terasvirta T, Dijk D V and Yang Y 2017 Panel smooth transition regression models CREATES Research Paper 2017-36 Department of Economics and Business Economics (Aarhus University)
Handler P 1984 Corn yields in the united states and sea surface temperature anomalies in the equatorial pacific ocean during the period 1868–1982 Agric. Forest Meteorol. 31 25–32
Hansen B E 1999 Threshold effects in non-linear panel estimation, testing, and inference J. Econometrics 93 345–68
Harris I, Jones P, Osborn T and Lister D 2014 Updated high-resolution grids of monthly climatic observations—the CRU TS3.10 dataset Int. J. Climatol. 34 623–42
Hertel T W and Lobell D B 2014 Agricultural adaptation to climate change in rich and poor countries: current modeling practice and potential for empirical contributions Energy Econ. 46 562–75
Hsiang S, Meng K and Cane M 2011 Civil conflicts are associated with the global climate Nature 476 438–41

ORCID iDs

David Ubilava https://orcid.org/0000-0002-8993-6766
Stige L C, Stave J, Chan K-S, Ciannelli L, Pettorelli N, Glantz M, Herren H R and Stenseth N C 2006 The effect of climate variation on agro-pastoral production in Africa Proc. Natl Acad. Sci. USA 103 3049–53

Stone R, Hammer G and Marcussen T 1996 Prediction of global rainfall probabilities using phases of the southern oscillation index Nature 384 252–5

Tack J and Ubilava D 2013 The effect of El Niño southern oscillation on US corn production and downside risk Clim. Change 121 689–700

Terasvirta T and Anderson H 1992 Characterizing nonlinearities in business cycles using smooth transition autoregressive models J. Appl. Econometrics 7 S119–36

Ubilava D 2018 The role of El Niño southern oscillation in commodity price movement and predictability Am. J. Agric. Econ. 100 239–63

Villoria N B and Delgado M S 2017 Worldwide crop supply responses to El Niño southern oscillation 2017 Agricultural & Applied Economics Association Annual Meeting (selected paper prepared for presentation) (Chicago, IL, 30 July–1 August)