THE UNIVERSITY OF SYDNEY

Economics Working Paper Series

2017 - 11

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April 2017

The El Niño Southern Oscillation and Economic Growth in the Developing World*

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April 18, 2017

Abstract

The El Niño Southern Oscillation (ENSO) affects weather around the globe. Through weather, ENSO thus can influence multiple factors of economic growth. Developing countries can be particularly susceptible to this climate phenomenon, as they typically lie in regions most affected by ENSO, and also because their economies tend to be most vulnerable to weather anomalies. In this study, we investigate the effect of ENSO on economic growth in 75 developing countries using (unbalanced) panel of annual data spanning 1961–2015 period. We find asymmetries in the growth response to ENSO shocks. An El Niño event results in up to one percent annual growth reduction, on average. A La Niña event, however, does not result in a growth increase of similar magnitude. We also find evidence of heterogeneity of ENSO events across climatic zones as well as continents. The effect of ENSO events is considerably larger in the tropical zone (relative to the temperate zone), where both El Niño and La Niña events have a growth–reducing impact. On a regional level, the negative impact of an El Niño is particularly pronounced in Africa, while both El Niño and La Niña events have a growth–reducing impact in Asia-Pacific. Findings of this study have two important implications. From the modeling standpoint, we find that the growth impacts of ENSO are nonlinear, and they vary across regions and climatic zones. From the policy-making standpoint, our findings suggest opportunities for short-term adjustments to climate shock management and international aid programs, depending on the existing state and the intermediate-term patterns of the ENSO cycle.

Keywords: Climate Shocks; Developing Countries; Economic Growth; El Niño Southern Oscillation; Nonlinear Effect

JEL Codes: O44; Q54; R11

*This paper has evolved from Sarah C. Smith's honours thesis, which she prepared as a student of the University of Sydney. From that version to the current, there are important changes in research execution and results. We thank Kadir Atalay, Colin Cameron, and Kevin Schnepel for their valuable comments and suggestions. Errors are ours.

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1 Introduction

Throughout the course of human history, climate has been an important factor in the development of nations, and it has also played a role in the demise of civilizations (Acemoglu et al., 2001; Haug et al., 2003; Tsonis et al., 2010). The link is hardly surprising, given the intrinsic nature of the relationship between weather and socio-economic variables (Raddatz, 2007; Noy, 2009; Burke et al., 2015a). To that end, economic consequences of climate shocks have been most evident for countries located closer to the equator, where weather extremes tend to be more frequent (Masters and McMillan, 2001; Sachs, 2001; Hsiang, 2010; Dell et al., 2012, 2014). The economic growth of developing countries can be more susceptible to climate variability, because these countries tend to be more dependent on sectors that are climate sensitive (e.g., agriculture and tourism), and also because developing countries are known to be poor "shock absorbers" of weather disasters (Loayza et al., 2007; Noy, 2009). Incidentally, weather patterns in the tropics, more so than in the temperate regions, are influenced by the El Niño Southern Oscillation (ENSO)—a climate phenomenon that occurs in the Pacific but has global weather implications (Hsiang et al., 2011; Hsiang and Meng, 2015). While ENSO can possibly affect an array of economic factors, the overarching goal of this study is to examine the overall economic growth impact of ENSO events in developing countries.

The ENSO phenomenon is the greatest source of inter-annual climate variability, owing to its strong presence in the Pacific and transmissions across the world (Zebiak et al., 2015). This climate anomaly comprises of two extreme phases that are referred to as *El Niño* (the *warm phase*) and *La Niña* (the *cool phase*). These deviations from an expected climatology—hence the term "climate anomaly"—re-occur irregularly every three-to-seven years to form the ENSO cycle. El Niño events are characterised by weakening trade winds, which typically cause droughts in Southeast Asia and Oceania and wetter-than-usual conditions over the western tier of the Americas. The trade winds intensify during La Niña events, resulting in weather conditions that are opposite to those experienced during El Niño events. Importantly, the effect of ENSO anomalies extend beyond the Pacific region, altering weather patterns in many distant parts of the world. Figure 1 illustrates the global weather effect of the ENSO anomalies, and shows that in addition to Southeastern Asia and Oceania, parts of Africa, Americas, and even Europe can be influenced by ENSO events. Two additional observations can be made from this figure. First, the same event (i.e., an El Niño or a La Niña), can have an opposite weather effect in different regions of the world. Second, the two opposite events (i.e., an El Niño and a La Niña), may not necessarily have an opposite weather effect in the same region.

There are several channels through which ENSO may affect economic growth. The crucial link of this causal chain is ENSO-induced anomalous temperatures and precipitation, as well as extended episodes of droughts and floods, and an intensified storm activity around the globe (Dilley and Heyman, 1995; Iizumi et al., 2014; Hsiang and Meng, 2015). To the extent that weather is the most important factor in agricultural production (Lobell and Field, 2007; Lobell et al., 2011),

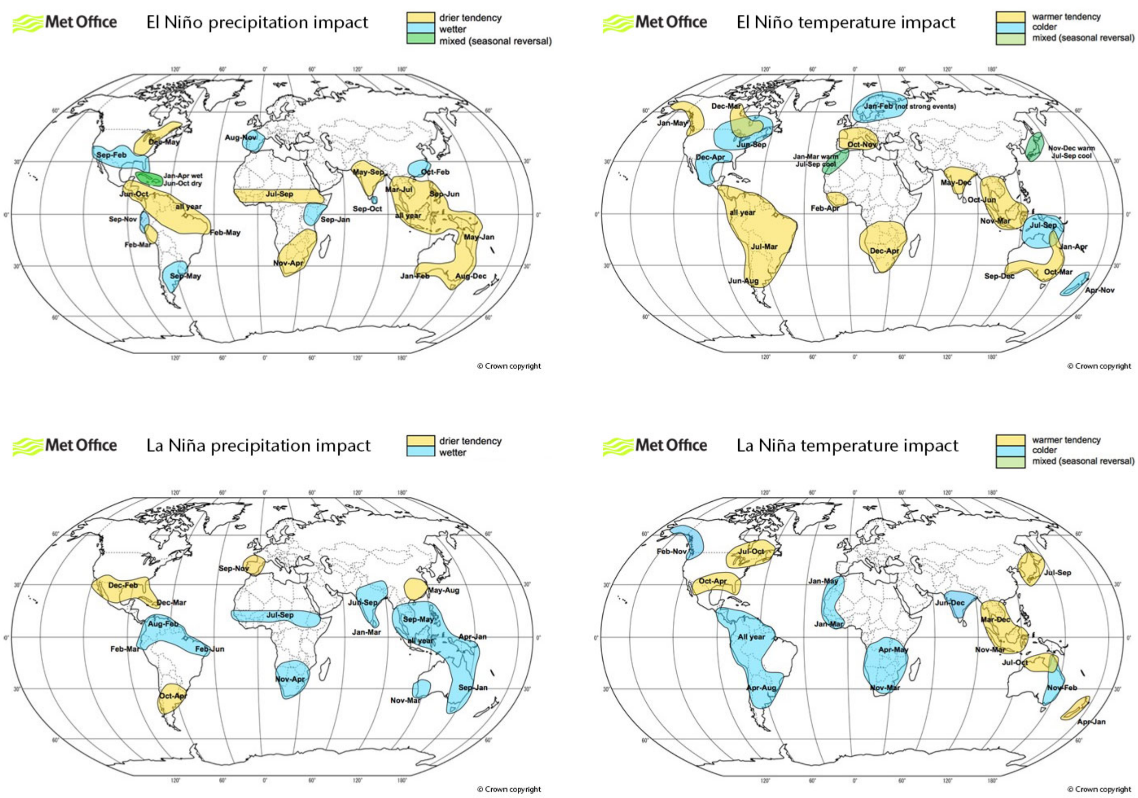

Figure 1: ENSO teleconnections

Source: http://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/el-nino-la-nina/enso-impacts the obvious link in the ENSO–growth relationship is agriculture, which remains to be a nontrivial component of economies in the developing world. In addition, and related to the aforementioned, ENSO influences real prices of some key primary commodity groups (Brunner, 2002; Ubilava, 2012; Ubilava and Holt, 2013; Cashin et al., 2017), and can impact the terms of trade of developing countries. Both commodity price inflation and terms of trade are important factors in economic growth (Barro, 1996). Furthermore, a combination of the food shortage and price spikes can increase an incidence of protests and riots in developing countries that rely on imports (Bellemare, 2015; Hendrix and Haggard, 2015), while commodity price downturns may facilitate civil conflicts in the commodity–exporting regions (Brückner and Ciccone, 2010). In turn, civil conflicts and political instability, which may be attributed to ENSO shocks (Hsiang et al., 2011), can also slow down economic growth (Barro, 1991). Of course, there may be several other—albeit more subtle—channels through which ENSO could affect economic growth. But the main point of the foregoing discussion is that agricultural production is not, by any means, the only link through which ENSO could manifest into economic growth. The corollary is that economic growth in a region can be linked to ENSO shocks even if the weather patterns in this region are not strongly influenced by ENSO *teleconnections*.[1]

To date, several studies have attempted to unveil causal linkages characterizing the relationship between ENSO and economic growth. Brunner (2002) examined the effect of the ENSO anomalies on international commodity prices and economic indicators of the G7 countries, finding up to one-half of a percentage point positive impact on aggregated GDP growth in response to an El Niño shock. Berry and Okulicz-Kozaryn (2008) studied the U.S. inflation and GDP growth responses to ENSO fluctuations, finding no evidence of causality; thus prompting the conclusion that the ENSO signals are either lost in the intricacies of the large economy, or that they are simply absent. Laosuthi and Selover (2007), in accordance with portfolio theory, hypothesized that less diversified or geographically smaller countries would be more likely to exhibit a greater response to ENSO–induced climatic shocks. They found little evidence of ENSO being a significant driver of business cycles during 1950–2000 in a majority of considered countries—notable exceptions include South Africa, Australia and, to some extent, India and Malaysia. Most recently, Cashin et al. (2017) examined the impact of El Niño events on macroeconomic variables of 21 individual countries/regions during the 1979–2013 period. In accord with the aforementioned studies, they found that directly affected countries, such as Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa, experience a brief slowdown in economic activity in response to El Niño shocks, while several developed economies, such as the United States and European region, manifest a growth–enhancing response.

While the previous studies have made notable contributions to the climate–growth literature, particularly in relation to the ENSO cycle, more work needs to be done to further unveil existing

[1]Teleconnection refers to climate and weather anomalies being related at large distances, wherein anomaly is defined as a deviation from the long-term average that characterizes a given climate.

linkages between this climate phenomenon and growth in the developing world. The present study builds upon the existing body of research and contributes to it in several directions. First of all, we analyze the ENSO effect in 75 developing countries in Africa, Asia and the Pacific, and Central and South America—a vast majority of which have yet to be studied in the context of economic growth. Second, we allow for the heterogeneity of ENSO effect across regions. That is, the economic importance and statistical significance of the ENSO effect can vary across regions, and this study allows for such variation. Finally, in this study we emphasize the potentially asymmetric nature of positive and negative ENSO shocks. We argue that El Niño and La Niña events of equivalent scale need not cause the growth rate change of opposite sign and that of similar magnitude. The downside impact of a dry event is likely to be larger than the upside impact of a wet event–in fact, wet events themselves can be damaging to growth because of the increased likelihood of flooding, storms and cyclones. The modeling framework of this study allows for such nonlinearity in the ENSO–growth relationship.

Using an (unbalanced) panel of annual data spanning 1961–2015 period, this study finds that per capita GDP growth rate (from here forward referred to as *economic growth* or *growth rate*) of several considered regions are influenced by ENSO events. El Niño shocks negatively impact growth rates of countries in Sub-Saharan Africa, Asia (including large economies of China and India) and South America. La Niña shocks result in a growth-enhancing outcome for countries in North Africa and Central America, but have negative impact on growth rates in East Asia. We find evidence of heterogeneity of ENSO events across climatic zones as well as continents. The effect of ENSO events is approximately twice–as–large in the tropics, as compared to the temperate climatic zones. By explicitly focusing on developing countries, this study adds considerably to the body of literature that has focused on large economies of developed countries (Brunner, 2002; Berry and Okulicz-Kozaryn, 2008), or a relatively small group of developing countries (Laosuthi and Selover, 2007; Cashin et al., 2017). Findings of this study are important for, at least, two reasons. First, from the modeling standpoint, the effect of ENSO shocks are found to vary in magnitude and direction across different regions of the world. Second, in terms of policy implications, because ENSO shocks can have varying and sometimes opposite effects for different groups of countries, there may be an opportunity for short-term adjustments to international aid programs, depending on the existing state and the expected intermediate-term pattern of the ENSO cycle.

2 The Model

This study applies the fixed effects panel data estimation technique to examine the relationship between ENSO and economic growth. To begin, let y_{it} be the growth rate of country i in period t; and let x_t be the sea surface temperature (SST) anomaly – a proxy continuous variable depicting ENSO occurrence. The following model then can be used to test the relationship between the two variables:

$$y_{it} = \boldsymbol{\theta}'\boldsymbol{x}_t + \boldsymbol{\delta}_i'\boldsymbol{d}_t + \alpha_i + \varepsilon_{it}, \tag{1}$$

where $i = 1, \ldots, N$, and $t = 1, \ldots, T$; further, $\boldsymbol{x}_t = (x_t, x_{t-1})'$ is a vector of the current and lagged SST anomalies; $\boldsymbol{\theta} = (\theta_0, \theta_1)'$ is the parameter vector depicting the effect of ENSO; α_i combines country-specific unobserved effects that, moreover, may be correlated with $\boldsymbol{x}_t$; ε_{irt} is an error term. The model, moreover, may be augmented with country-specific component, $\boldsymbol{\delta}_i'\boldsymbol{d}_t$, where $\boldsymbol{d}_t$ incorporates the deterministic trend or the lagged dependent variables, to account for heterogeneous trends or dynamics in the growth rates. This modeling setup also assumes that the SST anomaly is weakly exogenous; that is, ENSO can contemporaneously impact growth, but the converse is not true. This assumption – which serves as an identification condition – is hardly controversial, and is consistent with that made by previous studies (e.g., Brunner, 2002; Hsiang and Meng, 2015).

The model, as specified in equation (1), assumes linearity and homogeneity in the ENSO effect. That is, economic growth responses to a positive and a negative 1°C deviations in the SST (i.e., the El Niño and La Niña events of equal magnitude) are mirror images of each other; and the effect is similar across the countries in consideration. Neither of these need to be the case, of course. Responses to ENSO shocks are in fact very likely to be asymmetric and also vary across countries. First, ENSO cycles tend to follow asymmetric pattern. In particular, the El Niño events develop somewhat unexpectedly, whereas the La Niña events typically follow the previously realized El Niño-s (Hall et al., 2001; Ubilava and Helmers, 2013). Growth effect of ENSO shocks, due to a number of intermediary channels thus can be very different during El Niño and La Niña phases. Second, the effect of ENSO events on weather in different parts of the world is also nonlinear (Cai et al., 2010). That is, the El Niño and La Niña events do not necessarily manifest into the opposite weather patterns. For example, to the extent that agriculture is a sector that is most susceptible to weather anomalies, both El Niño and La Niña shocks can possibly result in reduced yields in major crop-producing regions (Legler et al., 1999; Mason and Goddard, 2001; Iizumi et al., 2014).

To examine the asymmetric effect of ENSO, we create the El Niño and La Niña variables by interacting the vector of SST anomalies, $\boldsymbol{x}_t$, with $I(x_{t-1} < 0)$ and $I(x_{t-1} \geq 0)$, where $I(\cdot)$ is an indicator function that takes on 1 if the condition inside the parentheses is satisfied, and 0 otherwise. To reliably identify and estimate the country–specific parameters associated with ENSO, we would need a longer time series that captures a large enough number of ENSO cycles (see, also, Chudik et al., 2017). Instead, we opt for a middle ground, and examine region–specific heterogeneity of the ENSO effect. The following augmented version of equation (1) then accounts for the foregoing:

$$y_{irt} = \boldsymbol{\beta}_r'\boldsymbol{x}_t I(x_{t-1} < 0) + \boldsymbol{\gamma}_r'\boldsymbol{x}_t I(x_{t-1} \geq 0) + \boldsymbol{\delta}_i'\boldsymbol{d}_t + \alpha_i + \varepsilon_{irt}, \tag{2}$$

where $r = 1, \ldots, R$ denotes a region, such that $R \ll N$. So, $\boldsymbol{\beta}_r = (\beta_{0r}, \beta_{1r})'$ and $\boldsymbol{\gamma}_r = (\gamma_{0r}, \gamma_{1r})'$ are the vectors of parameters that describe the economic growth effect of ENSO in a given region, associated with the preexisting La Niña or El Niño phase, respectively.

Note that equations (1) and (2) do not feature control variables. While a number of factors may influence the growth rate in a given economy—e.g., inflation, exchange rates, or political instability, to name a few—care is needed when deciding whether or not to include those in the regression (see, e.g., Hsiang et al., 2013; Burke et al., 2015b). A case in point is the so called "bad control"—a variable that itself is an outcome of the experiment at hand (Angrist and Pischke, 2008). In the context of the current exercise, an ENSO shock represents a "natural experiment" that impacts economic growth through multiple channels. These can involve country–specific factors as described above, as well as common factors, such as international (fuel or non-fuel) commodity prices, global business cycles, etc. By controlling for such variables in the model, we could possibly deteriorate the explanatory power and perhaps even introduce bias to the estimate of the ENSO effect. In fact, at the extreme, if we happen to incorporate all the factors through which ENSO affects economic growth, the coefficient describing the ENSO effect will become indistinguishable from zero, prompting to draw a false conclusion about the relationship between this climate anomaly and economic growth (see, also, Hsiang et al., 2013). On the other hand, if we fail to control for factors that impacts growth but are uncorrelated with ENSO, we would forfeit efficiency of parameter estimates, but there should be no concern over omitted variable bias. To summarize, because the ultimate goal here is to estimate the overall effect of ENSO shocks on economic growth, there will be little benefit, and likely more harm, in controlling for additional factors in the model.

3 Data

The measure of economic performance, in this study, is per capita GDP growth rate. Using per capita data has the advantage of scaling economic growth to better reflect the standard of living for citizens of that country. And while this measure alone is not enough to fully capture the multidimensional nature of poverty and development, it is considered in many cases to be a powerful correlate with development (Anand and Harris, 1994; Aturupane et al., 1994). We obtained the growth series for a total of 105 developing countries from World Development Indicators—the electronic data portal of the World Bank. In addition to the growth data, we also obtained (i) agriculture value added (% of GDP), and (ii) employment in agriculture (% of total employment). These variables are to serve as proxies for individual country vulnerability to ENSO–induced weather anomalies.

In selecting the countries for the analysis, we sourced all those, that were classified as *low–income* and *lower–middle–income* economies by the World Bank. In addition, these countries had no missing observations over the 1981–2013 period, although the time–range of the analysis spans from 1961 to 2015. Finally, from this list of countries, we omitted those with population less than one million, as well as those with unusually large growth rate volatility. This left 75 countries for analysis in an unbalanced panel. Table 1 presents some key statistics describing the composition of growth rates, as well as the aforementioned vulnerability measures. Appendix Table A1 offers a more complete, country–specific picture of these variables.

Table 1: Descriptive Statistics of Selected Variables

Countries	n	mean	s.d.	min	max
		Average growth rate			
All	75	1.8	1.5	-1.5	6.9
Temperate/Arid	28	2.2	1.8	-0.7	6.9
Tropical/Humid	47	1.6	1.3	-1.5	4.4
Africa	38	1.3	1.6	-1.5	5.5
Americas	23	2.0	0.8	0.5	3.1
Asia-Pacific	14	3.0	1.7	0.7	6.9
		Average agriculture value added (% of GDP)			
All	62	24.6	12.9	5.6	52.8
Temperate/Arid	36	23.8	13.0	6.9	52.8
Tropical/Humid	26	25.6	13.0	5.6	50.7
Africa	35	28.6	13.3	5.6	52.8
Americas	16	13.8	5.1	6.9	23.6
Asia-Pacific	11	27.7	11.2	8.8	50.7
		Average employment share in agriculture (% of total employment)			
All	57	41.9	21.9	5.4	92.2
Temperate/Arid	33	39.2	22.7	5.4	92.2
Tropical/Humid	24	45.5	20.7	7.3	83.0
Africa	30	49.7	22.4	7.3	92.2
Americas	16	22.4	9.5	5.4	40.7
Asia-Pacific	11	48.6	15.6	21.0	72.7

Note: n denotes the number of countries within each group; the rest are descriptive statistics in percentage terms.

We use the index of SST anomalies in the `Niño3.4` region as the measure of ENSO intensity. The index is sourced from the electronic database of the Climate Prediction Center at the National Oceanic and Atmospheric Administration. The SST anomaly represents the deviations in SST (measured in degree Celsius) in the equatorial Pacific in a given month from its long-run average during the 1980–2010 base period. To obtain the annualized measure of the SST anomaly, we aggregated the monthly indicators during the May–February period to mitigate the effect of the so called "spring barrier" (e.g. Sarachik and Cane, 2010). This approach is comparable with that of Hsiang et al. (2011), with an exception that when aggregating, we use the June–December period of a given year and the January–February period of the following year (see Figure 2 for illustration). Figure 3 illustrates the annualized SST anomaly along with cross-sectionally averaged growth rates. Notably, the time frame in consideration contains several extreme ENSO episodes of the recent history, including the well-documented 1997 El Niño, and strong La Niña occurrences of late 1980s and 1990s.

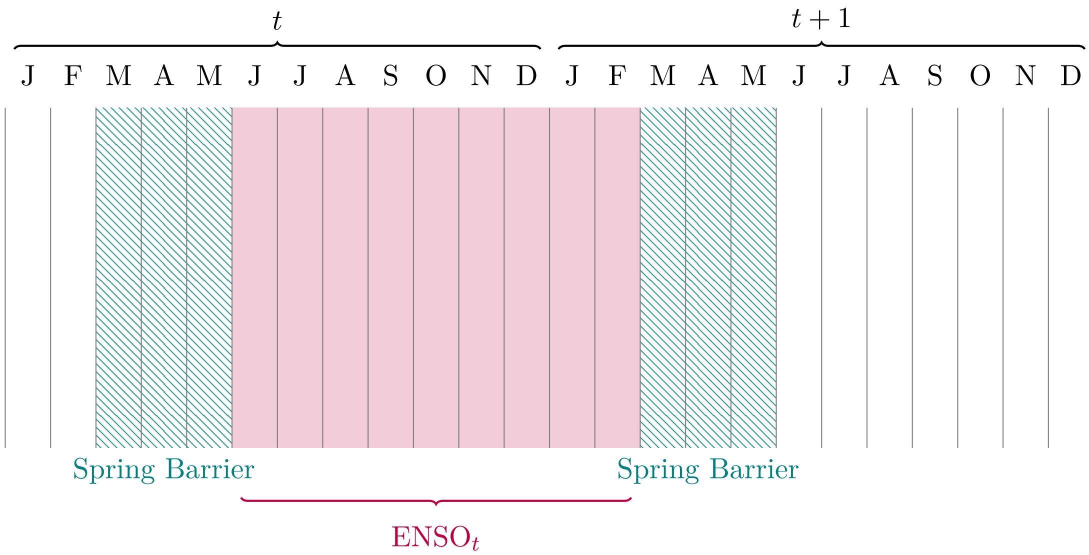

Figure 2: ENSO aggregation

Climatic zones, in this study, are identified based the Köppen–Geiger climate classification (Peel et al., 2007). The country aggregates of climatic zones were obtained from the online database of the Center for International Earth Science Information Network (CIESIN, 2012). In our analysis, the *Tropical/Humid* group includes countries that fall within `Af`, `Am`, `Aw`, and `Cfa` zones of the aforementioned classification. The *Temperate/Arid* group, in turn, includes countries that are predominantly in `Bw`, `Bsh`, `Bsk`, `Cs`, `Cw`, `Cfb`, `Cfc` zones. Figure 4 illustrates the geographical distribution of countries in these two aggregate climatic zones.

4 Estimation and Findings

We begin by estimating the benchmark model, which is a basic linear fixed effects model with homogeneous estimates of contemporaneous and lagged ENSO effect on growth. Table 2 summarizes the results from five candidate model specifications. These variants assume homogeneous effect of ENSO, but differ in the way country–specific trends and short term dynamics are specified. To that end, models 2 through 5 are equivalent to pooled mean group estimator of Pesaran et al. (1999). Notably here, as well as in subsequent tables, the parameter estimates associated with ENSO events are comparable across these five specifications. We find that average growth across the 75 countries is negatively affected by contemporaneous and lagged El Niño events (or, equivalently, positively affected by La Niña events). The foregoing benchmark model is restrictive in two dimensions, as it assumes growth responds linearly to El Niño and La Niña events and that the impact is similar across all countries. We first relax the assumption of linearity. That is, we allow the slope estimates

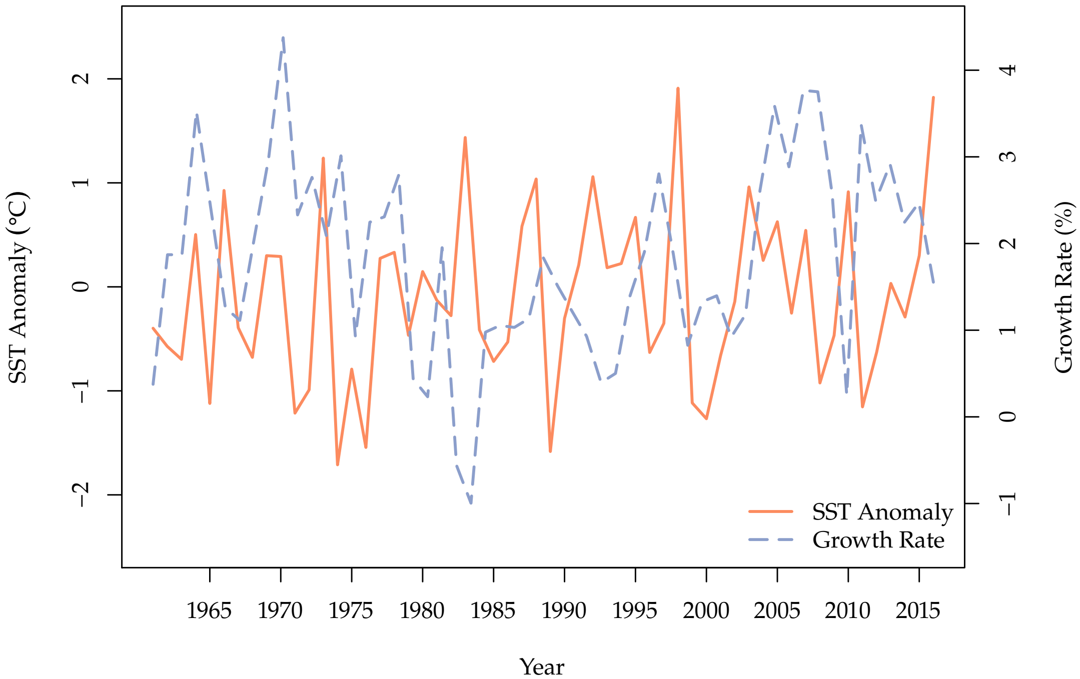

Figure 3: Dynamics of the average economic growth and the ENSO cycle

Note: SST Anomaly is seasonal average of the monthly index, where the season is defined as nine consecutive months in the June–February range; Growth Rate is cross–sectionally averaged growth rates across all countries in consideration.

Table 2: Linear ENSO Impact on Growth

Model	1	2	3	4	5
ENSO_t	-0.275^{***}	-0.308^{***}	-0.249^{***}	-0.248^{***}	-0.236^{***}
	(0.076)	(0.074)	(0.074)	(0.074)	(0.074)
ENSO_{t-1}	-0.148	-0.174^{*}	-0.086	-0.078	-0.070
	(0.096)	(0.092)	(0.095)	(0.096)	(0.095)
fixed effect	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.003	0.044	0.092	0.122	0.141

Note: values in parentheses are heteroskedasticity consistent cluster-robust standard errors, as per Arellano (1987); ***, **, and * denote statistical significance at 0.01 0.01 0.01 levels.

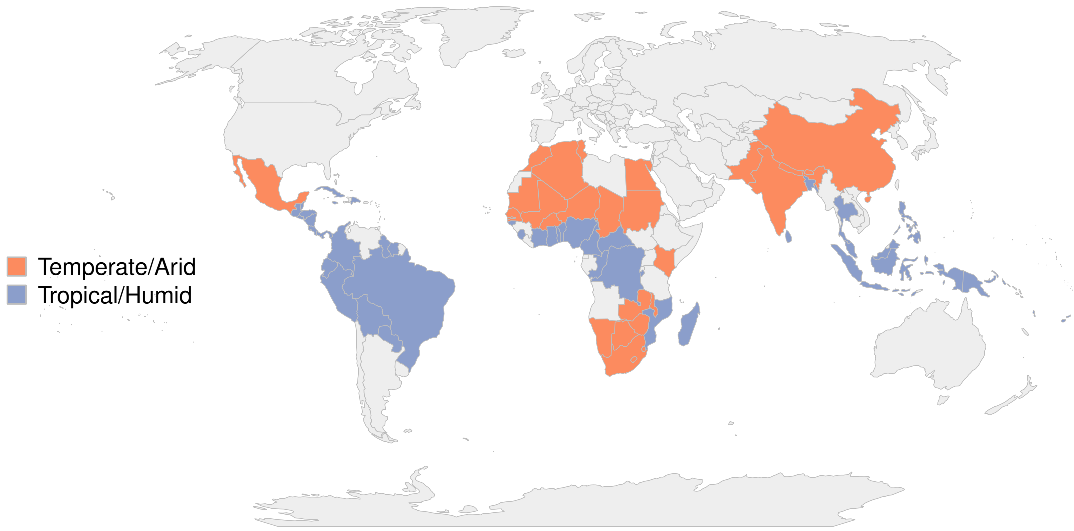

Figure 4: Climatic Zones

Note: Tropical/Humid are countries that are predominantly (50 percent or more of the total area) within `Af`, `Am`, `Aw`, and `Cfa` zones of the Köppen–Geiger climate classification. Temperate/Arid countries, in turn, are predominantly within `Bw`, `Bsh`, `Bsk`, `Cs`, `Cw`, `Cfb`, `Cfc` zones.

associated with positive deviations in the SST—i.e., the El Niño-like events—to be different from those associated with negative deviations in the SST—i.e., the La Niña-like events. Table 3 features threshold-like nonlinear effect of contemporaneous and lagged ENSO events on growth. Under this

Table 3: Nonlinear ENSO Impact on Growth

Model	1	2	3	4	5
El Niño$_t$	-0.679^{***}	-0.746^{***}	-0.562^{***}	-0.602^{***}	-0.580^{***}
	(0.146)	(0.138)	(0.136)	(0.140)	(0.141)
El Niño$_{t-1}$	-0.742^{***}	-0.782^{***}	-0.683^{***}	-0.735^{***}	-0.672^{***}
	(0.259)	(0.256)	(0.251)	(0.257)	(0.259)
La Niña$_t$	0.123	0.136	0.195	0.177	0.150
	(0.124)	(0.125)	(0.133)	(0.127)	(0.122)
La Niña$_{t-1}$	−0.171	−0.134	−0.299	−0.335	−0.291
	(0.190)	(0.189)	(0.200)	(0.205)	(0.205)
fixed effect	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.006	0.047	0.094	0.126	0.144

Note: values in parentheses are heteroskedasticity consistent cluster-robust standard errors, as per Arellano (1987); ***, **, and * denote statistical significance at 0.01 0.01 0.01 levels. Parameters associated with La Niña are multiplied by negative one, to facilitate their direct interpretation.

new specification, an El Niño is found to have a considerably large negative impact on economic growth, but the effect is nearly absent in the case of a La Niña. This is an interesting finding, particularly from the standpoint of policy-making, and builds importantly upon the current body of literature (notably, in an extention of their study, Cashin et al., 2017, find that asymmetries can be a characteristic fieature of ENSO–growth relationship in an array of countries). Indeed, a stronger effect is unveiled by allowing for asymmetries in the ENSO–growth relationship.

The foregoing model specifications assume the same growth effect of ENSO events across countries. At the other extreme, we can simply estimate country–specific equations. To that end, model 1 is, in effect, a distributed lag (DL) model with intercept, model 2 is a DL model with intercept and trend, and models 3, 4 and 5 are autoregressive distributed lag (ARDL) models of order one, two and three, respectively. Figure 5 presents the distribution of growth effects associated with current and lagged ENSO events. Several observations are notable. First, negative impacts prevail across countries and ENSO events. Second, while heterogeneity of the effect is apparent, there is considerable regional clustering of growth effects of ENSO. Finally, the mean group estimates of the ENSO effects are comparable with those from the fixed effects model in Table 3.

As a middle ground between the homogenous effect at one extreme, and the country–specific effects at the other extreme, we proceed by estimating the group–specific growth effects of ENSO. To begin, we group countries into the *Tropical/Humid* and *Temperate/Arid* regions, as described in the Data section. As previously, we estimate the relationship between economic growth and ENSO in a fixed effects setting. Table 4 summarizes the estimation results. Two observations are particularly apparent in these results. First, countries in the tropics appear to be more sensitive to ENSO anomalies. Second, the asymmetries in the ENSO effect is particularly pronounced in the tropical countries, as negative effect on growth tends to prevail due to El Niño as well as La Niña events. Figure 6 shows the intermediate–term dynamics of ENSO growth effects, based on mean group estimates, by climate region. The impact of an ENSO event appears to largely dissipate two years after the event in all zones. Alternatively, the effect of ENSO may vary across continents. This could be due to climatological reasons, as differing proximity to the `Niño3.4` region can result in varying growth effects of ENSO. But also, because socio-economic and political factors that characterizes a given geographic cluster of countries, irrespective of its climatic zones, can result in the heterogeneity of the ENSO effect across regions. To examine this, we grouped countries into three continents: Africa, Americas, and Asia-Pacific. Table 5 presents the regression results. In addition to the previously noted ENSO effects, several features of interest emerge from these parameter estimates. The negative impact of an El Niño event is strongest for African countries. Both ENSO events—i.e., El Niño and La Niña—are "bad news" for Asian-Pacific countries. This supports the hypothesis that both dry and wet events have the potential to be growth–limiting. Compared to other region, in the Americas, the growth impact is of lower magnitude and hardly statistically significant. These effects are further illustrated in Figure 7. As alluded from the

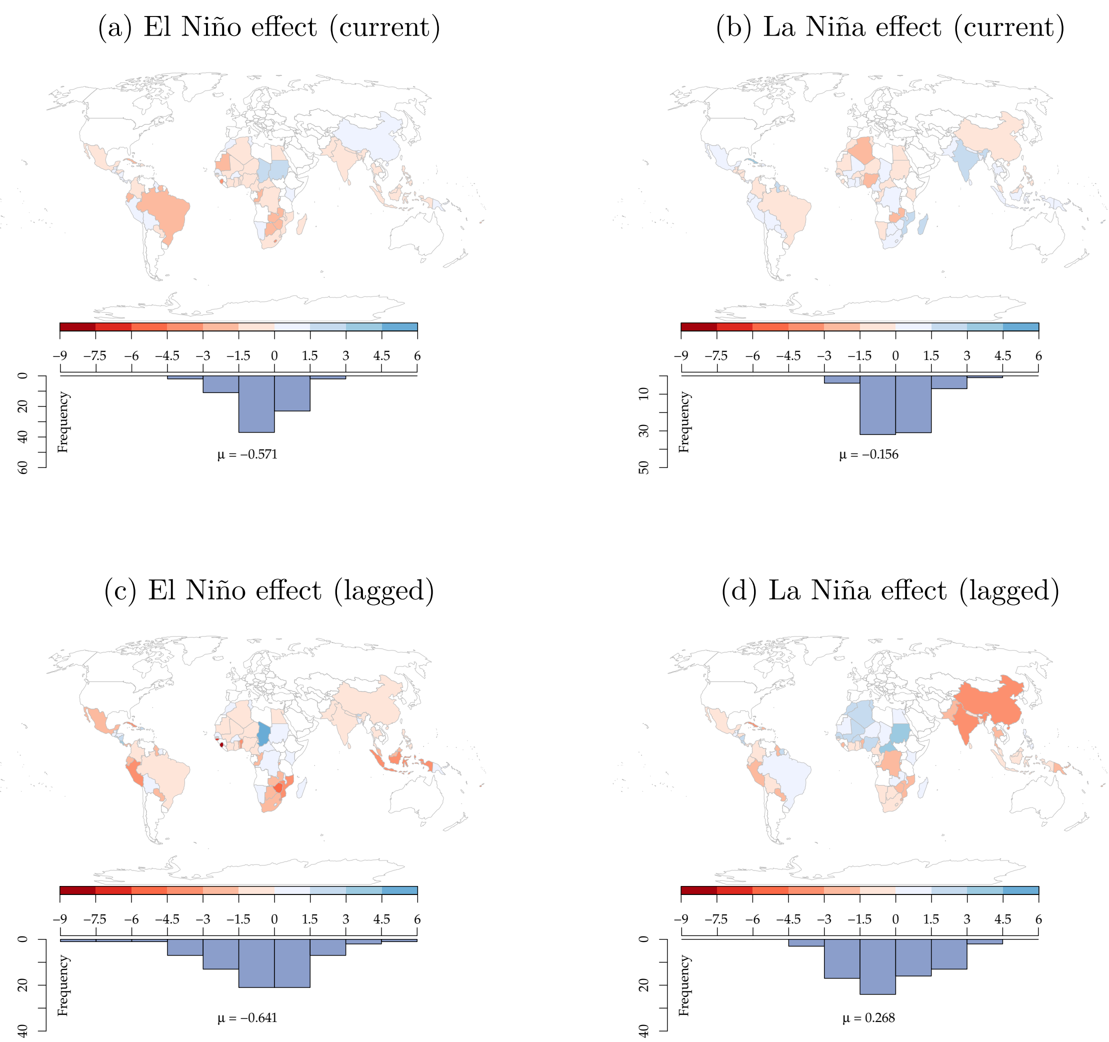

Figure 5: Heterogeneity of growth effects of ENSO

Table 4: Nonlinear ENSO Impact on Growth Across Climatic Zones

Model	1	2	3	4	5
			Temperate/Arid (n=28)		
El Niño$_t$	-0.596^{**}	-0.695^{***}	-0.484^{**}	-0.523^{**}	-0.473^{*}
	(0.260)	(0.231)	(0.234)	(0.250)	(0.260)
El Niño$_{t-1}$	-0.132	-0.197	-0.195	-0.263	-0.174
	(0.379)	(0.363)	(0.351)	(0.370)	(0.377)
La Niña$_t$	-0.098	-0.079	-0.001	0.059	0.030
	(0.229)	(0.228)	(0.205)	(0.178)	(0.173)
La Niña$_{t-1}$	0.404	0.445	0.146	0.105	0.165
	(0.327)	(0.331)	(0.364)	(0.362)	(0.361)
			Tropical/Humid (n=47)		
El Niño$_t$	-0.728^{***}	-0.776^{***}	-0.606^{***}	-0.649^{***}	-0.642^{***}
	(0.173)	(0.173)	(0.167)	(0.165)	(0.163)
El Niño$_{t-1}$	-1.107^{***}	-1.132^{***}	-0.977^{***}	-1.018^{***}	-0.970^{***}
	(0.335)	(0.336)	(0.336)	(0.340)	(0.339)
La Niña$_t$	0.255^{*}	0.265^{*}	0.314^{*}	0.248	0.222
	(0.139)	(0.141)	(0.171)	(0.173)	(0.164)
La Niña$_{t-1}$	-0.518^{**}	-0.483^{**}	-0.569^{**}	-0.603^{**}	-0.568^{**}
	(0.212)	(0.210)	(0.223)	(0.235)	(0.235)
fixed effect	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.008	0.049	0.096	0.127	0.145

Note: values in parentheses are heteroskedasticity consistent cluster-robust standard errors, as per Arellano (1987); ***, **, and * denote statistical significance at 0.01 0.01 0.01 levels. Parameters associated with La Niña are multiplied by negative one, to facilitate their direct interpretation.

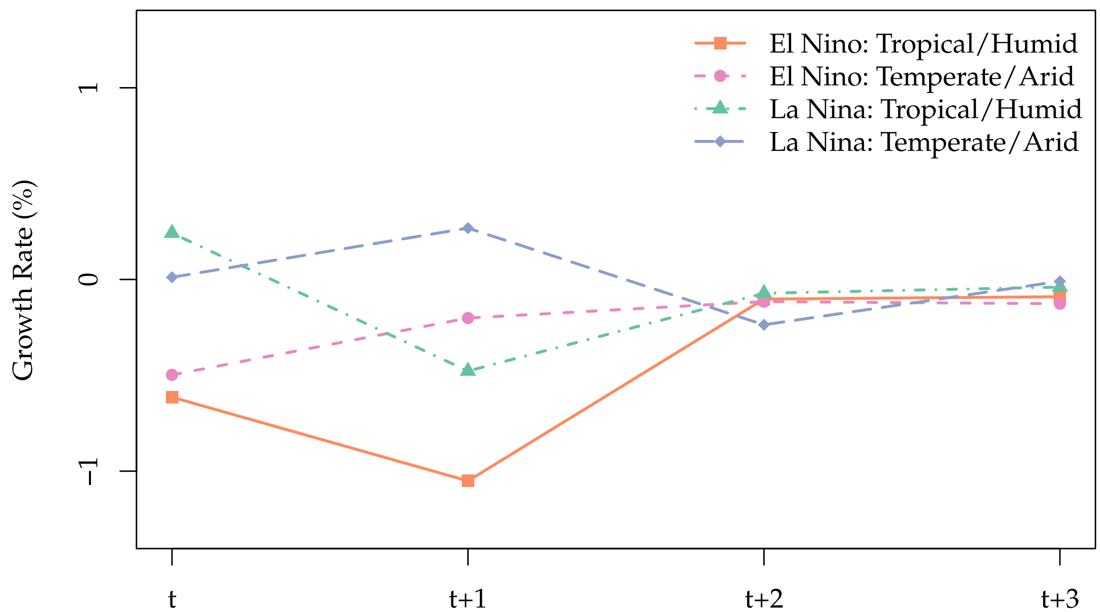

Figure 6: Dynamics of growth effects of ENSO events across climatic zones

Note: Each curve represents individual country dynamics obtained by iterating forward a 1°C equivalent El Niño (a positive deviation) or La Niña (negative deviation) shock in period t, and aggregated across countries. The La Niña effects are multiplied by negative one, to facilitate their direct interpretation.

Table 5: Nonlinear ENSO Impact on Growth Across Continents

Model	1	2	3	4	5
			Africa (n=38)		
El Niño$_t$	-0.949^{***}	-0.992^{***}	-0.800^{***}	-0.838^{***}	-0.794^{***}
	(0.237)	(0.218)	(0.225)	(0.233)	(0.235)
El Niño$_{t-1}$	-0.988^{**}	-1.001^{**}	-0.924^{**}	-0.959^{**}	-0.827^{**}
	(0.414)	(0.408)	(0.404)	(0.408)	(0.407)
La Niña$_t$	-0.062	-0.057	0.013	-0.002	-0.027
	(0.181)	(0.180)	(0.182)	(0.156)	(0.150)
La Niña$_{t-1}$	0.357	0.375	0.193	0.129	0.156
	(0.259)	(0.269)	(0.269)	(0.275)	(0.282)
			Americas (n=23)		
El Niño$_t$	-0.402^{*}	-0.422^{*}	-0.232	-0.301	-0.268
	(0.232)	(0.229)	(0.211)	(0.209)	(0.212)
El Niño$_{t-1}$	-0.379	-0.403	-0.245	-0.333	-0.277
	(0.425)	(0.428)	(0.419)	(0.434)	(0.447)
La Niña$_t$	0.288	0.292	0.304	0.230	0.192
	(0.222)	(0.225)	(0.275)	(0.279)	(0.260)
La Niña$_{t-1}$	-0.262	-0.238	-0.345	-0.386	-0.315
	(0.308)	(0.302)	(0.336)	(0.351)	(0.344)
			Asia-Pacific (n=14)		
El Niño$_t$	-0.400^{***}	-0.604^{***}	-0.461^{***}	-0.464^{***}	-0.498^{***}
	(0.153)	(0.177)	(0.135)	(0.149)	(0.151)
El Niño$_{t-1}$	-0.669^{*}	-0.801^{**}	-0.757^{**}	-0.804^{**}	-0.887^{**}
	(0.378)	(0.358)	(0.320)	(0.358)	(0.368)
La Niña$_t$	0.337	0.386^{*}	0.494^{**}	0.542^{**}	0.532^{**}
	(0.232)	(0.229)	(0.203)	(0.227)	(0.234)
La Niña$_{t-1}$	-1.436^{***}	-1.321^{***}	-1.529^{***}	-1.494^{***}	-1.458^{***}
	(0.298)	(0.282)	(0.358)	(0.368)	(0.364)
fixed effect	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.012	0.052	0.100	0.130	0.148

Note: values in parentheses are heteroskedasticity consistent cluster-robust standard errors, as per Arellano (1987); ***, **, and * denote statistical significance at 0.01 0.01 0.01 levels. Parameters associated with La Niña are multiplied by negative one, to facilitate their direct interpretation.

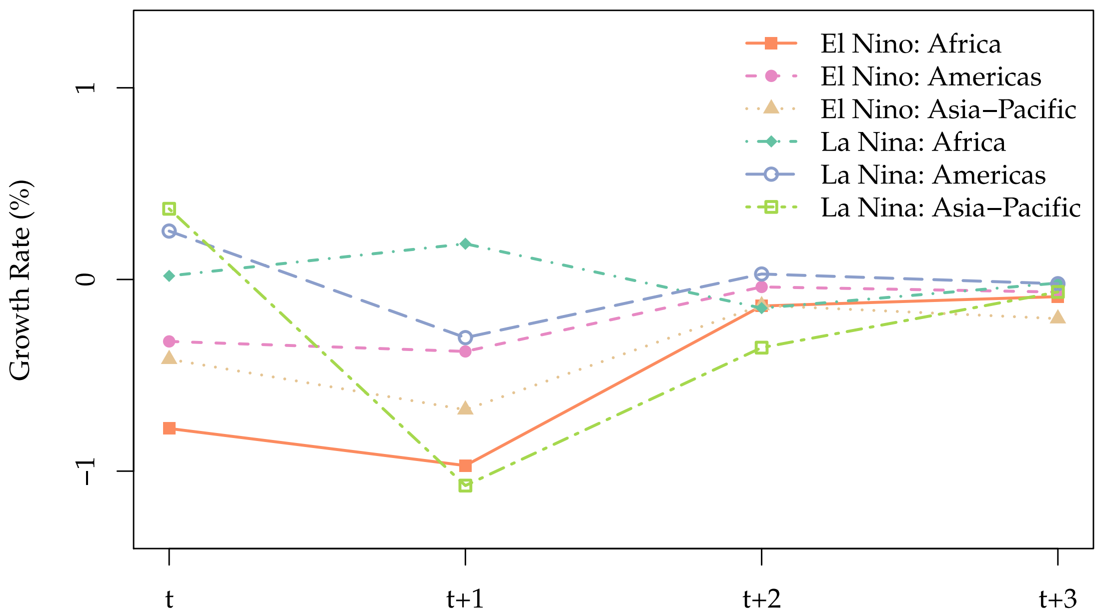

Figure 7: Dynamics of growth effects of ENSO events across continents

Note: Each curve represents individual country dynamics obtained by iterating forward a 1°C equivalent El Niño (a positive deviation) or La Niña (negative deviation) shock in period t, and aggregated across countries. The La Niña effects are multiplied by negative one, to facilitate their direct interpretation.

very beginning, one of the main channels through which ENSO events may translate in changes in economic growth is agriculture. In particular, countries where agriculture plays an important role in total economic output are likely to be more susceptible to ENSO shocks. We examine the role of agriculture by interacting the country–invariant SST anomaly with time–invariant country–specific vulnerability measure, which results in the following augmented equation:

$$y_{it} = \boldsymbol{\theta}'\boldsymbol{x}_t + \boldsymbol{\eta}'\boldsymbol{x}_t z_i + \boldsymbol{\delta}_i'\boldsymbol{d}_t + \alpha_i + \varepsilon_{it}, \tag{3}$$

where z_i is either the agriculture value added (% of GDP) or the employment share of agriculture (% of total employment). We use country–averages of these measures, partly to mitigate any temporal changes/adjustments to ENSO shocks (e.g., agriculture relative to GDP can be a function of weather; and the same can be true, albeit to a lesser extent, for the temporal labor displacement), but also due to data limitation, as in majority of cases, the length of the series is much shorter than that of growth and SST anomalies. To facilitate comparison with parameter estimates from previous models, these measures are cross–sectionally mean–centered. Tables 6 and 7 summarize the parameter estimates of models associated with each of the two vulnerability measures, respectively.

In accord with expectations, we find that the growth tends to be more sensitive to El Niño-s in countries with a larger agriculture share of GDP or larger employment share in agriculture. Moreover, the effect is very comparable across the two measures. On average, the negative growth effect of an El Niño event is approximately 0.2–0.4 percentage point larger in magnitude for countries that are 10 percent more agricultural (as measured by either of the two vulnerability indices). This difference, while certainly economically meaningful, is notably not statistically significant. There is no doubt, agriculture is one of the major pathways by which ENSO affects growth. But the signal in this causal mechanism may not be clear because of other socio-economic or political factors that can also mediate (though, not confound) climatic shocks on broader macroeconomic variables.

Notably, year–to–year growth variation among (neighboring) countries may be affected by (unobserved) common shocks. Recent developments in heterogeneous dynamic panel data modeling literature offer a possibility of addressing the error cross–section dependence (see, e.g., Pesaran, 2006; Chudik and Pesaran, 2015; Chudik et al., 2017). The approach involves augmenting the original model with cross–sectionally averaged dependent variable as well as independent variables (that vary across units and over time). While we acknowledge the benefits of the aforementioned methodology in certain circumstances, here we do not implement it for reasons discussed below. Because ENSO is an observed common factor, by introducing the cross–sectionally averaged dependent variable in the model, which in turn can be (and indeed is) correlated with ENSO, we will be altering conditioning set in a way that may not be desirable. Under the maintained assumption of exogeneity of ENSO, and to the extent that ENSO on average impacts growth rates of the countries in consideration, the cross–sectionally averaged dependent variable, in effect, will act as "bad control," and the related caveat, as discussed above, would be applicable here as well. For

Table 6: Agriculture Share of GDP as a factor in the ENSO–Growth Relationship

Model	1	2	3	4	5
El Niño$_t$	-0.678^{***}	-0.743^{***}	-0.559^{***}	-0.600^{***}	-0.576^{***}
	(0.144)	(0.136)	(0.133)	(0.136)	(0.138)
El Niño$_{t-1}$	-0.732^{***}	-0.772^{***}	-0.675^{***}	-0.728^{***}	-0.664^{***}
	(0.253)	(0.249)	(0.245)	(0.253)	(0.255)
La Niña$_t$	0.119	0.132	0.194	0.177	0.154
	(0.130)	(0.130)	(0.138)	(0.132)	(0.126)
La Niña$_{t-1}$	-0.173	-0.137	-0.310	-0.343^{*}	-0.306
	(0.189)	(0.188)	(0.199)	(0.203)	(0.202)
Ag Share × El Niño$_t$	-0.008	-0.013	-0.010	-0.011	-0.010
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)
Ag Share × El Niño$_{t-1}$	-0.029	-0.032	-0.029	-0.028	-0.022
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Ag Share × La Niña$_t$	0.002	0.004	0.001	0.002	0.000
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
Ag Share × La Niña$_{t-1}$	-0.003	0.000	0.003	0.001	0.007
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
fixed effect	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.007	0.049	0.096	0.127	0.145

Note: values in parentheses are heteroskedasticity consistent cluster-robust standard errors, as per Arellano (1987); ***, **, and * denote statistical significance at 0.01 0.01 0.01 levels. Parameters associated with La Niña are multiplied by negative one, to facilitate their direct interpretation.

Table 7: Employment Share in Agriculture as a factor in the ENSO–Growth Relationship

Model	1	2	3	4	5
El Niño$_t$	-0.640^{***}	-0.721^{***}	-0.518^{***}	-0.553^{***}	-0.537^{***}
	(0.149)	(0.141)	(0.139)	(0.142)	(0.144)
El Niño$_{t-1}$	-0.595^{**}	-0.639^{***}	-0.558^{**}	-0.611^{**}	-0.560^{**}
	(0.252)	(0.248)	(0.244)	(0.257)	(0.261)
La Niña$_t$	0.093	0.110	0.182	0.155	0.139
	(0.135)	(0.136)	(0.143)	(0.137)	(0.130)
La Niña$_{t-1}$	-0.180	-0.126	-0.327	-0.349	-0.316
	(0.199)	(0.197)	(0.208)	(0.212)	(0.209)
Emp Share $\times$ El Niño$_t$	-0.006	-0.009	-0.007	-0.007	-0.006
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Emp Share $\times$ El Niño$_{t-1}$	-0.013	-0.013	-0.013	-0.014	-0.009
	(0.012)	(0.011)	(0.012)	(0.013)	(0.013)
Emp Share $\times$ La Niña$_t$	0.002	0.003	0.004	0.004	0.003
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Emp Share $\times$ La Niña$_{t-1}$	-0.004	-0.002	-0.003	-0.004	-0.001
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
fixed effect	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.006	0.050	0.101	0.131	0.149

Note: values in parentheses are heteroskedasticity consistent cluster-robust standard errors, as per Arellano (1987); ***, **, and * denote statistical significance at 0.01 0.01 0.01 levels. Parameters associated with La Niña are multiplied by negative one, to facilitate their direct interpretation.

example, growth among neighboring countries may be correlated due to (positive) spillovers (e.g., related to trade). But if the change in trade is an outcome of an ENSO event, we would not want to control for it, as long as the goal remains to estimate the total effect of ENSO. Alternatively, if an unobserved common factor is in fact uncorrelated with ENSO, we could potentially benefit from model augmentation, but that would merely improve efficiency rather than stability of parameter estimates. Instead, in this study we apply heteroskedasticity consistent cluster robust standard errors to mitigate the issue.

5 Implications and Limitations

Linking ENSO shocks to the economic growth of an array of countries in Africa, Asia, and Americas has several important implications. El Niño and La Niña events should be explicitly considered when making macroeconomic decisions and forecasts. For example, the ENSO–related lower economic growth can be countered by expansionary macroeconomic policies, such as increased government spending. This might be an unattainable luxury for many developing countries, however. In such instances, the role international community—the developed world in particular—gains crucial importance to direct the aid flows to regions that are in most need due to the ENSO–induced weather shocks. Effective policy actions, moreover, can also be of the microeconomic nature, targeted towards reducing the climate sensitivity of lower-income rural communities.

Communicating ENSO forecasts to the relevant parties can provide them with the opportunity to decrease their climate vulnerability. While the prediction of ENSO events has certainly improved, the spatial variability of teleconnections across different events complicates forecasting for a specific region. Nonetheless, there are benefits to *a priori* knowledge that reduces uncertainty about future climate, and thus affected (and involved) parties can take beneficial and timely action (Meza et al., 2008). For example, the forecast of an El Niño event, combined with the knowledge that it increases the probability of dry conditions for a region, could lead to increased preparedness and cost mitigation via the planting of more drought resistance crops. Policy-makers aiming to curb climate-induced growth shocks and alleviate the risks of agricultural production can benefit from forecast communication. Moreover, efforts to improve trade and storage capacity would be effective in smoothing supply, as well as price and consumption. International aid, be that in cash or via food programs, can mitigate socio–economic issues associated with supply shortage and inflationary pressures due to the climate shocks.

Finally, it should be noted that the ENSO effect (or the lack of it) in any given region may be camouflaged in the current study for at least two potential reasons. First, the impact of ENSO may be too localized, or too short-term, to be reflected in movements of the annual country–wide economic growth measure. That is, the aggregation over time and across space may mask potentially important regional and temporal heterogeneities. Second, there may be limitations in using the SST anomalies to measure the impact of ENSO. While deviations in this index is closely linked to an increased probability of droughts and pluvial periods, there are spatial and intensity differences from one event to another that makes comparison difficult. That is, all else being equal, the broader macroeconomic implications could differ markedly during different ENSO episodes despite events recording identical worming or cooling phases. The aforementioned considerations should be factored in during the decision making process, especially in countries where little evidence is found in support of the ENSO role in per capita GDP growth.

6 Conclusion

Societies across the world are subjected to the repercussions of ENSO–induced climatic shocks. This is even more true for countries in the developing world. Many of these countries are reliant on agriculture and primary commodity exports as major sources of economic activity and a channel via which they develop. The historically strong links between agriculture and food security further amplify the adversity of ENSO events. The findings of this study make several notable additions to the body of literature concerned with the macroeconomic consequences of ENSO shocks.

In this study, we investigate the effect of ENSO on economic growth of a large set of developing countries. We find that growth rates respond asymmetrically to ENSO shocks. In particular, while an El Niño event considerably reduces economic growth, the effect of a La Niña event is much less apparent. Moreover, we find that the regional heterogeneities exist in the vulnerability to ENSO shocks. Of particular importance is strong evidence of the ENSO impact in tropical countries. An indication of such effect has been offered previously (Hsiang and Meng, 2015), but here we show that not only agriculture, but economy as a whole can be negatively affected by El Niño events. In addition, we find that countries in Asia-Pacific tend to react negatively to the events causing dry conditions, and also to those characterized by increased precipitation. Countries in Africa tends to experience significantly reduced growth during El Niño-s, whereas those in the Americas appear to be less affected by these climate events.

Several interesting directions for future research emerge from this analysis. A more complex modelling framework could assess mechanisms through which the ENSO shocks manifest into growth. Identifying such channels could assist policy-makers to pinpoint actions in reducing climate vulnerability. We refer readers to Cashin et al. (2017) for one such application. While the effect of ENSO on agricultural productivity has been already examined (e.g., Hsiang and Meng, 2015), another interesting line of further research would be to analyze the impact of ENSO on various other factors of development, such as education, health, and living standards. For example, the hypothesis that inequality is entrenched in regions exposed to ENSO events would be an interesting venue to examine. The aforementioned are potentially important questions—emerged from the main findings of the current research—which we shall leave for future studies to consider.

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Appendix

Table A1: Descriptive Statistics by Country

Country	ISO3	Climatic Zone	Growth Rate				T	μ_{AGR}	μ_{EMP}
			mean	s.d.	min	max			
Burundi	BDI	Tropical/Humid	0.1	5.5	-15.4	19.1	55	52.8	92.2
Benin	BEN	Tropical/Humid	0.9	3.0	-7.2	7.0	55	33.3	43.9
Burkina Faso	BFA	Temperate/Arid	1.9	3.0	-4.3	8.0	55	34.0	80.9
Bangladesh	BGD	Tropical/Humid	1.8	3.9	-15.5	7.7	55	35.9	57.2
Belize	BLZ	Tropical/Humid	2.7	4.0	-4.8	12.9	55		
Bolivia, Plurinational State of	BOL	Tropical/Humid	1.2	3.4	-13.9	5.7	55	17.0	29.4
Brazil	BRA	Tropical/Humid	2.3	3.8	-6.6	11.2	55	9.9	22.7
Bhutan	BTN	Temperate/Arid	5.6	4.6	-0.3	24.4	35		
Botswana	BWA	Temperate/Arid	5.5	5.4	-9.5	22.3	55	11.8	25.4
Central African Republic	CAF	Tropical/Humid	-1.1	6.3	-38.2	6.4	55	46.5	
China	CHN	Temperate/Arid	6.9	6.9	-26.6	16.1	55	24.2	33.7
Cote d'Ivoire	CIV	Tropical/Humid	0.5	5.1	-14.8	13.0	55	28.7	
Cameroon	CMR	Tropical/Humid	0.9	5.5	-13.0	18.6	55	25.9	69.1
Congo, Democratic Republic of	COD	Tropical/Humid	-1.5	6.0	-16.8	18.2	55		
Congo	COG	Tropical/Humid	1.5	5.3	-11.6	20.0	55	11.4	35.4
Colombia	COL	Tropical/Humid	2.3	2.1	-5.6	6.0	55	16.6	9.2
Comoros	COM	Tropical/Humid	-0.3	3.1	-8.1	8.1	34		
Cabo Verde	CPV	Temperate/Arid	5.0	4.5	-1.8	15.9	35		
Costa Rica	CRI	Tropical/Humid	2.3	3.2	-9.8	7.2	55	10.6	20.8
Cuba	CUB	Tropical/Humid	2.6	6.1	-15.4	19.1	43	10.7	22.2
Dominica	DMA	Tropical/Humid	2.9	5.3	-19.2	13.7	38		
Dominican Republic	DOM	Tropical/Humid	3.1	5.0	-15.2	14.9	55	14.6	15.8
Algeria	DZA	Temperate/Arid	1.5	7.3	-21.6	31.0	55	9.9	18.4
Ecuador	ECU	Tropical/Humid	1.6	3.0	-6.5	10.8	55	20.1	18.7
Egypt	EGY	Temperate/Arid	2.6	2.8	-1.8	12.1	50	20.0	33.2
Fiji	FJI	Tropical/Humid	1.6	4.5	-8.4	10.7	55		
Ghana	GHA	Tropical/Humid	1.0	4.3	-14.5	11.3	55	44.1	52.1
Gambia	GMB	Temperate/Arid	0.5	3.5	-7.4	9.0	48	25.8	48.1
Guinea-Bissau	GNB	Tropical/Humid	0.5	6.9	-29.6	15.8	45	48.6	
Grenada	GRD	Tropical/Humid	2.9	4.5	-6.9	12.9	38		
Guatemala	GTM	Tropical/Humid	1.3	2.3	-6.1	6.6	55	12.6	37.1
Guyana	GUY	Tropical/Humid	1.5	4.8	-14.9	8.4	55		
Honduras	HND	Tropical/Humid	1.4	2.9	-4.4	7.2	55	23.6	40.7
Indonesia	IDN	Tropical/Humid	3.6	3.6	-14.4	9.0	55	27.8	46.1
India	IND	Temperate/Arid	3.3	3.2	-7.4	8.8	55	30	54.0
Jamaica	JAM	Tropical/Humid	0.7	4.4	-7.8	16.2	49	6.9	20.5
Kenya	KEN	Temperate/Arid	1.5	4.4	-10.6	17.9	55	32.4	61.1
Saint Lucia	LCA	Tropical/Humid	2.5	6.6	-12.0	21.8	35		
Sri Lanka	LKA	Tropical/Humid	3.5	2.2	-2.3	8.3	54	8.8	36.7
Lesotho	LSO	Temperate/Arid	3.2	5.8	-15.5	23.8	54	27.6	40.9
Morocco	MAR	Temperate/Arid	2.9	3.7	-6.9	10.7	49	15.2	23.6
Madagascar	MDG	Tropical/Humid	-0.9	3.9	-15.3	6.8	55	29.4	78.4
Mexico	MEX	Temperate/Arid	1.8	3.2	-7.5	8.5	55	7.3	18.7
Mali	MLI	Temperate/Arid	2.9	5.6	-9.3	18.1	48	44.6	53.8
Mozambique	MOZ	Tropical/Humid	3.1	6.9	-17.4	23.0	35	32.1	80.5
Mauritania	MRT	Temperate/Arid	1.1	6.0	-7.8	24.0	54	31.7	
Mauritius	MUS	Tropical/Humid	3.6	3.2	-11.6	8.9	39	10.4	11.0
Malawi	MWI	Temperate/Arid	1.4	5.1	-10.5	15.6	55	40.7	64.1

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Table A1 – continued from previous page

Country	ISO3	Climatic Zone	Growth Rate				T	μ_{AGR}	μ_{EMP}
			mean	s.d.	min	max			
Malaysia	MYS	Tropical/Humid	3.8	3.2	-9.6	9.0	55	20.3	21.0
Namibia	NAM	Temperate/Arid	1.0	3.3	-4.5	11.0	35	9.3	31.5
Niger	NER	Temperate/Arid	-0.7	5.6	-19.3	10.3	55	47.4	56.9
Nigeria	NGA	Tropical/Humid	1.5	8.1	-17.6	30.3	55	32.7	43.4
Nicaragua	NIC	Tropical/Humid	0.5	5.9	-28.6	10.7	55	19.5	36.4
Nepal	NPL	Temperate/Arid	1.8	2.7	-5.2	7.2	55	50	72.7
Pakistan	PAK	Temperate/Arid	2.5	2.2	-2.2	8.4	55	30.0	47.6
Panama	PAN	Tropical/Humid	2.9	4.3	-15.2	13.3	55	7.0	21.1
Peru	PER	Tropical/Humid	1.6	4.8	-14.2	10.2	55	12.3	5.4
Philippines	PHL	Tropical/Humid	1.7	3.0	-9.8	6.0	55	21.6	41.3
Papua New Guinea	PNG	Tropical/Humid	1.6	4.7	-6.4	15.3	54	36.6	72.3
Paraguay	PRY	Tropical/Humid	2.5	3.9	-5.8	12.5	55	18.9	18.7
Sudan	SDN	Temperate/Arid	1.3	5.3	-9.1	12.9	55	39.3	44.6
Senegal	SEN	Temperate/Arid	0.0	3.5	-9.3	6.1	55	18.9	41.8
Sierra Leone	SLE	Tropical/Humid	0.6	6.7	-22.0	20.5	55	43.8	67.9
El Salvador	SLV	Tropical/Humid	1.1	3.8	-13.3	6.1	50	12.4	20.7
Suriname	SUR	Tropical/Humid	0.6	5.1	-15.7	10.2	40		
Swaziland	SWZ	Temperate/Arid	2.5	4.3	-5.1	17.0	45	20.2	
Chad	TCD	Temperate/Arid	0.9	8.0	-23.0	28.7	55	40.9	83.0
Togo	TGO	Tropical/Humid	1.0	5.8	-17.1	12.3	55	36.9	54.1
Thailand	THA	Tropical/Humid	4.4	3.3	-8.7	11.3	55	18.1	52.4
Tunisia	TUN	Temperate/Arid	2.8	3.4	-4.5	15.8	50	15.1	21.5
St Vincent and the Grenadines	VCT	Tropical/Humid	2.6	5.9	-12.1	24.4	55		
Vanuatu	VUT	Tropical/Humid	0.7	4.8	-13.7	11.3	35		
South Africa	ZAF	Temperate/Arid	1.0	2.5	-4.3	6.5	55	5.6	7.3
Zambia	ZMB	Temperate/Arid	0.2	4.7	-10.9	13.0	55	15.2	64.5
Zimbabwe	ZWE	Temperate/Arid	0.1	6.7	-18.9	18.6	55	17.1	63.5

Note: Growth Rate is defined as the per capita GDP growth rate measured in percentage terms. T is the number of growth rate observations available from the World Bank database between 1961 and 2015. μ_{AGR} is the within–country average of the agriculture value added (as a % of GDP). μ_{EMP} is the the within–country average of the employment share in agriculture (as a % of total employment).
Sources: The World Bank, and the Center for International Earth Science Information Network.