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

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Abstract

The El Niño Southern Oscillation (ENSO) affects weather around the globe, particularly in regions where developing countries typically lie. These countries are known to be most vulnerable to weather anomalies, and ENSO thereby has the potential to influence their economic growth. In this study, we investigate the effect of ENSO on economic growth in 69 developing countries, using annual data from 1961 to 2015. We find regime–dependent nonlinearity in the growth response to ENSO shocks. An El Niño event, equivalent to a 1°C deviation in sea–surface temperatures in the `Niño3.4` region of the equatorial Pacific, results in one–to–two percent annual growth reduction during the El Niño regime, but the effect is absent during the La Niña regime. In addition, we find that the effect of El Niño is twice–as–large in the tropics relative to temperate areas, and particularly pronounced in Africa and Asia-Pacific. The findings of this study have two important implications. From the modeling standpoint, we find that the growth impacts of ENSO shocks are nonlinear, and 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

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1 Introduction

Throughout the course of human history, climate has played an important role in the development of nations and the demise of civilizations (Acemoglu et al., 2001; Haug et al., 2003; Tsonis et al., 2010). The relationship between weather and socio-economic variables is intrinsic (Raddatz, 2007; Noy, 2009; Burke et al., 2015a), and is particularly evident in countries that are located closer to the equator. This is, in part, due to more frequent weather extremes in this geographic region (Masters and McMillan, 2001; Sachs, 2001; Hsiang, 2010; Dell et al., 2012, 2014), but also because these countries tend to be more dependent on sectors that are climate–sensitive (e.g., agriculture or tourism), and in general are poor "shock absorbers" (Loayza et al., 2007; Noy, 2009).

Incidentally, a climate phenomenon known as the El Niño Southern Oscillation (ENSO) influences weather patterns in the tropics, more so than in the temperate regions. ENSO 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). These transmissions—also referred to as *teleconnections*—relate the climatic conditions in the Pacific with weather anomalies at large distances (see Appendix Figure A1 for illustration of ENSO–induced global weather anomalies). The two extreme phases of this climate phenomenon are known as *El Niño* (the *warm phase*) and *La Niña* (the *cool phase*), which re-occur irregularly every three–to–seven years to form the ENSO cycle. El Niño events are characterized 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. ENSO teleconnections, moreover, extend beyond the Pacific region, and influence weather in parts of Africa, Asia, and the eastern tier of the Americas.

There are multiple channels through which ENSO may affect economic growth, and reasons to believe the impact is more significant in the developing world. ENSO causes anomalous temperatures and precipitation, which can manifest into extended episodes of droughts or floods 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), 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 and Holt, 2013; Cashin et al., 2017; Ubilava, 2017), and thus 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). Civil conflicts and political instability, which may be attributed to ENSO shocks (Hsiang et al., 2011), can also slow down economic growth (Barro, 1991). To summarize, agricultural production is not be the only link through which ENSO can impact economic growth. The corollary is that economic growth in a region can be linked to ENSO shocks, even if they do not directly influence weather patterns in this region. While there can be multiple direct and indirect channels that may relate ENSO events to economic growth, the overarching goal of this study is to examine the overall impact of this climate phenomenon on growth in developing countries.

To date, several studies have attempted to unveil causal linkages 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 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 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 between 1979 and 2013. 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 other 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 linkages between this climate phenomenon and growth in the developing world. The present study contributes to the existing body of research in several directions. First of all, we analyze the ENSO effect in 69 developing countries in Africa, Asia and the Pacific, and Central and South America—a vast majority of which have yet to be studied in this context. Second, we allow for heterogeneous effect of ENSO 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 a growth response of opposite sign and similar magnitude. For example, 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 and storm activity. The modeling framework of this study allows for such nonlinearity in the ENSO–growth relationship.

Using an (unbalanced) panel of annual data spanning the 1961–2015 period, this study finds that ENSO events have heterogeneous and nonlinear impacts on per capita GDP growth rates (this is what we refer to as *economic growth* in this study) in developing countries. We find evidence of heterogeneity in the impact of ENSO shocks across climatic zones as well as continents. The effect of ENSO events is approximately twice–as–large in the tropics compared to the temperate climatic zones. ENSO events detract from the economic growth of developing countries in Africa and Asia-Pacific (including large economies of China and India). In Africa, back–to–back El Niño events appear to be particularly damaging. Similarly, back–to–back La Niña events can significantly detract from growth in Asia-Pacific. 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). The 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, 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

To begin, consider a simple econometric representation that relates economic growth to the state of ENSO. Let y_{it} be the growth rate of country i in period t; and let $\boldsymbol{x}_t = (x_t, x_{t-1})'$ be a vector of current and lagged levels of the sea surface temperature (SST) anomaly—a proxy continuous variable depicting the state of ENSO.[1] The relationship can be represented by:

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

where $i = 1, \ldots, N$, and $t = 1, \ldots, T$; $\boldsymbol{\theta}$ is a set of parameters depicting the contemporaneous and lagged effect of ENSO; $\boldsymbol{d}_{it}$ is a country–specific vector of deterministic trend or lagged dependent variables, and $\boldsymbol{\delta}_i$ is the associated parameter vector; α_i combines country-specific unobserved effects that, moreover, may be correlated with $\boldsymbol{x}_t$ or $\boldsymbol{d}_{it}$. For example, observations in the data may not be missing at random, rather selected countries may be present in the sample during different ENSO phases (Hsiang et al., 2011); also, trends and dynamics in growth rates may be dependent on time-invariant characteristics of a country. Finally, ε_{it} is an error term.

We use both contemporaneous and lagged ENSO realizations as explanatory variables to follow the rationale—suggested by Hsiang and Meng (2015)—that an ENSO event can extend beyond a calendar year, and may also be temporally displaced (see, also, Hsiang, 2016). This modeling

[1] We apply levels of the SST anomaly—rather than their log-transformed variants—primarily to facilitate the interpretation of the associated parameters, which depict the effect of a 1°C change in SST on the growth rate. Moreover, given that SST anomalies are measured as deviations from the long-run mean, they can take negative values, and the log-transformation is not directly applicable. See the Data section for further details.

setup, moreover, assumes that the SST anomaly is weakly exogenous in the sense that ENSO can contemporaneously impact growth, but the converse is not true. This assumption—which also serves as an identification condition—is hardly controversial, and is consistent with previous studies (e.g., Brunner, 2002; Hsiang and Meng, 2015). The foregoing discussion also implies that inclusion of a lagged independent variable in the model is motivated by theoretical and statistical reasons, and is not done for the purposes of identification (for further analysis, and caveats associated with the use of lagged independent variables due to endogeneity, refer to Bellemare et al., 2017).

Note that equation (1) does not control for any time–varying economic variables. While a number of factors influence the growth rate in a given economy—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; Acharya et al., 2016). 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 commodity prices, global business cycles, etc. Controlling for variables of this nature runs the risk of introducing bias, because they are endogenous and therefore may be affected by confounding variables (see, also, Acharya et al., 2016). Moreover, we could possibly estimate a coefficient describing the ENSO effect that has been deteriorated and has no practical interpretation, because some of explanatory power of ENSO has been assigned to another variable. 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 phenomenon and economic growth (see, also, Hsiang et al., 2013). On the other hand, if we fail to control for factors that impact growth but are uncorrelated with ENSO, while we would forfeit efficiency of parameter estimates, we would not introduce omitted variable bias. As our ultimate goal is to estimate the overall (direct and indirect) impact of ENSO shocks on economic growth, there will be little benefit, and likely more harm, in controlling for additional factors in the model.

The model, as specified in equation (1), assumes linearity and homogeneity in the ENSO effect. These assumptions imply that the economic growth responses to positive and negative 1°C deviations in SST (i.e., the El Niño–like and the La Niña–like events of equal magnitude) are mirror images of each other; and that the effect is similar across all countries in consideration. Neither of these need to be the case. Responses to ENSO shocks are in fact very likely to be asymmetric and vary across countries. First, ENSO cycles tend to follow an asymmetric pattern. In particular, El Niño events develop somewhat unexpectedly, whereas La Niña events typically follow the previously realized El Niño events (Hall et al., 2001; Ubilava and Helmers, 2013). The growth effect of ENSO shocks—due to a number of intermediary channels—can therefore 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 (see, also, Appendix Figure A2). Finally, any weather anomaly may be damaging. For example, both positive and negative SST anomalies can possibly result in reduced yields in major crop-producing regions (Legler et al., 1999; Mason and Goddard, 2001; Iizumi et al., 2014; Anderson et al., 2017).

To examine the asymmetric effect of ENSO, we interact the vector of current and lagged SST anomalies, $\boldsymbol{x}_t$, with Heaviside indicators, $I(x_{t-1} < 0)$ and $I(x_{t-1} \geq 0)$, where $I(\cdot)$ 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 potential nonlinearity and heterogeneity in the ENSO effect:

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

where $r = 1, \ldots, R$ denotes a region, such that $R \ll N$. So, for a given region r, the parameter vector $\boldsymbol{\beta}$ depicts the contemporaneous and lagged effects of SST anomalies given a La Niña event in the previous period, and the parameter vector $\boldsymbol{\gamma}$ depicts the contemporaneous and lagged effect of SST anomalies given an El Niño event in the previous period; the remaining variables and parameters are as described above.

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. 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 economic series from World Development Indicators—the electronic data portal of the World Bank. In addition to 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, we sourced all those that the World Bank classifies as *low–income*, *lower–middle–income*, or *upper–middle–income* economies, and at no point were classified as *high–income* economies between 1987 and 2015. In addition, these countries had at least 30 observations between 1981 and 2015, although the time–range of the analysis spans from 1961 to 2015. Notably, these data can be inaccurate, and are to be considered as a proxy, at best (or an educated guess, at worst).[2] Such measurement error in the dependent variable can inflate standard errors and thus affect inference. To mitigate the issue, we omitted countries with unusually large growth rate volatility (i.e., those with the growth rate standard deviation exceeding 10%, or with a growth rate greater than 35% in any given period). This left a total of 69 countries for analysis. Table 1 presents some key statistics describing the composition of growth rates and aforementioned vulnerability measures. Appendix Table A1 offers a more complete, country–specific picture of these variables.

We use 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

[2]We thank the anonymous referee for emphasizing this caveat.

Table 1: Descriptive Statistics of Selected Variables

Countries	n	mean	s.d.	min	max
		Average growth rate			
All	69	1.9	1.5	-1.5	6.9
Tropical/Humid	39	1.8	1.4	-1.5	4.9
Temperate/Arid	30	2.0	1.6	-0.7	6.9
Africa	38	1.4	1.4	-1.5	5.5
Americas	16	1.8	0.8	0.5	3.1
Asia-Pacific	15	3.4	1.4	1.6	6.9
		Average agriculture value added (% of GDP)			
All	69	24.8	13.1	5.5	52.8
Tropical/Humid	39	23.9	13.0	6.5	52.8
Temperate/Arid	30	26.0	13.2	5.5	50.7
Africa	38	28.3	13.4	5.5	52.8
Americas	16	13.6	5.1	6.5	23.4
Asia-Pacific	15	27.9	11.7	8.8	50.7
		Average employment in agriculture (% of total employment)			
All	55	38.5	21.0	5.1	83.6
Tropical/Humid	32	37.9	21.4	8.0	77.4
Temperate/Arid	23	39.5	20.9	5.1	83.6
Africa	25	41.7	22.8	5.1	83.6
Americas	16	21.9	10.6	8.0	44.0
Asia-Pacific	14	51.9	14.0	20.8	72.3

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

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 averaged the monthly SST anomalies between May of a given year and February of the following year to mitigate the effect of the so called "spring barrier" (e.g. Sarachik and Cane, 2010; Hsiang et al., 2011). Figure 2 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.

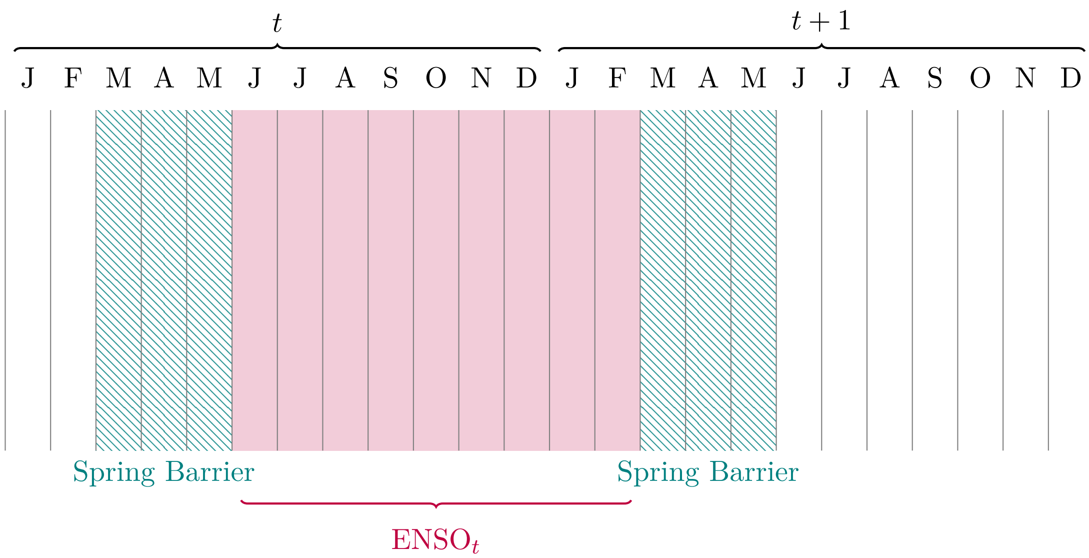

Figure 1: Obtaining the yearly measure of ENSO from monthly SST anomaly

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 are predominantly (50% or more of the total area) within `Af`, `Am`, `Aw`, and `Cfa` zones of the aforementioned classification. The *Temperate/Arid* group includes countries that are predominantly in `Bw`, `Bsh`, `Bsk`, `Cs`, `Cw`, `Cfb`, `Cfc` zones. Figure 3 illustrates the geographical distribution of countries in these two aggregate climatic zones.

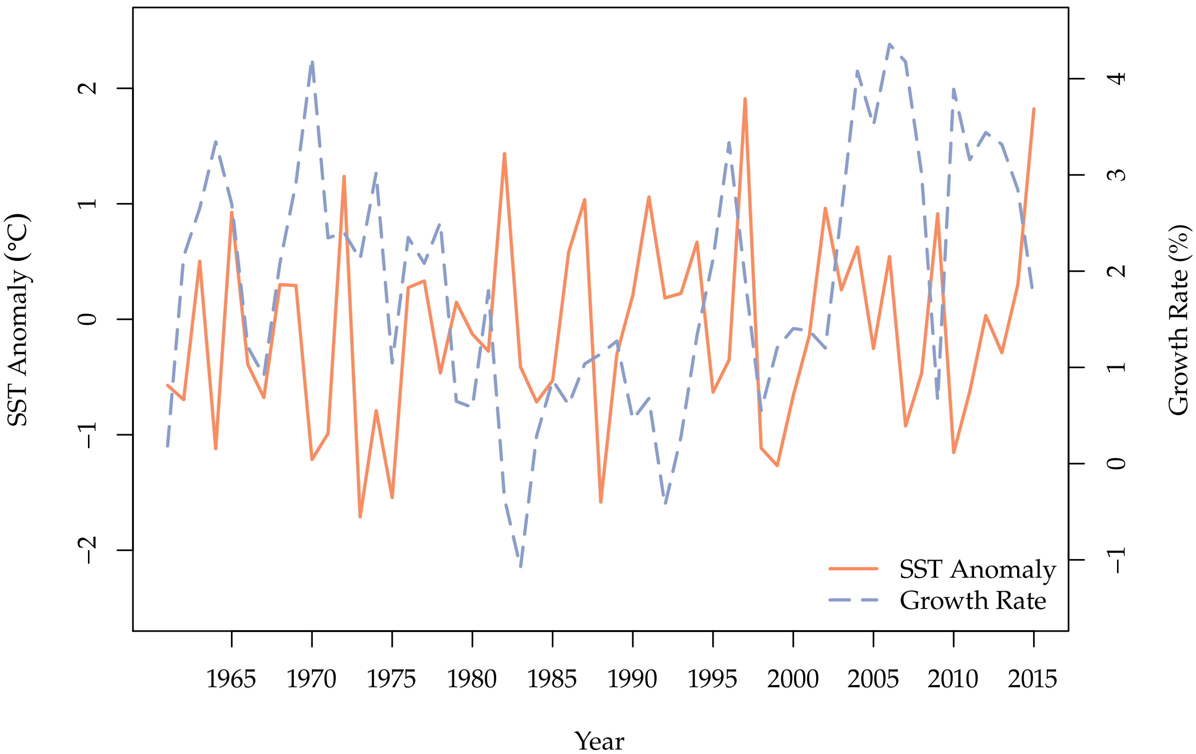

Figure 2: Dynamics of the average economic growth and the ENSO cycle

Note: SST Anomaly is an average of monthly SST deviations over nine consecutive months in the June–February range; Growth Rate is cross–sectionally averaged growth rates across all countries in consideration.

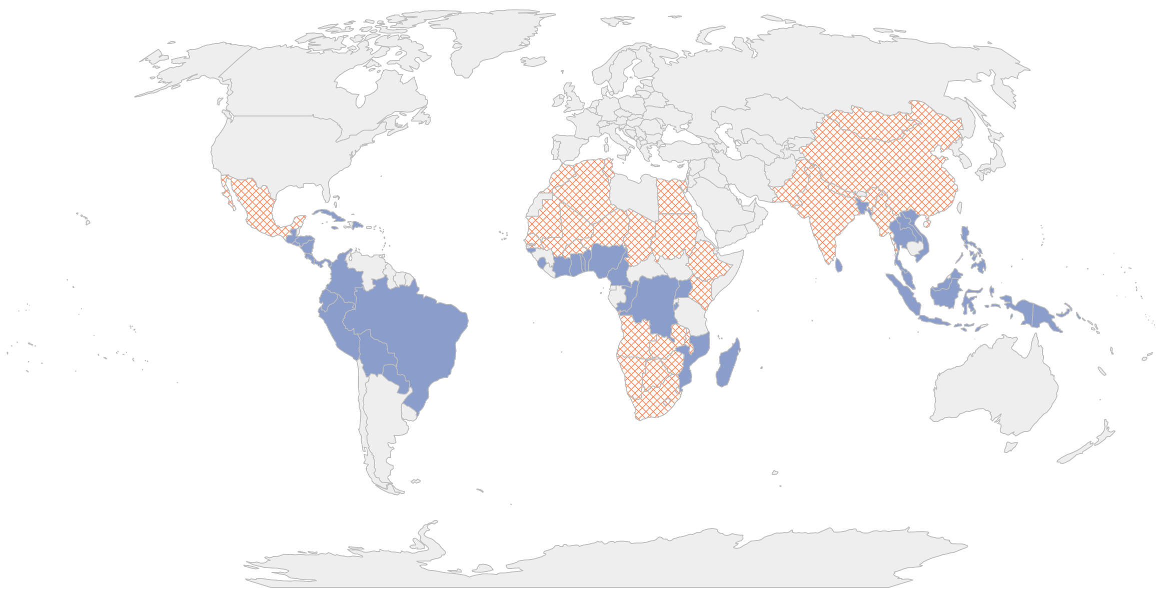

Figure 3: Climatic Zones

Note: Tropical/Humid countries (solid blue) are those with 50% or more of the total area within `Af`, `Am`, `Aw`, and `Cfa` zones; and Temperate/Arid countries (hatched orange) are those with 50% or more of the total area within `Bw`, `Bsh`, `Bsk`, `Cs`, `Cw`, `Cfb`, `Cfc` zones of the Köppen–Geiger climate classification.

4 Estimation and Findings

We begin by estimating the benchmark model, which is a basic linear fixed effects model with homogeneous estimates of the contemporaneous and lagged ENSO effect on growth. Table 2 summarizes the results from five candidate model specifications. These model variants assume homogeneous effect of ENSO, but differ in the way country–specific trends and short term dynamics are specified. Models 2 through 5 are equivalent to pooled mean group estimator of Pesaran et al. (1999). Here and in subsequent tables, the parameter estimates associated with ENSO events are comparable across these five specifications. We find that contemporaneous and lagged El Niño events on average negatively affect growth rates across the 69 countries (equivalently, La Niña events have growth–enhancing impact on economic growth).

Table 2: Linear Impact of ENSO on Growth

	1	2	3	4	5
SST_t	-0.269^{**}	-0.305^{**}	-0.226^{*}	-0.227^{*}	-0.227^{*}
	(0.103)	(0.100)	(0.096)	(0.093)	(0.092)
SST_{t-1}	-0.237^{*}	-0.248^{*}	-0.159	-0.136	-0.104
	(0.114)	(0.111)	(0.105)	(0.104)	(0.103)
fixed effects	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.004	0.059	0.115	0.149	0.169

Note: values in parentheses are standard errors that are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels.

4.1 Nonlinear and Heterogeneous Impact of ENSO

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 during the El Niño regime—i.e., when the lagged SST anomaly is greater than zero—to be different from those during the La Niña regime—i.e., when the lagged SST anomaly is less than zero. Table 3 features such regime–dependent nonlinear effect of contemporaneous and lagged SST anomalies on growth.

Table 3: Nonlinear Impact of ENSO on Growth

	1	2	3	4	5
$\text{SST}_t \vert \text{SST}_{t-1} \geq 0$	-0.763^{**}	-0.818^{**}	-0.576^{**}	-0.616^{**}	-0.596^{**}
	(0.164)	(0.158)	(0.148)	(0.145)	(0.142)
$\text{SST}_{t-1} \vert \text{SST}_{t-1} \geq 0$	-1.093^{**}	-1.046^{**}	-0.890^{**}	-0.935^{**}	-0.855^{**}
	(0.296)	(0.287)	(0.270)	(0.265)	(0.263)
$\text{SST}_t \vert \text{SST}_{t-1} < 0$	−0.135	−0.131	−0.188	−0.177	−0.179
	(0.164)	(0.157)	(0.154)	(0.148)	(0.147)
$\text{SST}_{t-1} \vert \text{SST}_{t-1} < 0$	0.277	0.192	0.328	0.386	0.383
	(0.226)	(0.224)	(0.210)	(0.209)	(0.209)
fixed effects	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.009	0.065	0.119	0.153	0.173

Note: values in parentheses are standard errors that are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels.

Under this new specification, SST anomalies are found to have a considerably large negative impact on economic growth during the El Niño regime, but the effect is small and statistically insignificant during the La Niña regime. This is an interesting finding, particularly from the standpoint of policy-making, and builds importantly upon the current body of literature (notably, in an extension of their study, Cashin et al., 2017, find that asymmetries can be a characteristic feature 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 effectively 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 4 presents the distribution of growth effects associated with SST anomalies (see Appendix Figure A2 for geographical distribution of these effects).

Several observations are notable. First, the effect is heterogeneous across countries, but some regional clustering is apparent. Second, the negative impact, particularly due to back–to–back

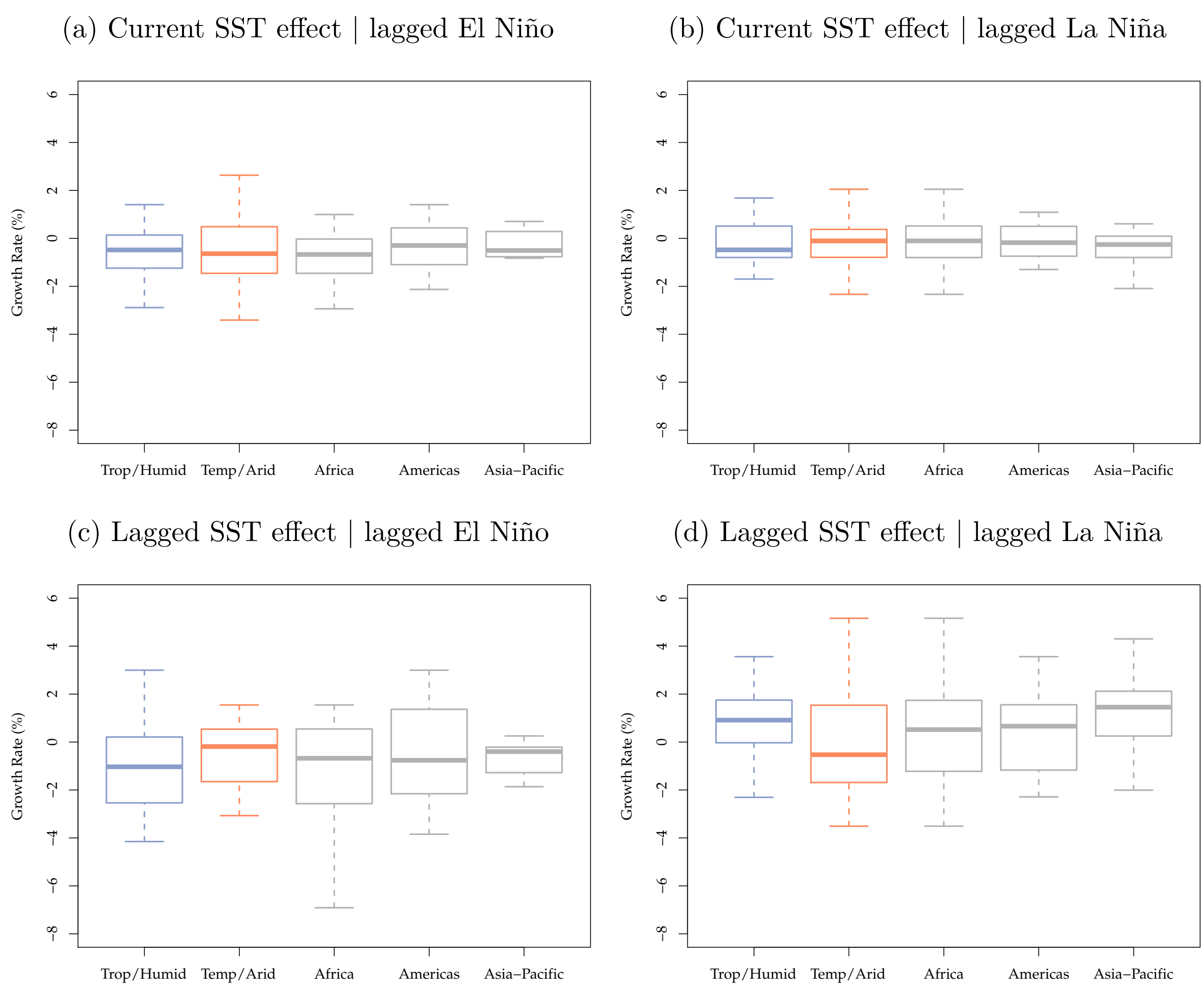

Figure 4: Heterogeneous impact of ENSO on growth

El Niño or La Niña events, prevail across countries. Finally, the mean group estimates of the ENSO effects are comparable with those from the fixed effects model in Table 3.

4.2 The ENSO Impact Across Climatic Zones and Geographic Regions

As a middle ground between the homogeneous effect at one extreme and the country–specific effects at the other extreme, we proceed by estimating the group–specific growth effects of SST anomalies. 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.

Table 4: Nonlinear Impact of ENSO on Growth Across Climatic Zones

	1	2	3	4	5
			Tropical/Humid (n=39)		
$SST_t \mid SST_{t-1} \geq 0$	$-0.833^{**\ddagger}$	$-0.874^{**\ddagger}$	$-0.670^{**\ddagger}$	$-0.692^{**\ddagger}$	$-0.680^{**\ddagger}$
	(0.205)	(0.202)	(0.183)	(0.183)	(0.183)
$SST_{t-1} \mid SST_{t-1} \geq 0$	$-1.487^{**\ddagger}$	$-1.465^{**\ddagger}$	$-1.263^{**\ddagger}$	$-1.266^{**\ddagger}$	$-1.194^{**\ddagger}$
	(0.407)	(0.400)	(0.369)	(0.357)	(0.355)
$SST_t \mid SST_{t-1} < 0$	-0.278	-0.284	-0.342	-0.253	-0.241
	(0.213)	(0.207)	(0.199)	(0.193)	(0.190)
$SST_{t-1} \mid SST_{t-1} < 0$	0.693^{*}	0.639^{*}	$0.710^{**\dagger}$	$0.759^{**\dagger}$	$0.739^{**\dagger}$
	(0.286)	(0.293)	(0.259)	(0.252)	(0.252)
			Temperate/Arid (n=30)		
$SST_t \mid SST_{t-1} \geq 0$	$-0.671^{**\dagger}$	$-0.744^{**\dagger}$	-0.448	-0.512^{*}	-0.479^{*}
	(0.255)	(0.242)	(0.237)	(0.231)	(0.221)
$SST_{t-1} \mid SST_{t-1} \geq 0$	-0.576	-0.498	-0.404	-0.499	-0.409
	(0.389)	(0.371)	(0.367)	(0.367)	(0.365)
$SST_t \mid SST_{t-1} < 0$	0.056	0.073	0.017	-0.075	-0.093
	(0.243)	(0.237)	(0.229)	(0.219)	(0.219)
$SST_{t-1} \mid SST_{t-1} < 0$	-0.272	-0.397	-0.177	-0.105	-0.087
	(0.342)	(0.333)	(0.326)	(0.327)	(0.329)
fixed effects	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.011	0.067	0.120	0.155	0.174

Note: n denotes the number of countries. Values in parentheses are standard errors that are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels; ‡ and † denote statistical significance at 0.01 and 0.05 levels after Bonferroni correction.

Two observations are particularly apparent in these results. First, the tropical countries are most susceptible to ENSO anomalies. Second, the asymmetries in the ENSO effect are particularly pronounced, as negative growth effects during El Niño conditions are not matched by positive growth effects in the wake of La Niña.

To better illustrate these asymmetries, for each country we simulated 1000 paths of growth dynamics by randomly sampling five–year vectors of historical realizations of the SST anomalies, $\boldsymbol{x}_t^* = (x_{t-1}, x_t, \ldots, x_{t+1})'$, and then iterating forward the growth rates using these data to generate the baseline scenario. Similarly, we generated two additional paths of growth rates, where in period t, a unit shock (i.e., 1°C) was added to or subtracted from the SST realization, thus forming the El Niño and La Niña scenarios, respectively. The difference between these scenarios and the baseline scenario, averaged across 1000 simulated paths, form the expected path of growth rate dynamics illustrated in Figure 5. Besides the asymmetries, the figure also shows that the impact of an ENSO event largely dissipates 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. Moreover, socio-economic and political factors that characterizes a given geographic cluster of countries may also result in regional heterogeneity of the ENSO effects. To examine this, we grouped countries into three geographic regions: *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. In Africa, back–to–back El Niño events are growth limiting, but this adverse effect can be mitigated by a La Niña after an El Niño. Similarly, in Asia-Pacific, back–to–back La Niña events significantly reduce economic growth, but an El Niño after a La Niña can induce growth in the region. Compared to these two geographic regions, in the Americas, the growth impact is of lower magnitude and not statistically significant. Figure 6 illustrates the dynamics of these effects using a simulation method outlined previously.

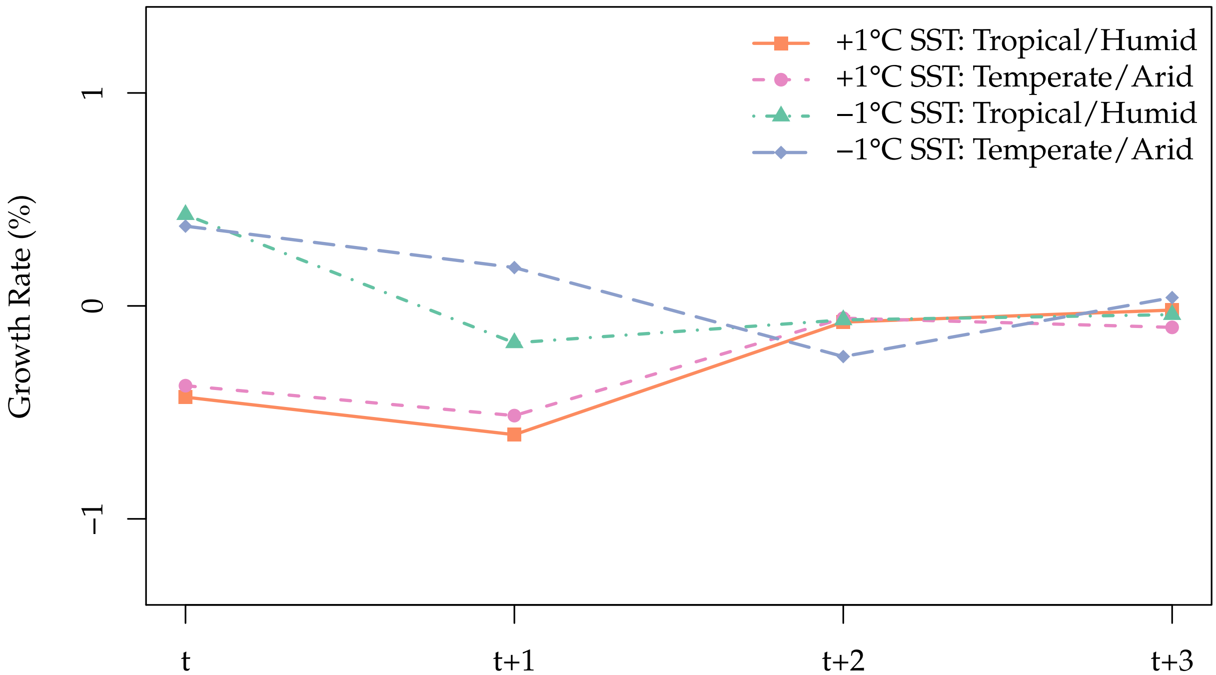

Figure 5: Dynamics of nonlinear impact of ENSO on growth across climatic zones

Note: Each curve represents an average of individual country dynamics obtained by iterating forward a positive or negative 1°C SST deviation in period t, given 1000 randomly sampled vectors of SST realizations for periods $\{t-1, t, \ldots, t+3\}$.

Table 5: **Nonlinear Impact of ENSO on Growth Across Geographic Regions**

	1	2	3	4	5
			Africa (n=38)		
$SST_t \vert SST_{t-1} \geq 0$	$-1.010^{**\ddagger}$	$-1.017^{**\ddagger}$	$-0.794^{**\ddagger}$	$-0.843^{**\ddagger}$	$-0.811^{**\ddagger}$
	(0.249)	(0.240)	(0.225)	(0.219)	(0.212)
$SST_{t-1} \vert SST_{t-1} \geq 0$	$-1.241^{**\dagger}$	$-1.158^{**\dagger}$	$-1.099^{**\dagger}$	$-1.152^{**\dagger}$	-0.979^{*}
	(0.435)	(0.422)	(0.402)	(0.391)	(0.389)
$SST_t \vert SST_{t-1} < 0$	−0.010	0.004	−0.063	−0.046	−0.053
	(0.239)	(0.230)	(0.232)	(0.219)	(0.217)
$SST_{t-1} \vert SST_{t-1} < 0$	−0.145	−0.198	0.001	0.069	0.058
	(0.336)	(0.337)	(0.318)	(0.318)	(0.319)
			Americas (n=16)		
$SST_t \vert SST_{t-1} \geq 0$	−0.492	−0.496	−0.258	−0.317	−0.319
	(0.287)	(0.289)	(0.251)	(0.262)	(0.262)
$SST_{t-1} \vert SST_{t-1} \geq 0$	−0.679	−0.676	−0.488	−0.486	−0.467
	(0.483)	(0.481)	(0.399)	(0.412)	(0.410)
$SST_t \vert SST_{t-1} < 0$	−0.296	−0.298	−0.329	−0.254	−0.225
	(0.316)	(0.318)	(0.289)	(0.282)	(0.276)
$SST_{t-1} \vert SST_{t-1} < 0$	0.285	0.280	0.407	0.421	0.373
	(0.392)	(0.393)	(0.345)	(0.321)	(0.306)
			Asia-Pacific (n=15)		
$SST_t \vert SST_{t-1} \geq 0$	−0.432	-0.666^{**}	−0.374	−0.372	−0.343
	(0.272)	(0.245)	(0.234)	(0.225)	(0.218)
$SST_{t-1} \vert SST_{t-1} \geq 0$	-1.174^{*}	-1.169^{*}	−0.811	−0.886	−0.982
	(0.570)	(0.554)	(0.537)	(0.537)	(0.533)
$SST_t \vert SST_{t-1} < 0$	−0.263	−0.279	−0.332	−0.404	−0.429
	(0.283)	(0.250)	(0.260)	(0.259)	(0.258)
$SST_{t-1} \vert SST_{t-1} < 0$	$1.339^{**\ddagger}$	$1.079^{**\dagger}$	$1.067^{**\dagger}$	$1.152^{**\dagger}$	$1.244^{**\dagger}$
	(0.414)	(0.405)	(0.390)	(0.394)	(0.412)
fixed effects	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.014	0.068	0.122	0.156	0.176

Note: n denotes the number of countries. Values in parentheses are standard errors that are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels; ‡ and † denote statistical significance at 0.01 and 0.05 levels after Bonferroni correction.

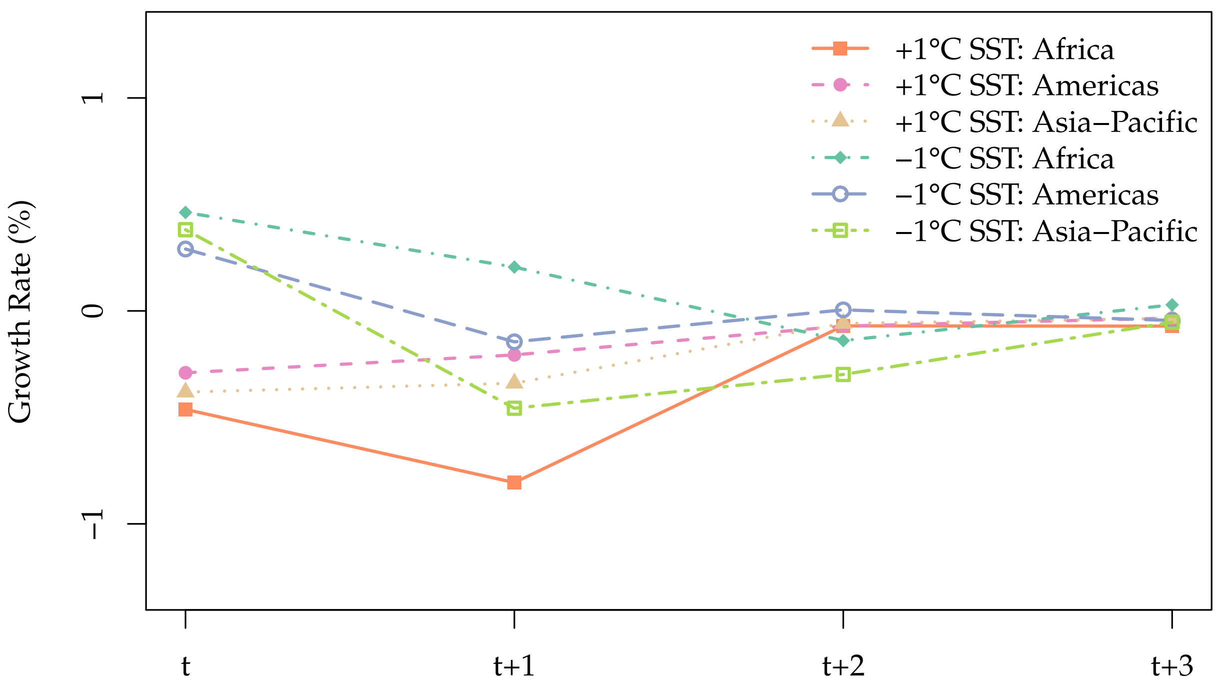

Figure 6: Dynamics of nonlinear impact of ENSO on growth across geographic regions

Note: Each curve represents an average of individual country dynamics obtained by iterating forward a positive or negative 1°C SST deviation in period t, given 1000 randomly sampled vectors of SST realizations for periods $\{t-1, t, \ldots, t+3\}$.

4.3 The ENSO Impact Through Agriculture

As alluded from the very beginning, 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 the time–invariant and country–specific vulnerability measure, the latter being either the agriculture value added (% of GDP) or the employment share of agriculture (% of total employment). We use country–averages of these measures, partly because agriculture (relative to GDP)—and, to a lesser extent, temporal labor displacement—can be a function of weather; but also due to data limitations, as for many countries the lengths of these series are much shorter than those of growth and SST anomalies. Finally, 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.

In accord with expectations, we find that the growth tends to be more sensitive to ENSO events in countries with a larger agriculture share of GDP or larger employment share in agriculture. Moreover, the results for the two vulnerability measures are very similar. On average, the negative growth effect of El Niño event is up to 0.2 percentage points larger in magnitude for countries that are 10% more agricultural (as measured by either of the two vulnerability indices). This difference, while economically meaningful, is 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 be mitigated as other socio-economic or political factors also mediate (though, not confound) climatic shocks on broader macroeconomic variables.

4.4 Cross Sectional Dependence and Sensitivity Analyses

Unobserved common shocks can influence growth rates in neighboring countries. Recent developments in the heterogeneous dynamic panel data modeling literature offer a possibility of addressing the error cross sectional 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

Table 6: Nonlinear Impact of ENSO Through Agriculture Share of GDP

	1	2	3	4	5
$\text{SST}_t \vert \text{SST}_{t-1} \geq 0$	$-0.763^{**\ddagger}$	$-0.819^{**\ddagger}$	$-0.575^{**\ddagger}$	$-0.616^{**\ddagger}$	$-0.595^{**\ddagger}$
	(0.164)	(0.158)	(0.147)	(0.145)	(0.142)
$\text{SST}_{t-1} \vert \text{SST}_{t-1} \geq 0$	$-1.097^{**\ddagger}$	$-1.050^{**\ddagger}$	$-0.892^{**\ddagger}$	$-0.938^{**\ddagger}$	$-0.858^{**\ddagger}$
	(0.296)	(0.287)	(0.270)	(0.266)	(0.264)
$\text{SST}_t \vert \text{SST}_{t-1} < 0$	−0.137	−0.134	−0.189	−0.179	−0.181
	(0.164)	(0.157)	(0.155)	(0.149)	(0.147)
$\text{SST}_{t-1} \vert \text{SST}_{t-1} < 0$	0.280	0.194	0.328	0.387	0.383
	(0.226)	(0.224)	(0.210)	(0.209)	(0.210)
$\text{AGR}_i \times \text{SST}_t \vert \text{SST}_{t-1} \geq 0$	0.001	−0.006	−0.004	−0.003	−0.002
	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)
$\text{AGR}_i \times \text{SST}_{t-1} \vert \text{SST}_{t-1} \geq 0$	−0.024	−0.024	−0.023	−0.018	−0.017
	(0.023)	(0.023)	(0.022)	(0.021)	(0.021)
$\text{AGR}_i \times \text{SST}_t \vert \text{SST}_{t-1} < 0$	−0.011	−0.012	−0.007	−0.006	−0.007
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
$\text{AGR}_i \times \text{SST}_{t-1} \vert \text{SST}_{t-1} < 0$	0.013	0.006	−0.002	−0.001	−0.002
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
fixed effects	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.010	0.066	0.120	0.154	0.174

Note: values in parentheses are standard errors that are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels; ‡ and † denote statistical significance at 0.01 and 0.05 levels after Bonferroni correction.

Table 7: Nonlinear Impact of ENSO Through Employment Share in Agriculture

	1	2	3	4	5
$\text{SST}_t \vert \text{SST}_{t-1} \geq 0$	$-0.776^{**\ddagger}$	$-0.840^{**\ddagger}$	$-0.575^{**\ddagger}$	$-0.640^{**\ddagger}$	$-0.646^{**\ddagger}$
	(0.170)	(0.165)	(0.152)	(0.151)	(0.149)
$\text{SST}_{t-1} \vert \text{SST}_{t-1} \geq 0$	$-1.029^{**\ddagger}$	$-0.982^{**\ddagger}$	$-0.789^{**\ddagger}$	$-0.906^{**\ddagger}$	$-0.866^{**\ddagger}$
	(0.302)	(0.293)	(0.272)	(0.274)	(0.272)
$\text{SST}_t \vert \text{SST}_{t-1} < 0$	−0.095	−0.091	−0.130	−0.171	−0.184
	(0.175)	(0.168)	(0.165)	(0.158)	(0.158)
$\text{SST}_{t-1} \vert \text{SST}_{t-1} < 0$	0.336	0.238	0.381	0.445^{*}	0.476^{*}
	(0.235)	(0.230)	(0.218)	(0.217)	(0.217)
$\text{EMP}_i \times \text{SST}_t \vert \text{SST}_{t-1} \geq 0$	−0.001	−0.007	−0.005	−0.003	−0.003
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
$\text{EMP}_i \times \text{SST}_{t-1} \vert \text{SST}_{t-1} \geq 0$	−0.012	−0.016	−0.011	−0.011	−0.013
	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
$\text{EMP}_i \times \text{SST}_t \vert \text{SST}_{t-1} < 0$	−0.002	−0.003	−0.001	−0.003	−0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\text{EMP}_i \times \text{SST}_{t-1} \vert \text{SST}_{t-1} < 0$	0.012	0.008	0.003	0.006	0.005
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
fixed effects	Y	Y	Y	Y	Y
linear trend	N	Y	N	N	N
lag order	N	N	1	2	3
R-squared	0.011	0.071	0.141	0.176	0.196

Note: standard errors that are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels; ‡ and † denote statistical significance at 0.01 and 0.05 levels after Bonferroni correction.

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 into the model the cross–sectionally averaged dependent variable that is very likely 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 will act as "bad control", and bring with it the caveats discussed in the Model section. For example, growth among neighboring countries may be correlated due to trade–induced spillovers. 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 a general method of moments approach put forward by Conley (1999), which allows for adjustments in spatial and temporal correlation in error terms (see, also, Hsiang, 2010; Hsiang and Meng, 2015) .

The applied *specific–to–general* modeling approach allows us to examine several model specifications that range from a parsimonious linear fixed effects to flexible nonlinear and heterogeneous alternatives. To complete the modeling cycle, we conducted an array of robustness checks (see Appendix Tables A2 and A3). In particular, to test for a placebo effect, we added two–year–ahead leads of SST anomalies to the originally estimated models. The results show hardly any indication of the placebo effect, while the parameter estimates of current and lagged SST anomalies remain comparable to those reported previously. As an alternative test, we regressed population growth rate on current and lagged SST anomalies. Again, the results reveal no evidence of spurious correlation. Finally, to check that very small or very large countries in the sample are not systemically altering the results—an effect that, in part, could be attributed to the previously discussed issue of the measurement error—we re-estimated parameters using a subset of data that exclude small countries (with 2010 population less than 5 million) or large countries (with 2010 population greater than 100 million). The results are qualitatively similar to those reported previously, with an exception of the Asia-Pacific region, where the large economies, such as China and India among others, appear to be playing a considerable role in the previously reported results.

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, ENSO–related lower economic growth can be countered by expansionary macroeconomic policies, such as increased government spending. However, this may be an unattainable luxury for many developing countries. In such instances, the international community—the developed world in particular—could provide relief by directing aid flows to regions that are most affected by ENSO–induced weather shocks. Effective policy actions, moreover, can also be of the microeconomic nature, targeted towards reducing 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 to 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, in the current study the ENSO effect may be camouflaged 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 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 are 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 warming 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 weather anomalies. 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 impact of 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 not only events causing dry conditions but also those characterized by increased precipitation. Countries in Africa also experience significantly reduced growth during El Niño events, particularly those back-to-back, whereas developing economies 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 modeling framework may uncover 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 that emerged from the main findings of the current research—which we shall leave for future studies to consider.

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Appendix

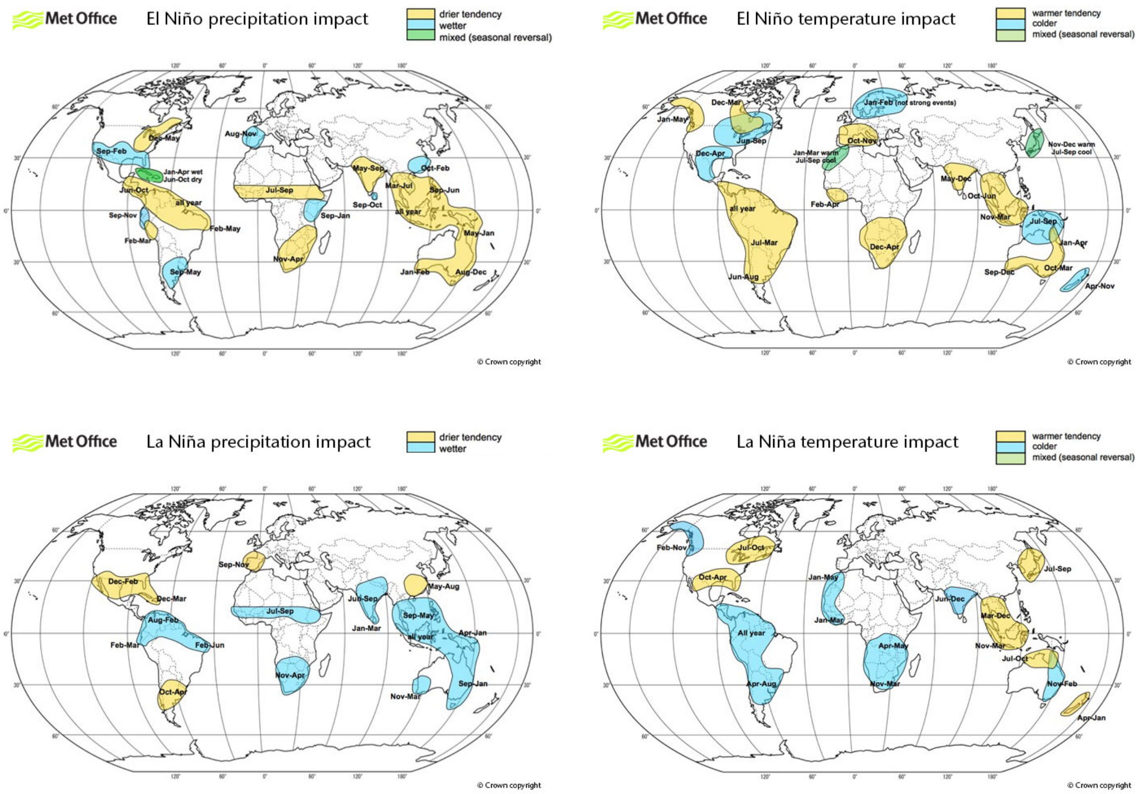

Figure A1: ENSO teleconnections

Source: http://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/el-nino-la-nina/enso-impacts

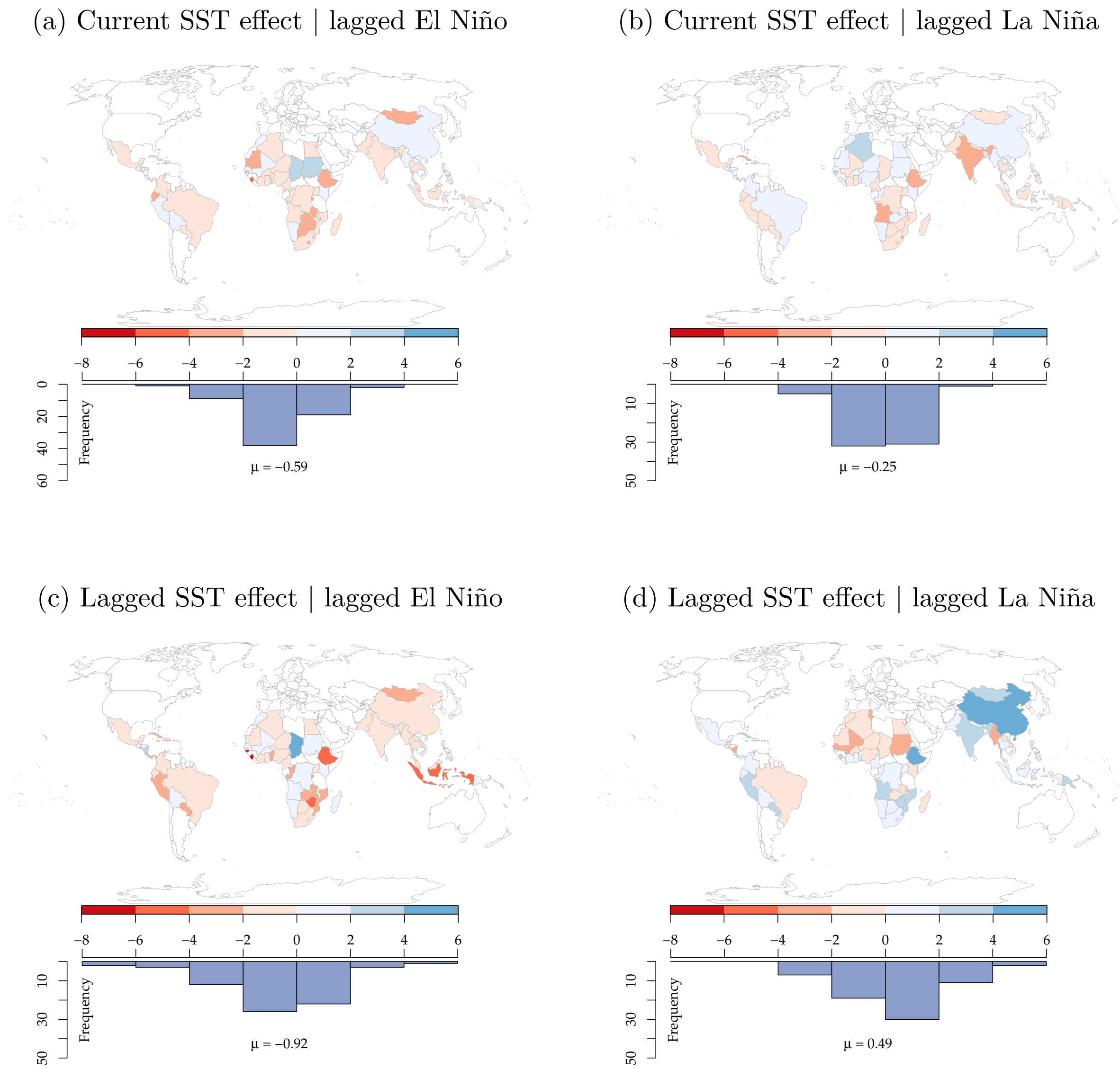

Figure A2: Heterogeneous impact of ENSO on growth

Table A1: Descriptive Statistics by Country

Country	ISO3	Climatic Zone	T	Growth Rate mean	s.d.	min	max	μ_{AGR}	μ_{EMP}
Angola	AGO	Temperate/Arid	30	1.7	8.4	-27.1	18.5	12.2	5.1
Burundi	BDI	Tropical/Humid	55	0.1	5.5	-15.4	19.1	52.8	
Benin	BEN	Tropical/Humid	55	0.8	3.0	-7.2	7.0	33.1	45.1
Burkina Faso	BFA	Temperate/Arid	55	1.9	3.0	-4.3	8.0	33.9	83.6
Bangladesh	BGD	Tropical/Humid	55	1.8	3.9	-15.5	7.7	35.5	57.8
Bolivia	BOL	Tropical/Humid	55	1.2	3.5	-13.9	5.7	17.0	30.7
Brazil	BRA	Tropical/Humid	55	2.3	3.8	-6.6	11.2	9.7	22.2
Botswana	BWA	Temperate/Arid	55	5.5	5.4	-9.5	22.3	11.2	25.4
China	CHN	Temperate/Arid	55	6.9	6.8	-26.5	16.1	24.2	54.5
Cote d'Ivoire	CIV	Tropical/Humid	55	0.5	5.1	-14.8	13.0	23.3	48.3
Cameroon	CMR	Tropical/Humid	55	0.9	5.5	-13.0	18.6	25.9	76.9
Congo, Dem. Rep.	COD	Tropical/Humid	55	-1.5	6.0	-16.8	18.2	28.8	
Congo, Rep.	COG	Tropical/Humid	55	1.5	5.3	-11.6	20.0	11.2	
Colombia	COL	Tropical/Humid	55	2.3	2.1	-5.6	6.0	16.6	8.2
Costa Rica	CRI	Tropical/Humid	55	2.2	3.0	-9.8	6.7	10.6	20.5
Cuba	CUB	Tropical/Humid	45	2.6	6.0	-15.4	19.1	9.5	21.4
Dominican Republic	DOM	Tropical/Humid	55	3.1	5.0	-15.2	14.9	14.6	14.6
Algeria	DZA	Temperate/Arid	55	1.5	7.3	-21.6	31.0	9.9	16.5
Ecuador	ECU	Tropical/Humid	55	1.6	3.0	-6.5	10.8	19.9	11.4
Egypt, Arab Rep.	EGY	Temperate/Arid	50	2.6	2.8	-1.8	12.1	20.0	36.2
Ethiopia	ETH	Temperate/Arid	34	2.5	6.8	-13.9	10.4	50.5	24.0
Ghana	GHA	Tropical/Humid	55	1.0	4.3	-14.5	11.3	44.1	42.0
Gambia, The	GMB	Temperate/Arid	49	0.5	3.4	-7.4	9.0	25.8	31.5
Guinea-Bissau	GNB	Tropical/Humid	45	0.5	6.9	-29.6	15.8	48.6	
Guatemala	GTM	Tropical/Humid	55	1.3	2.3	-6.1	6.6	12.6	35.9
Honduras	HND	Tropical/Humid	55	1.4	2.9	-4.4	7.2	23.4	44.0
Indonesia	IDN	Tropical/Humid	55	3.2	3.4	-14.4	7.9	16.6	47.8
India	IND	Temperate/Arid	55	3.3	3.2	-7.4	8.8	30.3	53.4
Jamaica	JAM	Tropical/Humid	49	0.6	4.4	-7.8	16.2	6.9	20.5
Kenya	KEN	Temperate/Arid	55	1.5	4.4	-10.6	17.9	32.3	
Lao PDR	LAO	Tropical/Humid	31	4.3	3.0	-4.8	10.9	43.9	
Sri Lanka	LKA	Tropical/Humid	54	3.5	2.2	-2.3	8.3	8.8	36.2
Lesotho	LSO	Temperate/Arid	55	3.2	5.7	-15.5	23.8	26.4	35.8
Morocco	MAR	Temperate/Arid	49	2.9	3.7	-6.9	10.7	15.2	24.1
Madagascar	MDG	Tropical/Humid	55	-0.9	3.9	-15.3	6.8	29.4	77.4
Mexico	MEX	Temperate/Arid	55	1.8	3.2	-7.5	8.5	7.3	17.4
Mali	MLI	Temperate/Arid	48	1.7	5.1	-9.3	18.1	44.6	41.5
Myanmar	MMR	Temperate/Arid	55	4.1	5.8	-12.9	12.8	41.5	66.5
Mongolia	MNG	Temperate/Arid	34	3.1	5.3	-10.3	15.3	21.5	40.6
Mozambique	MOZ	Tropical/Humid	35	3.1	6.9	-17.4	23.0	32.1	
Mauritania	MRT	Temperate/Arid	54	1.1	6.0	-7.8	24.0	31.4	
Mauritius	MUS	Tropical/Humid	39	3.7	3.2	-11.6	8.9	10.4	10.1
Malawi	MWI	Temperate/Arid	55	1.4	5.1	-10.5	15.6	40.5	
Malaysia	MYS	Tropical/Humid	55	3.8	3.3	-9.6	9.0	19.8	20.8
Namibia	NAM	Temperate/Arid	35	1.0	3.3	-4.5	11.0	9.3	30.0
Niger	NER	Temperate/Arid	55	-0.7	5.6	-19.3	10.3	40.1	
Nigeria	NGA	Tropical/Humid	55	1.5	8.1	-17.6	30.3	32.7	48.1
Nicaragua	NIC	Tropical/Humid	55	0.5	5.9	-28.6	10.7	19.5	37.2
Nepal	NPL	Temperate/Arid	55	1.8	2.7	-5.2	7.2	50.7	71.9

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Table A1 – continued from previous page

Country	ISO3	Climatic Zone	T	Growth Rate				AGR	EMP
				mean	s.d.	min	max		
Pakistan	PAK	Temperate/Arid	55	2.5	2.2	-2.2	8.4	29.7	49.4
Panama	PAN	Tropical/Humid	55	3.1	4.3	-15.2	10.4	6.5	23.4
Peru	PER	Tropical/Humid	55	1.6	4.8	-14.2	10.2	12.1	8.0
Philippines	PHL	Tropical/Humid	55	1.7	3.0	-9.8	6.0	21.5	43.3
Papua New Guinea	PNG	Tropical/Humid	54	1.6	4.7	-6.4	15.3	36.6	72.3
Paraguay	PRY	Tropical/Humid	55	2.5	3.9	-5.8	12.5	18.9	11.7
Sudan	SDN	Temperate/Arid	55	1.4	5.4	-9.1	12.9	39.0	
Senegal	SEN	Temperate/Arid	55	0.0	3.5	-9.3	6.1	18.9	39.9
Sierra Leone	SLE	Tropical/Humid	55	0.6	6.8	-22.3	20.5	43.8	68.5
El Salvador	SLV	Tropical/Humid	50	1.1	3.8	-13.3	6.1	12.4	23.2
Swaziland	SWZ	Temperate/Arid	45	2.8	4.2	-5.1	17.0	20.0	
Chad	TCD	Temperate/Arid	55	0.9	8.0	-23.0	28.7	40.9	
Togo	TGO	Tropical/Humid	55	1.0	5.8	-17.1	12.3	36.6	
Thailand	THA	Tropical/Humid	55	4.4	3.3	-8.7	11.3	17.8	55.0
Tunisia	TUN	Temperate/Arid	50	2.8	3.3	-3.9	15.2	15.1	26.4
Uganda	UGA	Tropical/Humid	33	2.5	3.0	-6.4	8.1	47.1	71.4
Vietnam	VNM	Tropical/Humid	31	4.9	1.8	0.4	7.8	20.5	57.6
South Africa	ZAF	Temperate/Arid	55	1.0	2.5	-4.6	6.1	5.5	7.7
Zambia	ZMB	Temperate/Arid	55	0.2	4.7	-10.9	13.0	15.2	62.1
Zimbabwe	ZWE	Temperate/Arid	55	0.1	6.7	-18.9	18.6	17.1	64.5

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

Table A2: Placebo Tests

	Tropical/Humid	Temperate/Arid	Africa	Americas	Asia-Pacific
	Dependent Variable: per capita GDP growth rate				
$SST_{t+2} \vert SST_{t+1} \geq 0$	-0.315^{*}	-0.198	-0.372	-0.293	0.031
$SST_{t+2} \vert SST_{t+1} < 0$	0.085	0.454	0.186	0.121	0.529^{*}
$SST_{t} \vert SST_{t-1} \geq 0$	$-0.755^{**\ddagger}$	-0.429	$-0.857^{**\dagger}$	-0.313	-0.346
$SST_{t-1} \vert SST_{t-1} \geq 0$	$-1.259^{**\ddagger}$	-0.227^{*}	-1.052^{*}	-0.475	-0.598
$SST_{t} \vert SST_{t-1} < 0$	-0.298	0.217	0.027	-0.271	-0.116
$SST_{t-1} \vert SST_{t-1} < 0$	0.694^{*}	-0.319	-0.037	0.399	0.854^{*}
	Dependent Variable: population growth rate				
$SST_{t} \vert SST_{t-1} \geq 0$	0.028	0.039	0.038	0.016	0.038
$SST_{t-1} \vert SST_{t-1} \geq 0$	0.009	0.044	0.016	0.013	0.059
$SST_{t} \vert SST_{t-1} < 0$	-0.004	-0.010	-0.012	0.001	0.000
$SST_{t-1} \vert SST_{t-1} < 0$	0.034	-0.006	0.030	0.004	-0.004

Note: in all instances, fixed effects model with lag order of one are applied; standard errors (not reported here) are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels; ‡ and † denote statistical significance at 0.01 and 0.05 levels after Bonferroni correction.

Table A3: Nonlinear Impact of ENSO in Subsets of Countries

	Tropical/Humid	Temperate/Arid	Africa	Americas	Asia-Pacific
	Countries with population greater than 5 million (n=56)				
$SST_t \mid SST_{t-1} \geq 0$	$-0.989^{**\ddagger}$	-0.543^{*}	$-0.981^{**\ddagger}$	-0.715^{*}	-0.512^{*}
$SST_{t-1} \mid SST_{t-1} \geq 0$	$-1.379^{**\ddagger}$	-0.535	-1.136^{*}	-0.717	-1.094
$SST_t \mid SST_{t-1} < 0$	-0.351	0.165	0.069	-0.421	-0.283
$SST_{t-1} \mid SST_{t-1} < 0$	0.655^{*}	-0.464	-0.289	0.211	$1.157^{**\dagger}$
	Countries with population less than 100 million (n=61)				
$SST_t \mid SST_{t-1} \geq 0$	$-0.811^{**\ddagger}$	-0.711^{*}	$-0.981^{**\ddagger}$	-0.386	-0.533
$SST_{t-1} \mid SST_{t-1} \geq 0$	$-1.405^{**\ddagger}$	-0.427	$-1.144^{**\dagger}$	-0.530	-1.095
$SST_t \mid SST_{t-1} < 0$	-0.297	0.181	-0.019	-0.305	-0.073
$SST_{t-1} \mid SST_{t-1} < 0$	0.699^{*}	-0.852^{*}	-0.165	0.349	0.373

Note: the population numbers are for 2010; n denotes the number of countries; in all instances, the fixed effects model with lag order of one are applied; standard errors (not reported here) are adjusted to account for spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over three years as per Conley (1999); ** and * denote statistical significance at 0.01 and 0.05 levels; ‡ and † denote statistical significance at 0.01 and 0.05 levels after Bonferroni correction.