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Fair Weather or Foul? The Macroeconomic Effects of El Niño*

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Abstract

This paper employs a dynamic multi-country framework to analyze the international macroeconomic transmission of El Niño weather shocks. This framework comprises 21 country/region-specific models, estimated over the period 1979Q2 to 2013Q1, and accounts for not only direct exposures of countries to El Niño shocks but also indirect effects through third-markets. We contribute to the climate-macroeconomy literature by exploiting exogenous variation in El Niño weather events over time, and their impact on different regions cross-sectionally, to causatively identify the effects of El Niño shocks on growth, inflation, energy and non-fuel commodity prices. The results show that there are considerable heterogeneities in the responses of different countries to El Niño shocks. While Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa face a short-lived fall in economic activity in response to an El Niño shock, for other countries (including the United States and European region), an El Niño occurrence has a growth-enhancing effect. Furthermore, most countries in our sample experience short-run inflationary pressures as both energy and non-fuel commodity prices increase. Given these findings, macroeconomic policy formulation should take into consideration the likelihood and effects of El Niño weather episodes.

JEL codes: C32, F44, O13, Q54

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1 Introduction

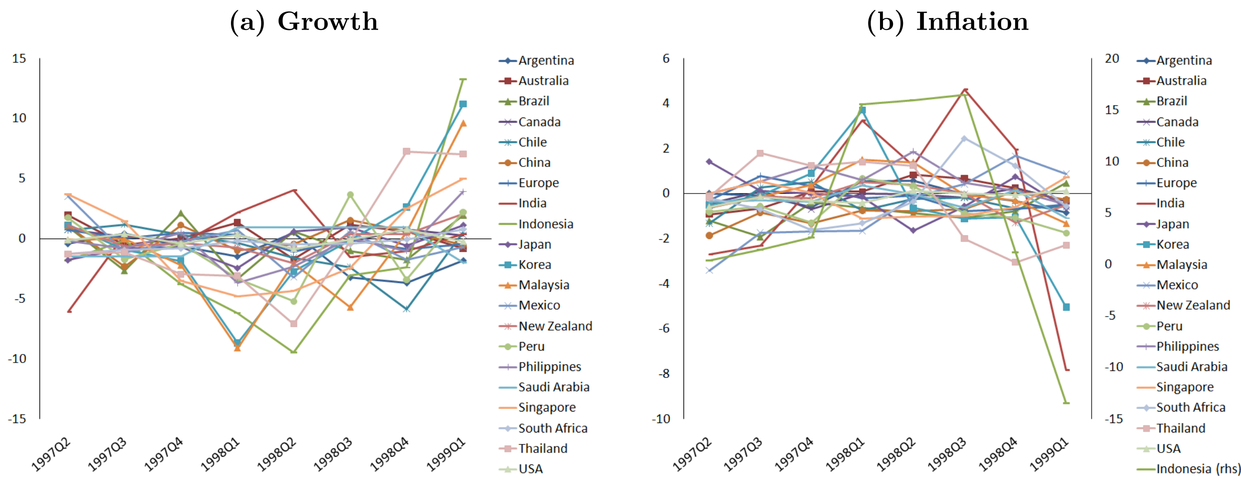
A rapidly growing literature investigates the relationship between climate (temperature, precipitation, storms, and other aspects of the weather) and economic performance (agricultural production, labor productivity, commodity prices, health, conflict, and economic growth)—see the recent surveys by Dell et al. (2014) and Tol (2009). This is important as a careful understanding of the climate-economy relationship is essential to the effective design of appropriate institutions and macroeconomic policies, as well as enabling forecasts of how future changes in climate will affect economic activity. However, a key challenge in studying such a relationship is "identification", i.e. distinguishing the effects of climate on economic activity from many other characteristics potentially covarying with it. We contribute to the climate-economy literature by exploiting the exogenous variation in weather-related events (with a special focus on El Niño[1]) over time, and their impact on different regions cross-sectionally, to causatively identify the effects of El Niño weather shocks on growth, inflation, energy and non-fuel commodity prices within a compact model of the global economy.

Our focus on El Niño weather events is motivated by growing concerns about their effects not only on the global climate system, but also on commodity prices and the macroeconomy of different countries—see Figure 1 for the evolution of growth and inflation across countries following the most recent strong El Niño episode which started in 1997Q2 and ended in 1998Q1. These extreme weather conditions can constrain the supply of rain-driven agricultural commodities, create food-price and generalized inflation, and may trigger social unrest in commodity-dependent countries that primarily rely on imported food. It has been suggested, by both historians and economists, that El Niño shocks may even have played a role in a substantial number of civil conflicts, see Hsiang et al. (2011). To analyze the macroeconomic transmission of El Niño shocks, both nationally and internationally, we employ a dynamic multi-country framework (combining time series, panel data, and factor analysis techniques), which takes into account economic interlinkages and spillovers that exist between different regions. It also controls for macroeconomic determinants of energy and non-fuel commodity prices, thereby disentangling the El Niño shock from many other possible sources of omitted variable bias. This is crucial, given the global dimension of commodity-price dynamics, and the interrelated macroeconomic performance of most countries.

Despite their importance, the macroeconomic effects of the most recent strong El Niño events of 1982/83 and 1997/98, along with the more frequent occurrences of weak El Niños, are under-studied. There are a number of papers looking at the effects of El Niño on:

[1] El Niño is a band of above-average ocean surface temperatures that periodically develops off the Pacific coast of South America, and causes major climatological changes around the world.

Figure 1: Growth and Inflation Following the 1997/98 El Niño Episode



Source: Authors' calculations.
Notes: Year on year percent change in growth and inflation following the 1997/98 El Niño episode.

particular countries, for example, Australia and the United States (Changnon 1999 and Debelle and Stevens 1995); a particular sector, for instance, agriculture and mining (Adams et al. 1995 and Solow et al. 1998); or particular commodity markets, including coffee, corn, and soybean (Handler and Handler 1983, Iizumi et al. 2014, and Ubilava 2012). Regarding the economic importance of El Niño events, Brunner (2002) argues that the Southern Oscillation (ENSO) cycle can explain about 10–20 percent of the variation in the GDP growth and inflation of G-7 economies, and about 20% of real commodity price movements over the period 1963–1997.[2] He shows that a one-standard-deviation positive shock to ENSO raises real commodity price inflation by about 3.5 to 4 percentage points (but this effect is only statistically significant in the second quarter following such a shock), and although the median responses of G-7 economies' *aggregate* CPI inflation and GDP growth are positive in the first four quarters, they are both in fact statistically insignificant. While Brunner (2002) focuses on the economic effects El Niño shocks over time (only taking advantage of the temporal dimension of the data), his sample is mostly restricted to regions which are not directly affected by El Niño.

We contribute to the literature that assesses the macroeconomic effects of weather shocks in several dimensions, including a novel multi-country methodology. Our modelling framework accounts for the effects of common factors (whether observed or unobserved), and

[2]The Southern Oscillation index (SOI) measures air-pressure differentials in the South Pacific (between Tahiti and Darwin). Deviations of the SOI index from their historical averages indicate the presence of El Niño (warm phase of the Southern Oscillation cycle) or La Niña (cold phase of the Southern Oscillation cycle) events—see Section 2 for more details.

ensures that the El Niño-economy relationship is identified from idiosyncratic local characteristics (using both time-series and cross-section dimensions of the data). To the extent that El Niño events are exogenously determined, reverse causation is unlikely to be a concern in our empirical analysis. Nevertheless, we allow for a range of endogenous control regressors, where country-specific variables are affected by El Niño shocks and possibly simultaneously determined by other observed or unobserved factors. We also have a different macroeconomic emphasis—while Brunner (2002) mainly focuses on the effects of El Niño on commodity prices, we concentrate on the implications of El Niño for national economic growth and inflation, in addition to global energy and non-fuel commodity prices. Moreover, we study the effects of El Niño shocks on 21 individual countries/regions (some of which are directly affected by El Niño) in an interlinked and compact model of the world economy, rather than focusing on an *aggregate* measure of global growth and inflation (which Brunner 2002 takes to be those of G-7 economies). Furthermore, we explicitly take into account the economic interlinkages and spillovers that exist between different regions in our interconnected framework (which may also shape the responses of different macroeconomic variables to El Niño shocks), rather than undertaking a country-by-country analysis. Finally, we contribute to the Global VAR (GVAR) literature that mostly relies on reduced-form impulse-response analysis by introducing El Niño as a dominant and causal variable in our framework.

Our framework comprises 21 country/region-specific models, among which is a single European region. These individual-economy models are solved in a global setting where core macroeconomic variables of each economy are related to corresponding foreign variables and a set of global factors—including a measure of El Niño intensity as a dominant unit. The model has the following variables: real GDP, inflation, real exchange rate, short-term and long-term interest rates, real energy and non-fuel commodity prices, and the Southern Oscillation index (SOI) anomalies as a measure of the magnitude of El Niño. This framework accounts for not only direct exposures of countries to El Niño shocks but also indirect effects through third-markets; see Dees et al. (2007) and Pesaran et al. (2007). We estimate the 21 individual VARX* models over the period 1979Q2–2013Q1. Having solved the Global VAR model, we examine the effect of El Niño shocks on the macroeconomic variables of different countries (especially those that are most susceptible to this weather phenomenon).[3]

Contrary to the findings of earlier studies, the results of our dynamic multi-country model of the world economy indicate that the economic consequences of El Niño shocks are large, statistically significant, and highly heterogeneous across different regions. While

[3]The GVAR methodology is a novel approach to global macroeconomic modeling as it combines time series, panel data, and factor analysis techniques to address the curse of dimensionality problem in large models, and is able to account for spillovers and the effects of ubserved and unobserved common factors (e.g. commodity-price shocks and global finacial cycle)—see Section 3.1 for additional details.

Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa face a short-lived fall in economic activity in response to a typical El Niño shock, for other countries, an El Niño event has a growth-enhancing effect; some (for instance the United States) due to direct effects while others (for instance the European region) through positive spillovers from major trading partners.[4] Overall, the larger the geographical area of a country, the smaller the primary sector's share in national GDP, and the more diversified the economy is, the smaller is the impact of El Niño shocks on GDP growth. Furthermore, most countries in our sample experience short-run inflationary pressures following an El Niño shock (depending mainly on the share of food in their CPI baskets), while global energy and non-fuel commodity prices increase. Therefore, we argue that macroeconomic policy formulation should take into consideration the likelihood and effects of El Niño weather episodes.

The rest of the paper is organized as follows. Section 2 gives a brief description of the Southern Oscillation cycle. Section 3 describes the GVAR methodology and outlines our modelling approach. Section 4 investigates the macroeconomic effects of El Niño shocks. Finally, Section 5 concludes and offers some policy recommendations.

2 The Southern Oscillation

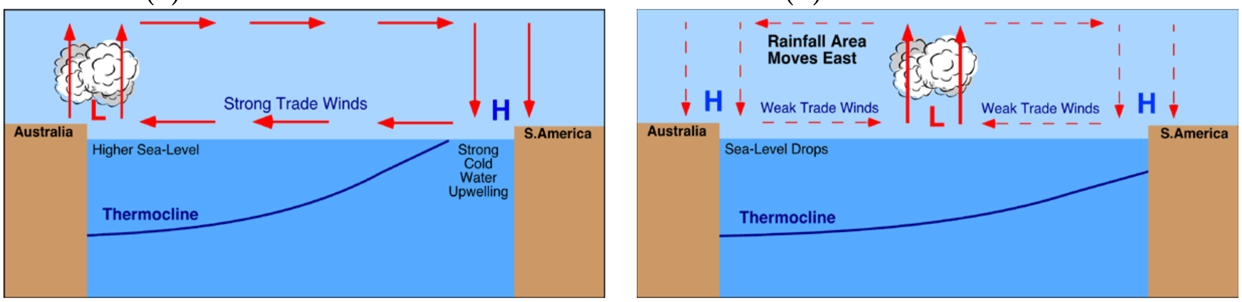
During "normal" years, a surface high pressure system develops over the coast of Peru and a low pressure system builds up in northern Australia and Indonesia (see Figure 2a). As a result, trade winds move strongly from east to west over the Pacific Ocean. These trade winds carry warm surface waters westward and bring precipitation to Indonesia and Australia. Along the coast of Peru, cold nutrient-rich water wells up to the surface, and thereby boosts the fishing industry in South America.

However, in an El Niño year, air pressure drops along the coast of South America and over large areas of the central Pacific. The "normal" low pressure system in the western Pacific also becomes a weak high pressure system, causing the trade winds to be reduced and allowing the equatorial counter current (which flows west to east) to accumulate warm ocean water along the coastlines of Peru (Figure 2b). This phenomenon causes the thermocline (the separation zone between the mixed-layer above, much influenced by atmospheric fluxes, and the deep ocean) to drop in the eastern part of Pacific Ocean, cutting off the upwelling of cold deep ocean water along the coast of Peru. Overall, the development of an El Niño brings drought to the western Pacific (including Australia), rains to the equatorial coast of South America, and convective storms and hurricanes to the central Pacific. The global

[4] Changnon (1999) also argues that an El Niño event can benefit the economy of the United States on a net basis—amounting to 0.2% of GDP during the 1997/98 period.

Figure 2: Southern Oscillation

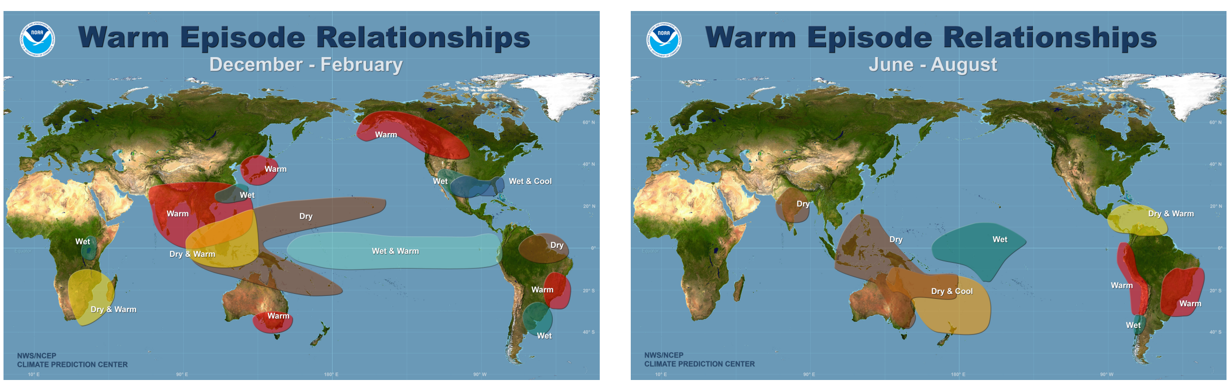
(a) Southern Oscillation **(b) El Niño Conditions**



Source: Pidwirny (2006).

climatological effects of El Niño are summarized in Figure 3, showing the effects across two different seasons. These changes in weather patterns have significant effects on agriculture, fishing, and construction industries, as well as on national and global commodity prices. Moreover, due to linkages of the Southern Oscillation with other climatic oscillations around the world, El Niño effects reach far beyond the realm of the Pacific Ocean region.[5]

Figure 3: Global Climatological Effects of El Nino



Source: National Atmospheric and Oceanic Administration's (NOAA) *Climate Prediction Center*.

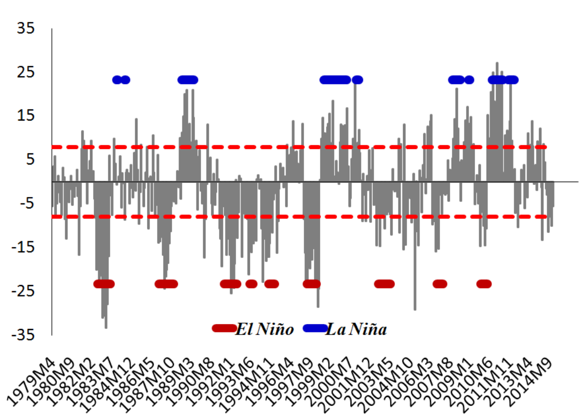
One of the ways of measuring El Niño intensity is by using the Southern Oscillation index (SOI), which is calculated based on air-pressure differentials in the South Pacific (between Tahiti and Darwin). Sustained negative SOI values below -8 indicate El Niño episodes, which typically occur at intervals of three to seven years and last about two years. Figure 4 shows that the 1982–83 and 1997–98 El Niños were quite severe (and had large adverse macroeconomic effects in many regions of the world), whereas other El Niños in our sample

[5]La Niña weather events (cold phases of the Southern Oscillation cycle) produce the opposite climate variations from El Niño occurances. Since the effects of La Niña on fisheries along the coast of South America, where El Niño was named, are benign, they received relatively little attention.

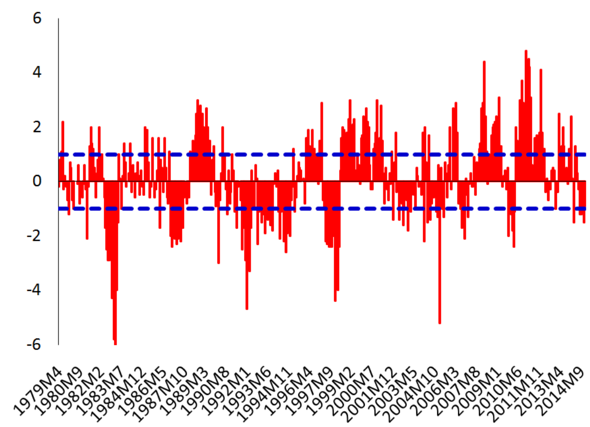
period were relatively moderate: 1986-88, 1991-92, 1993, 1994-95, 2002-03, 2006-07, and 2009-10. SOI "anomalies", which we use in our model, are defined as the deviation of the SOI index from their historical averages and divided by their historical standard deviations. Sustained negative SOI anomaly values below -1 indicate El Niño episodes (Figure 4b).

Figure 4: Southern Oscillation Index (Anomalies), 1979M4–2014M12

(a) SOI



(b) SOI Anomalies



Source: Authors' construction based on data from the Australian Bureau of Meteorology and the U.S. National Oceanic and Atmospheric Administration's *National Climatic Data Centre*.
Notes: Dashed-lines indicate thresholds for identifying El Niño and La Niña events.

3 Modelling the Climate-Macroeconomy Relationship in a Global Context

We employ the Global VAR (GVAR) methodology to analyze the international macroeconomic transmission of El Niño shocks. This framework takes into account both the temporal and cross-sectional dimensions of the data; real and financial drivers of economic activity; interlinkages and spillovers that exist between different regions; and the effects of unobserved or observed common factors (e.g. energy and non-fuel commodity prices). This is crucial as the impact of El Niño shocks cannot be reduced to one country but rather involve multiple regions, and may be amplified or dampened depending on the degree of openness of the countries and their trade structure. Before describing the data and our model specification, we provide a short exposition of the GVAR methodology below.

3.1 The Global VAR (GVAR) Methodology

We consider $N+1$ countries in the global economy, indexed by $i = 0, 1, ..., N$. With the exception of the United States, which we label as 0 and take to be the reference country; all other N countries are modelled as small open economies. This set of individual VARX* models is used to build the GVAR framework. Following Pesaran (2004) and Dees et al. (2007), a VARX* (p_i, q_i) model for the ith country relates a $k_i \times 1$ vector of domestic macroeconomic variables (treated as endogenous), $\mathbf{x}_{it}$, to a $k_i^* \times 1$ vector of country-specific foreign variables (taken to be weakly exogenous), $\mathbf{x}_{it}^*$:

$$\mathbf{\Phi}_i \left(L, p_i\right) \mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1} t + \mathbf{\Lambda}_i \left(L, q_i\right) \mathbf{x}_{it}^* + \mathbf{u}_{it}, \tag{1}$$

for $t = 1, 2, ..., T$, where $\mathbf{a}_{i0}$ and $\mathbf{a}_{i1}$ are $k_i \times 1$ vectors of fixed intercepts and coefficients on the deterministic time trends, respectively, and $\mathbf{u}_{it}$ is a $k_i \times 1$ vector of country-specific shocks, which we assume are serially uncorrelated with zero mean and a non-singular covariance matrix, $\mathbf{\Sigma}_{ii}$, namely $\mathbf{u}_{it} \sim i.i.d. \left(0, \mathbf{\Sigma}_{ii}\right)$. For algebraic simplicity, we abstract from observed global factors in the country-specific VARX* models. Furthermore, $\mathbf{\Phi}_i \left(L, p_i\right) = I - \sum_{i=1}^{p_i} \mathbf{\Phi}_i L^i$ and $\mathbf{\Lambda}_i \left(L, q_i\right) = \sum_{i=0}^{q_i} \mathbf{\Lambda}_i L^i$ are the matrix lag polynomial of the coefficients associated with the domestic and foreign variables, respectively. As the lag orders for these variables, p_i and q_i, are selected on a country-by-country basis, we are explicitly allowing for $\mathbf{\Phi}_i \left(L, p_i\right)$ and $\mathbf{\Lambda}_i \left(L, q_i\right)$ to differ across countries.

The country-specific foreign variables are constructed as cross-sectional averages of the domestic variables using data on bilateral trade as the weights, w_{ij}:

$$\mathbf{x}_{it}^* = \sum_{j=0}^{N} w_{ij} \mathbf{x}_{jt}, \tag{2}$$

where $j = 0, 1, ...N$, $w_{ii} = 0$, and $\sum_{j=0}^{N} w_{ij} = 1$. For empirical application, the trade weights are computed as three-year averages:[6]

$$w_{ij} = \frac{T_{ij,2009} + T_{ij,2010} + T_{ij,2011}}{T_{i,2009} + T_{i,2010} + T_{i,2011}}, \tag{3}$$

where T_{ijt} is the bilateral trade of country i with country j during a given year t and is calculated as the average of exports and imports of country i with j, and $T_{it} = \sum_{j=0}^{N} T_{ijt}$ (the total trade of country i) for $t = 2009$, 2010 and 2011, in the case of all countries.

[6] The main justification for using bilateral trade weights, as opposed to financial weights, is that the former have been shown to be the most important determinant of national business cycle comovements (see Baxter and Kouparitsas (2005)).

Although estimation is done on a country-by-country basis, the GVAR model is solved for the world as a whole, taking account of the fact that all variables are endogenous to the system as a whole. After estimating each country VARX*(p_i, q_i) model separately, all the $k = \sum_{i=0}^{N} k_i$ endogenous variables, collected in the $k \times 1$ vector $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$, need to be solved simultaneously using the link matrix defined in terms of the country-specific weights. To see this, we can write the VARX* model in equation (1) more compactly as:

$$\mathbf{A}_i\left(L, p_i, q_i\right)\mathbf{z}_{it} = \boldsymbol{\varphi}_{it}, \tag{4}$$

for $i = 0, 1, ..., N$, where

$$\begin{aligned} \mathbf{A}_i\left(L, p_i, q_i\right) &= \left[\boldsymbol{\Phi}_i\left(L, p_i\right) - \boldsymbol{\Lambda}_i\left(L, q_i\right)\right], \quad \mathbf{z}_{it} = \left(\mathbf{x}'_{it}, \mathbf{x}'^{*}_{it}\right)', \\ \boldsymbol{\varphi}_{it} &= \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \mathbf{u}_{it}. \end{aligned} \tag{5}$$

Note that given equation (2) we can write:

$$\mathbf{z}_{it} = \mathbf{W}_i\mathbf{x}_t, \tag{6}$$

where $\mathbf{W}_i = (\mathbf{W}_{i0}, \mathbf{W}_{i1}, ..., \mathbf{W}_{iN})$, with $\mathbf{W}_{ii} = 0$, is the $(k_i + k_i^*) \times k$ weight matrix for country i defined by the country-specific weights, w_{ij}. Using (6) we can write (4) as:

$$\mathbf{A}_i\left(L, p\right)\mathbf{W}_i\mathbf{x}_t = \varphi_{it}, \tag{7}$$

where $\mathbf{A}_i\left(L, p\right)$ is constructed from $\mathbf{A}_i\left(L, p_i, q_i\right)$ by setting $p = \max\left(p_0, p_1, ..., p_N, q_0, q_1, ..., q_N\right)$ and augmenting the $p - p_i$ or $p - q_i$ additional terms in the power of the lag operator by zeros. Stacking equation (7), we obtain the Global VAR(p) model in domestic variables only:

$$\mathbf{G}\left(L, p\right)\mathbf{x}_t = \varphi_t, \tag{8}$$

where

$$\mathbf{G}\left(L, p\right) = \begin{pmatrix} \mathbf{A}_0\left(L, p\right)\mathbf{W}_0 \\ \mathbf{A}_1\left(L, p\right)\mathbf{W}_1 \\ . \\ . \\ . \\ \mathbf{A}_N\left(L, p\right)\mathbf{W}_N \end{pmatrix}, \quad \varphi_t = \begin{pmatrix} \varphi_{0t} \\ \varphi_{1t} \\ . \\ . \\ . \\ \varphi_{Nt} \end{pmatrix}. \tag{9}$$

For an early illustration of the solution of the GVAR model, using a VARX*$(1, 1)$ model, see Pesaran (2004), and for an extensive survey of the latest developments in GVAR modeling, both the theoretical foundations of the approach and its numerous empirical applications, see Chudik and Pesaran (2014). The GVAR(p) model in equation (8) can be solved recursively and used for a number of purposes, such as forecasting or impulse response analysis.

Chudik and Pesaran (2013) extend the GVAR methodology to a case in which common variables are added to the conditional country models (either as observed global factors or as dominant variables). In such circumstances, equation (1) should be augmented by a vector of dominant variables, $\boldsymbol{\omega}_t$, and its lag values:

$$\boldsymbol{\Phi}_i\left(L, p_i\right)\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i1}t + \boldsymbol{\Lambda}_i\left(L, q_i\right)\mathbf{x}_{it}^{*} + \boldsymbol{\Upsilon}_i\left(L, s_i\right)\boldsymbol{\omega}_t + \mathbf{u}_{it}, \tag{10}$$

where $\boldsymbol{\Upsilon}_i\left(L, s_i\right) = \sum_{i=0}^{s_i}\boldsymbol{\Upsilon}_i L^i$ is the matrix lag polynomial of the coefficients associated with the common variables. Here, $\boldsymbol{\omega}_t$ can be treated (and tested) as weakly exogenous for the purpose of estimation. The marginal model for the dominant variables can be estimated with or without feedback effects from $\mathbf{x}_t$. To allow for feedback effects from the variables in the GVAR model to the dominant variables via cross-section averages, we define the following model for $\boldsymbol{\omega}_t$:

$$\boldsymbol{\omega}_t = \sum_{l=1}^{p_w}\boldsymbol{\Phi}_{\omega l}\boldsymbol{\omega}_{i,t-l} + \sum_{l=1}^{p_w}\boldsymbol{\Lambda}_{\omega l}\mathbf{x}_{i,t-l}^{*} + \boldsymbol{\eta}_{\omega t} \tag{11}$$

It should be noted that contemporaneous values of star variables do not feature in equation (11) and $\boldsymbol{\omega}_t$ are "causal". Conditional (10) and marginal models (11) can be combined and solved as a complete GVAR model as explained earlier.

3.2 Model Specification

Key countries in our sample include those likely to be directly affected by El Niño—mainly countries in the Asia and Pacific region as well as those in the Americas, see Table 1 and Section 2. To investigate the possible indirect effects of El Niño (through trade, commodity price and financial channels), we also include other major economies, such as European countries, in the model. However, the main focus of the present study is not Europe, given that it is not likely to be directly affected by an El Niño shock. Therefore, for this empirical application, we create a region consisting of 13 European countries. The time series data for the Europe block are constructed as cross-sectionally weighted averages of the domestic variables, using Purchasing Power Parity GDP weights, averaged over the 2009-2011 period. Thus, as displayed in Table 1, our model includes 33 countries (with 21 country/region-specific models) covering over 90% of world GDP.

Table 1: Countries and Regions in the GVAR Model

Asia and Pacific	**North America**	**Europe**
Australia	Canada	Austria
China	Mexico	Belgium
India	United States	Finland
Indonesia		France
Japan	**South America**	Germany
Korea	Argentina	Italy
Malaysia	Brazil	Netherlands
New Zealand	Chile	Norway
Philippines	Peru	Spain
Singapore		Sweden
Thailand	**Middle East and Africa**	Switzerland
	Saudi Arabia	Turkey
	South Africa	United Kingdom

We specify two different sets of individual country-specific models. The first model is common across all countries, apart from the United States. These 20 VARX* models include a maximum of six domestic variables (depending on whether data on a particular variable is available), or using the same terminology as in equation (1):

$$\mathbf{x}_{it} = \left[y_{it},\ \pi_{it},\ eq_{it},\ r^S_{it},\ r^L_{it},\ ep_{it}\right]', \tag{12}$$

where y_{it} is the log of the real Gross Domestic Product at time t for country i, π_{it} is inflation, eq_{it} is the log of real equity prices, r^S_{it} (r^L_{it}) is the short (long) term interest rate, and ep_{it} is the real exchange rate. In addition, all domestic variables, except for that of the real exchange rate, have corresponding foreign variables computed as in equation (2):

$$\mathbf{x}^*_{it} = \left[y^*_{it},\ \pi^*_{it},\ eq^*_{it},\ r^{*S}_{it},\ r^{*L}_{it}\right]'. \tag{13}$$

Following the GVAR literature, the twenty-first model (United States) is specified differently, mainly because of the dominance of the United States in the world economy. First, given the importance of U.S. financial variables in the global economy, the U.S.-specific foreign financial variables, $eq^*_{US,t}$, $r^{*S}_{US,t}$, and $r^{*L}_{US,t}$, are not included in this model. The appropriateness of exclusion of these variables was also confirmed by statistical tests, in which the weak exogeneity assumption was rejected for $eq^*_{US,t}$, $r^{*S}_{US,t}$, and $r^{*L}_{US,t}$. Second, since e_{it} is expressed as the domestic currency price of a United States dollar, it is by construction determined outside this model. Thus, instead of the real exchange rate, we included $e^*_{US,t} - p^*_{US,t}$

as a weakly exogenous foreign variable in the U.S. model.[7]

Given our interest in analyzing the macroeconomic effects of El Niño shocks, we need to include the Southern Oscillation index anomalies (SOI_t) in our framework. We model SOI_t as a dominant variable because there is no reason to believe that any of the macroeconomic variables described above influences it. In other words, SOI_t is included as a weakly exogenous variable in each of the 21 country/region-specific VARX* models, with no feedback effects from any of the macro variables to SOI_t (hence a unidirectional causality).

Moreover, there is some anecdotal evidence that SOI_t influences global commodity markets—for example, hot and dry summers in southeast Australia increases the frequency and severity of bush fires, which reduces Australia's wheat exports and thereby drives up global wheat prices, see Bennetton et al. (1998). We test this hypothesis formally by including the price of various commodities in our model. A key question is how should these commodity prices be included in the GVAR model? The standard approach to modelling commodity markets in the GVAR literature (see Cashin et al. 2014) is to include the log of nominal oil prices in U.S. dollars as a "global variable" determined in the U.S. VARX* model; that is the price of oil is included in the U.S. model as an endogenous variable while it is treated as weakly exogenous in the model for all other countries.[8] The main justification for this approach is that the U.S. is the world's largest oil consumer and a demand-side driver of the price of oil. However, it seems more appropriate for oil prices to be determined in global commodity markets rather in the U.S. model alone, given that oil prices are also affected by, for instance, any disruptions to oil supply in the Middle East.

Furthermore, given that El Niño events potentially affect the global prices of food, beverages, metals and agricultural raw materials, we also need to include the prices of these non-fuel commodities in our model. However, rather than including the individual prices of non-fuel commodities (such as wheat, coffee, timber, and nickel) we use a measure of real non-fuel commodity prices in logs, p_t^{nf}, constructed by the International Monetary Fund, with the weight of each of the 38 non-fuel commodities included in the index being equal to average world export earnings.[9] Therefore, our commodity market model includes both the real crude oil price (p_t^{oil}) and the real non-fuel commodity price as endogenous variables, where the former can be seen as a good proxy for fuel prices in general. In addition, to capture the effects of global economic conditions on world commodity markets, we include seven weakly exogenous variables in this model. More specifically, real GDP, the rate of

[7] Weak exogeneity test results for all countries and variables are available upon request.

[8] An exception is Mohaddes and Pesaran (2015) which explicitly models the oil market as a dominant unit in the GVAR framework.

[9] See http://www.imf.org/external/np/res/commod/table2.pdf for the details on these commodities and their weights.

inflation, short and long-term interest rates, real equity prices, and the real exchange rate are included as weakly exogenous variables (constructed using purchasing power parity GDP weights, averaged over 2009-2011), as is the SOI_t.

4 Empirical Results

We obtain data on $\mathbf{x}_{it}$ for the 33 countries included in our sample (see Table 1) from the GVAR website: https://sites.google.com/site/gvarmodelling, see Smith and Galesi (2014) for more details. Oil price data is also from the GVAR website, while data on non-fuel commodity prices are from the International Monetary Fund's *International Financial Statistics.* Finally, the Southern Oscillation index (SOI) anomalies data are from National Oceanic and Atmospheric Administration's *National Climatic Data Centre.* We use quarterly observations over the period 1979Q2–2013Q1 to estimate the 21 country-specific VARX*(p_i, q_i) models. However, prior to estimation, we determine the lag orders of the domestic and foreign variables, p_i and q_i. For this purpose, we use the Akaike Information Criterion (AIC) applied to the underlying unrestricted VARX* models. Given data constraints, we set the maximum lag orders to $p_{\max} = q_{\max} = 2$. The selected VARX* orders are reported in Table 2. Moreover, the lag order selected for the univariate SOI_t model is 1 and for the commodity price model is $(1, 2)$, both based on the AIC.

Having established the lag order of the 21 VARX* models, we proceed to determine the number of long-run relations. Cointegration tests with the null hypothesis of no cointegration, one cointegrating relation, and so on are carried out using Johansen's maximal eigenvalue and trace statistics as developed in Pesaran et al. (2000) for models with weakly exogenous $I(1)$ regressors, unrestricted intercepts and restricted trend coefficients. We choose the number of cointegrating relations (r_i) based on the maximal eigenvalue test statistics using the 95% simulated critical values computed by stochastic simulations and 1000 replications.

We then consider the effects of system-wide shocks on the exactly-identified cointegrating vectors using persistence profiles developed by Lee and Pesaran (1993) and Pesaran and Shin (1996). On impact the persistence profiles (PPs) are normalized to take the value of unity, but the rate at which they tend to zero provides information on the speed with which equilibrium correction takes place in response to shocks. The PPs could initially over-shoot, thus exceeding unity, but must eventually tend to zero if the vector under consideration is indeed cointegrated. In our analysis of the PPs, we noticed that the speed of convergence was very slow for Korea and for Saudi Arabia where the system-wide shocks never really died out, so we reduced r_i by one for each country resulting in well behaved PPs overall. The final selection of the number of cointegrating relations are reported in Table 2.

Table 2: Lag Orders of the Country-Specific VARX*(p,q) Models Together with the Number of Cointegrating Relations (r)

Country	VARX* Order		Cointegrating	Country	VARX* Order		Cointegrating
	p_i	q_i	relations (r_i)		p_i	q_i	relations (r_i)
Argentina	2	2	1	Malaysia	1	1	2
Australia	1	1	4	Mexico	1	2	2
Brazil	2	2	1	New Zealand	2	2	2
Canada	1	2	2	Peru	2	2	1
China	2	1	1	Philippines	2	1	2
Chile	2	2	1	South Africa	2	2	3
Europe	2	2	3	Saudi Arabia	2	1	1
India	2	2	3	Singapore	2	1	1
Indonesia	2	1	3	Thailand	1	1	1
Japan	2	2	3	USA	2	2	2
Korea	2	1	2				

Notes: p_i and q_i denote the lag order for the domestic and foreign variables respectively and are selected by the Akaike Information Criterion (AIC). The number of cointegrating relations (r_i) are selected using the maximal eigenvalue test statistics based on the 95% simulated critical values computed by stochastic simulations and 1000 replications for all countries except for Korea and Saudi Arabia, for which we reduced r_i below those suggested by the maximal eigenvalue statistic to ensure that the persistence profiles were well behaved.
Source: Authors' estimations.

4.1 The Effects of El Niño on Real Output

In general, identification of shocks in economics is not a straightforward task, however, in our application it is clear that the El Niño shock, a negative unit shock (equal to one standard error) to SOI anomalies, SOI_t, is identified by construction (as $\boldsymbol{\omega}_t$ are "causal"). Table 3 reports the estimated median impulse responses of real GDP growth to an El Niño shock, where the median responses on impact as well as the cumulated effects after the first, second, third, and fourth quarters are reported. The results show that an El Niño event has a statistically significant effect on real GDP growth for most of the countries in our sample—there are only four countries for which the median effects are not statistically significant at two or one standard deviations.[10]

Table 3: The Effects of an El Niño Shock on Real GDP Growth (in percent)

Country	Impact	Cumulated Responses After			
		1 Quarter	2 Quarters	3 Quarters	4 Quarters
Argentina	-0.08	0.03	0.29*	0.64**	1.08**
Australia	-0.03	-0.18**	-0.30**	-0.37*	-0.41
Brazil	-0.06	0.04	0.20	0.42*	0.68*
Canada	0.00	0.13**	0.33*	0.58**	0.85**
China	-0.01	0.03	0.16*	0.36*	0.56*
Chile	-0.19*	-0.10	0.16*	0.42*	0.70*
Europe	0.02	0.09	0.27**	0.49**	0.69**
India	-0.03	-0.15*	-0.23	-0.25	-0.25
Indonesia	-0.35**	-0.61*	-0.91*	-1.02	-1.01
Japan	-0.10*	-0.12	0.01*	0.20*	0.37*
Korea	0.11	0.29*	0.44	0.58	0.67
Malaysia	0.08	0.06	0.13	0.27	0.43
Mexico	0.03	0.37**	0.71*	1.12*	1.57**
New Zealand	-0.16**	-0.29*	-0.37	-0.42	-0.43
Peru	-0.07	-0.28	-0.35	-0.34	-0.33
Philippines	0.06	0.09	0.11	0.17	0.21
South Africa	-0.11**	-0.24*	-0.47**	-0.63*	-0.72
Saudi Arabia	-0.09	-0.17	-0.14	0.00	0.18
Singapore	0.09	0.28*	0.54*	0.87*	1.18*
Thailand	0.47**	0.78**	1.11**	1.49**	1.81**
USA	0.05*	0.10	0.23*	0.39*	0.55*

Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies. The impact is in percentage points and the horizon is quarterly. Symbols ** and * denote significance at 5–95% and 16–84% bootstrapped error bounds respectively.
Source: Authors' estimations.

[10] Note that significance (for a particular variable and country) does not have to be seen on impact as the effects of El Niño in most regions are felt during one specific season and hence could happen in a particular quarter rather than all quarters.

As noted earlier, El Niño causes hot and dry summers in southeast Australia (Figure 3); increases the frequency and severity of bush fires; reduces wheat export, and drives up global wheat prices. Exports and global prices of other commodities (food and raw agricultural materials) are also affected by drought in Australia, further reducing output growth (the primary sector constitutes 10% of Australia's GDP, Table 4). New Zealand often experiences drought in parts of the country that are normally dry and floods in other places, resulting in lower agricultural output (the El Niño of 1997/98 was particularly severe in terms of output loss for New Zealand). Therefore, it is not surprising that we observe a statistically-significant drop in GDP growth of 0.37% for Australia and 0.29% for New Zealand, three and one quarters after an El Niño shock, respectively.[11]

Table 4: Share of Primary Sector in GDP (in percent), Averages over 2004-2013

Asia and Pacific		**North America**	
Australia	10	Canada	10
China	11	Mexico	12
India	21	United States	3
Indonesia	25		
Japan	1	**South America**	
Korea	3	Argentina	11
Malaysia	22	Brazil	7
New Zealand	6	Chile	18
Philippines	14	Peru	20
Singapore	0		
Thailand	15	**Africa**	
		South Africa	10

Notes: Primary sector is the sum of agriculture, forestry, fishing and mining.
Source: *Haver*.

Moreover, El Niño conditions usually coincide with a period of weak monsoon and rising temperatures in India (see Figure 3) which adversely affects India's agricultural sector and increases domestic food prices. This is confirmed by our econometric analysis where India's GDP growth falls by 0.15% after the first quarter. The negative effect of El Niño is rather muted in India, due to a number of mitigating factors. One such factor is the declining share of agricultural output in Indian GDP over time—the share of India's primary sector in GDP was 28% in 1997 and has dropped to 20% in 2013. The increase in the contribution of Rabi crops (sown in winter and harvested in the spring) and the decline in the contribution of Kharif crops (sown in the rainy monsoon season) over the past few decades is another

[11] See Kamber et al. (2013) for an analysis of the economic effects of drought in New Zealand.

mitigating factor as sowing of Rabi crops is not "directly" affected by the monsoon.[12] Note also that the total irrigated area for major crops in India has increased from 22.6 million hectares in 1950-51 to 86.4 million hectares in 2009-10. Moreover, due to more developed agricultural markets and policies, rising agriculture yield, and climatological early warning systems, farmers are better able to switch to more drought-resistant and short-duration crops (with government assistance), at reasonably short notice. Furthermore, any severe rainfall deficiency in India could have implications for public agricultural spending and government finances. However, one should note that an El Niño year has not always resulted in weak monsoons in India, see Saini and Gulati (2014).

Drought in Indonesia is also harmful for the local economy, and pushes up world prices for coffee, cocoa, and palm oil, among other commodities. Furthermore, mining equipment in Indonesia relies heavily on hydropower; with deficient rain and low river currents, then less nickel (which is used to strengthen steel) can be produced by the world's top exporter of nickel. Indonesian GDP growth falls by 0.91% at the end of the second quarter, and metal prices increase as global supply drops. This large growth effect is expected given that the share of the primary sector (agricultural and mining) in Indonesian GDP is around 25 percent (see Table 4).

Looking beyond the Asia and Pacific region, South Africa also experiences hot and dry summers during an El Niño episode (Figure 3), which has adverse effects on its agricultural production (the primary sector makes up 10% of South Africa's GDP) with the empirical results suggesting a fall in GDP growth by 0.63% after the third quarter. Moreover, El Niño typically brings stormy winters in Chile and affects metal prices through supply chain disruption—heavy rain in Chile will reduce access to its mountainous mining regions, where large copper deposits are found. Therefore, we would expect an increase in metal prices and a reduction in output growth, which we estimate to be -0.19% on impact. More frequent typhoon strikes and cooler weather during summers are expected for Japan, which could depress consumer spending and growth. Our analysis suggests an initial drop of only 0.10% in Japanese output growth. However, we also observe that for both Chile and Japan, the overall effect after four quarters is positive, by 0.70% and 0.37% respectively. This is most likely due to positive spillovers from their major trading partners. For instance, trade with China, Europe, and the U.S. constitutes over 57% of each country's total trade (see Table 5). The construction sector also sees a large boost following typhoons in Japan, which can partly explain the increase in growth after an initial decline. Finally, for northern Brazil, there is a high probability of a low rainfall year when El Niño is in force. Drought in

[12] In 1980-81 the ratio of Kharif to Rabi crop production was 1.5. In 2013-14 it is estimated at 0.95 (see, India Economic Survey 2014-15).

Table 5: Trade Weights, Averages over 2009–2011

	Argentina	Australia	Brazil	Canada	China	Chile	Europe	India	Indonesia	Japan	Korea	Malaysia	Mexico	New Zealand	Peru	Philippines	South Africa	Saudi Arabia	Singapore	Thailand	USA
Argentina	0.00	0.00	0.11	0.00	0.01	0.05	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.00
Australia	0.01	0.00	0.01	0.00	0.04	0.01	0.03	0.04	0.03	0.06	0.04	0.04	0.00	0.24	0.00	0.02	0.02	0.01	0.03	0.05	0.01
Brazil	0.32	0.01	0.00	0.01	0.03	0.08	0.04	0.02	0.01	0.01	0.02	0.01	0.01	0.00	0.06	0.00	0.02	0.02	0.01	0.01	0.02
Canada	0.02	0.01	0.02	0.00	0.02	0.02	0.04	0.01	0.01	0.02	0.01	0.01	0.03	0.02	0.07	0.01	0.01	0.01	0.01	0.01	0.20
China	0.13	0.25	0.19	0.08	0.00	0.24	0.25	0.16	0.14	0.27	0.28	0.16	0.09	0.16	0.19	0.12	0.18	0.15	0.14	0.16	0.18
Chile	0.06	0.00	0.03	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.01
Europe	0.21	0.15	0.28	0.12	0.23	0.19	0.00	0.30	0.11	0.14	0.12	0.13	0.08	0.16	0.20	0.13	0.38	0.19	0.14	0.15	0.22
India	0.02	0.04	0.03	0.01	0.03	0.02	0.05	0.00	0.05	0.01	0.03	0.03	0.01	0.02	0.01	0.01	0.06	0.08	0.04	0.02	0.02
Indonesia	0.01	0.03	0.01	0.00	0.02	0.00	0.01	0.04	0.00	0.04	0.04	0.05	0.00	0.02	0.00	0.03	0.01	0.02	0.10	0.05	0.01
Japan	0.02	0.16	0.05	0.03	0.15	0.09	0.08	0.04	0.16	0.00	0.14	0.14	0.03	0.09	0.05	0.17	0.08	0.14	0.08	0.20	0.07
Korea	0.02	0.07	0.04	0.01	0.10	0.06	0.04	0.04	0.08	0.08	0.00	0.05	0.03	0.04	0.04	0.07	0.03	0.11	0.07	0.04	0.03
Malaysia	0.01	0.03	0.01	0.00	0.04	0.00	0.02	0.03	0.07	0.04	0.02	0.00	0.01	0.03	0.00	0.04	0.01	0.01	0.15	0.07	0.01
Mexico	0.03	0.01	0.03	0.04	0.01	0.03	0.02	0.01	0.00	0.01	0.02	0.01	0.00	0.01	0.03	0.00	0.00	0.00	0.01	0.00	0.15
New Zealand	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Peru	0.01	0.00	0.01	0.01	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Philippines	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.02	0.01	0.02	0.00	0.01	0.00	0.00	0.00	0.01	0.03	0.02	0.01
South Africa	0.01	0.01	0.01	0.00	0.01	0.00	0.03	0.03	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.01
Saudi Arabia	0.00	0.01	0.02	0.00	0.02	0.00	0.03	0.07	0.02	0.04	0.05	0.01	0.00	0.02	0.00	0.03	0.04	0.00	0.03	0.03	0.02
Singapore	0.00	0.05	0.01	0.00	0.03	0.00	0.03	0.05	0.14	0.03	0.04	0.15	0.00	0.04	0.00	0.12	0.01	0.04	0.00	0.06	0.02
Thailand	0.01	0.04	0.01	0.00	0.03	0.01	0.02	0.02	0.05	0.05	0.02	0.07	0.01	0.03	0.01	0.06	0.02	0.03	0.05	0.00	0.01
USA	0.10	0.09	0.16	0.67	0.19	0.17	0.27	0.13	0.09	0.17	0.13	0.12	0.68	0.12	0.23	0.16	0.11	0.16	0.11	0.11	0.00

Notes: Trade weights are computed as shares of exports and imports, displayed in columns by country (such that a column, but not a row, sum to 1).
Source: International Monetary Fund's *Direction of Trade Statistics*, 2009-2011.

northern parts of Brazil can drive up world prices for coffee, sugar, and citrus. However, south-eastern Brazil gets plentiful rain in the spring/summer of an El Niño year, which leads to higher agricultural output. We do not observe any significant effects for Brazil in the first two quarters, suggesting perhaps that the loss in agricultural output from drought in the northern part is to some extent mitigated by above average yields in the south. More importantly, trade spillovers from other Latin American countries and systemic countries (China, Europe, and the U.S.) seem to suggest a positive overall effect on Brazil from an El Niño event in the third and fourth quarters following the shock.

El Niño years feature below-normal rainfall for the Philippines. However, the authorities have extensive early-warning systems in place, including conservation management of the water supply for Manila. As a result, we do not observe any significant growth effects. Moreover, the fisheries industry in Peru suffers because of the change in upwelling of nutrient-rich water along the coast. As Peru is the world's largest exporter of fishmeal used in animal feed, a lower supply from Peru has ramifications for livestock prices worldwide. However, at the same time agricultural output in Peru rises due to the wetter weather. Although the median growth effect for Peru is negative (-0.33% after four quarters), it is in fact statistically insignificant, so the positive growth effect from agricultural output (being 5.8% of GDP) offsets the negative impact on the fisheries industry (constituting 0.6% of GDP).

While an El Niño event results in lower growth for some economies, others may actually benefit due to lower temperatures, more rain, and less natural disasters. For instance, plentiful rains can help boost soybeans production in Argentina, which exports 95% of the soybeans it produces, and for which the primary sector is around 11% of GDP (Table 4). Canada enjoys warmer weather in an El Niño year, and in particular a greater return from its fisheries. In addition, the increase in oil prices means larger oil revenues for Canada, which is the world's fifth-largest oil producer (averaging 3,856 million barrels per day in 2012). For Mexico we observe less hurricanes on the east coast and more hurricanes on the west coast, which brings generally stability to the oil sector and boosts exports (oil revenue is around 8% of GDP in Mexico). For the United States, El Niño typically brings wet weather to California (benefiting crops such as limes, almonds and avocados), warmer winters in the Northeast, increased rainfall in the South, diminished tornadic activity in the Midwest, and a decrease in the number of hurricanes that hit the East coast (see Figure 3). Therefore, not surprisingly, Table 3 shows an increase in GDP growth of 1.08%, 0.85%, 1.57%, and 0.55% in the fourth quarter following an El Niño shock for Argentina, Canada, Mexico, and the U.S., respectively. These estimates also take into account the positive spillover effects that an increase in U.S. GDP growth has on the Canadian and Mexican economies, given the extensive trade exposure of these two economies to the United States (trade weights are 67 and 68 percent respectively, see Table 5) as well as other third-market effects. The positive growth effect of 0.55% for the U.S. might seem large at first glance, however, it is not far from the estimated net benefits of $15 billion following the severe El Niño event of 1997-1998, which is equivalent to 0.2% of GDP, see Changnon (1999). These net benefits are calculated based on a direct cost-benefit analysis—$4 billion (cost) and $19 billion (benefit)—and a larger shock associated with the 1997-98 El Niño event, but they do not take into account the indirect growth effects through third markets, which is captured in our GVAR framework.

Although El Niño is associated with dry weather in northern China and wet weather in southern China (Figure 3), it is not clear that we should observe any direct positive or negative effects on China's output growth. In fact Table 3 shows that initially there are no statistically-significant effects following an El Niño shock, but Chinese GDP growth increases by 0.56% in the fourth quarter following an El Niño shock. This is mainly due to positive spillovers from trade with other major economies—Chinese trade with the U.S. is about 19%

Table 6: The Effects of an El Niño Shock on Real Commodity Prices (in percent)

Series	Impact	Cumulated Responses After			
		1 Quarter	2 Quarters	3 Quarters	4 Quarters
Non-Fuel Commodity Prices	0.42	0.77	1.97**	3.75**	5.31**
Oil Prices	1.20*	4.23*	7.80**	11.09**	13.87**

Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies. The impact is in percentage points and the horizon is quarterly. Symbols ** and * denote significance at 5–95% and 16–84% bootstrapped error bounds respectively.
Source: Authors' estimations.

of the total, and given that the U.S. is benefiting from an El Niño event, so does China. Moreover, a number of economies which are not directly affected by El Niño do benefit from the shock, mainly due to positive indirect spillovers from commercial trade and financial market links. For instance, Europe experiences an increase in real GDP growth of 0.69% in the fourth quarter following an El Niño event, and Singapore by 1.18% (mainly due to an increase in the shipping industry following the increase in demand from U.S. and other major economies).

4.2 The Effects of El Niño on Real Commodity Prices

The higher temperatures and droughts following an El Niño event, particularly in Asia-Pacific countries, not only increases the prices of non-fuel commodities (by 5.31% after four quarters, see Table 6), but also leads to higher demand for coal and crude oil as lower electricity output is generated from both thermal power plants and hydroelectric dams. In addition, farmers increase their water demand for irrigation purposes, which further increases the fuel demand for power generation and drives up energy prices. This is indeed confirmed here as crude oil prices (as a proxy for fuel prices) sustain a statistically significant and positive change following an El Niño shock (see Table 6).

However, although the initial increase in oil prices arises from higher demand for power from countries such as India and Indonesia, oil prices remain high even four quarters after the initial shock (Table 6). This is because an El Niño event has positive growth effects on major economies (for example, China, European countries, and the U.S.) which demand more oil to be able to sustain higher production. Therefore, what was initially an increase in oil prices due to higher demand from Asia translates into a global oil demand shock (oil prices increasing at the same time as global output rises; see Cashin et al. 2014 and Cashin et al. 2012 for details) a couple of quarters later. Excess demand also arises for non-fuel commodities (food, beverages, metals, and agricultural raw materials) and as a result their prices remain significant in the fourth quarter following an El Niño event, mainly due to lower supply from the Asia-Pacific region, but also due to higher global demand for non-fuel commodities.

4.3 The Effects of El Niño on Inflation

Turning to the inflationary effects of El Niño shocks, we find that for most countries in our sample, there exists statistically-significant upward pressure on inflation in the range of 0.09 to 1.01 percentage points (Table 7). This is mainly due to higher fuel as well as non-fuel commodity prices (Table 6), but is also the result of government policies (including buffer stock releases), inflation expectations, as well as aggregate demand-side pressures for those countries which experience a growth pick-up following an El Niño episode. Highest inflation 'jumps' in Asia are observed in India (0.56% after three quarters), Indonesia (0.87% after two quarters), and Thailand (0.55% after four quarters). These relatively large effects are due to the high weight placed on food in the CPI basket of these countries: 47.6%, 32.7% and 33.5%, respectively. To examine this further we plot the weight of food in the CPI basket of the 20 countries in our sample and the European region against the median impulse responses of inflation to an El Niño shock in those countries. Figure 5 shows a clear positive relationship between the two variables, with a correlation of 0.5, thereby providing further support to the null hypothesis that inflation responses are larger in economies that have higher share of food in their CPI baskets.

Note that production of perishables (i.e. fruits and vegetables) in India is affected less by monsoon than food grains, while the prices of fruits and vegetables are relatively more volatile. Moreover, inflation in food grains has historically been affected by government procurement policies and administered minimum support prices in agriculture. During the last decade, inflation increased sharply after the 2009 drought in India, however, in the previous episodes of drought in 2002 and 2004, inflation remained subdued. In 2009, drought conditions were accompanied by a steep increase in minimum support prices, resulting in high food grain inflation and consequently higher CPI inflation.[13] Overall, government policies, tight monetary stances, high water reservoir levels, and excess food grain stocks could partly offset the inflationary impact of El Niño shocks on prices in India. For other Asian economies, which generally place lower weight on food in the CPI index, we notice a smaller increase in inflation: China by 0.11% (32.5), Japan by 0.10% (24), Korea by 0.44% (13.9), Malaysia by

[13] During the years 2002, 2004 and 2009 (all years of poor monsoons), CPI inflation averaged 4.1%, 3.9%, and 12.3% in India, respectively.

Table 7: The Effects of an El Niño Shock on Inflation (in percent)

Country	Impact	Cumulated Responses After			
		1 Quarter	2 Quarters	3 Quarters	4 Quarters
Argentina	0.51	0.79	0.57	0.92	0.64
Australia	-0.01	0.02	0.02	0.01	0.00
Brazil	-0.30	-0.21	1.01	1.49	0.97
Canada	-0.05*	-0.10	-0.08	-0.07	-0.07
China	0.00	-0.02	0.00	0.06*	0.11*
Chile	0.14**	0.14	0.29**	0.32	0.39*
Europe	0.00	0.00	0.02	0.06*	0.09*
India	0.15*	0.16	0.42**	0.56**	0.60
Indonesia	0.25*	0.61**	0.87*	0.95	0.91
Japan	0.03*	0.05	0.04	0.06	0.10**
Korea	0.01	0.12**	0.22**	0.34**	0.44**
Malaysia	0.05*	0.09	0.16*	0.23*	0.28*
Mexico	0.22	0.60*	1.01*	1.12	1.04
New Zealand	-0.06	-0.23**	-0.39**	-0.55**	-0.61*
Peru	-0.06	-0.73	-0.48	-0.38	0.65
Philippines	0.11	0.06	0.19*	0.22	0.27
South Africa	0.10**	-0.01**	0.02	0.06	0.09
Saudi Arabia	0.01	-0.03*	-0.02	-0.01	-0.02
Singapore	-0.07**	-0.06	-0.06	-0.06	-0.06
Thailand	0.01	0.21**	0.35**	0.46**	0.55**
USA	0.01	0.02	0.10*	0.14*	0.15

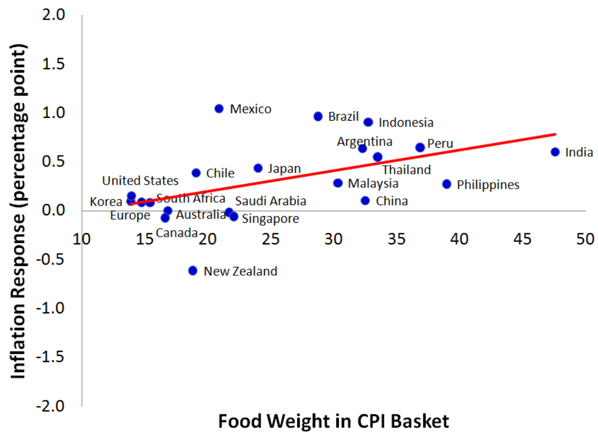
Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies. The impact is in percentage points and the horizon is quarterly. Symbols ** and * denote significance at 5–95% and 16–84% bootstrapped error bounds respectively.
Source: Authors' estimations.

0.28% (30.3), and Philippines by 0.19% (39), with the numbers in brackets representing the weight of food as a percentage of total consumption in the CPI basket.

Inflation in the U.S. and Europe increases by smaller amounts 0.14 and 0.09 percentage points, respectively, but perhaps surprisingly Mexico sees an increase of 1.01% after two quarters (with a 21 percent food share in its CPI basket). Finally, in South America inflation in the fourth quarter following an El Niño event increases by between 0.39% and 0.97%, but it is only statistically significant for Chile with an increase of 0.39%. There are only two countries that experience a reduction in inflation following an El Niño event—New Zealand by 0.61% after four quarters and Singapore by 0.07% on impact. For the former, this can be explained by very large disinflation pressures during the initial occurrences of the El Niño (recessions, wage and price freezes, and structural reforms), and its well-anchored inflation expectations[14]—with an inflation target range of 1–3% on average over the medium-term

[14] See also Buckle et al. (2002) for similar findings.

Figure 5: Food Weight in CPI Basket and Inflation Responses



Source: Authors' calculations based on data from *Haver* and impulse response estimates in Table 7.

and an average CPI inflation of around 2.5% since 1990.

4.4 Robustness Checks

To make sure that our results are not driven by the type of weights used to create country-specific foreign variable or solve the GVAR model as a whole, we experimented using Trade in Value Added (TiVA) weights (to account for supply chain factors) and found the impulse responses to be very similar to those with trade weights, w_{ij}, as used above. Therefore, as is now standard in the literature, we only report the results with the weights calculated as the average of exports and imports of country i with j (Table 5). We also estimated our model with the foreign variables computed using trade weights averaged over 2007-2009 and 2000-2013, and obtained very similar results to the benchmark weights (2009-2011) used in the earlier analysis. Moreover, we estimated a version of the model splitting the European region into Euro Area and 5 separate country VARX* models, thereby having a total of 26 country/region-specific VARX* models, and found the results to be robust to these changes. These results are not reported here, but are available on request.

5 Concluding Remarks

This paper contributed to the climate-macroeconomy literature by exploiting exogenous variation in El Niño weather events over time to causatively identify the effects of El Niño shocks on growth, inflation, energy and non-fuel commodity prices. To analyze the international macroeconomic transmission of El Niño shocks we estimated a Global VAR (GVAR) model for 21 countries/regions over the period 1979Q2–2013Q1. Our modelling framework took into account real and financial drivers of economic activity; interlinkages and spillovers that exist between different regions; and the effects of unobserved or observed common factors (e.g. energy and non-fuel commodity prices). This is crucial as the impact of El Niño shocks cannot be reduced to one country, but rather involves multiple regions, and may be amplified or reduced depending on the degree of openness of the countries and their trade structure.

We showed that there are considerable heterogeneities in the responses of different countries to El Niño shocks. While Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa face a short-lived fall in economic activity following an El Niño weather shock, the United States, Europe and China actually benefit (possibly indirectly through third-market effects) from such a climatological change. We also found that most countries in our sample experience short-run inflationary pressures following an El Niño episode, as global energy and non-fuel commodity prices increase.

The sensitivity of growth and inflation in different countries, as well as global commodity prices, to El Niño developments raises the question of which policies and institutions are needed to counter the adverse effects of such shocks. These measures could include changes in the cropping pattern and input use (e.g. seeds of quicker-maturing crop varieties), rainwater conservation, judicious release of food grain stocks, and changes in imports policies/quantities—these measures would all help to bolster agricultural production in low-rainfall El Niño years. On the macroeconomic policy side, any uptick in inflation arising from El Niño shocks could be accompanied by a tightening of the monetary stance (if second-round effects emerge), to help anchor inflation expectations. Investment in agriculture sector, mainly in irrigation, as well as building more efficient food value chains should also be considered in the longer-term. Our results also have policy implications for the design of appropriate bands around inflation targets in countries that are directly affected by El Niño shocks. This depends on the share of food in their CPI basket and structural-food inflation, as well as their susceptibility to El Niño shocks.

The research in this paper can be extended in a number of directions. A more complete model for the climate, including perhaps temperature, precipitation, storms, and other aspects of the weather, could be developed and integrated within our compact model of the world economy. This framework could then be utilized to investigate the effects of climate change and/or global weather shocks on economic activity. Modelling the global climate, however, is in itself a major task and we shall therefore leave it as a task for future research.

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