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

Paul Cashin[a], Kamiar Mohaddes[b†], and Mehdi Raissi[a]

[a] International Monetary Fund, Washington DC, USA

[b] Faculty of Economics and Girton College, University of Cambridge, UK

January 23, 2017

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 (direct and total) 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 Classifications: C32, F44, O13, Q54.

Keywords: El Niño weather shocks, oil and non-fuel commodity prices, global macroeconometric modelling, international business cycle.

*We are grateful to Tiago Cavalcanti, Hamid Davoodi, Govil Manoj, Rakesh Mohan, Sam Ouliaris, Hashem Pesaran, Vicki Plater, Ajay Shah, Ian South, Garima Vasishtha, Rick van der Ploeg, Yuan Yepez and seminar participants at the IMF's Asia and Pacific Department Discussion Forum, the IMF's Institute for Capacity Development, Oxford University, the 13th Research Meeting of the National Institute of Public Finance and Policy and the Department of Economic Affairs of the Ministry of Finance in India, and University of Southern California, as well as conference participants at the 11th World Congress of the Econometric Society, Weather Risk Management Association 18th Annual Meeting, and the El Niño 2015 Conference for constructive comments and suggestions. We would also like to thank the editor in charge of our paper and two anonymous referees for helpful suggestions. The views expressed in this paper are those of the authors and do not necessarily represent those of the International Monetary Fund or IMF policy.

†Corresponding author. Email address: km418@cam.ac.uk.

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. 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, 1997/98 and 2015/16 along with the more frequent occurrences of moderate El Niños, are under-studied. There are a number of papers looking at the effects of El Niño on: particular countries, for example, Australia and the United States (Changnon 1999 and Debelle and Stevens 1995); a particular sector, for instance, agriculture and min-

[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.

ing (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, 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 not statistically significant. 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, his analysis rests on a strong assumption (homogeneity of impact) and it does not take into account the indirect effects of El Niño shocks.

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 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), in addition to undertaking a country-by-country analysis. Finally, we contribute to the Global VAR (GVAR) literature that mostly relies on reduced-form

[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.

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 equity prices, 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 vector autoregressive models with weakly-exogenous foreign variables (VARX* models) over the period 1979Q2–2013Q1. Having solved the Global VAR model, we examine the direct and indirect effects 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 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] To illustrate the importance of these indirect effects, we decompose the impact of an El Niño shock on real GDP growth into two parts: the direct effect on economic activity in these countries and the total impact (direct plus indirect effects). As expected, the results reveal that for those countries that are not at the epicenter of an El Niño event, the indirect effects are, if anything, more important than the direct effects. This provides further evidence in support of our modelling strategy, namely when it comes to studying the effect of climate on individual economies, it is important to take into account both direct and indirect effects. Overall, the larger the geographical area of a country, the smaller the

[3]The GVAR methodology is a novel approach to global macroeconomic modelling 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 observed and unobserved common factors (e.g. commodity-price shocks and global financial cycle)—see Section 4.1 for additional details.

[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.

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.

To illustrate the robustness of our results to potential model misspecifications, in a separate exercise, we conduct a simple bivariate country-by-country analysis of the impulse responses of real output growth to El Niño shocks via the Local Projections (LP) method of Jordà (2005), using the same sample of countries and time period. We show that the shape of these impulse responses are broadly in line with those obtained from our multi-country framework, and they are consistent with the likely impact of El Niño shocks on real GDP growth across the globe based on anecdotal evidence. We argue that while such a country-by-country analysis provides some useful insights on the economic significance of El Niño shocks, there are many advantages to using a carefully-specified multi-country framework, like that of the GVAR model adopted in this paper, for the analysis—see Section 3 for details.

The rest of the paper is organized as follows. Section 2 gives a brief description of the Southern Oscillation cycle. Section 3 reports the LP impulse responses of growth to El Niño shocks. Section 4 describes the GVAR methodology and outlines our modelling approach. Section 5 investigates the macroeconomic effects of El Niño shocks within our multi-country framework. Finally, Section 6 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. 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. This phenomenon causes the thermocline (the separation zone between the mixed-layer shallow ocean above, much influenced by atmospheric fluxes, and the deep ocean below) 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), more rain to the equatorial coast of South America, and convective storms and hurricanes to the central Pacific. The global climatological effects of El Niño are summarized in Figure 1, 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]

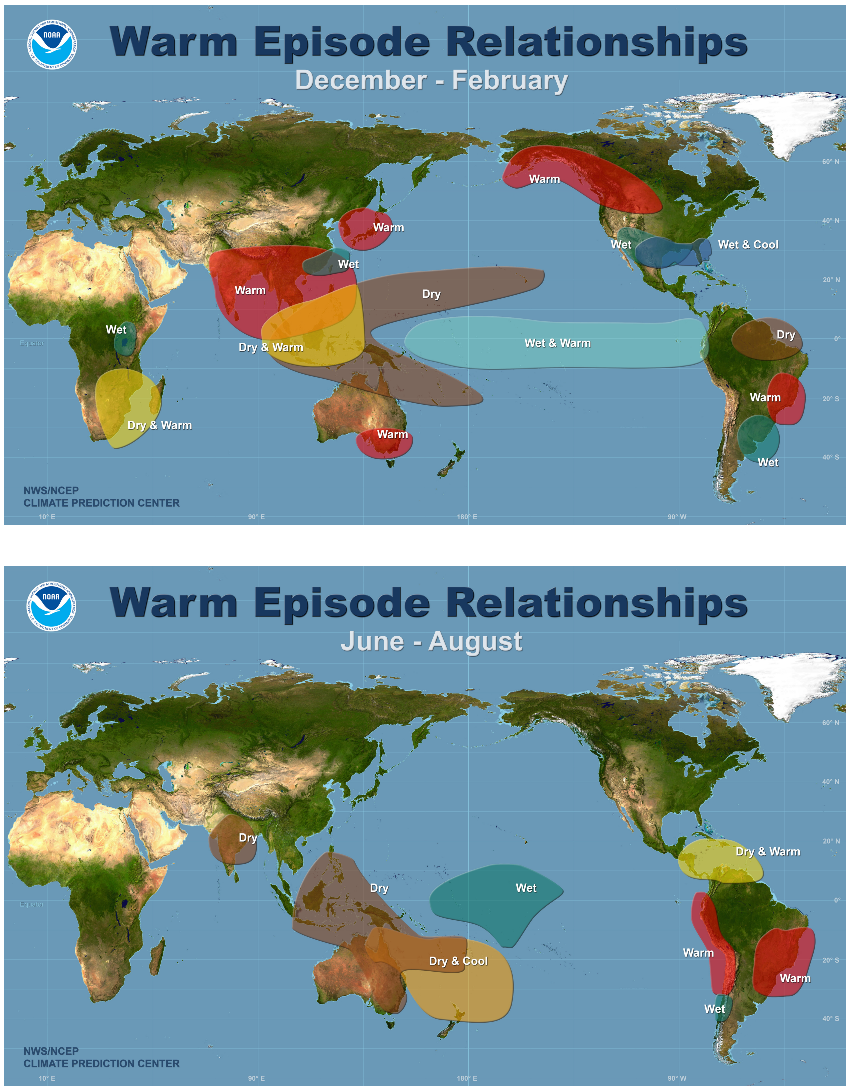
One of the ways of measuring El Niño intensity is by using the Southern Oscillation index (SOI), which is calculated based on air-pressure differentials in the South Pacific (between Tahiti and Darwin). Sustained negative SOI values below -8 indicate El Niño episodes, which typically occur at intervals of three to seven years and last about two years. Figure 2 shows that the 1982–83, 1997–98, and 2015–16 El Niños were quite severe (and had large adverse macroeconomic effects in many regions of the world), whereas other El Niños in our sample 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 in any given quarter from its historical average, normalized (divided) by its historical standard deviation. Sustained negative SOI anomaly values below -1 indicate El Niño episodes (Figure 2b).

3 A Country-by-Country Analysis

We begin by analyzing impulse responses of real output growth to El Niño shocks via the local projections method of Jordà (2005) on the grounds that such projections may be more robust to model misspecifications. The LP method involves evaluating the h-period response of real GDP growth in each country to an El Niño shock by means of a direct h-step forecasting regression in which the information set consists of real GDP growth and a measure of El Niño intensity. The LP method does not require specification and estimation of the unknown true underlying multivariate system itself (which is even more complicated in a global setting), and therefore, serves as a first-step test of the significance of El Niño's impact on output growth. To examine the individual significance of coefficients in a given trajectory (i.e. the shape of impulse responses), we rely on Jordà (2009) and report the conditional error bands

[5]La Niña weather events (cold phases of the Southern Oscillation cycle) produce the opposite climate variations from El Niño occurrences. However, they tend to have weaker effects than those of El Niño events, and are less frequent and shorter in duration.

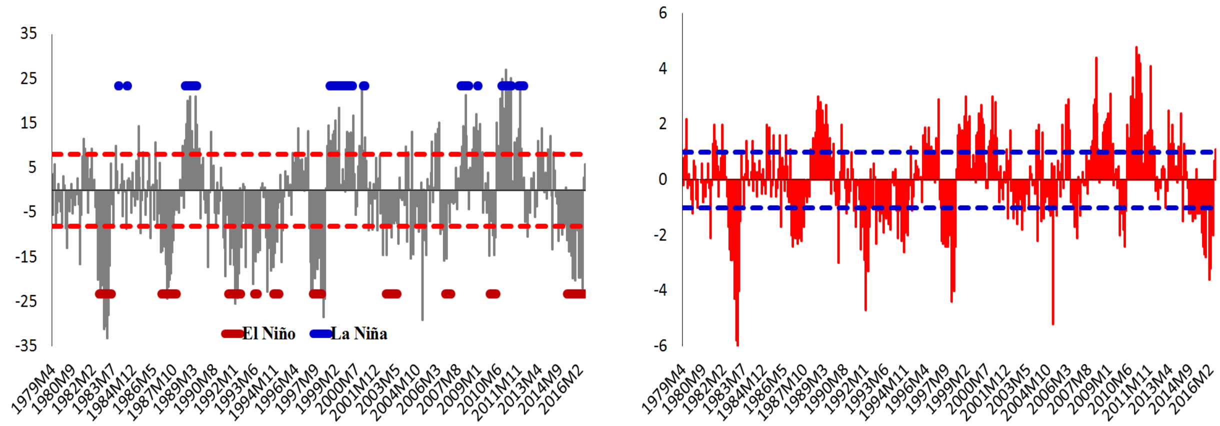
Figure 1: Global Climatological Effects of El Nino



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

Figure 2: Southern Oscillation Index (Anomalies), 1979M4–2016M2

(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.

(which accounts for serial correlation in impulse response coefficient estimates).

To conduct this country-by-country analysis, we obtain data on Southern Oscillation index (SOI) anomalies from National Oceanic and Atmospheric Administration's *National Climatic Data Centre* as well as data on real output growth 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. Given that the growth impact of an El Niño shock is likely to be homogeneous across the 13 European countries in our sample, we create a real output growth series for Europe using the GDP of these countries and Purchasing Power Parity GDP weights, averaged over 2009-2011. Therefore, our sample includes 21 country/region-specific models over the period 1979Q2-2013Q1.

Our results, based on the shape of impulse responses in Figure 3 (obtained from two variable VAR models with a maximum lag order of 6), indicate that an El Niño shock has a negative impact on real economic activity in Australia, Brazil, Indonesia, Peru, the Philippines, and South Africa. However, the effects in Argentina, Canada, China, Chile, Europe, Singapore, Thailand, and the U.S. are positive. These results are broadly consistent with the likely impact of El Niño across the globe based on anecdotal evidence (see Table 1). To ensure that our results survive when looking at the longer time horizon (including more El Niño events), we conducted an additional analysis for the case of the United States (given that reliable quarterly data is available for the U.S.) over the period 1951Q1–2016Q2. During the past six decades, twenty El Niño episodes have been recorded by the U.S. National Oceanic and Atmospheric Administration including the most recent one in 2015–16. The LP

Table 1: El Niño's Impact Across the Globe

Asia and Pacific		
Australia	(−)	Drought in Southeast, bush fires, lower wheat exports
China	(?)	Dry (wet) weather in North (South)
India	(−?)	Weak monsoon rains
Indonesia	(−)	Drought, wildfire and lower hydropower output
Japan	(−?)	More frequent typhoon strikes
Korea	(?)	Drought
Malaysia	(?)	
New Zealand	(−)	More rain in wet areas and less precipitation in dry parts
Philippines	(−?)	Below normal rainfall and cyclone
Singapore	(?)	Shipping industry maybe affected
Thailand	(−?)	Drier weather
North America		
Canada	(+)	Warmer weather
Mexico	(+?)	Dry summers, fewer (more) hurricanes in East (West) coast
United States	(+)	More rain in South and California, warmer winter in Northeast, diminished tornadic activity in Midwest, fewer hurricanes in East coast
South America		
Argentina	(+?)	Plentiful rains
Brazil	(?)	Drought (plentiful rain) in North (South)
Chile	(−?)	Stormy winters and lower mining activity
Peru	(−?)	Fisheries industry suffers, cold wave and floods
Europe*	(?)	
Middle East and Africa		
Saudi Arabia	(?)	
South Africa	(−)	Drought

Notes: * Europe includes the following 13 countries: Austria, Belgium, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, Turkey and the United Kingdom. (+), (-), and (?) indicate a positive, negative and ambiguous effects of El Niño on real growth respectively.

median impulse responses and the associated conditional error bands are reported in Figure 4 mirroring those from the shorter time period (the last three decades), thereby, illustrating the robustness of the results in Figure 3.

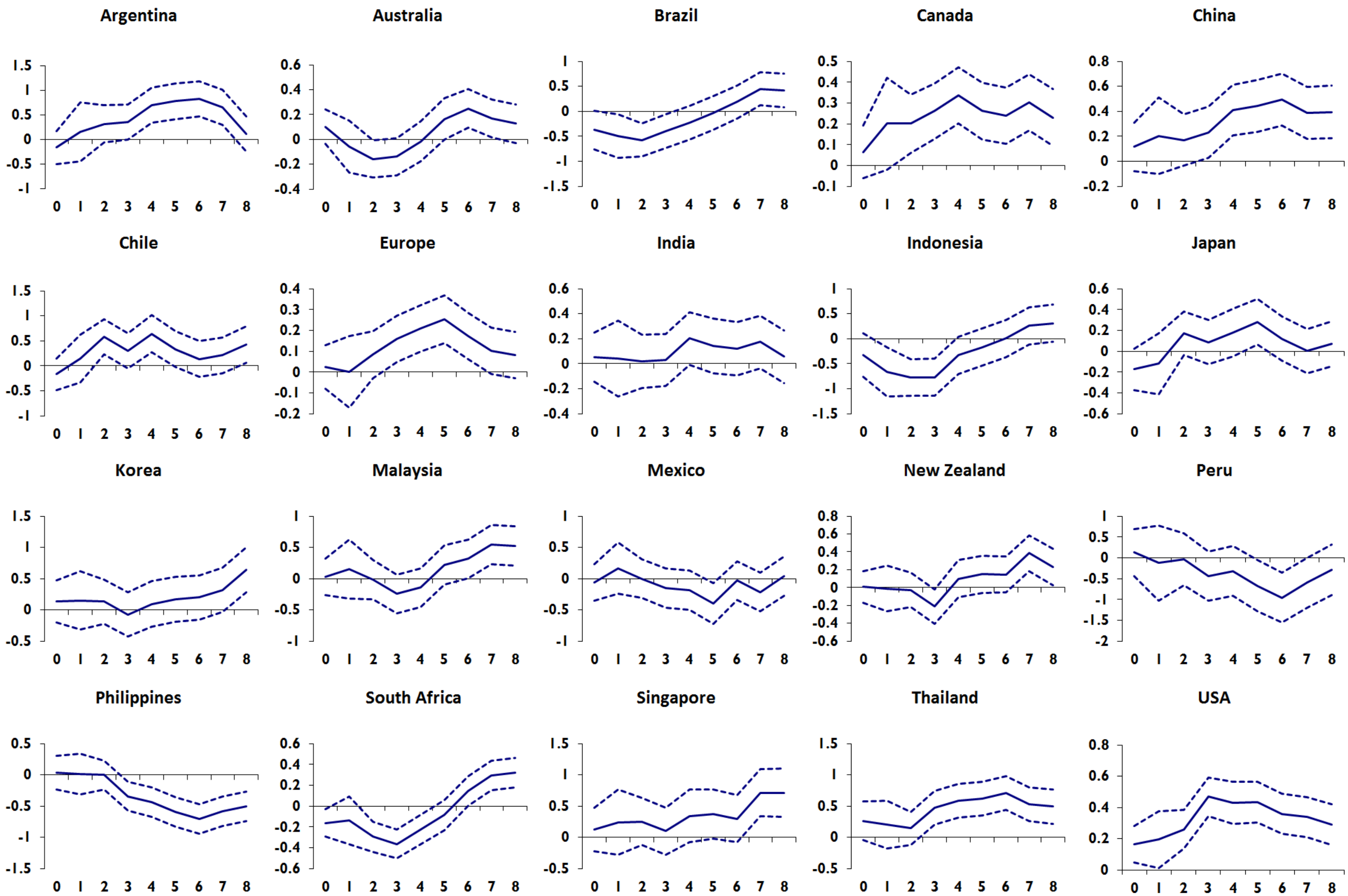
It is worth noting that much of the literature on climate and the macroeconomy does not use a multi-country framework, and instead focuses on single-country models (and not even those utilized above which may be more robust to potential model misspecifications). While we have shown that the country-by-country analysis provides some useful insights on the significance of El Niño shocks, there are many advantages to using a multi-country framework, like that of the GVAR model, for the analysis. Firstly, as Kilian and Kim (2009) argue, the LP estimator tends to have higher variance when the data generating process is well approximated by a VAR because local projections impose less structure on the estimation problem. Since the impact of El Niño shocks cannot be reduced to one country but rather involve multiple regions, and it may be amplified or dampened depending on the degree of openness of the countries and their trade structure, relying on a Global VAR model is advantageous. Furthermore, the GVAR model is proven to be a good approximation of the data generating process in the literature (see, for instance, Pesaran (2015)). Secondly, this compact model of the world economy allows one to take into account the economic interlinkages and spillovers that exist between different regions, thereby enabling a study of the indirect effects of El Niño shocks through third markets in a coherent manner as opposed to undertaking country-by-country analysis, or using a single-country VAR model to represent the global economy as in Brunner (2002).

4 Modelling the Climate-Macroeconomy Relationship in a Global Context

The rest of the paper employs the 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).[6] This is crucial as the impact of El Niño shocks cannot be reduced to a single country but rather involves multiple regions, and this impact may be amplified or dampened depending on the degree of openness of the countries and their trade structure. Before describing the data and our

[6] Dees et al. (2007) derive the GVAR as an approximation to a global unobserved common factor model, and show that it is quite effective in dealing with the common factor interdependencies and international co-movements of business cycles.

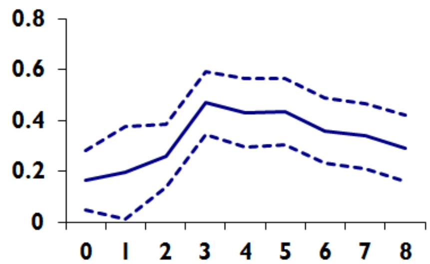
Figure 3: The Effects of an El Niño Shock on Real GDP Growth (in percentage points), using the Local Projections Method

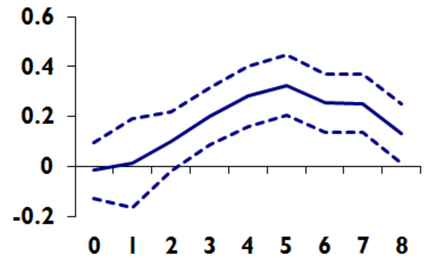


Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies, together with the 5th and 95th percentile conditional error bands. The impact is in percentage points and the horizon is quarterly.

Figure 4: The Effects of an El Niño Shock on United States Real GDP Growth (in percentage points), using the Local Projections Method

(a) Based on data from 1979Q2 to 2013Q1 (b) Based on data from 1951Q1 to 2016Q2





Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies, together with the 5th and 95th percentile conditional error bands. The impact is in percentage points and the horizon is quarterly.

model specification, we provide a short exposition of the GVAR methodology below.

4.1 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), $\mathbf{x}_{it}^*$:

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

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 $\mathbf{u}_{it} \sim i.i.d. (0, \mathbf{\Sigma}_{ii})$. For algebraic simplicity, we abstract from observed global factors in the country-specific VARX* models. Furthermore, $\mathbf{\Phi}_i (L, p_i) = I - \sum_{i=1}^{p_i} \mathbf{\Phi}_i L^i$ and $\mathbf{\Lambda}_i (L, q_i) = \sum_{i=0}^{q_i} \mathbf{\Lambda}_i L^i$ 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 $\mathbf{\Phi}_i (L, p_i)$ and $\mathbf{\Lambda}_i (L, q_i)$ 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 $\sum_{j=0}^{N} w_{ij} = 1$.[7] For empirical application, the trade weights are computed as three-year averages:[8]

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

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.

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:

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

[7] To the extent that unobserved common shocks affect any of the variables in the GVAR model (e.g. uncertainty factor or risk shocks may manifest themselves in equity price movements, fluctuations in exchange rates, spreads, and commodity prices, among others), country-specific foreign variables act as proxies for those latent factors. This is also confirmed by Monte Carlo experiments reported in Kapetanios and Pesaran (2007), where they show that the estimators that make use of cross-section averages (star variables in the context of VARX*) out-perform other estimators based on principal components.

[8] 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)).

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:

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

where $\mathbf{A}_i (L, p)$ is constructed from $\mathbf{A}_i (L, p_i, q_i)$ by setting $p = \max (p_0, p_1, ..., p_N, q_0, q_1, ..., q_N)$ 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:

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

where

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

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 modelling, both the theoretical foundations of the approach and its numerous empirical applications, see Chudik and Pesaran (2016). 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:

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

where $\mathbf{\Upsilon}_i (L, s_i) = \sum_{i=0}^{s_i} \mathbf{\Upsilon}_i L^i$ 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.

4.2 Model Specification

Key countries in our sample include those likely to be directly affected by El Niño events—mainly countries in the Asia and Pacific region as well as those in the Americas, see Table 1 and Section 2. As discussed in Section 3, we also create a region out of the 13 European countries in our sample. 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 2009-2011. Thus, as displayed in Table 1, our model includes 33 countries (with 21 country/region-specific models) covering over 90% of world GDP.

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.

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, drought conditions (hot and dry summers) in southeast Australia increases the frequency and severity of bush fires and reduces crop yields, which reduce the volume of 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.[9] 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.[10] Therefore, our commodity market model includes both the real crude oil price (p_t^{oil}) and the real non-fuel commodity price (p_t^{nf}) 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,

[9] Two exceptions are Mohaddes and Pesaran (2016) and Mohaddes and Raissi (2015) which explicitly model the oil market as a dominant unit in the GVAR framework.

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

we include seven weakly exogenous variables in this model. More specifically, real GDP, the rate of 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.

5 Empirical Results Based on the Multi-Country Model

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) and Appendix A 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.[11] 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

[11] All estimations and test results are obtained using the GVAR Toolbox 2.0. For further technical details see Smith and Galesi (2014).

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. For brevity, we present the country-specific estimates and tests in Appendix B, including evidence for the weak exogeneity assumption of the foreign variables and discuss the issue of structural breaks in the context of our GVAR model.

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

Country	VARX* Order		Cointegrating relations (r_i)	Country	VARX* Order		Cointegrating relations (r_i)
	p_i	q_i			p_i	q_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.

5.1 The Macro Effect of El Niño

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"). Below we examine the direct and indirect effects of El Niño shocks on the world economy, on a country-by-country basis but in a global context, and provide the time profile of the effects on commodity prices as well as inflation and real output growth across countries.

5.1.1 The Effects of El Niño on Real Output Growth

Figure 5 reports the estimated median impulse responses of real GDP growth to an El Niño shock together with the 5-95% and 16-84% bootstrapped error bounds. We report the median responses on impact as well as up to eight quarters. The results show that an El Niño event has a statistically significant effect on real GDP growth for several countries in our sample at the 5-95% (blue short-dashed) or 16-84% (red long-dashed) levels.[12]

As noted earlier, El Niño causes hot and dry summers in southeast Australia (Figure 1); increases the frequency and severity of bush fires; reduces wheat exports due to yield reductions; 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 3). 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 an average fall in GDP growth of about 0.22 and 0.28 percentage points for Australia and New Zealand, one year after an El Niño shock, respectively.[13]

Table 3: 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

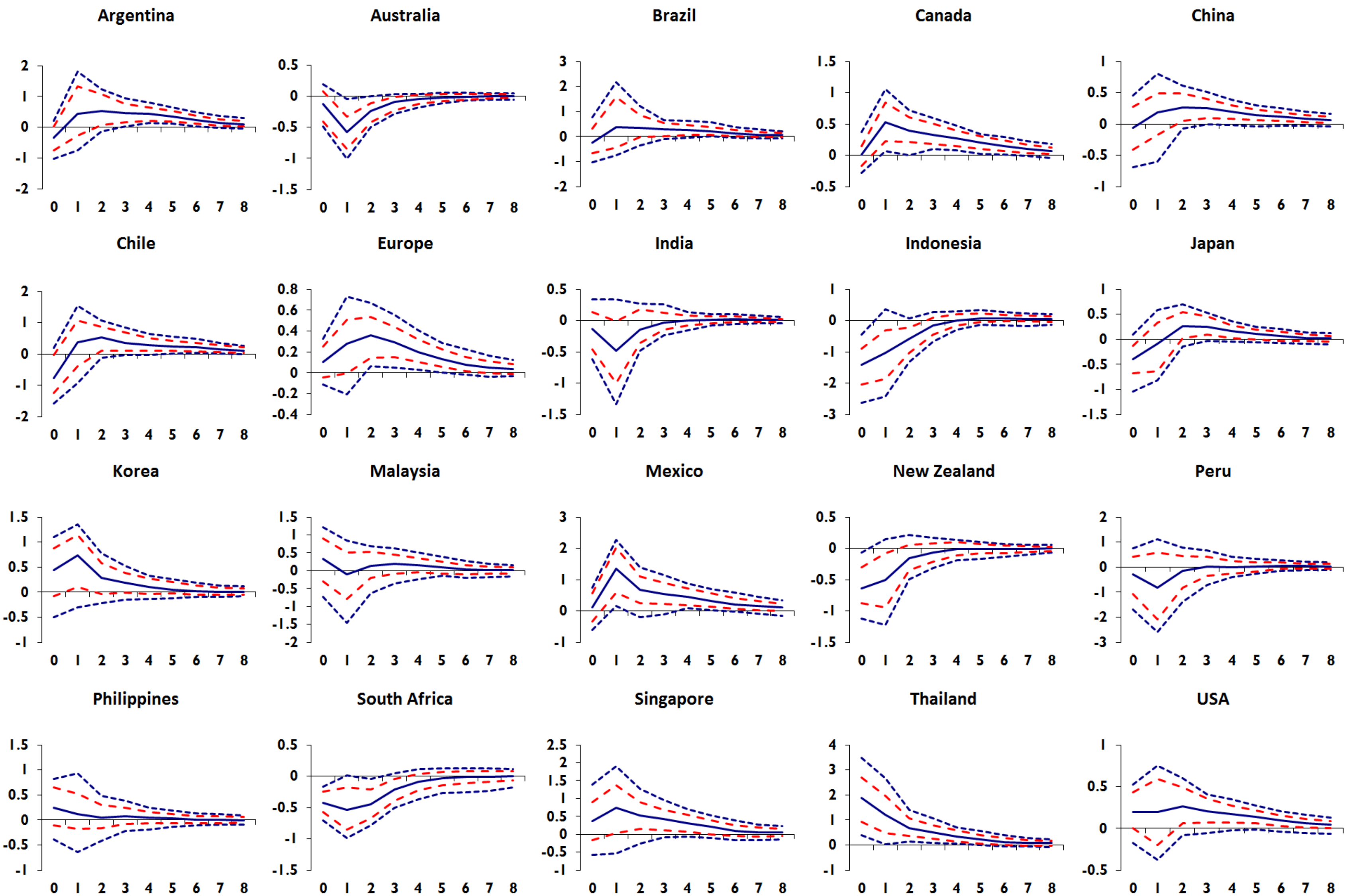
Notes: Primary sector is the sum of agriculture, forestry, fishing and mining.
Source: *Haver*.

Moreover, El Niño conditions usually coincide with a period of weak monsoon and rising

[12] 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.

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

Figure 5: The Effects of an El Niño Shock on Real GDP Growth (in percentage points)



Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies, together with the 5-95% (blue short-dashed) and 16-84% (red long-dashed) bootstrapped error bounds. The impact is in percentage points and the horizon is quarterly.

temperatures in India (see Figure 1) 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 0.16 percentage points on average over the course of the year (though not statistically significant at all quarters). 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 mitigating factor as sowing of Rabi crops is not "directly" affected by the monsoon.[14] 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 real GDP growth falls by 0.64 percentage points on average over the first four quarters after the shock, 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 3).

Looking beyond the Asia and Pacific region, South Africa also experiences hot and dry summers during an El Niño episode (Figure 1), 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 real output growth by 0.35 percentage points after one year. 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 observe initially in Figure 5

[14] 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).

(though not statistically significant at the 5-95% level). More frequent typhoon strikes and cooler weather during summers are expected for Japan in El Niño conditions, which could depress consumer spending and growth. This is indeed confirmed by the impulse responses in Figure 5, as there is an initial drop in Japanese GDP growth. However, we also observe that for both Chile and Japan, the average effect after four quarters is positive, by 0.15 and 0.04 percentage points, respectively. This is most likely due to positive spillovers from their major trading partners—see Section 5.2 for details. For instance, trade with China, Europe, and the U.S. constitutes over 57% of each country's total trade in goods (see Table 4). 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 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 after one year as average output growth increases by 0.21 percentage points.

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 statistically significant growth effects for the case of the Philippines. 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 GDP growth effect for Peru is negative (-0.25 percentage points on average during the year), it is in fact not statistically significant, 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 fewer 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 3). 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,

Table 4: 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 of goods, 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.

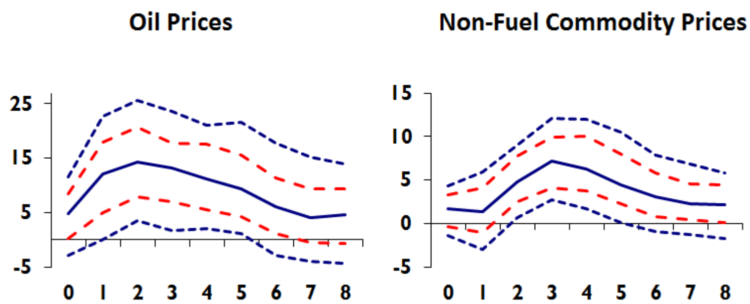
which is the world's fifth-largest oil producer (averaging 3,856 million barrels per day in 2012). For Mexico, in an El Niño year, we observe fewer hurricanes on the east coast and more hurricanes on the west coast, which brings general stability to the oil sector and boosts exports (oil revenue is around 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 1). Therefore, not surprisingly, Figure 5 shows an increase in real GDP growth of 0.31, 0.31, 0.63, and 0.21 on average over the course of the year 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 4) as well as other third-market effects. The positive average annual growth effect of 0.21 percentage points 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—see also Section 5.2.

Although El Niño is associated with dry weather in northern China and wet weather in southern China (Figure 1), it is not clear that we should observe any direct positive or negative effects on China's output growth. In fact Figure 5 shows that initially there are no statistically-significant effects following an El Niño shock, but Chinese GDP growth increases by 0.17 percentage points four quarters 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% 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 0.24 percentage points and Singapore by 0.48 percentage points (mainly due to an increase in the shipping industry following the increase in demand from U.S. and other major economies) one year following an El Niño event—see also Section 5.2.

5.1.2 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 (see Figure 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.[15] 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 in Figure 6 as crude oil prices (as a proxy for fuel prices) sustain a statistically significant and positive change following an El Niño shock.

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



Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies, together with the 5-95% (blue short-dashed) and 16-84% (red long-dashed) bootstrapped error bounds. The impact is in percentage points and the horizon is quarterly.

Moreover, 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 (Figure 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. 2016a 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 statistically significant even after one year 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.

[15] See, for instance, World Bank (2013) and the references therein.

5.1.3 The Effects of El Niño on Inflation

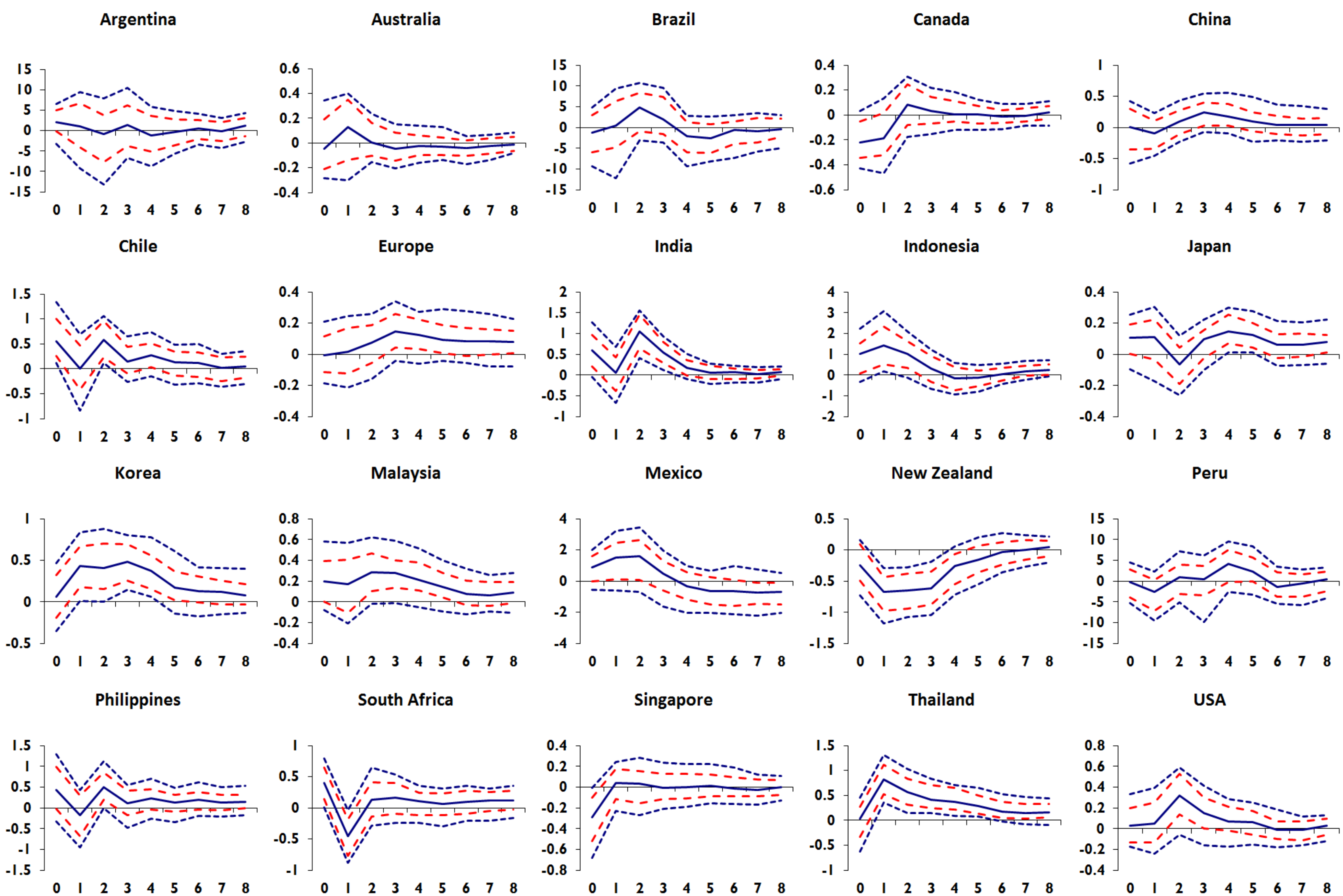
Turning to the inflationary effects of El Niño shocks, we find that for most countries in our sample, there exists statistically-significant upward pressure on inflation at the 5-95% (blue short-dashed) or 16-84% (red long-dashed) levels, see Figure 7. This is mainly due to higher fuel as well as non-fuel commodity prices (Figure 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 average inflation 'jumps' (after one year) in Asia are observed in Indonesia (73 basis points, bps), India (48 bps), and Thailand (44 bps). These relatively large effects are due to the high weight placed on food in the CPI basket of these countries: 32.7%, 47.6%, 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 (average over the year) to an El Niño shock in those countries. Figure 8 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.[16] 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 average inflation over the first year: China by 8 bps (32.5), Japan by 8 bps (24), Korea by 35 bps (13.9), Malaysia by 23 bps (30.3), and Philippines by 22 bps (39), with the numbers in brackets representing the weight of food in the CPI basket.

Inflation in the U.S. and Europe increases by smaller amounts, 0.12 and 0.07 percentage points, respectively, but perhaps surprisingly Mexico sees an average increase of 84 bps after four quarters (with a 21 percent food share in its CPI basket). Finally, in South America average inflation following an El Niño event increases by between 31 and 77 bps, but it

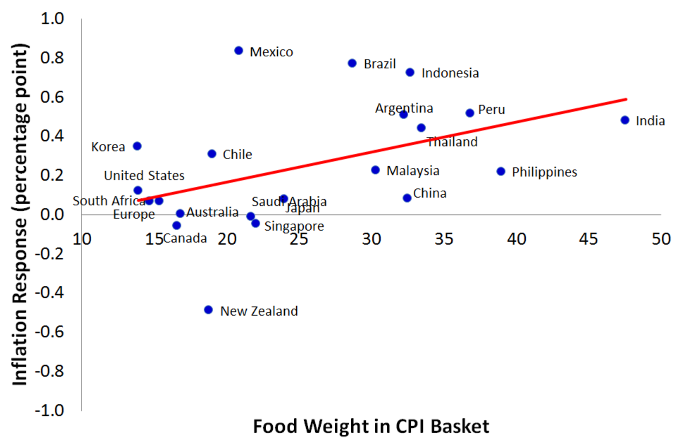
[16] During the years 2002, 2004 and 2009 (all years of poor monsoons), CPI inflation averaged 4.1%, 3.9%, and 12.3% in India, respectively.

Figure 7: The Effects of an El Niño Shock on Inflation (in percentage points)



Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies, together with the 5-95% (blue short-dashed) and 16-84% (red long-dashed) bootstrapped error bounds. The impact is in percentage points and the horizon is quarterly.

Figure 8: Food Weight in CPI Basket and Inflation Responses



Source: Authors' calculations based on data from *Haver* and impulse response in Figure 7. The inflation responses are averages over the first year following an El Niño event.

is only statistically significant for Chile with an increase of 31 bps. There are only two countries that experience a reduction in inflation following an El Niño event—New Zealand by 49 bps and Singapore by 5 bps on average after one year. 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[17]—with an inflation target range of 1–3% on average over the medium-term and an average CPI inflation of around 2.5% since 1990.

5.2 Comparing Direct and Total Growth Effects of El Niño

Using a compact model of the world economy, we modelled the climate-macroeconomy relationship in a global context, thereby attempting to capture the complicated patterns of global economic interactions; taking into account not only the direct exposure of countries to El Niño shocks but also the indirect effects through secondary or tertiary channels. To illustrate the importance of such indirect effects we try to decompose the impact of an El Niño shock on real GDP growth of the 21 region/countries in our sample into two parts: the direct effect on economic activity in these countries; and the total impact (direct plus indirect effects). In our setting in Section 5.1 the indirect impact mainly stems from the shock's impact on economic activity of partner countries and their trade structure.

To proceed with this analysis, we use the estimates of the 21 country-specific vector

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

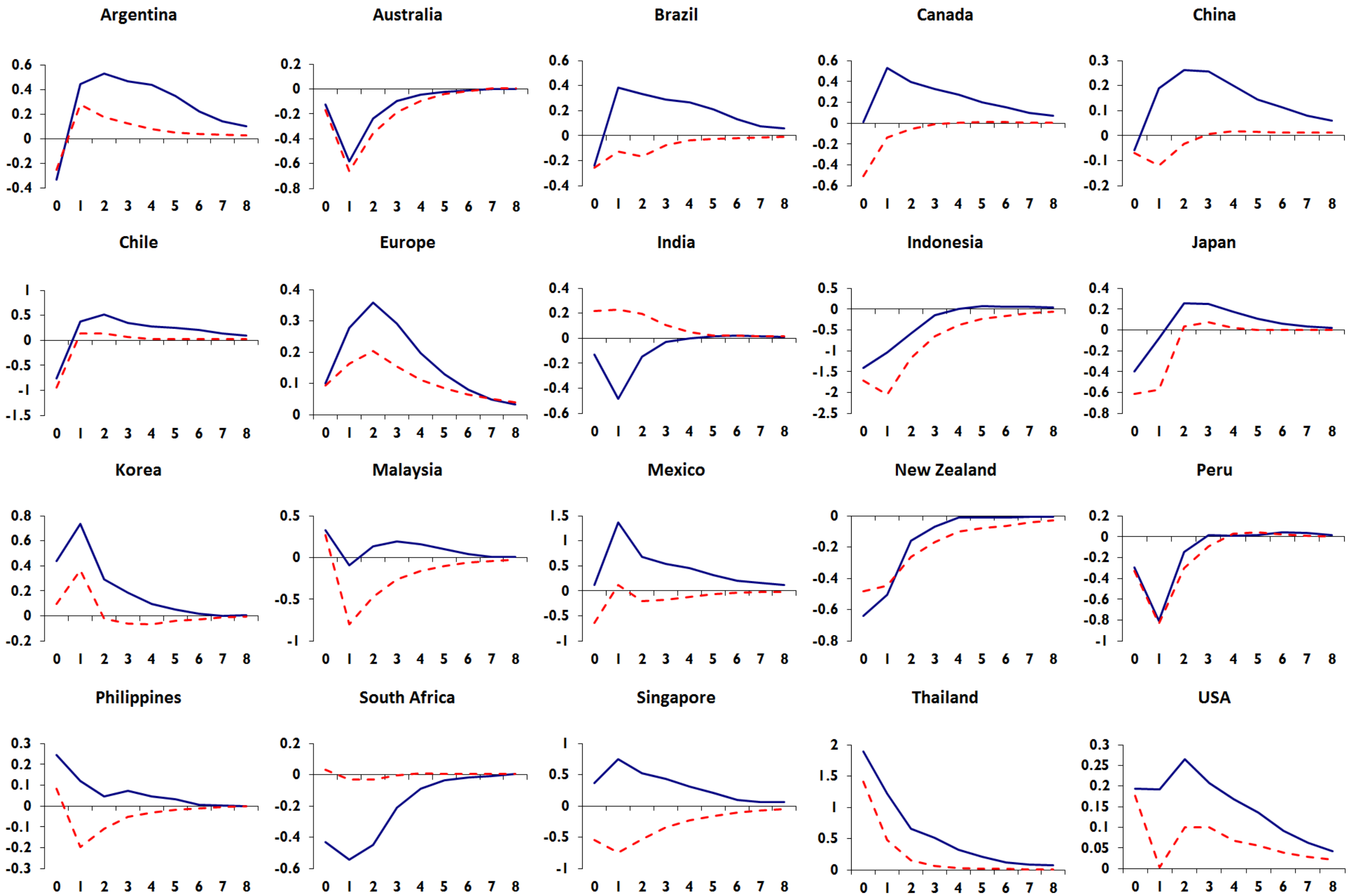
error correction models from the baseline regression in Section 5.1 (with exactly identical model specifications, including lag orders, and unchanged coefficient estimates), and solve the global model by combining these 21 country-specific models via a counterfactual matrix of predetermined (that is, not estimated) trade weights in which w_{ij} are zero. We can then compare the median impulse responses obtained from our baseline GVAR model in Section 5.1, with those in which counterfactual trade weights replace the actual ones (see Cesa-Bianchi et al. (2012) for methodological details). This procedure attempts, to the extent possible, to disentangle direct effects of El Niño shocks and indirect effects of the influence of trade partners (global factors). The results of the decomposition, reported in Figure 9, reveal that for those countries that are not at the epicenter of an El Niño event, the indirect effects are, if anything, more important than the direct effects. Specifically, for close-to-epicenter countries of Australia, Chile, Indonesia, New Zealand, and Peru the direct and total effects are close to each other. For the rest of the countries, taking into account the economic interlinkages and spillovers that exist between different regions in an interconnected framework shapes the responses of GDP growth to El Niño shocks. See, for instance, the impulse responses of real GDP growth in China where the direct effects (dashed red line) are pretty much flat, which is perhaps not surprising as an El Niño shock usually coincides with wet weather in the south of the country and dry weather in the north. Similar flat responses are also observed for the case of Mexico, as there is no a priori clear negative or positive direct effect from an El Niño event on economic activity in Mexico. However, the indirect effects (solid blue line), mainly spillovers from trade with other major economies such as the United States, are clearly important and lead to positive output growth responses for both China and Mexico. This provides further evidence in support of our modelling strategy: when it comes to studying the effects of climate on the individual economies, it is important to take into account both direct and indirect effects.

5.3 Robustness Checks

To make sure that our results are not driven by the type of weights used to create country-specific foreign variables 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.[18] Therefore, as is now standard in the GVAR literature (see, for instance, Pesaran (2015)), we only report the results with the weights calculated as the average of exports and imports of country i

[18] See also Cashin et al. (2016b), who demonstrate that the choice of weights is of second-order importance when the underlying variables are sufficiently correlated, and that using trade, financial, or mixed weights produces very similar results.

Figure 9: Direct and Total Effects of an El Niño Shock on Real GDP Growth (in percentage points)



Notes: Figures are median impulse responses to a one standard deviation reduction in SOI anomalies from our baseline GVAR model in Section 5.1 (blue solid) as compared with those in which counterfactual trade weights replace the actual ones (red dashed). The impact is in percentage points and the horizon is quarterly.

with j (Table 4). 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.

6 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. We began by conducting a country-by-country analysis in which we investigated the effects of El Niño shocks on output growth for the 21 countries in our sample using the local projections method. The impulse responses, broadly consistent with the likely impact of El Niño across the globe based on anecdotal evidence, indicated that an El Niño shock has a negative impact on real economic activity in Australia, Brazil, Indonesia, Peru, the Philippines, and South Africa. However, the effects in Argentina, Canada, China, Chile, Europe, Singapore, Thailand, and the U.S. were positive. While the country-by-country analysis provides some useful insights on the significance of El Niño shocks, we argued that there are many advantages to using a multi-country framework, like that of the GVAR model, for the analysis.

To this end, we analyzed the international macroeconomic transmission of El Niño shocks by estimating a GVAR model for 21 countries/regions over the period 1979Q2–2013Q1. This multi-country 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.

Moreover, we decomposed the impact of an El Niño shock on real GDP growth of the above 21 countries/region into two parts: the direct effect on economic activity and the total impact (direct plus indirect effects). As expected, the results revealed that for those countries that are not at the epicenter of an El Niño event, the indirect effects are, if anything, more important than the direct effects. In contrast, in the close-to-epicenter countries of Australia, Chile, Indonesia, New Zealand, and Peru, the direct and total effects are close to each other. For the rest of the countries, accounting for the economic interlinkages and spillovers that exist between different regions in an interconnected framework shapes the responses of GDP growth to El Niño shocks.

The sensitivity of growth and inflation in different countries, as well as global commodity prices, to El Niño developments raises the question as to 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 (see Reserve Bank of India (2014) for a discussion of inflation targeting in the case of India).

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. There is also a large literature using weather (temperature and precipitation) as an instrumental variable (IV) for real output growth. See, for instance, Miguel et al. (2004) who show that economic growth is negatively associated with civil conflict in Sub-Saharan Africa, where they use precipitation as an IV for GDP growth. Since El Niño events are clearly exogenous, and as this paper has demonstrated their significant impact on economic activity, they might similarly serve as useful instruments when studying the relationship between social unrest, conflict, and crime (to name but a few), with that of economic growth.

References

Adams, R. M., K. J. Bryant, B. A. Mccarl, D. M. Legler, J. O'Brien, A. Solow, and R. Weiher (1995). Value of Improved Long-Range Weather Information. *Contemporary Economic Policy 13*(3), 10–19.

Andrews, D. W. K. and W. Ploberger (1994). Optimal Tests when a Nuisance Parameter is Present Only Under the Alternative. *Econometrica 62*(6), pp. 1383–1414.

Baxter, M. and M. A. Kouparitsas (2005). Determinants of Business Cycle Comovement: A Robust Analysis. *Journal of Monetary Economics 52*(1), pp. 113–157.

Bennetton, J., P. Cashin, D. Jones, and J. Soligo (1998). An Economic Evaluation of Bushfire Prevention and Suppression. *Australian Journal of Agricultural and Resource Economics 42*(2), 149–175.

Brunner, A. D. (2002). El Niño and World Primary Commodity Prices: Warm Water or Hot Air? *Review of Economics and Statistics 84*(1), 176–183.

Buckle, R. A., K. Kim, H. Kirkham, N. McLellan, and J. Sharma (2002). A Structural VAR Model of the New Zealand Business Cycle. *New Zealand Treasury Working Paper 02/26*.

Cashin, P., K. Mohaddes, and M. Raissi (2016a). The Global Impact of the Systemic Economies and MENA Business Cycles. In I. A. Elbadawi and H. Selim (Eds.), *Understanding and Avoiding the Oil Curse in Resource-Rich Arab Economies*, pp. 16–43. Cambridge University Press, Cambridge.

Cashin, P., K. Mohaddes, and M. Raissi (2016b). China's Slowdown and Global Financial Market Volatility: Is World Growth Losing Out? *IMF Working Paper WP/16/63*.

Cashin, P., K. Mohaddes, M. Raissi, and M. Raissi (2014). The Differential Effects of Oil Demand and Supply Shocks on the Global Economy. *Energy Economics 44*, 113–134.

Cesa-Bianchi, A., M. H. Pesaran, A. Rebucci, and T. Xu (2012). China's Emergence in the World Economy and Business Cycles in Latin America. *Economia, The Journal of LACEA 12*, 1–75.

Changnon, S. A. (1999). Impacts of 1997-98 El Niño Generated Weather in the United States. *Bulletin of the American Meteorological Society 80*, 1819–1827.

Chudik, A. and M. H. Pesaran (2013). Econometric Analysis of High Dimensional VARs Featuring a Dominant Unit. *Econometric Reviews 32*(5-6), 592–649.

Chudik, A. and M. H. Pesaran (2016). Theory and Practice of GVAR Modeling. *Journal of Economic Surveys 30*(1), 165–197.

Debelle, G. and G. Stevens (1995). Monetary Policy Goals for Inflation in Australia. *Reserve Bank of Australia Research Discussion Paper 9503*.

Dees, S., F. di Mauro, M. H. Pesaran, and L. V. Smith (2007). Exploring the International Linkages of the Euro Area: A Global VAR Analysis. *Journal of Applied Econometrics 22*, 1–38.

Dell, M., B. F. Jones, and B. A. Olken (2014). What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature 52*(3), 740–798.

Dong, B. (2005). Asymmetry between El Niño and La Niña in a Global Coupled GCM with an Eddy-Permitting Ocean Resolution. *Journal of Climate 18*(16), 3373–3387.

Handler, P. and E. Handler (1983). Climatic Anomalies in the Tropical Pacific Ocean and Corn Yields in the United States. *Science 220*(4602), 1155–1156.

Hansen, B. (1992). Efficient Estimation and Testing of Cointegrating Vectors in the Presence of Deterministic Trends. *Journal of Econometrics 53*, pp. 87–121.

Harbo, I., S. Johansen, B. Nielsen, and A. Rahbek (1998). Asymptotic Inference on Cointegrating Rank in Partial Systems. *Journal of Business & Economic Statistics 16*, pp. 388–399.

Hsiang, S. M., K. C. Meng, and M. A. Cane (2011). Civil Conflicts are Associated with the Global Climate. *Nature 476*, 438–441.

Iizumi, T., J.-J. Luo, A. J. Challinor, G. Sakurai, M. Yokozawa, H. Sakuma, M. E. Brown, and T. Yamagata (2014). Impacts of El Niño Southern Oscillation on the Global Yields of Major Crops. *Nature Communications 5*.

Johansen, S. (1992). Cointegration in Partial Systems and the Efficiency of Single-equation Analysis. *Journal of Econometrics 52*(3), pp. 389–402.

Jordà, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review 95*(1), 161–182.

Jordà, Ò. (2009). Simultaneous Confidence Regions for Impulse Responses. *The Review of Economics and Statistics 91*(3), 629–647.

Kamber, G., C. McDonald, and G. Price (2013). Drying Out: Investigating the Economic Effects of Drought in New Zealand. *Reserve Bank of New Zealand Analytical Note Series AN2013/02*.

Kapetanios, G. and M. H. Pesaran (2007). Alternative Approaches to Estimation and Inference in Large Multifactor Panels: Small Sample Results with an Application to Modelling of Asset Returns. In G. Phillips and E. Tzavalis (Eds.), *The Refinement of Econometric Estimation and Test Procedures: Finite Sample and Asymptotic Analysis*. Cambridge University Press, Cambridge.

Kilian, L. and Y. J. Kim (2009). Do Local Projections Solve the Bias Problem in Impulse Response Inference? *Centre for Economic Policy Research Discussion Paper DP7266*.

Lee, K. and M. H. Pesaran (1993). Persistence Profiles and Business Cycle Fluctuations in a Disaggregated Model of UK Output Growth. *Ricerche Economiche 47*, 293–322.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of Political Economy 112*(4), 725–753.

Mohaddes, K. and M. H. Pesaran (2016). Country-Specific Oil Supply Shocks and the Global Economy: A Counterfactual Analysis. *Energy Economics 59*, 382–399.

Mohaddes, K. and M. Raissi (2015). The U.S. Oil Supply Revolution and the Global Economy. *IMF Working Paper No. 15/259*.

Nyblom, J. (1989). Testing for the Constancy of Parameters Over Time. *Journal of the American Statistical Association 84*(405), pp. 223–230.

Park, H. and W. Fuller (1995). Alternative Estimators and Unit Root Tests for the Autoregressive Process. *Journal of Time Series Analysis 16*, pp. 415–429.

Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. *IZA Discussion Paper No. 1240*.

Pesaran, M. H. (2015). Time Series and Panel Data Econometrics. Oxford University Press, Oxford.

Pesaran, M. H. and Y. Shin (1996). Cointegration and Speed of Convergence to Equilibrium. *Journal of Econometrics 71*, 117–143.

Pesaran, M. H., Y. Shin, and R. J. Smith (2000). Structural Analysis of Vector Error Correction Models with Exogenous I(1) Variables. *Journal of Econometrics 97*, 293–343.

Pesaran, M. H., L. Vanessa Smith, and R. P. Smith (2007). What if the UK or Sweden had Joined the Euro in 1999? An Empirical Evaluation Using a Global VAR. *International Journal of Finance & Economics 12*(1), 55–87.

Ploberger, W. and W. Krämer (1992). The CUSUM Test with OLS Residuals. *Econometrica 60*(2), pp. 271–285.

Quandt, R. E. (1960). Tests of the Hypothesis that a Linear Regression System Obeys Two Separate Regimes. *Journal of the American Statistical Association 55*(290), pp. 324–330.

Reserve Bank of India, . (2014). Report of the Expert Committee to Revise and Strengthen the Monetary Policy Framework. *Reserve Bank of India: Mumbai*.

Saini, S. and A. Gulati (2014). El Niño and Indian Droughts - A Scoping Exercise. *Indian Council for Research on International Economic Relations Working Paper 276*.

Smith, L. and A. Galesi (2014). GVAR Toolbox 2.0. University of Cambridge: Judge Business School.

Solow, A., R. Adams, K. Bryant, D. Legler, J. O'Brien, B. McCarl, W. Nayda, and R. Weiher (1998). The Value of Improved ENSO Prediction to U.S. Agriculture. *Climatic Change 39*(1), 47–60.

Tol, R. S. J. (2009). The Economic Effects of Climate Change. *Journal of Economic Perspectives 23*(2), 29–51.

Ubilava, D. (2012). El Niño, La Niña, and World Coffee Price Dynamics. *Agricultural Economics 43*(1), 17–26.

World Bank, . (2013). Turn Down the Heat: Climate Extremes, Regional Impacts, and the Case for Resilience. *World Bank Working Paper No 78424, Washington, DC: World Bank*.

A Data Appendix

A.1 Data Sources

The main data source used to estimate the GVAR model is Smith and Galesi (2014), which provides quarterly observations on all of the country-specific macro variables covering the period 1979Q2-2013Q1 as well as oil prices. This data can be downloaded from: https://sites.google.com/site/gvarmodelling. We augment this database with quarterly observations on Southern Oscillation index (SOI) anomalies data from National Oceanic and Atmospheric Administration's *National Climatic Data Centre*.

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

A.2 Construction of the Variables

Log real GDP, y_{it}, the rate of inflation, π_{it}, short-term interest rate, r_{it}^S, long-term interest rate, r_{it}^L, the log deflated exchange rate, ep_{it}, and log real equity prices, eq_{it}, are six variables included in our model, as well as most of the GVAR applications in the literature. These six variables are constructed as

$$\begin{aligned} y_{it} &= \ln(GDP_{it}), \quad \pi_{it} = p_{it} - p_{it-1}, \quad p_{it} = \ln(CPI_{it}), \quad ep_{it} = \ln\left(E_{it}/CPI_{it}\right), \\ r_{it}^S &= 0.25\ln(1 + R_{it}^S/100), \quad r_{it}^L = 0.25\ln(1 + R_{it}^L/100), \; eq_{it} = \ln\left(EQ_{it}/CPI_{it}\right), \end{aligned} \tag{14}$$

where GDP_{it} is the real Gross Domestic Product at time t for country i, CPI_{it} is the consumer price index, E_{it} is the nominal exchange rate in terms of the U.S. dollar, EQ_{it} is the nominal Equity Price Index, and R_{it}^S and R_{it}^L are short-term and long-term interest rates, respectively. In addition to the above variables we also include the log of real oil prices, p_t^{oil}, and the log of non-fuel commodity prices, p_t^{nf}, in our dataset.

B Country-Specific Estimates and Tests

The estimation of individual VARX*(p_i, q_i) models is conducted under the assumption that the country-specific foreign and common variables are weakly exogenous and that the parameters of the models are stable over time. As both assumptions are needed for the construction and the implementation of the GVAR model, we will test and provide evidence for these assumptions in Sections B.2 and B.3

B.1 Unit Root Tests

For the interpretation of the long-run relations, and also to ensure that we do not work with a mixture of $I(1)$ and $I(2)$ variables, we need to consider the unit root properties of the core variables in our country-specific models, see equations (12) and (13). If the domestic, $\mathbf{x}_{it}$, foreign, $\mathbf{x}^*_{it}$, and dominant, $\boldsymbol{\omega}_t$, variables included in the country-specific models are indeed integrated of order one, $I(1)$, we are not only able to distinguish between short- and long-run relations but also to interpret the long-run relations as cointegrating. Therefore, we perform Augmented Dickey-Fuller (ADF) tests on the level and first differences of all the variables. However, as the power of unit root tests are often low, we also utilize the weighted symmetric ADF test (ADF-WS) of Park and Fuller (1995), as it has been shown to have better power properties than the ADF test. This analysis results in a large number of unit root tests (around 2,000), which overall, as a first-order approximation, support the treatment of the variables in our model as being $I(1)$. For brevity, these test results are not reported here but are available from the authors upon request.

B.2 Testing the Weak Exogeneity Assumption

Weak exogeneity of country-specific foreign variables, $\mathbf{x}^*_{it} = \left(y^*_{it},\ \pi^*_{it},\ eq^*_{it},\ r^{*S}_{it},\ r^{*L}_{it}\right)'$, and the global variables, p^{oil}_t, p^{nf}_t, and SOI_t, with respect to the long-run parameters of the conditional model is vital in the construction and the implementation of the GVAR model. We formally test this assumption following the procedure in Johansen (1992) and Harbo et al. (1998). Thus, we first estimate the 21 VARX*(p_i, q_i) models separately under the assumption that the foreign and common variables are weakly exogenous and then run the following regression for each lth element of $\mathbf{x}^*_{it}$

$$\Delta x^*_{it,l} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ij,l} \widehat{ECM}_{ij,t-1} + \sum_{n=1}^{p^*_i} \varphi'_{ik,l} \Delta \mathbf{x}_{i,t-k} + \sum_{m=1}^{q^*_i} \vartheta_{im,l} \Delta \widetilde{\mathbf{x}}^*_{i,t-m} + \varepsilon_{it,l}, \quad (15)$$

where $\widehat{ECM}_{ij,t-1}$, $j = 1, 2, ..., r_i$, are the estimated error correction terms corresponding to the r_i cointegrating relations found for the ith country model, p_i^* and q_i^* are the orders of the lag changes for the domestic and foreign variables, and $\Delta\widetilde{\mathbf{x}}_{it}^* = \left(\Delta\mathbf{x}_{it}^{\prime *},\ \Delta ep_{it}^*, \Delta p_t^{oil}, \Delta p_t^{nf}, \Delta SOI_t\right)^{\prime}$.[19] Under the null hypothesis that the variables are weakly exogenous, the error correction term must not be significant; therefore, the formal test for weak exogeneity is an F-test of the joint hypothesis that $\gamma_{ij,l} = 0$ for each $j = 1, 2, ..., r_i$ in equation (15).

Table 5: F-Statistics for Testing the Weak Exogeneity of the Country-Specific Foreign Variables, Oil Prices, Non-Fuel Commodity Prices, and SOI

Country	F-test	Critical Value	y*	Δp*	eq*	ep*	r*	lr*	poil	pnonfuel	soi
Argentina	F(1,105)	3.93	4.96*	1.03	0.24	-	1.96	0.68	2.11	0.23	0.93
Australia	F(4,114)	2.45	0.86	2.66*	0.48	-	0.96	1.48	0.36	0.46	0.62
Brazil	F(1,111)	3.93	0.02	0.05	0.01	-	0.03	0.02	3.39	0.00	0.07
Canada	F(2,116)	3.07	2.77	3.67*	0.08	-	1.54	0.32	1.24	1.71	0.01
China	F(1,107)	3.93	1.61	2.01	0.21	-	0.16	0.55	0.27	0.00	1.31
Chile	F(1,110)	3.93	0.03	0.13	1.25	-	1.13	7.78*	0.13	0.45	3.21
Europe	F(3,115)	2.68	0.91	1.93	0.34	-	0.09	0.71	0.61	1.19	0.81
India	F(3,116)	2.68	1.25	2.73*	2.52	-	1.60	1.48	0.63	0.64	1.84
Indonesia	F(3,117)	2.68	0.60	0.41	1.20	-	1.03	0.62	0.80	0.64	0.45
Japan	F(3,115)	2.68	3.21*	4.97*	4.22*	-	0.83	0.55	2.51	1.21	0.42
Korea	F(2,116)	3.07	2.03	0.48	0.97	-	0.78	1.32	0.78	0.21	0.26
Malaysia	F(2,109)	3.08	2.43	1.20	3.49*	-	2.80	0.03	1.00	0.59	1.59
Mexico	F(2,118)	3.07	1.22	2.23	2.97	-	0.68	1.36	2.14	1.00	1.50
New Zealand	F(2,116)	3.07	4.09*	0.69	0.00	-	0.06	0.02	0.32	2.42	1.14
Peru	F(1,119)	3.92	0.53	0.00	0.01	-	0.86	1.01	1.15	2.43	0.35
Philippines	F(2,109)	3.08	0.36	1.10	1.11	-	1.03	1.42	2.74	2.98	0.43
South Africa	F(3,115)	2.68	1.06	0.63	0.82	-	0.41	2.34	4.02*	4.18*	1.81
Saudi Arabia	F(1,117)	3.92	0.14	1.36	2.91	-	0.58	0.45	0.13	0.24	0.20
Singapore	F(1,118)	3.92	0.38	0.06	5.06*	-	3.42	3.39	1.87	1.13	1.20
Thailand	F(1,118)	3.92	1.12	0.42	2.54	-	0.06	0.21	0.00	0.00	0.49
USA	F(2,119)	3.07	0.63	7.58*		1.09			0.51	1.86	0.34

Notes: * denotes statistical significance at the 5% level.

The test results together with the 95% critical values are reported in Table 5, from which we see that the weak exogeneity assumption cannot be rejected for the overwhelming majority of the variables considered. In fact, only 14 out of 166 exogeneity tests turned out to be statistically significant at the 5% level. Considering the significance level assumed here, even if the weak exogeneity assumption is always valid, we would expect up to 8 rejections, being 5% of the 166 tests. Therefore, overall, the available evidence in Table 5 supports our treatment of the foreign and global variables in the individual VARX* models as weakly exogenous.

[19] Note that the U.S. model is specified differently, mainly because of the dominance of the United States in the world economy. See the discussion in Section 4.2.

B.3 Tests of Structural Breaks

The possibility of structural breaks is a fundamental problem in macroeconomic modelling. However, given that the individual VARX* models are specified conditional on the foreign variables in $\mathbf{x}^*_{it}$, they are more robust to the possibility of structural breaks in comparison to reduced-form VARs, as the GVAR setup can readily accommodate co-breaking. See Dees et al. (2007) for a detailed discussion. We test the null of parameter stability using the residuals from the individual reduced-form error correction equations of the country-specific VARX*(q_i, p_i) models, initially looking at the maximal OLS cumulative sum statistic (PK_{sup}) and its mean square variant (PK_{msq}) of Ploberger and Krämer (1992). We also test for parameter constancy over time against non-stationary alternatives as proposed by Nyblom (1989) (NY), and consider sequential Wald statistics for a single break at an unknown change point. More specifically, the mean Wald statistic of Hansen (1992) (MW), the Wald form of the Quandt (1960) likelihood ratio statistic (QLR), and the Andrews and Ploberger (1994) Wald statistics based on the exponential average (APW) are utilized. Finally, we also examine the heteroskedasticity-robust versions of NY, MW, QLR, and APW.

Table 6 presents the number of rejections of the null hypothesis of parameter constancy per variable across the country-specific models at the 5% significance level. For brevity, test statistics and bootstrapped critical values are not reported here but are available on request. Overall, it seems that most regression coefficients are stable, although the results vary considerably across different tests. In the case of the two PK tests, the null hypothesis is rejected between $9\% - 14\%$ of the time. For the NY, MW, QLR, and APW tests on the other hand, we note that the rejection rate is much larger, between $21\% - 57\%$ of the time. The QLR and APW rejection rates, for the joint null hypothesis of coefficient and error variance stability, are particularly high with 60 cases each out of 105 being rejected. However, looking at the robust version of these tests, we note that the rejection rate falls considerably to between 8% and 13% of the time. Therefore, although we find some evidence for structural instability, it seems that possible changes in error variances rather than changes in parameter coefficients is the main reason for this. We deal with this issue by using bootstrapped means and confidence bounds when undertaking the impulse response analysis. Table 7 presents the break dates with the QLR statistics at the 5% significance level.

Table 6: Number of Rejections of the Null of Parameter Constancy per Variable across the Country-Specific Models at the 5 percent Significance Level

Tests	y	π	eq	ep	r^S	r^L	Total
PK_{sup}	3	4	1	3	4	0	15(14)
PK_{msq}	2	1	2	1	3	0	9(9)
NY	2	5	4	4	2	5	22(21)
robust-NY	2	1	1	4	3	2	13(12)
QLR	13	14	6	8	15	4	60(57)
robust-QLR	0	3	1	1	2	1	8(8)
MW	7	8	7	7	5	5	39(37)
robust-MW	3	2	2	4	2	1	14(13)
APW	13	14	6	8	14	5	60(57)
robust-APW	1	3	2	0	2	1	9(9)

Notes: The test statistics PK_{sup} and PK_{msq} are based on the cumulative sums of OLS residuals, NY is the Nyblom test for time-varying parameters and QLR, MW and APW are the sequential Wald statistics for a single break at an unknown change point. Statistics with the prefix 'robust' denote the heteroskedasticity-robust version of the tests. All tests are implemented at the 5% significance level. The number in brackets are the percentage rejection rates.

Table 7: Break Dates Computed with Quandt's Likelihood Ratio Statistic

Country	y	Δp	eq	ep	r	lr
Argentina	1985Q2	1989Q2	1987Q3	1989Q3	1989Q4	-
Australia	1984Q3	1984Q3	1992Q4	1986Q3	1986Q2	1989Q1
Brazil	1990Q1	1989Q4	-	1999Q1	1989Q4	-
Canada	1987Q3	1999Q3	1984Q3	2003Q4	1987Q1	1986Q3
China	1994Q4	1988Q3	-	1994Q4	1991Q1	-
Chile	1985Q2	1985Q4	1985Q3	1985Q4	1985Q2	-
Europe	1986Q1	1985Q4	1987Q1	2000Q1	1986Q2	1987Q4
India	1997Q2	1998Q4	1993Q2	1991Q4	1994Q4	-
Indonesia	1984Q4	1998Q1	-	1997Q2	1997Q2	-
Japan	1989Q4	1986Q2	1991Q2	1998Q3	1986Q3	1987Q4
Korea	2000Q1	1984Q3	1997Q3	1997Q3	1997Q1	1984Q3
Malaysia	1993Q2	2008Q1	1998Q3	1995Q3	1998Q2	-
Mexico	1997Q3	1989Q2	-	1988Q3	1988Q1	-
New Zealand	1986Q4	1987Q1	1990Q4	1995Q4	1987Q1	1986Q3
Peru	1990Q4	1990Q4	-	1991Q2	1989Q4	-
Philippines	1989Q1	1984Q3	1986Q1	1984Q3	1984Q4	-
South Africa	1986Q2	1998Q2	1986Q1	1988Q1	1986Q1	1986Q3
Saudi Arabia	1989Q2	1994Q3	-	1986Q3	-	-
Singapore	2008Q1	1984Q3	1991Q1	1996Q4	1984Q3	-
Thailand	2008Q1	1985Q1	1990Q3	1997Q2	1994Q4	-
USA	1984Q3	2000Q3	1996Q3	-	1984Q3	1984Q3

Notes: All tests are implemented at the 5% significance level.

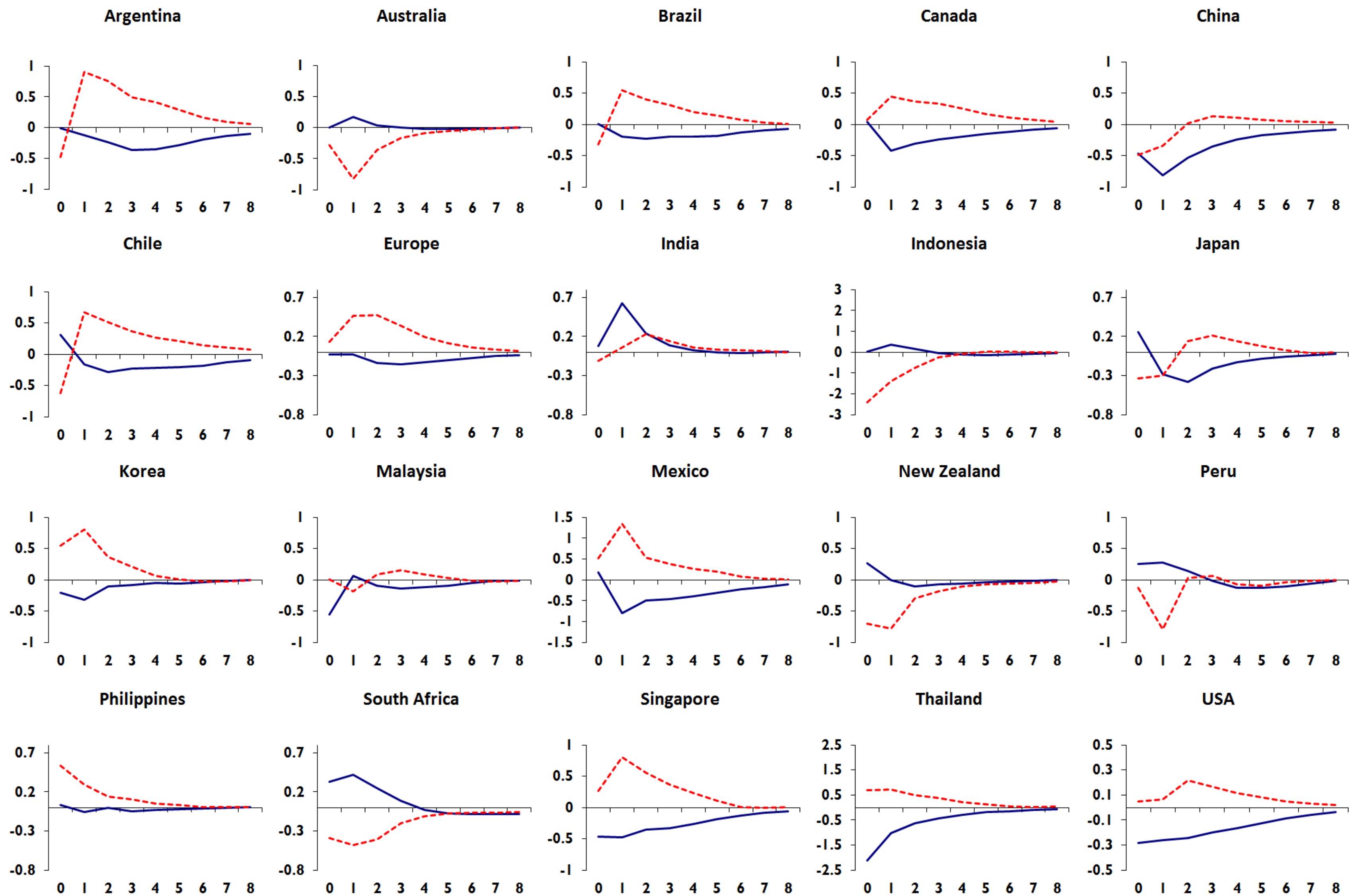
C Asymmetric Effects of El Niño and La Niña

While La Niña events cause weather extremes in various parts of the world that are typically opposite to those associated with El Niño episodes, they tend to have weaker effects than those of El Niño events, and are less frequent and shorter in duration (see, for instance, Dong (2005)). More specifically, since 1900 thirty four El Niño episodes and only twenty three La Niña events have been recorded.

As explained in Section 2, an El Niño year usually 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. La Niña years, on the other hand, are characterized by wetter than normal conditions over Australia and Indonesia, the Philippines, South Africa and northern Brazil. During La Niña episodes, the Indian monsoon rainfall tends to be greater than normal, especially in the northwest region. Drier than normal conditions are observed in the Gulf Coast and South America (southern Brazil to central Argentina). As regards the United States, a La Niña event typically features below normal precipitation in the Southwest, the central and southern regions, and unusually cold weather in the Northwest.

To investigate the asymmetrical economic impact of El Niño and La Niña shocks, we estimated two additional GVAR models. We use quarterly observations over the period 1979Q2–2013Q1 and the exact same specification for the 21 country-specific VARX*(p_i, q_i) models as before, see Table 2 and the discussion in Section 4.2. The only difference between the models is that in the first one we include negative values of SOI anomalies to capture El Niño events, while in the second model we include positive values of SOI anomalies to feature La Niña episodes. Figure 10 compares the median impulse responses of real GDP growth to El Niño, given by the dashed red lines, and La Niña events, given by the solid blue lines, for the countries in our sample. We observe that for most countries the response of GDP growth to a La Niña shock is of opposite sign to that of an El Niño event, but they tend to be smaller in magnitude, clearly illustrating the asymmetric effects of the two shocks.

Figure 10: The Asymmetric Effects of El Niño and La Nina Shocks on Real GDP Growth (in percentage points)



Notes: Figures are median impulse responses to an El Niño shock (red dashed) as compared with a La Nina shock (blue solid). The impact is in percentage points and the horizon is quarterly.