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The Effect of ENSO Shocks on Commodity Prices: A Multi-Time Scale Approach

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The Effect of ENSO Shocks on Commodity Prices: A Multi-Time Scale Approach*

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Abstract

We investigate the effect of changing ENSO patterns on global commodity prices, including energy, metals/minerals and agriculture real commodity price subsets, while controlling for global economic output and interest rate via a global factor local projections (GFALP) model. We study the responses to climate shocks using a nonlinear multivariate model to assess differential effects across ENSO climate regimes. We find that commodity inflation is reactive to El Niño and La Niña events, but that this sensitivity can occur either in the short- or long-term depending on the commodity under investigation. For commodities in agriculture, we uncover an asymmetric influence of El Niño and La Niña shocks. More central banks are questioning whether climate change is part of their mission to stabilize prices. Our results indicate the existence of a direct link between weather anomalies and commodity inflation, one that should be integrated into the central banks' inflation targeting framework.

JEL Classification: C32, F44, O13, Q54.
Keywords: ENSO, Weather, Commodity Price, Agriculture, Energy.

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1 Introduction

Global climate is changing, and there is growing concern it increases the frequency and intensity of weather patterns (e.g., Timmermann et al. (1999), Chen et al. (2001), An and Wang (2000)). Climate change poses serious threats to the core fabrics of our ecological, social and economic systems, yet the impact of changing climate is shrouded in uncertainty. Central to this concern is the effect on economic stability.

This paper explores the global dimensions of changing weather patterns and the international energy and agriculture commodity prices as they affect economic conditions. This research overlaps with two strands of literature. The first strand relates to a voluminous body of literature analyzing the effects that changing oil prices have on the macroeconomy (e.g., Hamilton (1983), Hamilton (2008), Kilian (2009), Bodenstein et al. (2011), Kilian (2014), Kang et al. (2017), Arouri et al. (2014), You et al. (2017), among others). Commodity prices (in real terms) tend to be endogenous and pro-cyclical to the global business cycle (e.g., Kilian (2009), Kilian and Zhou (2018)). Kilian (2009) distinguishes between demand and supply shocks in the oil price, and finds that increases in the oil price since 2003 are primarily driven by demand. The similar increases in the food price has raised concerns about inflationary pressures. This finding is also confirmed by Joëts et al. (2017) for corn, soybeans and wheat. This identification is consistent with Alquist and Kilian (2010), who finds that the oil price is determined endogenously and simultaneously.

The second strand relates to only a handful of papers to address the transmission that weather shocks has on economic conditions (Brunner (2002), Cashin et al. (2017), De Winne and Peersman (2018) and Peersman (2018)). Brunner (2002) finds that weather shocks has important and statistically important effects on global commodity prices. Cashin et al. (2017) estimates a global vector autoregression to investigate weather shocks for twenty-one country/regions. Cashin et al. (2017) find heterogeneous responses of a weather shocks with regard to output growth. Peersman (2018) find that food price shocks can explain 30% inflation volatility in euro area. De Winne and Peersman (2018) show that increases in global agricultural commodity prices that are caused by unfavorable harvest shocks in other regions of the world can curtail domestic economic activity.

This paper provides three main contributions to the literature. First, using a rich dataset for nine economies representing circa two-thirds of global output[1], we analyze to what extent a global El Niño weather and commodity price shock transmit a disturbance on the global factor economy. This paper is based on monthly data over the period 2002:04 to 2019:12, which has the potential benefit of capturing the short-term temporal effect that weather has on the economy (e.g., Barnston (2015)), as opposed to using quarterly data as in previous studies (Brunner (2002), Cashin et al. (2017)). Most of the existing research climate change relates to disasters, which is primarily *ex ante* (Noy, 2009), and mainly on prediction and preparation (Cavallo and Noy, 2009). This paper explores the transmission of changing ENSO weather conditions on agriculture, energy and metals/minerals price subsets, *ex post*.

Second, this paper employs a global factor augmented local projections model (GFALP) framework to assess the transmission of weather shocks on commodity, while controlling for global ouput, the interest rate and VIX. As the impact of El Niño or La Niña cannot be reduced to one country, but rather has global dimensions, this paper exploits a global factor model framework which paves the way to further our understanding how changing ENSO climate patterns affect global commodity prices.

Third, of the rich literature that considers commodity prices, most papers include the oil price. This paper considers not only the energy price, which is more representative of the global economy than the oil price (Vasishtha and Maier, 2013), but also the agriculture and metals/minerals price subsets. The global factor model approach further allows an identification such that agriculture, energy and metals/minerals prices are treated endogenously. An important benefit of this approach can be considered a structural extension to Cashin et al. (2017), such that the authors treat oil and non-fuel commodities endogenous only to the US business cycle within a global VAR. Our model framework incorporates not only the effects of global ENSO

[1]The nine economies include: Canada ("CAN"), China ("CHN"), Euro zone (19 countries; "EUR"), United Kingdom ("GBR"), India ("IND"), Japan ("JPN"), South Korea ("KOR"), Russia ("RUS") and the United States ("USA"). Based on IMF data in purchasing power parity terms, the nine economies considered in this paper represent 66.1% of global output, see https://www.imf.org/external/datamapper/PPPSH@WEO/OEMDC/ADVEC/WEOWORLD/EU. The Euro zone values are based on the 19 member countries (i.e., Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain).

weather patterns, but also facilitates an endogenous treatment of commodity prices. This framework allows us to further inform our understanding of the consequential effects of changing ENSO weather patterns *ex post*, an area of paramount importance, considering current assessments of future climate scenarios are shrouded in uncertainty. Abril-Salcedo et al. (2020) looks at a non-linear relationship between ENSO and domestic Colombian food inflation. The closest paper to this research is Ubilava (2018), who employs a TV-STAR model to estimate El Niño and La Niña weather patterns on global commodity prices.

Our paper differs from theirs on two crucial points.

First, we take into account the results from the rapidly expanding climate science literature which shows that changes in El Niño and La Niña operate in multiscale dimensions. Indeed, changes in climate system (temperature, precipitation, surface water pressure, etc) can be caused by changes in the structural mechanisms that govern the interdependencies of the components of this system. Such changes modify climatic *regimes* that must be differentiated from normal disturbances that are due to the stochastic nature of certain climatic components. The multiscale approach then allows us to differentiate structural climate shocks from shocks whose effects dissipate rapidly. To do this, rather than estimating the smoothness parameter of the transition function, it is preferable to examine the response to shocks for different values of this parameter. An advantage of this approach is that it allows to account for the diversity of responses observed historically in commodity inflation following El Niño and La Niña events. We know, for example, that from one region to another, these events have differentiated effects (positive or negative responses, small or big magnitudes) on countries' GDP (see for example Cashin et al. (2017)). Another advantage of looking at the effects of changing smoothness parameter is to facilitate possible counterfactual analysis.

Second, we use a multivariate framework. Indeed, not only are commodity markets interconnected, but El Niño and La Niña phenomena are weather shocks common to different commodities. A multivariate model has an advantage over the univariate models frequently used in the literature on commodity prices. It allows us to identify and estimate the true causal effects of climate change and to avoid over- or underestimating their effects due to biases linked to omitted variables. For example, we know that the prices of many commodities are impacted by energy prices, hence the importance of studying simultaneously the dynamics of oil prices with those of other agricultural products and raw materials. We use the framework of a local projection model with a transition function, in order to differentiate the climate change regimes associated with cold or warm temperatures. In order to differentiate between the effects of climate variations and those of other factors common to commodity price changes, we introduce other common factors, notably the international macro-financial environment that can influence price movements in international commodity markets: GDP and short term monetary policy rates in the world's major industrialized and emerging countries. Another benefit of the local projections model framework is that the system does not necessarily remain static in a regime conditional that the system has entered the regime as in the smooth transition model by Ubilava (2018).

Our paper highlights the fact that the impact of climate shocks can vary depending on the time scale at which they occur. These variations can concern the long-term components of the climate cycle, or the short-term components. Hence the importance of a multi-resolution analysis. We highlight this by showing the diversity of price responses to shocks for different values of the transition function parameter that measures temperature changes between warm (El Niño) and cold (La Niña) climate regimes. We find a significant influence of El Niño and La Niña events, considering both changes in the average levels of the indicators or in their extreme values (anomalies). Agricultural commodity prices appear to be more sensitive to climate variations reflecting changes in weather patterns than energy and non-energy commodity prices.

The rest of the paper is structured as follows: in Section 2 describes the data. Section 3 discusses the global dimensions of the business cycle considered in the paper. The modelling methodology and empirical results are summarized in Section 4. Section 5 concludes the paper.

2 Data

The GFALP model is based on the first principal component of nine economies covering output and the interest rate. The sample period is monthly which covers 2002:04 to 2019:12.[2] The variables considered include a weather index via the Equatorial Southern Oscillation Index (ESOI) and Sea Surface Temperature (SST) index; industrial production index[3]; the short-term interest rate[4]; and 34 commodity prices. The data is summarized in Table 1.

Table 1: Variable Selection

Item	Symbol	Source	Description
ESOI Weather	$W_t^{G,ESOI}$	NOAA	Equatorial Southern Oscillation Index
SST Weather	$W_t^{G,SST}$	NOAA	Sea Surface Temperature
Output Growth	$\Delta \ln Y_t$	OECD, FRED	Industrial Production
Commodity Inflation	$\Delta \ln P_t^G$	World Bank (see [a])	34 International Commodity Prices Considered
Interest Rate	R_t	OECD, FRED, CEIC	Short-term interest rate
CBOE Volatility Index	$\ln VIX_t$	FRED	VIXCLS

[a]: https://www.worldbank.org/en/research/commodity-markets.

All variables are converted to logarithm with the exception of the interest rate and weather indices. The commodity price data, denominated in U.S. dollars, is deflated by dividing by the U.S. CPI. The ESOI and SST indices are used as a global measure of weather, which is collected from the National Oceanic and Atmospheric Administration (NOAA).

3 Global Dimensions of the Business Cycle

Three types of global variables are considered: two weather indices (ESOI and SST); global factors (output and interest rate); and 34 global commodity prices. Each are discussed in turn.

3.1 Global Weather Patterns

When a major El Niño (La Niña) occurs, there is an anomalous loss (increase) of heat from the ocean to atmosphere so that global mean temperatures rise (fall) (McPhaden et al., 2020). The anomalous atmospheric patterns are known as the Southern Oscillation. El Niño, La Niña Southern Oscillation (ENSO) is one of the most important climate indicators, which has a major influence of global weather conditions (e.g., Ropelewski and Halpert (1987), Rosenzweig et al. (2001), McPhaden et al. (2006), Dai (2013) and Brönnimann et al. (2007)).[5]

ENSO relates to cyclical, environmental conditions that occur across the equatorial Pacific Ocean. Changes to ENSO are due to natural interactions between sea surface temperature, rainfall, air pressure, atmospheric and oceanic circulation. The effects of ENSO, commonly called ”teleconnections”, emphasize that changing conditions can have a profound effect on global climate, which can in turn directly affect people’s livelihoods (e.g., Barlow et al. (2001), Diaz et al. (2001), and Alexander et al. (2002)).

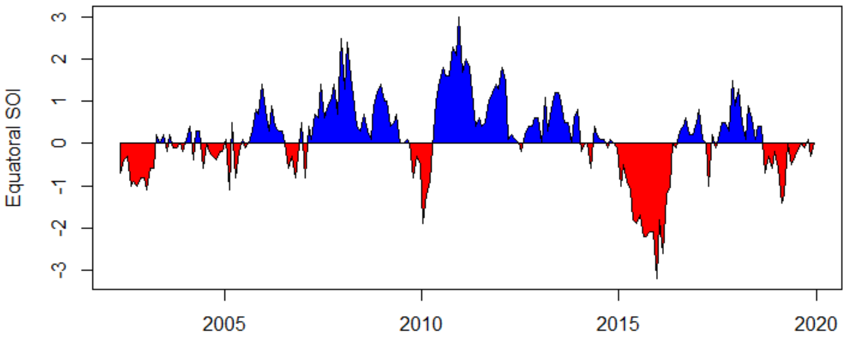
[2] The choice of economies and sample period combination is, in part, based on data availability. The sample period is quite extensive (213 observations per economy), while the nine economies considered represent the majority (66.12%) of global output at purchasing power parity using IMF data. The sample period also overlaps with the commodity price booms that occurred in 2004 (Radetzki, 2006).

[3] For India, manufacturing production index (FRED mnemonic INDPRMNTO01IXOBM) is used as opposed to total production index (FRED mnemonic INDPROINDMISMEI), considering data availability (the correlation between the is 0.9918 for Jan 2000 to Dec 2018). For China, we use total production excluding construction (FRED mnemonic CHNPRINTO01IXPYM). As the production index for China includes missing values, the Kalman smoother using an ARIMA state space representation is used to impute missing values.

[4] For India, the interest rate is based on the 90 day Treasury Bill interest rate (e.g., Patnaik et al. (2011), Gabriel et al. (2012), Saxegaard et al. (2010), Anand et al. (2014) and Ginn and Pourroy (2020)).

[5] The NOAA considers ENSO as ”one of the most important climatic phenomena on Earth”, see https://www.weather.gov/mhx/ensowhat.

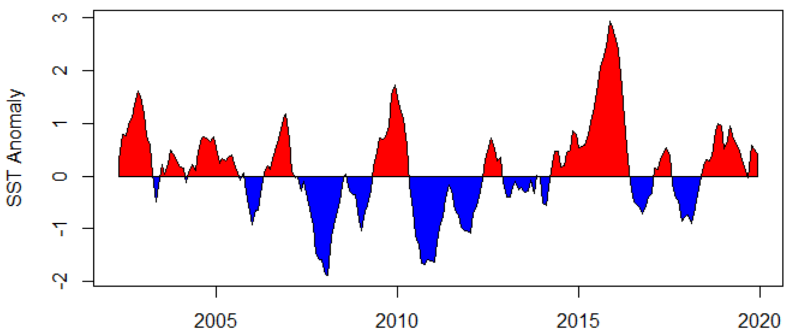
Figure 1: Equatorial SOI Anomalies



While the Southern Oscillation Index (SOI), which is a commonly used indicator of ENSO, has been used in empirical papers as an indicator of weather as it relates to economic conditions (e.g., Brunner (2002), Cashin et al. (2017)), the Equatorial Southern Oscillation Index (ESOI) is considered in this paper. According to Shi and Su (2020), ESOI is superior to SOI since the former has a stronger correlation with the Niño 3.4 region sea surface temperature anomaly as well as with westerly/easterly wind bursts. Furthermore, Barnston (2015) in a NOAA report suggests that ESOI overcomes two limitations of the SOI. First, SOI is based on the sea level pressure at just two stations (Tahiti and Darwin), which means "it can be affected by shorter-term, day-to-day or week-to-week fluctuations unrelated to ENSO." Second, the SOI is based on Tahiti and Darwin, both of which are located south of the equator whereas "the ENSO phenomenon is focused more closely along the equator." Taking these facts into consideration, the empirical analysis is based ESOI at monthly frequency (as opposed to quarterly data as in Brunner (2002) and Cashin et al. (2017)). The ESOI is plotted in Figure 1, where blue (red) indicates La Niña (El Niño) conditions.

We also consider the Sea Surface Temperatures (SST) data, which is a 3-month running mean of sea surface temperature (SST) anomalies in the Niño 3.4 region that is above (below) the threshold of +0.5°C (-0.5°C). The SST is plotted in Figure 2, where blue (red) indicates La Niña (El Niño) conditions.

Figure 2: Sea Surface Temperature Anomalies



3.2 Global Factors

Following the approach by Ratti and Vespignani (2016), we construct a global factor using the principal component indices for output and interest rate using normalized loadings. The benefit of this approach is that by taking the first principal component establishes a dimension reduction techniques that can replicate the main features of a global environment. The global factors represent nine economies which approximate two-thirds of global output using an extensive data from 2002:04 to 2019:12.

$$Y_t^G = [Y_t^{CAN}, Y_t^{CHN}, Y_t^{EUR}, Y_t^{GBR}, Y_t^{IND}, Y_t^{JPN}, Y_t^{KOR}, Y_t^{RUS}, Y_t^{USA}] \tag{1}$$

$$R_t^G = [R_t^{CAN}, R_t^{CHN}, R_t^{EUR}, R_t^{GBR}, R_t^{IND}, R_t^{JPN}, R_t^{KOR}, R_t^{RUS}, R_t^{USA}] \tag{2}$$

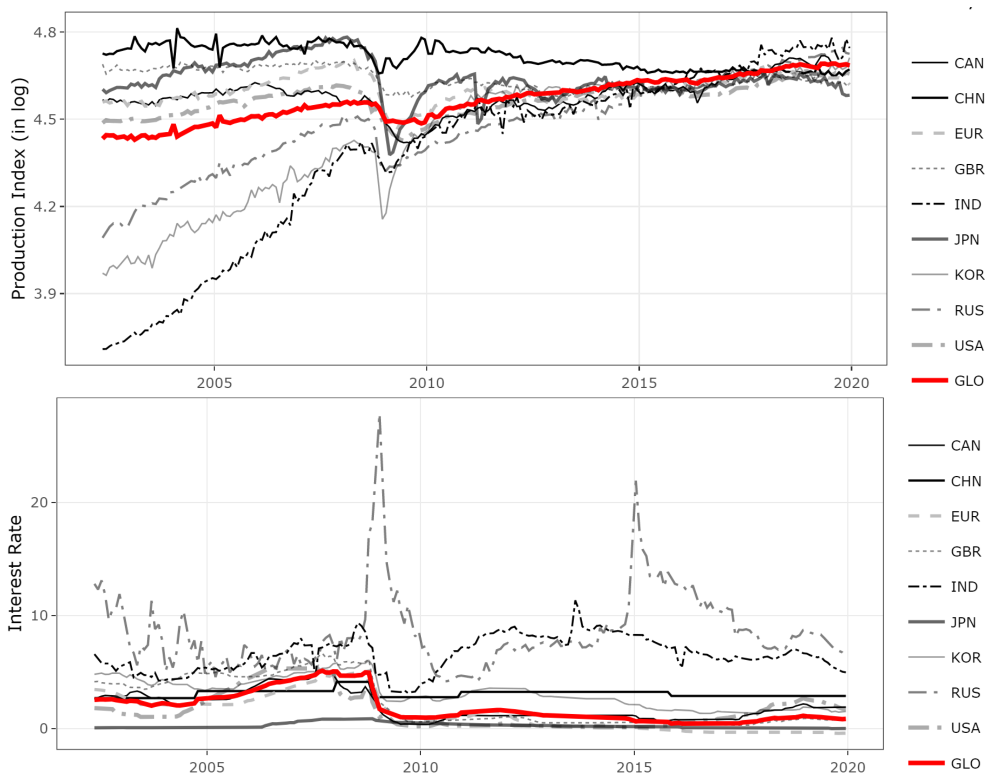
We use one factor (the principal component) for the global variables (Ratti and Vespignani, 2016). The results are provided in Table 2, which shows the top three principal components of each global variable for the nine economies. The first principle component captures significant share of the variance relating to output (54.9%) and the interest rate (54.1%).[6]

Figure 3 plots the global factors along with the economy data. The top-pane shows a sizable decline in output which occured during the global financial crisis.[7]

Table 2: Variation Explained by First Three Principal Components

	Global Output	Global Interest Rate
First Principal Component	54.9%	54.1%
Second Principal Component	33.5%	18.3%
Third Principal Component	6.4%	12.3%

Figure 3: Global Factors



The correlation between global variables (output and interest rate) is provided in Table 3. The correlation between global factor and country output is quite high for CAN, RUS and USA; and somewhat moderate for EUR and IND. There is lower correlation between the China and global output. The negative correlation between the UK and global output may be due to higher uncertainty in the UK related with Brexit. While it remains unclear to the extent that Brexit has had an impact on the domestic economy, a common thread is uncertainty, which has been linked with reduced investment, employment and productivity growth (Bloom et al., 2018).

[6]The higher dimensions of the principal components are provided in the Appendix, see the Scree plot in Figure 12. These values are similar to Ratti and Vespignani (2016), where the first principle component in their paper captures for global output and interest rate represents 60.0% and 44.5% of the total variance, respectively.

[7]According to the NBER, the recession dates for the U.S. is between 2007:DEC to 2009:JUN.

Table 3: Correlation by Country and Global Variable

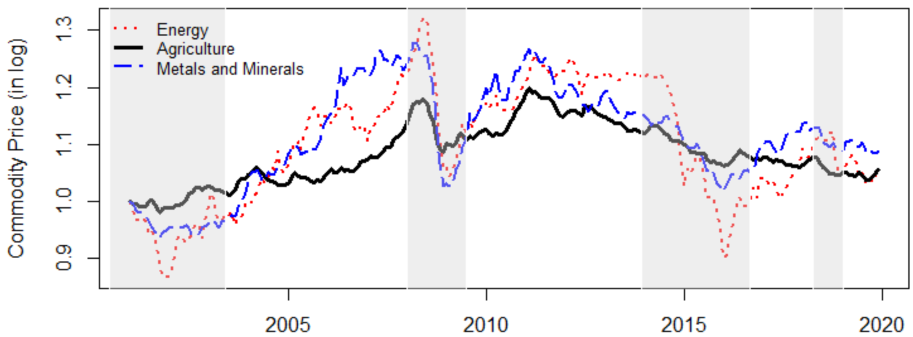
Country	GLO	CAN	CHN	EUR	GBR	IND	JPN	KOR	RUS	USA
Global Output	1.00	0.63	-0.81	0.51	-0.46	0.92	-0.1	0.91	0.98	0.81
Global Interest Rate	1.00	0.92	0.56	0.95	0.94	0.01	0.61	0.91	-0.25	0.81

3.3 Global Commodities

A total of 34 international commodities are analyzed in this study. The global factor model approach further allows an identification such that agriculture, energy and metals/minerals prices are treated endogenously. This allows us to analyze the effect that weather has on important commodity prices, while controlling for output, the interest rate and VIX.

Since the early 2000s, the world experienced elevated and persistent prices of many commodities relative to the somewhat more tranquil period after the mid-1980s. Several authors have dubbed this phenomena as a commodity price "super cycle".[8] Hamilton (2008) motivates an argument of the importance of oil prices; that nine of ten recessions in the US since World War II have been preceded by an increase in oil prices. Yet the same argument can be conveyed for not only the broader set of energy prices, but also for metals/minerals and agriculture prices, at least since the turn of the century on a global scale at the onset of all four recessions (see Figure 4).[9] Kilian and Vigfusson (2017) do not find evidence of a "mechanical relationship" between an increase in the oil price and recessions.

Figure 4: International Energy and Agriculture Price



Source: World Bank (real terms). Indexed 2001:01 = 1. Shaded areas indicate OECD recession dates for 35 OECD member and non-member economies as proxy for global recession.

4 Weather shock identification

4.1 Multiple time scales in the oscillations of El Niño and La Niña

El Niño and La Niña phenomena result from nonlinear and complex interactions of the ocean-atmosphere system, implying that the succession of cool phases and warms phases of sea surface temperature are described by quasi-periodic fluctuations of different durations nested within each other. Geophysicists and climatologists explain the coexistence of quasi-periodic fluctuations by the interaction of different climatic subsystems (the physical and atmospheric factors that drive the different cycles are not necessarily identical). Climate change can therefore be analyzed at different time scales. On the geological time scale, the time unit of measurement is the millennium. On the time scale of human activity, climate variations are described by the coexistence of long cycles lasting several decades, or 5 to 10 years, and shorter cycles of biennial, annual or infra-annual duration

[8]For example, Radetzki (2006) identifies the commodity price booms also occurred in the early 1950s, 1973/1974 and 2004 as the start of the third commodity price boom since the second world war.

[9]To illustrate this point, Figure 4 shows the international energy, metals/minerals and agriculture price movements against recession dates for 35 OECD member and non-member countries, where latter is used as a proxy for a global recessionary period.

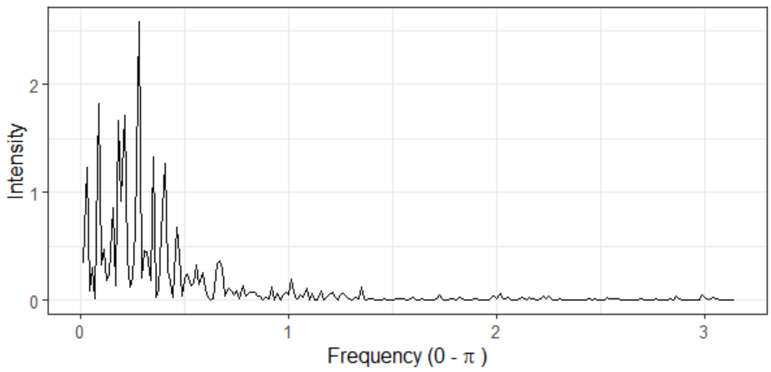
The durations of the cycles do not have the same effect on the transition phases between warming and cooling temperatures. Fluctuations of short duration involve very rapid transitions from one regime to the other, while fluctuations associated with cycles of longer duration have more persistent transition dynamics.

From a statistical point of view, a given observation of ESOI can be located on several cycles at the same time insofar as the fluctuations of different durations are nested. For example, a country may experience a cooling of temperatures by evolving in a state corresponding to La Niña on a cycle of short duration, while evolving at the same time in a phase of rising temperatures corresponding to El Niño on a cycle of longer duration. The impact of climate change on commodity inflation thus depends on the sensitivity of prices to each of these cycles.

To highlight the existence of multiple cycles in the dynamics of the ESOI series, a first approach is based on the estimation of long memory models. In their seminal paper Baillie and Chung (2002) show that annual temperature and width of tree ring time series data can be modelled by long-memory ARFIMA (autoregressive fractionally integrated moving average) type models and that such models are consistent with temperature upward trend and global warming. More recently, Rypdal and Rypdal (2014) studied global warming from a system that includes the contribution of solar, volcanic, and anthropogenic activities and concludes that the system generates a long-memory temperature change process. Such studies are important, because it is known since the work by Diebold and Inoue (2001) that the presence of long-memory dynamics in time series are typical of processes subject to regime shifts. Using Northern hemisphere temperature data, Mills (2007) has shown that this applies in particular to climate data, where models with slowly changing levels and changes mimick long memory behavior.

The presence of cycles of long durations in the ESOI time series can be seen by estimating its spectrum (see Figure 5). Indeed, we observe important peaks of the spectral density in the vicinity of 0. The series thus includes long cycles. And these can mask the presence of short cycles. We estimate a Gegenbauer ARMA (GARMA) model, which is more general than the ARFIMA models usually used in the literature.

Figure 5: Spectrum of ESOI over 1949-2020



We estimate the following k-factor Gegenbauer process:

$$\Phi(L)\, \Pi_{i=1}^{k}(1-2u_i+L^2L)^{d_i}(1-L)^{id}(X_t-\mu)=\Theta(L)\, \epsilon_t \tag{3}$$

where

- L is the lag operator defined by $L^j\, X_t = X_{t-j}$,
- $\Phi(L)$ is the short-memory autoregressive component of order p,
- $\Theta(L)$ is is the short-memory moving average component of order q,
- $(1-2u_i+L^2L)^{d_i}$ s the long-memory Gegenbauer component,
- id is the degree of integer differencing (here 0,
- X_t is ESOI,

- ϵ_t is an *iid* normal random component.

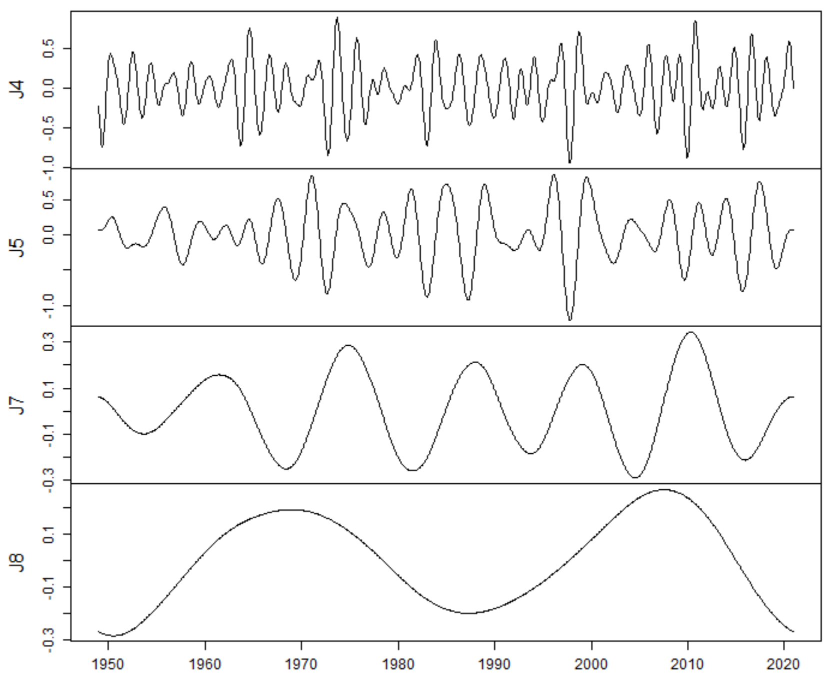
Our best model is obtained for $p = q = 1, k = 3$. The estimates in Table 4 suggest that the ESOI series has cycles that varies, with the longest cycle between 5 and 6 years (i.e., 67.88 months), followed by a cycle between 3 to 4 years (i.e., 42.99 months) and between 2 to 3 years (i.e. 29.47 months). The K-GARMA model has nevertheless several disadvantages. They are parametric models and therefore the number of factors that can be taken is limited by the non-linearity and the difficulties of convergence in the estimation of this type of model. This means that they do not capture all the cycles or quasi-fluctuations of the series. Moreover, long cycles can mask the presence of shorter cycles. An alternative is then to use non-parametric approaches.

Table 4: Estimate of a 3-factor GARMA model

	Intercept	u1	d1	u2	d2	u3	d3	ar1	ma1
Coefficient	-0.0568	0.9957	0.1664	0.9893	0.1551	0.9773	0.1734	-0.3597	-0.1287
Standard Error	0.0011	0.0005	0.0021	0.0006	0.0007	0.0008	0.0011	0.0015	0.0028
Gegenbauer	Factor1	Factor2	Factor3						
Frequency:	0.0147	0.0233	0.0339						
Period:	67.8793	42.9931	29.4697						
Exponent:	0.1664	0.1551	0.1734						

Wavelet analysis can be used to quantify ENSO variability. It is more general than Fourier-based transform and allows multiple time scale analysis. It has been successfully applied in the climatology literature (for a recent survey, the reader can refer to Rhif et al. (2019)). We perform a multi-resolution decomposition by applying J-level wavelet filters to ESOI where $J = \{1, ..., 9\}$ (Mallat decomposition). Low values of J capture high frequency components (short-term), while as J increases the decomposition filter low-frequency components (long-term). Figure 6 shows cycles of different lengths depending on the value of J (as an example, we have selected the graphs corresponding to $J = \{4, 5, 7, 8\}$).

Figure 6: ESOI Cycles Using Wavelet Decomposition

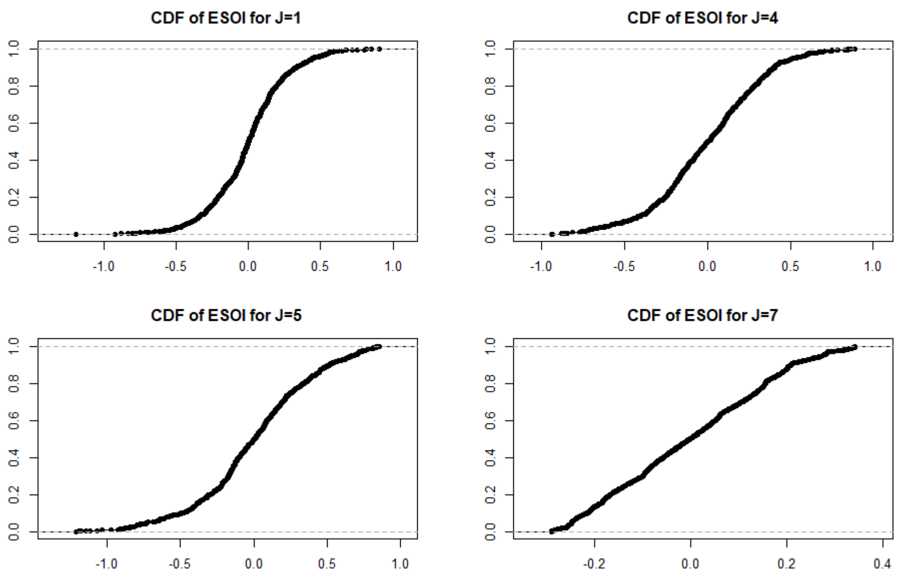


For J= 8, we observe long fluctuations with a modification of their duration in time. Until 1980, the ESOI series is negative for about ten years (El Niño regime), then positive for about 20 years (La Niña regime). From 1980, we observe a long El Niño regime that lasts almost 20 years, followed by an La Niña regime that lasts about the same duration.

For J=7 we see other quasi-periodic fluctuations of shorter length with average durations of the El Niño and La Niña regimes of about ten years. For $J = \{4, 5\}$, we observe quasi-periodic fluctuations of much shorter length corresponding to short-term climate variations.

The length of the fluctuations conditions the speed at which the transition from El Niño regime to La Niña regime takes place. We estimate the empirical distribution of each of the quasi-periodic fluctuations from the wavelet analysis (see Figure 7, for $J = \{1, 4, 5, 7\}$). These distributions have a sigmoidal shape. We note that as the value of J increases, the slope decreases. This suggests that as the length of the fluctuations increases, the time spent in a given regime becomes longer, which explains why the transition times between an El Niño regime and a La Niña regime are smoother.

Figure 7: ESOI cumulative distribution function for different time scales



We will now investigate the response of commodity inflation to ENSO shocks, taking into account that ENSO is composed of cycles of varying lengths embedded in each other. In addition to the fact that the response depends on the warming or cooling regimes, it varies depending on whether the shocks are persistent (because they belong to long quasi-cycles) or non-persistent (because they reflect the effect of short-term fluctuations.

4.2 Baseline Model

The local projections model with transition function, developed by Jordà (2005), is employed to estimate the dynamic responses that changing ENSO weather patterns have on commodity prices. In the benchmark specification, we estimate commodity inflation in real terms (π_t) as follows:

$$\pi_{t+h} = trend_t + F(\zeta_{t-1})(\alpha_{h,EN} + \phi_{h,EN}(L)x_{t-1} + \beta_{h,EN}shock_t) + \\ (1 - F(\zeta_{t-1}))(\alpha_{h,LN} + \phi_{h,LN}(L)x_{t-1} + \beta_{h,LN}shock_t) + \epsilon_{t+h} \quad (4)$$

which accounts for an asymmetry, which we define as an El Niño and La Niña climate state. $F(\zeta_t)$ is a smooth transition function that represents the state of the climate:

$$F(\zeta_t) = \frac{\exp(-\gamma\zeta_t)}{1 + \exp(-\gamma\zeta_t)} = 1 - \frac{1}{1 + \exp(-\gamma\zeta_t)}, \quad \gamma > 0, \quad |\zeta_t| < \infty. \quad (5)$$

π_{t+h} is projected on the space generated by a set of control variables (x_{t-1}). The vector of control variables includes lags of the respective commodity price inflation, global output growth, global interest rate and VIX. In this specification, we allow the prediction of π_{t+h} to differ according to the state of the climate (i.e., in an El Niño and La Niña state) when a weather shock ($shock_t$) occurs. The coefficient $\beta_{h,EN}$ ($\beta_{h,LN}$) corresponds with the estimated impact of the weather shock in a El Niño (La Niña) state.

ζ_t is a standardized transition variable and γ controls the degree of smoothness of the transition between states. The transition variable is taken as ESOI. Following Gorodnichenko and Auerbach (2013) and Ramey and Zubairy (2018), the transition variable (ζ_t) is standardized by taking the cyclical component using the Hodrick and Prescott (HP) filter.[10] Consistent with Auerbach and Gorodnichenko (2012), the transition function is dated $t-1$ in Equation (9) to avoid contemporaneous feedback from policy actions with regard to the state of the economy (i.e., $F(\zeta_{t-1})$). For the baseline model, we consider $\gamma = 3$, albeit we do consider alternative values (which we describe in the next section).

When γ is large and $\zeta_t > 0$, the logistic function $F(\zeta_t)$ approaches zero and the observed regime is La Niña. When γ is large and $\zeta_t < 0$, the ratio approaches 1, and the observed regime is El Niño. When γ is large and ζ_t is near zero there is an indeterminate form (one can be in either one regime or the other). As a consequence, when γ is large the logistic function behaves like an indicator function, thereby implying that any change from El Niño to La Niña regimes is instantaneous. In this case, we cannot differentiate the effect of climate shocks from a cold or warm temperature regime from the impulse response functions. The effects captured are therefore average effects.

When $\gamma \to 0$, the logistic function approaches a constant (1/2) and the models reduces to a linear model with a single regime.

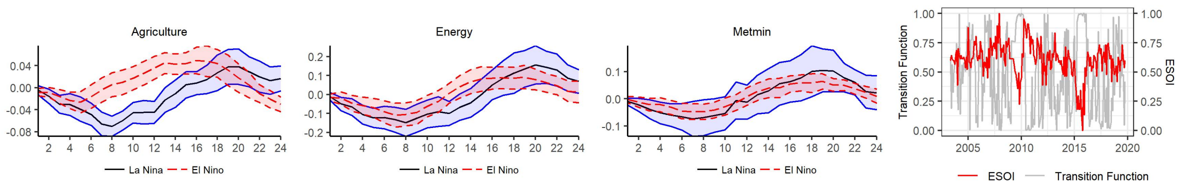
When $0 < \gamma < \infty$, the transition between the two regimes is more or less smooth and the responses to shocks occurring when temperatures are cold or warm can be differentiated.

With respect to the previous section, by varying the value of the γ coefficient, we consider the effect of climate variations corresponding to different time scales, i.e. the regime changes take place over cycles of different length. This is important because the different fluctuations "overlap", and we would like to know which cycles induce a change in commodity inflation during climate variations.

A caveat when we estimate the value of γ (rather than studying the impulse response function for different values of this parameter) is that we are unable to know how much of the observed climate change comes from persistent shocks (because the changes occur on a cycle with a long length) and how much comes from non-persistent shocks (because they reflect short-term fluctuations). Changing the values γ is important because of the consequences for policies of resilience to climate shocks. Persistent shocks require structural resilience policies (improved storage conditions, changes in irrigation and water retention systems to reduce the effects of possible droughts, adaptation of groundwater pumping strategies, etc). To limit the consequences of inflationary and deflationary effects of commodities linked to short-term climatic variations, policies that reduce income volatility may be more appropriate (hedging strategies, stabilization funds, etc).

The impulse response functions (IRF) and transition function for the model including the ESOI are presented in Figure 8. For robustness, the IRFs and transition function based on SST weather data are presented in Figure 14. As there is serial correlation present in the error terms, the IRF plots include the 90% confidence band using the Newey West standard errors.

Figure 8: IRFs and Transition Function for ESOI on Commodity Prices



[10]The Hodrick-Prescott filter is applied using smoothing parameter λ = 129,600 (see e.g. Ravn and Uhlig (2002)), a standard value for data at monthly frequency.

4.3 Sensitivity for varying γ

In Figure 9 we represent the impulse response functions for the three main types of commodities: agriculture, energy, metals and minerals. The effects on the commodities that make up these three types are reported in the Appendix[11]. The occurrence of an El Niño event is interpreted as bringing high temperature, while the occurrence of La Niña is considered as bringing cold temperature.

The reading of the figures is as follows: what happens if we increase by one standard deviation -up or down depending on whether we are in an El Niño or La Niña regime- the value of ESOI? The effects of shocks are not significant when zero crosses the confidence interval.

For agriculture, we can clearly see the effect that changes in the γ coefficient have on IRFs. The difference between the confidence intervals narrows as the coefficient increases. The significance and duration of the shock response increases when changes in climate conditions capture long-term effects. For instance, when $\gamma = 0.1$, prices rise or fall 6 months after the onset of an El Niño or La Niña shock and the effect lasts about 1 year (it fades after the 17th month). As the value of γ increases, the response to shocks occurs later and lasts for a very short time. One explanation for why agricultural commodity inflation are less sensitive to changes in climatic conditions occurring on short-term scales (larger γ values) is that changes in weather conditions are more predictable than structural changes and this facilitates the adoption of policies that are more resilient to shocks and thereby reduces the volatility of prices. We can see on the graph that the amplitude of the response is 10 times lower for $\gamma > 3$ compared to $\gamma = 0.1$.

The positive (resp. negative) response to the El Niño (resp. La Niña) shock is not compatible with the Cobweb theoretical model based on adaptive or rational expectations. Indeed, according to this model, a positive (resp. negative) shock should imply a cyclical dynamic of the response to shocks over time, which we do not observe here. Instead, the graphs suggest a positive autocorrelation in the responses to shocks, which is more compatible with the theoretical model of Laroque and Deaton (1996) where speculative behaviors increase autocorrelation and volatility in prices (such behaviors happen regularly in reality in times of significant temperature variations affecting agricultural yields).

The reaction of energy prices is different. For low values of γ, the price response is insignificant, while for values of the coefficient above 3, we have an immediate reaction with persistent price response over time. The response shows an S-shaped profile. It is significantly negative in the short term (up to 10 months), and then significantly positive from the 18^{th} month onwards. Prices react in the same direction to both types of shocks (El Niño and La Niña).

The relationships between energy demand/supply and temperature changes are usually determined by composition effects resulting from geographical diversity (hot countries and cold countries), seasonal variability, type of energy input and output (fuel, electricity, oil, coal,etc), heterogeneous household income level, or the average of cold and hot days. So, the global effects on international prices following changes in weather conditions can be either positive or negative. Our results are consistent with the following interpretations. Climate warming (temperature increase during El Niño, or decrease during La Niña) reduces the demand for heating fuel, thereby implying a fall in oil prices. On our graphs, if such an event happens, it does so in the short-run. But, on the other hand it also cause severe natural disasters such as floods or droughts which are likely to reduce production capacity in energy sector and thus drive energy prices to increase. The positive reaction is also consistent with the theoretical intertemporal CAPM model (ICAPM). According to our figures, if such events occur, they do so at long horizons (roughly 18 months after the initial shock).

The importance of the multivariate approach can be seen here because of the negative correlation between the responses of agricultural commodity prices and the responses of energy commodity prices. Indeed, an upsurge of El Niño events can lead to a decrease in agricultural production of different commodities such as wheat, soy, sugar, rice. When the phenomenon reaches the major producing countries in the world, the prices of agricultural commodities on international markets increase. However, the drop in agricultural production is synonymous with a decrease in exports from these countries (and therefore a drop in income), which leads to a constraint on the capacity to import energy products. The drop in demand can therefore

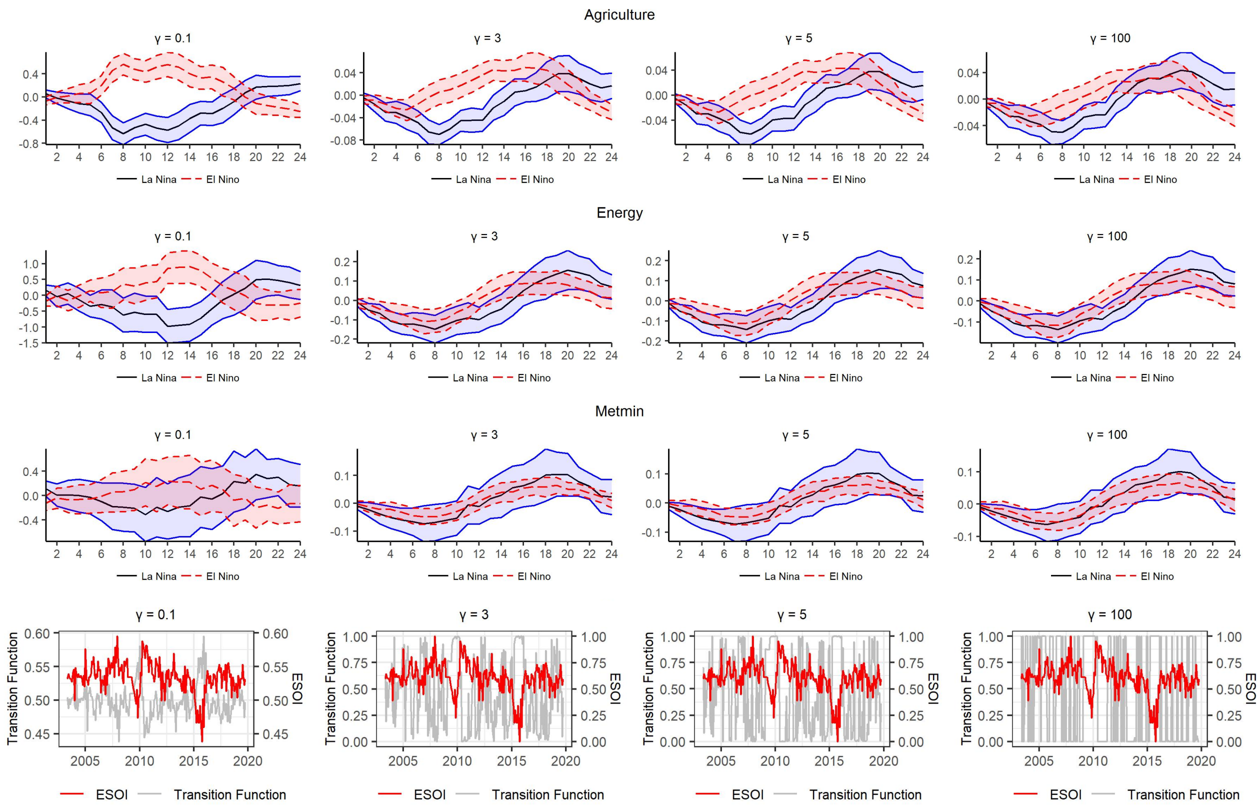
[11] See Figure 15 in the Appendix.

lead to a drop in the price of energy commodities. According to our figures, we observe both a positive reaction of agricultural commodities to El Niño shocks and a decrease in energy commodity prices.

Our findings differ from some previous nonlinear weather-dependent energy models in the literature, and are in line with others. Moral-Carcedo and Vicéns-Otero (2005) finds that the temperature-energy correlation is negative for the lowest temperatures, positive for the highest temperatures, but the link is less distinct for intermediate temperatures. In our case this would mean that the response should be asymmetric, which is not the case. Using a wavelet analysis, Qin et al. (2020) find that El Niño phenomenon has a negative impact on oil prices, but only in the long-run. Conversely, Cashin et al. (2017) find that El Niño phenomenon leads an increase in the oil prices in short-term, a reaction that can be explained by a higher demand from major industrialized and emergent economies such as the United States, Europe or China.

For metals and minerals (non-energy), we find insignificant effects when γ is small, but significant deflationary pressure lasting 10 months after the shocks started when $\gamma > 3$. As with energy commodities, prices decreases for both El Niño and La Niña shocks.

Figure 9: IRFs and Transition Function for ESOI and Commodity Prices, Sensitivity to γ



Similar to Ubilava (2018), we estimate regime-dependent non-linearities of commodity price dynamics. Different from the author, we find it interesting to address the question: does an anomalous and a non-anomalous weather state matter, when an El Niño or La Niña condition enters into that state in relation to commodity inflation? To test this hypothesis, we employ a GFALP and further delineate between an anomalous ("A") and non-anomalous ("NA") regime, conditional on the ENSO type (i.e., El Niño and La Niña). We therefore relax the assumption of symmetry conditional on the weather shock. This allows us to assess whether the effect of an anomalous weather shock is asymmetric. Each regime-dependence model is discussed in turn.

We motivate this investigation with regard to the literature that is developing on the role of climate uncertainty on global commodity markets, the concept of uncertainty being associated with the extreme values of climate change indicators, i.e. when their values deviate too much from the average values (for a recent example, see Nam (2021)). We use a threshold frequently chosen in the literature, i.e. that an anomaly exists as soon as the indicator exceeds 1 in absolute value.[12]

4.3.1 El Niño Anomalies Weather Conditions

To estimate whether an anomalies weather conditions matter in an El Niño state, Equation 9 is extended to include a latent variable and interaction terms:

$$\pi_{t+h} = trend_t + F(\zeta_{t-1}^{EN,A})(\alpha_{h,A} + \phi_{h,A}(L)x_{t-1} + \kappa_{h,A}(x_{t-1} \times I_t^{EN}) + \beta_{h,A}(shock_t \times I_t^{EN}) + \gamma_{h,A} I_t^{EN}) + \\ (1 - F(\zeta_{t-1}^{EN,A}))(\alpha_{h,NA} + \phi_{h,NA}(L)x_{t-1} + \kappa_{h,NA}(x_{t-1} \times I_t^{EN}) + \beta_{h,NA}(shock_t \times I_t^{EN}) + \gamma_{h,NA} I_t^{EN}) + \epsilon_{t+h} \tag{6}$$

where $\zeta_t^{EN,A}$ is a standardized transition variable and indicates an anomalous weather-dependent regime when an El Niño shock hits:

$$\zeta_t^{EN,A} = \begin{cases} W_t^{G,ESOI}, & \text{if } W_t^{G,ESOI} \leq -1 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

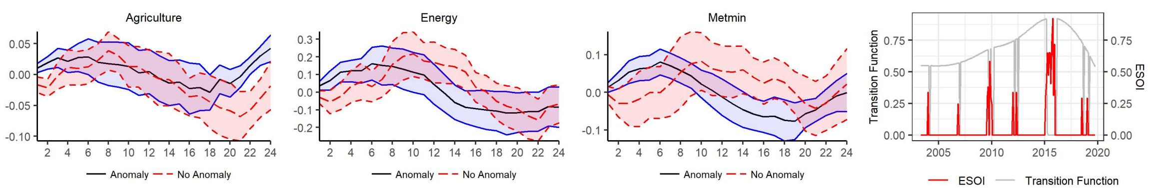
For an El Niño impact, we define an anomalous weather value as follows:

$$I_t^{EN} = \begin{cases} 1, & \text{if } W_t^{G,ESOI} < 0 \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

The IRFs and transition function plot for an El Niño regime-dependent model are presented in Figure 10.[13] The IRFs indicate that while an anomalous weather shock has heterogenous effects by commodity, the magnitude of the weather shock in an anomalous state tends to be higher relative to a non-anomalous state. We highlight the following empirical findings:

- **Agriculture:** inflation is higher at the onset of the shock in an anomalous weather state. A closer inspection of the results shows that food commodities, particularly barley, beef, cocoa, grains, maize, sorghum and soybeans, are sensitive to an anomalous El Niño for most if not all periods. We also note that there is a lesser or even counter effect observed for banana (U.S. and Europe), chicken, and sugar prices in relation to anomalous weather. The effect on beverages is also inflationary on impact, where a non-anomalous weather impact emerges to cause higher inflation between periods 8 and 14.
- **Energy:** inflation is higher at the onset of the shock in an anomalous weather state, whereas inflation in the non-anomalous state transition into marginally higher inflation approximately 9 months after the shock.
- **Metals and Minerals:** inflation is higher at the onset of the shock in an anomalous weather state, where a non-anomalous state evolves with higher inflation between periods 8 and 20. These results are fairly consistent for the individual metals and minerals commodities (i.e., natural gas, nickel, platinum, silver and gold).

Figure 10: IRFs and Transition Function for El Niño (ESOI) on Commodity Prices



[12] For Consistency with the baseline model, we keep $\gamma = 3$ and $\lambda = 129,600$.
[13] See Figure 16 in the Appendix for the IRFs by commodity price.

4.3.2 La Niña Anomalous Weather Conditions

The model is similarly estimated for a La Niña shock:

$$\pi_{t+h} = trend_t + F(\zeta_{t-1}^{LN,A})(\alpha_{h,EN} + \phi_{h,EN}(L)x_{t-1} + \kappa_{h,LN}(x_{t-1} \times I_t^{LN}) + \beta_{h,A}(shock_t \times I_t^{LN}) + \gamma_{h,A} I_t^{LN}) + (1 - F(\zeta_{t-1}^{LN,A}))(\alpha_{h,LN} + \phi_{h,NA}(L)x_{t-1} + \kappa_{h,NA}(x_{t-1} \times I_t^{LN}) + \beta_{h,NA}(shock_t \times I_t^{LN}) + \gamma_{h,NA} I_t^{LN}) + \epsilon_{t+h} \quad (9)$$

An anomalous La Niña weather shock is symmetrically defined as follows:

$$\zeta_t^{LN,A} = \begin{cases} W_t^{G,ESOI}, & \text{if } W_t^{G,ESOI} \geq 1 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

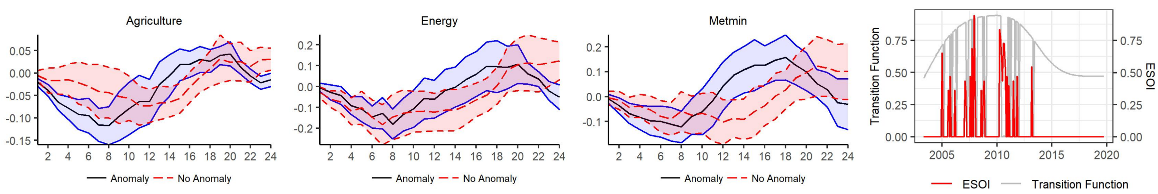
We define we define an anomalous La Niña weather value as follows:

$$I_t^{LN} = \begin{cases} 1, & \text{if } W_t^{G,ESOI} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

The IRFs and transition function plot for an La Niña regime-dependent model are presented in Figure 11.[14] The IRFs indicate that while an anomalous weather shock has heterogenous effects by commodity, the magnitude of the weather shock in an anomalous state tends to be higher relative to a non-anomalous state. We highlight the following findings for an anomalous La Niña weather shock:

- **Agriculture:** inflation is higher in magnitude at the onset of the shock in an anomalous weather state. The effect is reasonably consistent for food and beverage commodities. The difference between an anomalous and non-anomalous weather state is less intense for food commodity in a La Niña event relative to an El Niño event.
- **Energy:** we do not observe major differences between inflation at the onset of the shock in an anomalous and non-anomalous weather state, noting that inflation in the non-anomalous state transitions into marginally higher inflation approximately 9 months after the shock.
- **Metals and Minerals:** inflation is higher in magnitude at the onset of the shock in an anomalous weather state, where a non-anomalous state evolves with higher inflation between periods 8 and 20. These results are fairly consistent for the individual metals and minerals commodities considered (i.e., natural gas, nickel, platinum, silver and gold).

Figure 11: IRFs and Transition Function for La Niña (ESOI) on Commodity Prices



5 Conclusion

This paper analyzes the global transmission of weather on commodity prices. We estimate a global factor augmented local projections model using a rich and extensive monthly data set from 2002:04 to 2019:12 relating to nine economies representing circa two-thirds of global output and 34 international commodity price sets.

We contribute to a narrow literature on the "new climate economy" (Dell et al., 2014) in two ways. First, this paper exploits the global factor structure to investigate the global dimensions of weather and commodity

[14] See Figure 17 in the Appendix for the IRFs by commodity price.

shocks. Second, we exploit the multivariate dimension of data using a nonlinear framework to account for possible changes in climate *regimes*.

We estimate a k-factor Gegenbauer ARMA process to isolate the multiple time scales in the oscillations of El Niño and La Niña states. We uncover the presence of cycles of various duration in the ESOI time series. What we observe at a given date is the combination of this set of cycles of different frequencies. Based on a Mallat decomposition, we are able to decompose and distinguish ESOI fluctuations as cycles of different lengths.

We then observe that the shape of the cumulative distribution function (CDF) is specific to each cycle: the longer the cycle, the smoother the CDF. A major contribution of our paper is that we later use this information on the CDF shape to calibrate the degree of smoothness of the transition function of a local projections model. Therefore we can plot the IRFs on shocks associated to the different ENSO cycle frequencies.

Assuming a low degree of smoothness of the transition function (γ) means that the model remains in a given state for longer periods of time, which corresponds to smooth CDF. Under this assumption (small γ), the estimated dynamic responses of a one standard deviation shock on ESOI has on agriculture commodities is strongly dependent on the ENSO regime: the agriculture commodity price reaction is positive (negative) during an El Niño (a La Niña) state. Interestingly energy, metal and minerals commodity price reaction is insignificant, meaning these commodities are not exposed to long cycle shocks.

A polar case for larger values of γ is associated with a faster transition from one state to another (El Niño / La Niña) and are therefore associated with shorter cycles. Under this calibration (high γ), the estimated dynamic impact of ESOI shocks on energy and metals and minerals commodities is strongly deflationary. Also, a key result is that agricultural commodity inflation is less sensitive to climatic conditions when considering short cycles than long cycles.

These results are relevant to understand the different challenges posed by climate change on commodities. Agricultural commodities are more impacted by shocks on long cycles than on short cycles. One possible explanation may be that agricultural production choices are long memory processes. As an example, we can think that in some regions of Latin America where potatoes have been grown for thousands of years, farmers will continue to grow them even if climate changes drastically. Changing this type of habits is extremely long as it calls for structural changes. Persistent shocks require structural resilience policies : improved storage conditions, changes in irrigation and water retention systems to reduce the effects of possible droughts, adaptation of groundwater pumping strategies, etc.

On the other hand, energy, metal and mineral commodities are more impacted by shocks on short cycles. These sectors being more capital intensive than agriculture, our results could reflect the ability of capital markets to shift investment in the medium run and therefore to avert from long run cycles shocks. Energy, metal and mineral commodities sensitivity to short cycle shocks could reflect both demand and supply conditions. To limit the consequences of inflationary and deflationary effects of commodities linked to short-term climatic variations, policies that reduce income volatility may be more appropriate (hedging strategies, stabilization funds, etc).

Climate change can be seen both as a change in long term trend and a change in the distribution of shocks, which could lead to a potential increase of extreme events. We therefore find it interesting to investigate whether commodities react to anomalous weather conditions. Using a local projections model, we show that the distinction between anomalies and standard conditions matter in the transmission of weather shocks to commodities: an anomalous El Niño weather shock leads to higher inflation at the onset of the shock for all three categories (agriculture, energy, metals and minerals commodities). Similarly, an anomalous La Niña weather shock leads to higher inflation at the onset of the shock (with the exception of energy). This result is particularly relevant as it highlights how climate change, if defined as more frequent extreme events, could impact financial markets via the valuation of commodities. More broadly, as commodity price pass through to consumer prices, this result shows how an increase of extreme events could impact the whole economy through the price channel. More central banks are questioning whether climate change is part of their mission to stabilize prices (see NGSF (2021)). Our results indicate the existence of a direct link between weather anomalies and commodity inflation, one that should be integrated into the inflation targeting framework.

The results from this research have both immediate and long-term policy implications regarding the adaptation to climate changes. A starting point for short-term policy is to establish sources of vulnerability that could create economic risks. The findings from this paper serve to do just that in a global factor environment by analyzing the propagation mechanisms through which weather shocks influence commodity inflation. These insights are of paramount importance to central bank policies designed to understand sources of price changes to stabilize agriculture and aggregate prices, *inter alia*. Similarly fiscal policy is subject to endogenous policy responses to smooth household consumption via food subsidy program.

Over the longer term, policy makers should address the adaptation with regard to climate change. Policy needs to address changes to the social and economic systems from multiple fronts. The central bank must craft an appropriate policy response that monitors and addresses sectoral price developments as they relate to the changing business cycle and the effects of climate change. This is of growing importance as climate change is expected to increase the frequency and intensity of weather patterns (e.g., Timmermann et al. (1999), Chen et al. (2001), An and Wang (2000)). The impact of climate change may influence the central bank's interest rate, which can in turn influence the stock market and investment decisions. Overlooking the effects of changing weather patterns has on future inflation could potentially move inflation away from central bank's target, thereby weakening central bank's monetary anchoring. Similarly, a weather shock that results in higher food prices may create a source of vulnerability with regards to a combination of debt and taxes needed to finance food subsidies.

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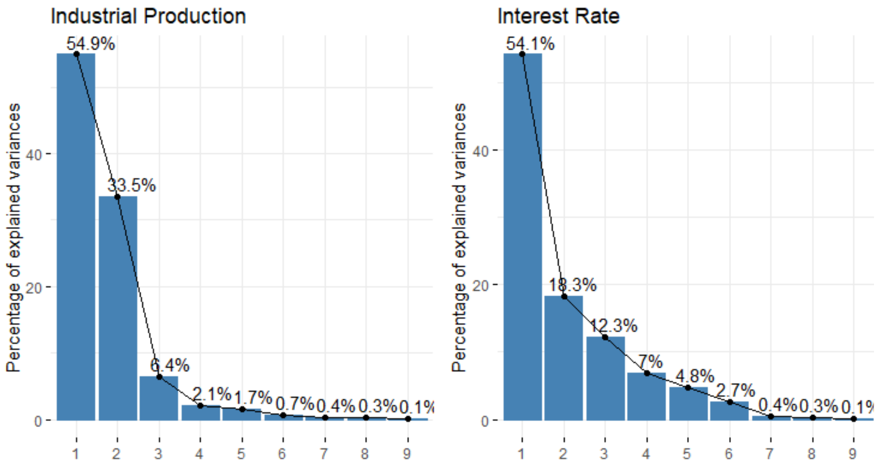
7 Appendix

7.1 Scree Plots

The scree plots are provided for the global factor analysis of output and interest rate. The scree plot is a plot of the eigenvalues of principal components.

Figure 12: Scree Plots for Global Variables



7.2 Additional IRFs

We provide additional IRFs (referenced and described in the main text).

Figure 13: IRFs and Transition Function for ESOI and Commodity Prices

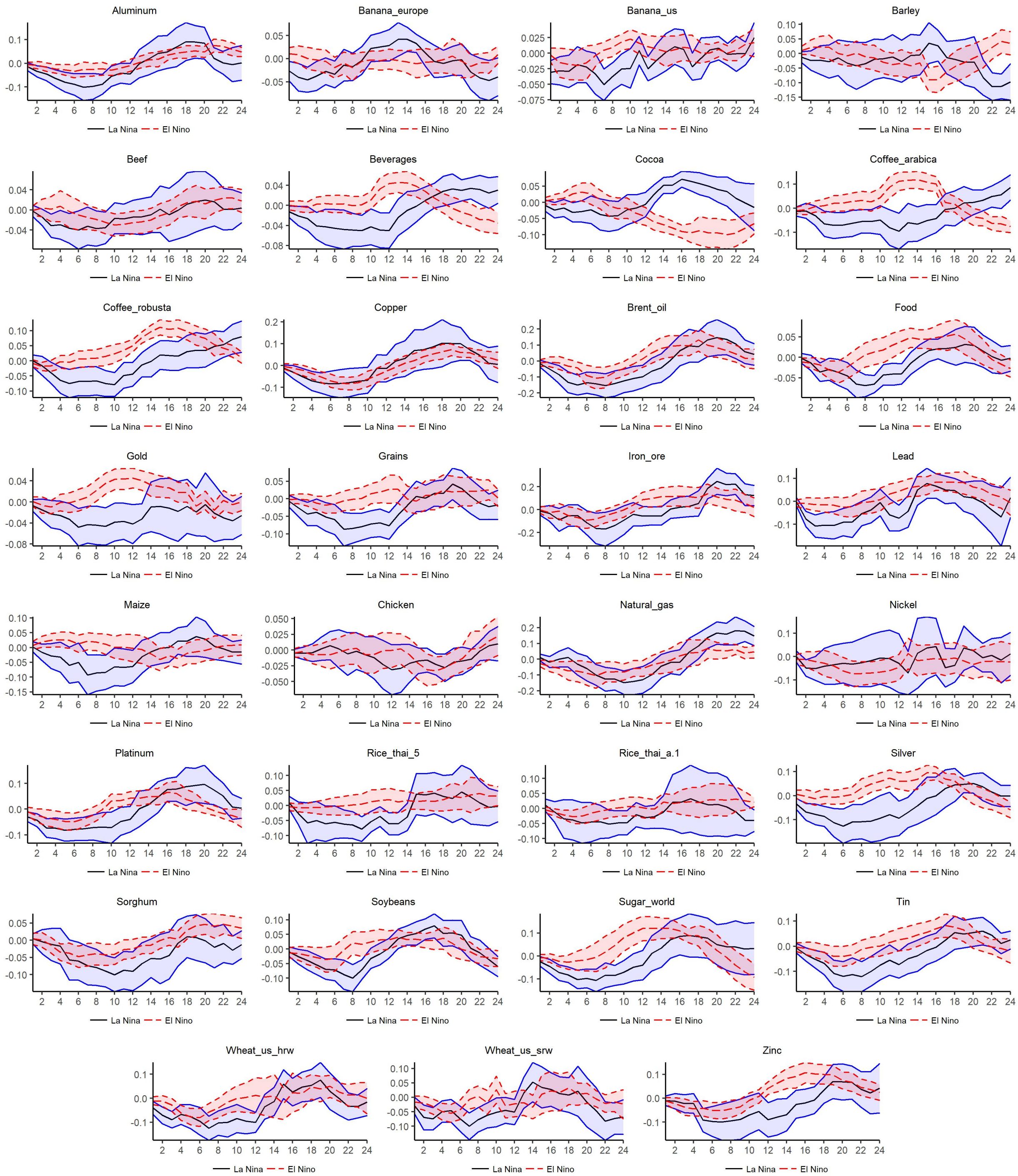


Figure 14: IRFs and Transition Function for SST and Commodity Prices

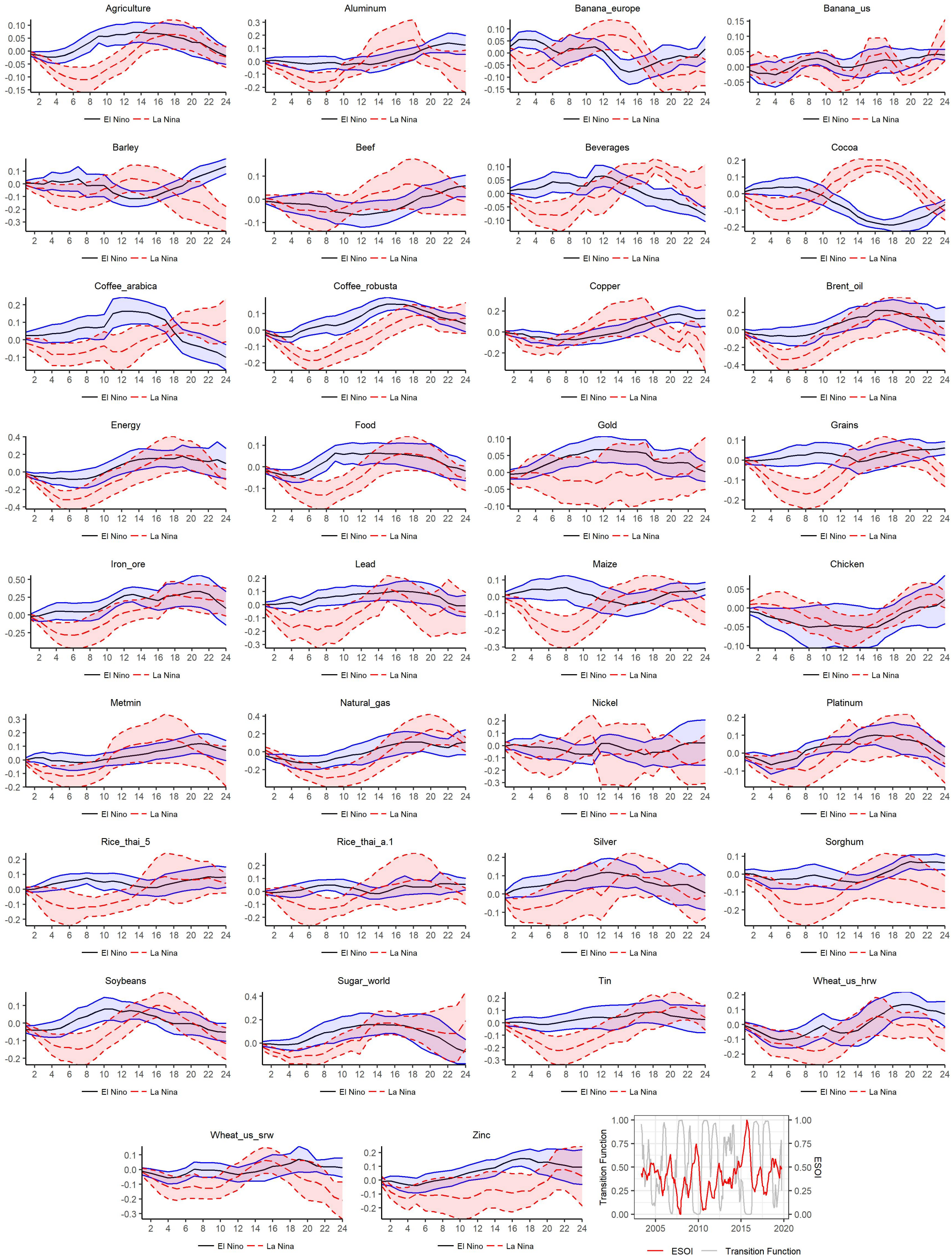


Figure 15: IRFs for ESOI and Commodity Prices, Sensitivity to γ

Figure 15: IRFs for ESOI and Commodity Prices, Sensitivity to γ, continued

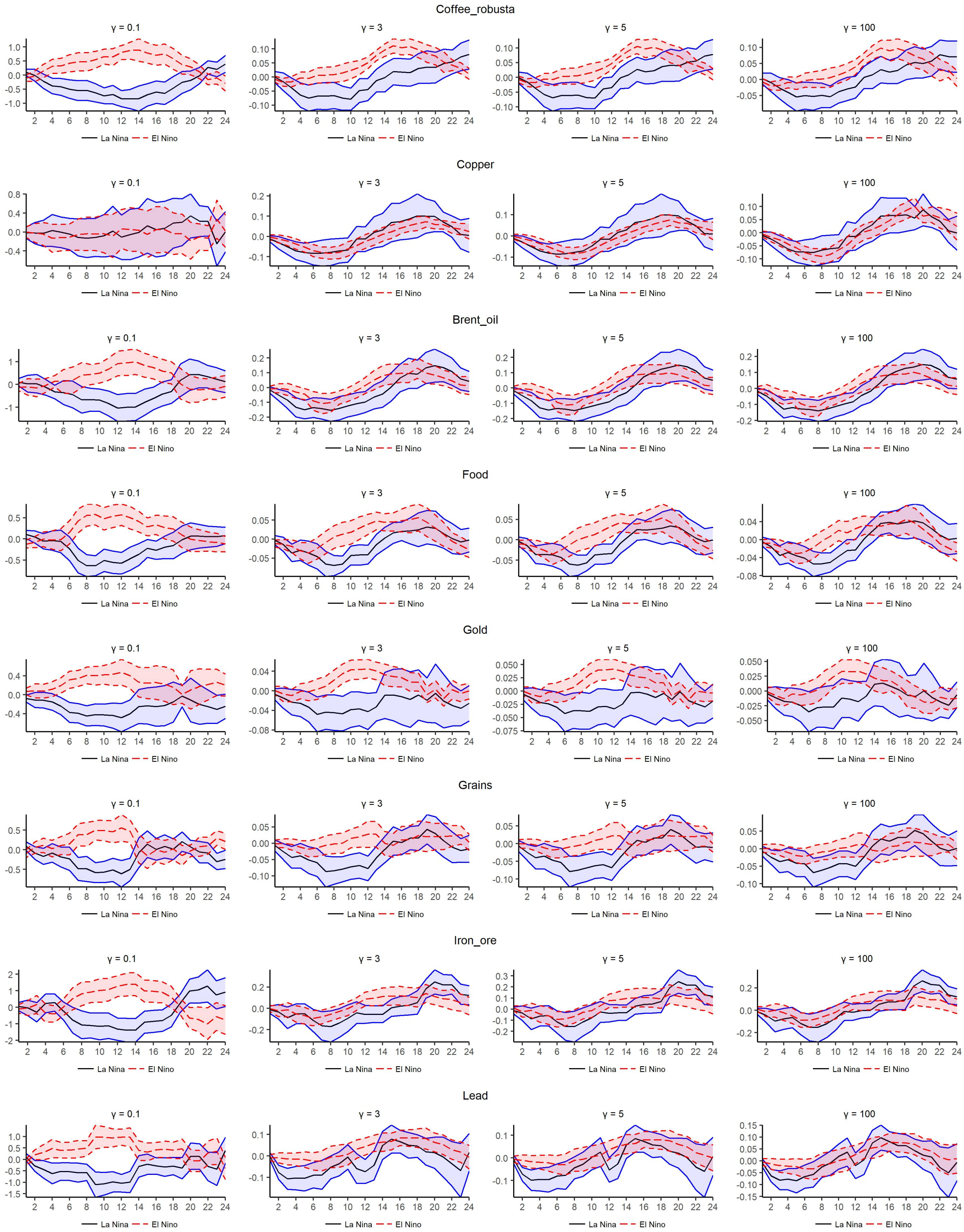


Figure 15: IRFs for ESOI and Commodity Prices, Sensitivity to γ, continued

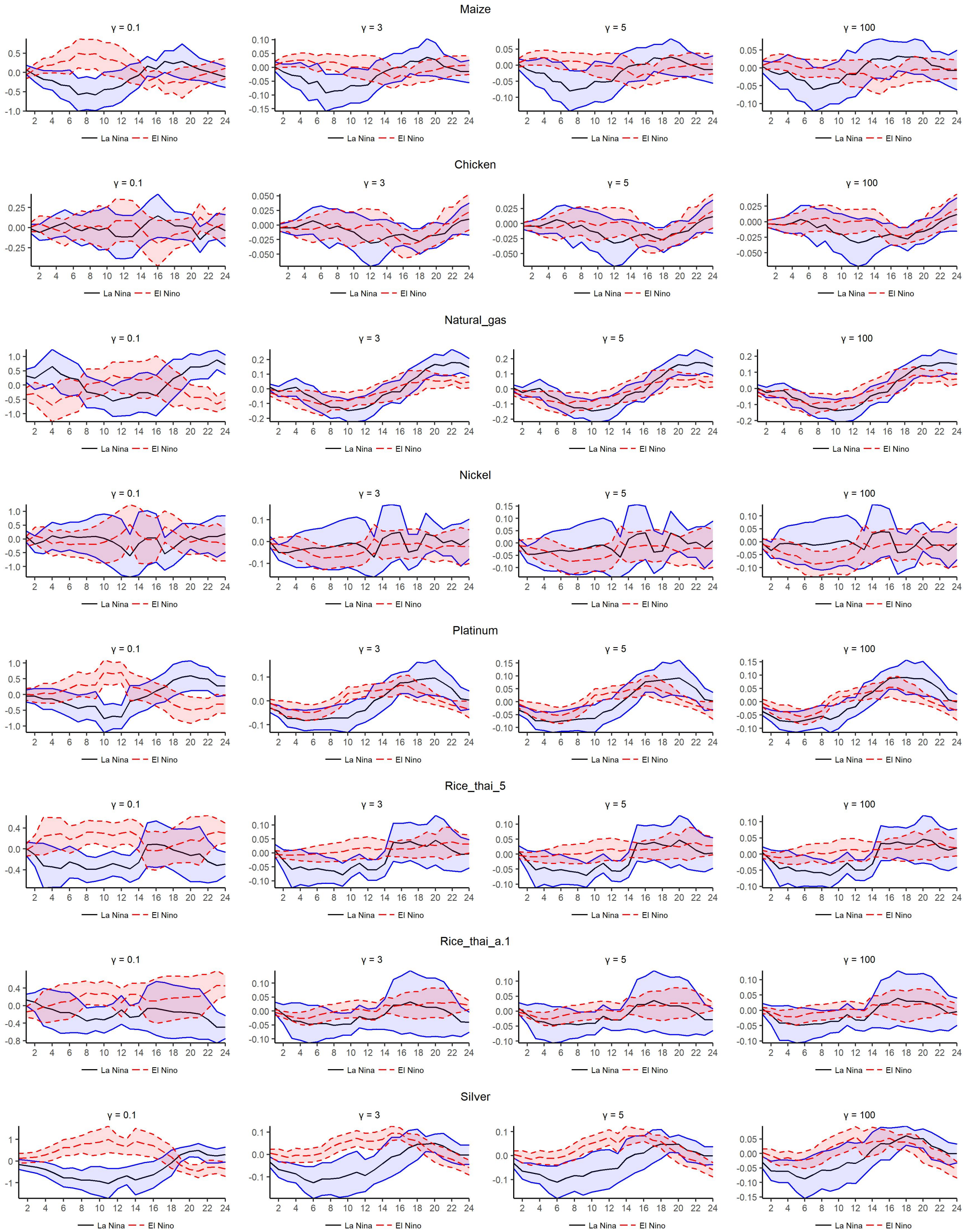


Figure 15: IRFs for ESOI and Commodity Prices, Sensitivity to γ, continued

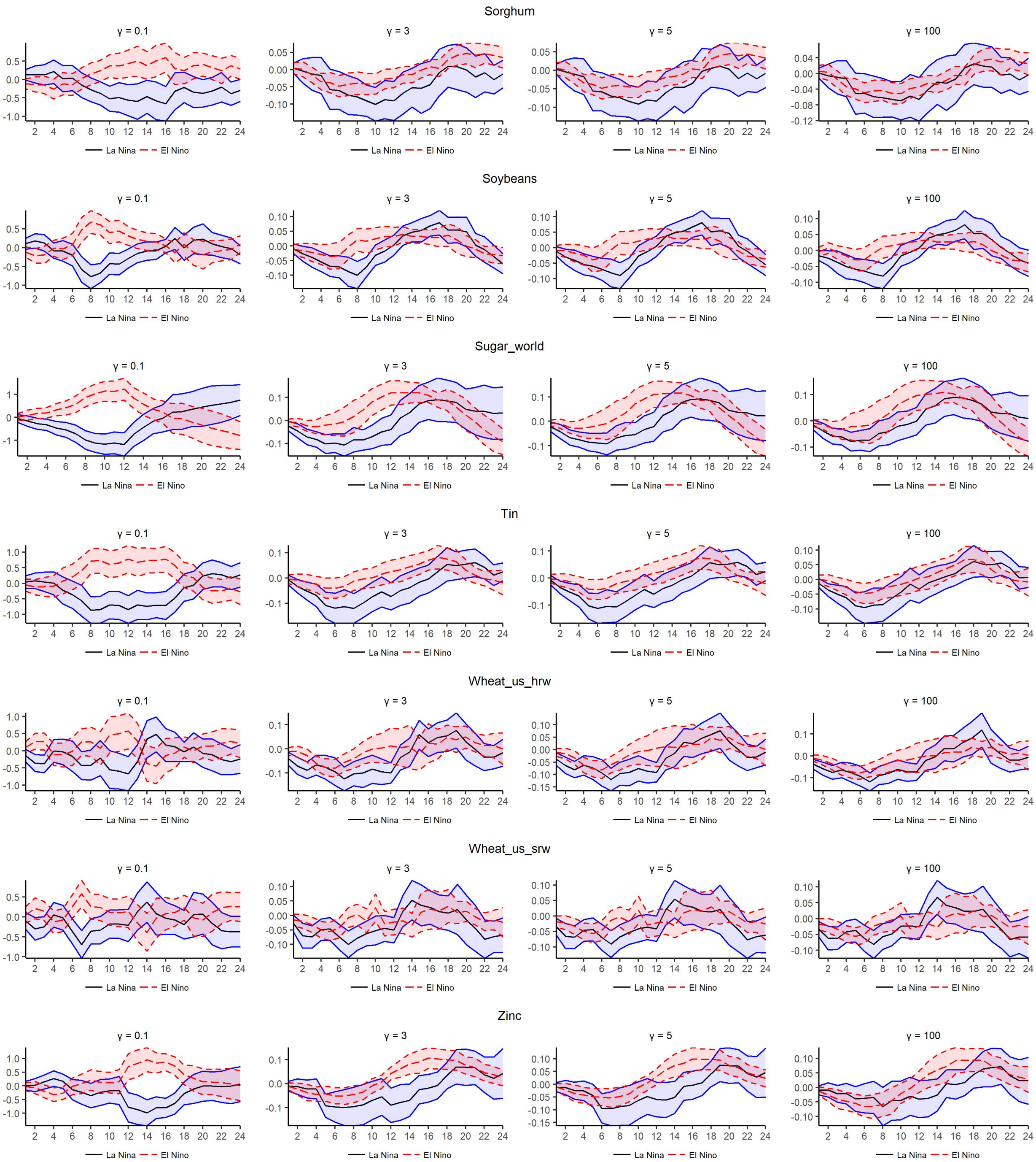


Figure 16: IRFs and Transition Function for El Niño (ESOI) on Commodity Prices

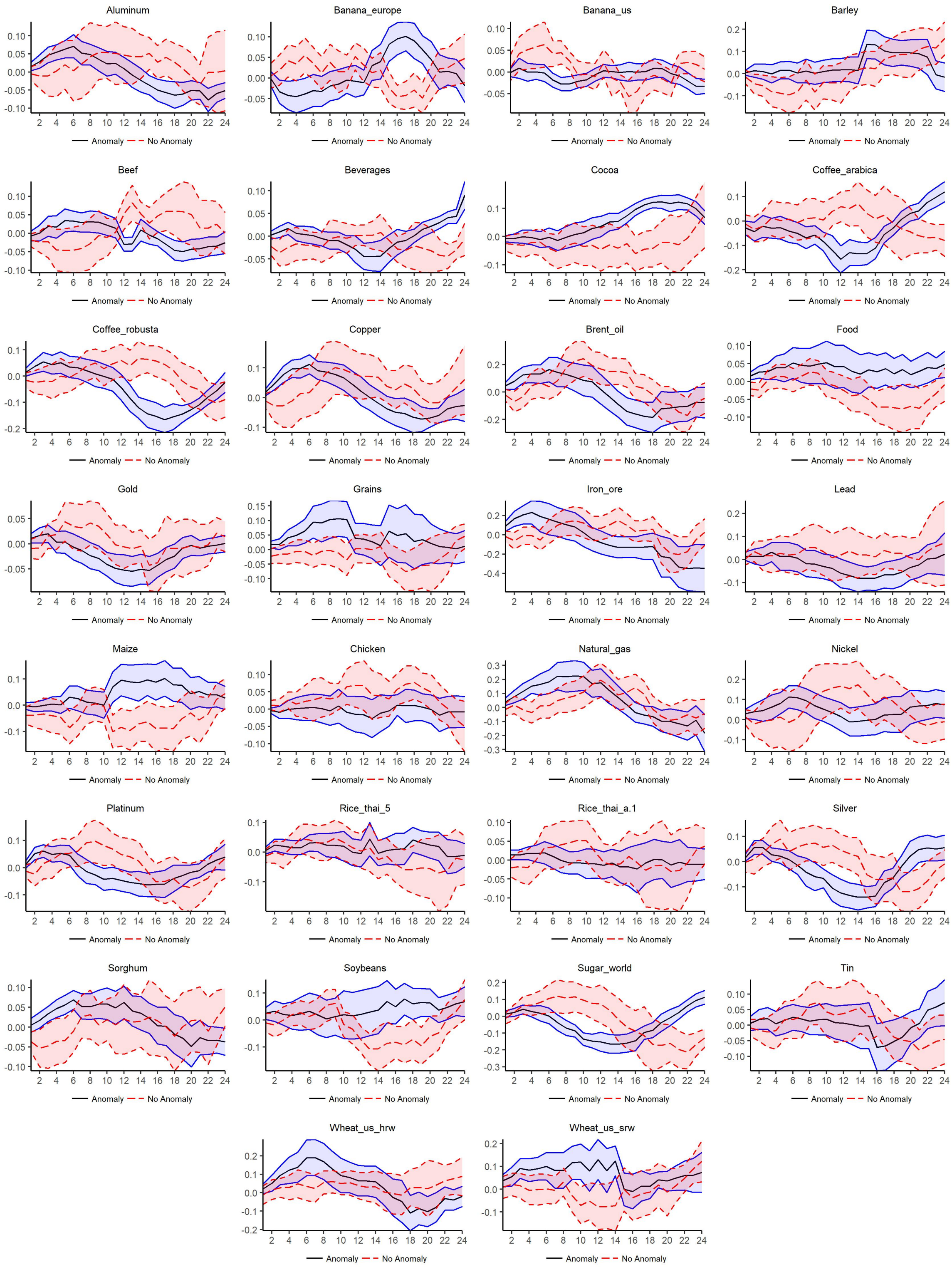


Figure 17: IRFs and Transition Function for La Niña (ESOI) on Commodity Prices