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# El Niño Southern Oscillation and Primary Agricultural Commodity Prices: Causal Inferences from Smooth Transition Models

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# El Niño Southern Oscillation and Primary Agricultural Commodity Prices: Causal Inferences from Smooth Transition Models\*

## Abstract

Global climate anomalies affect world economies and primary commodity prices. One of the more pronounced climate anomalies is El Niño Southern Oscillation (ENSO). In this study I examine the relationship between ENSO and world commodity prices using monthly time series of the sea-surface temperature anomalies in the Nino 3.4 region, and real prices of thirty primary agricultural commodities. I apply smooth transition autoregressive (STAR) modelling techniques to assess causal inferences that could potentially be camouflaged in the linear setting. I illustrate dynamics of ENSO and commodity price behavior using generalized impulse-response functions.

Keywords: El Niño Southern Oscillation, Primary Commodity Prices, Smooth Transition Autoregression

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\* Preliminary and incomplete.

# 1 Introduction

Global climate anomalies affect world economies. One of the obvious reasons for this relationship is that local weather events in many regions are linked to global climate phenomena (Ropelewski and Halpert, 1987; Stone et al., 1996; Barlow et al., 2001). These links are known as “teleconnections” (Rasmusson, 1991). Within a set of larger-scale lower-frequency climate anomalies, a particular attention has been paid to a phenomenon known as El Niño Southern Oscillation, or simply, ENSO. Studies have found statistically significant and economically meaningful connections between ENSO and agricultural production, commodity prices, and even civil conflicts (Handler and Handler, 1983; Adams et al., 1999; Chen et al., 2001; Brunner, 2002; Hsiang et al., 2011).

Several obvious reasons justify seemingly causal relationship between climate anomalies and primary commodity prices. First of all, weather and agriculture are intrinsically linked. Unfavorable weather conditions deteriorate agricultural yields, which result in shortage of supply and, thus, increased prices. Second, weather and energy consumption are correlated. Extreme weather conditions (such as unusually hot summers or extremely cold winters) manifest in increased demand for energy products (natural gas and crude oil derivatives), which are also used as inputs in food and agricultural production. As a result, increased input prices push the commodity prices upward. Finally, hazardous weather conditions can damage infrastructure and thus affect international logistics, resulting in increased transportation costs and, by corollary, increased world commodity prices.

Objective of this research is to quantify economically meaningful causal connections between the sea-surface temperature anomalies and world commodity prices. To this point, several studies have addressed the causality issue. For example, Brunner (2002) examined the relationship between ENSO and primary commodity prices using quarterly data in a linear vector autoregressive setting. He found that the world food and agricultural commodity prices could be highly responsive to ENSO variations. In contrast, Berry and Okulicz-Kozaryn (2008) used annual data spanning back to late 1800’s, and found no evidence of co-cyclical relationship between ENSO shocks and the U.S. economy.

Conflicting (although, perhaps complementing) results from the two studies by Brunner (2002) and Berry and Okulicz-Kozaryn (2008) suggest

that more work needs to be done to investigate the peculiar nature of ENSO – commodity prices relationship. This study examines the relationship between the climate anomaly and selected primary commodity prices using a nonlinear modelling technique. Nonlinearities in ENSO cycles and commodity price movements could prove to be a crucial augmentation of modelling the relationship between the two variables. This is because ENSO cycles are characterized by asymmetric behavior (Hall [et al., 2001](#); [Ubilava and Helmers, 2012](#)), as well, commodity prices are known to move in a nonlinear manner (Craig [and Holt, 2008](#); [Balagtas and Holt, 2009](#)). Moreover, the current study will consider monthly time series to account for features that could be camouflaged in lower frequency data. Unlike [Brunner \(2002\)](#) and [Berry and Okulicz-Kozaryn \(2008\)](#) this study will omit economic growth variables; however, the study will implicitly consider overall price inflation by using the real commodity price data.

To account for possible nonlinearities in the time series, this study adopts smooth transition autoregressive (STAR) modelling framework. Conceptually, smooth transition regressions were first proposed by [Bacon and Watts \(1971\)](#). Afterwards, [Chan and Tong \(1986\)](#) suggested the use of the smooth transition model in the time series setting. Subsequently, in a number of related studies, a group of authors introduced and developed STAR modelling and testing framework ([Luukkonen et al., 1988](#); [Teräsvirta and Anderson, 1992](#); [Teräsvirta, 1994](#); [Eitrheim and Teräsvirta, 1996](#)).

Since its introduction, the STAR modelling approach has gained popularity and has been widely applied in studies modelling asymmetric cyclical variations (e.g. [Teräsvirta, 1995](#); [Hall et al., 2001](#)). Using STAR models a large body of studies have examined the potential nonlinearities of unemployment rates, GDP, monetary demand, and interest rates (e.g. [Teräsvirta, 1995](#); [Eitrheim and Teräsvirta, 1996](#); [Sarantis, 1999](#); [Skalin and Teräsvirta, 2002](#)). More recently, the STAR modelling approach has been utilized to investigate nonlinear features of agricultural production and prices (e.g. [Craig and Holt, 2008](#); [Balagtas and Holt, 2009](#); [Ubilava, 2012b](#)), climate variables, including ENSO ([Hall et al., 2001](#)), and the effects of climate anomalies on commodity prices ([Ubilava, 2012a](#)).

In what follows, I will first briefly outline the modelling and testing frameworks of the current exercise. I will then describe the data used in this study. Afterwards, I will illustrate the results of this research using generalized impulse-response functions.

## 2 Econometric Framework

This section briefly outlines a smooth transition autoregression, and the suggested testing framework within the model. Refer to [Luukkonen et al. \(1988\)](#); [Teräsvirta \(1994\)](#) for more in-depth description of this model, and [Craig and Holt \(2008\)](#); [Balagtas and Holt \(2009\)](#) for the applications of this modelling framework in agricultural economics and commodity price analysis.

### 2.1 A Smooth Transition Autoregressive Model

Consider an additive nonlinear time series model as follows:

$$\Delta y_t = \alpha_0 + \beta_0 y_{t-1} + \sum_{i=1}^{p-1} \phi_{0,i} \Delta y_{t-i} + \sum_{j=0}^q \pi_{0,j} z_{t-j} + \sum_{k=1}^K \left[ \alpha_k + \beta_k y_{t-1} + \sum_{i=1}^{p-1} \phi_{k,i} \Delta y_{t-i} + \sum_{j=0}^q \pi_{k,j} z_{t-j} \right] G_k s_{k,t}; \theta + \varepsilon_t \quad (1)$$

where  $y_t$  is a dependent variable, and  $z_t$  is an exogenous variable;  $\Delta$  is a first-difference operator, and  $p$  and  $q$  denote maximum lag lengths of the dependent and exogenous variables, and  $K$  is the maximum number of

additive regimes. Further,  $G_k s_{k,t}; \theta$  are bounded between 0 and 1, and are functions of regime-switching variables,  $s_{k,t}$ , and the associated vector

of parameters,  $\theta$ .  $s_{k,t}$  can be a lagged dependent variable,  $y_{t-d}$ , a lagged exogenous variable,  $z_{t-d}$ , some other variable not included the regression,  $w_t$ , or some function of the any aforementioned variables. Finally,

$\varepsilon_t \sim \text{iid}(0, \sigma_\varepsilon)$  is a white noise process.

By imposing certain restrictions, Equation (1) can yield a number of

well-known autoregressive models. If  $G_k s_{k,t}; \theta, \forall k$ , is set to 0, for example, Equation (1) becomes a linear autoregressive (AR) process with exogenous variables, expressed in an Augmented Dickey-Fuller form as follows:

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + \sum_{j=0}^q \pi_j z_{t-j} + \varepsilon_t \quad (2)$$

Further, an additional restriction of  $\beta = 0$  in the equation (2) will impose a

linear unit root process. Alternatively, if in equation (1)  $G_k s_{k,t}; \theta$  only take values of 0 and 1 Equation (1) becomes a threshold autoregressive

(TAR) process (Tong and Lim, 1980; Tsay, 1989). Or, if  $G(s_t; \theta)$  takes

continuum of values between 0 and 1, wherein the parameter vector,  $\theta$ , consists of the smoothness parameter  $\gamma > 0$  and the centrality parameter  $c$ , Equation (1) becomes a smooth transition autoregressive (STAR) process (Luukkonen et al., 1988; Teräsvirta, 1994). Note, that TAR and STAR specifications allow for the possibility of unit root process in one regime and stationary process in another, for example, if  $K = 1$ ,  $\beta_0 = 0$  and  $\beta_1 = 0$ .

Let's concentrate on STAR modelling framework, which, moreover, embeds AR and TAR models as the special cases. A generalized version of one of the more frequently applied transition functions is represented as follows:

$$G(s_t; \gamma, c) = 1 + \exp\left(-\gamma \left(\frac{s_t - c}{\sigma_{s_t}}\right)^m\right) \quad (3)$$

where  $\sigma_{s_t}$  is the standard deviation of the transition variable. By setting  $m = 1$  and  $m = 2$ , one obtains logistic and quadratic transition functions, respectively, resulting in logistic STAR (LSTAR) and quadratic STAR (QSTAR) models. The LSTAR and QSTAR models converge to a linear AR model when  $\gamma \rightarrow 0$ , and a threshold autoregressive (TAR) model when  $\gamma \rightarrow \infty$ . Graphical illustrations of these functions are presented in figure 1.

## 2.2 Testing Nonlinearities, Causality, and Nonlinear Causality

The question of whether STAR-type nonlinearity is truly an underlying feature of the data is a testable hypothesis. However, one cannot directly test the linearity hypothesis,  $H_0: \gamma = 0$ , in a STAR model due to unidentified nuisance parameters, which manifests in Davies' problem (Davies, 1977, 1987). Specifically, in the context of Equation (1), where  $K = 1$ , the nonlinear model will reduce to the linear AR model by imposing the restriction  $\gamma_1 = 0$  or

$\alpha_1 = \beta_1 = \phi_{1,1} = \dots = \phi_{1,p-1} = \pi_{1,0} = \dots = \pi_{1,q} = 0$ . Therefore, the standard test statistics are no longer applicable. Luukkonen et al. (1988) proposed a solution to the problem by approximating the transition function,  $G(s_t; \gamma, c)$ , using a third order Taylor series expansion. This results in a testable auxiliary regression, expressed as Equation (4):

$$\Delta y_t = \phi_0 x_t + \sum_{i=1}^3 \phi_i x_t s_i + \xi_{it} \quad (4)$$



where  $x_t = (1, y_{t-1}, \Delta y_{t-1}, \dots, \Delta y_{t-p+1}, z_t, \dots, z_{t-q})$ ; and  $\xi_t$  combines the original error term,  $\varepsilon_t$ , and the approximation error resulting from the Taylor expansion. The new specification allows the application of conventional testing methods, particularly in the test for linearity against the STAR specification. This is now equivalent to testing the null hypothesis of  $H_0: \phi_1 = \phi_2 = \phi_3 = 0$ , where  $\phi_i$ ,  $i = 1, 2, 3$ , are vectors of parameters from the auxiliary regression.

The test of in-sample Granger causality within the linear specification is equivalent to testing the null  
hypothesis of  $H_0: \pi_0 = \pi_1 = \dots = \pi_q = 0$ , in equation (2). This test is valid given that nonlinearity is not a feature of the data generating process. However, in presence of nonlinearities, the aforementioned test could yield faulty statistical inferences, because potential causality may be camouflaged by nonlinear features of the data. The test of causality within the STAR framework can be associated with the same Davies' problem as discussed previously. To circumvent the issue, we will adopt the testing framework similar to [Balagtas and Holt \(2009\)](#), and apply it in the current context to test for both nonlinearity and Granger causality in the underlying series. In particular, the combined test of nonlinearity and causality is equivalent to testing the null hypothesis of  $_{nc}H_0: \phi_0 = \phi_1 = \phi_2 = \phi_3 = 0$ , in equation (4), where  $\phi_0$  is a set of parameters associated with  $(z_t, \dots, z_{t-q})$ .

In practice, the transition variable is often a priori unknown. One is, therefore, required to test a set of candidate transition variables and select the suitable transition variable based on probability values associated with the aforementioned hypotheses. Once the transition variable (and the associated transition function) is selected, one may proceed to estimate the related STAR model using a nonlinear optimization procedure<sup>1</sup>.

### 3 Data

The sample consists of monthly observations between January 1982 and December 2011. The ENSO anomaly is represented by sea-surface temperature (SST) in the Niño 3.4 region, and is derived from the index tabulated by the Climate Prediction Center at the National Oceanic and

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<sup>1</sup>Refer to [Luukkonen et al. \(1988\)](#); [Teräsvirta \(1995\)](#); [Eitrheim and Teräsvirta \(1996\)](#) for additional details regarding the testing sequence, including remaining nonlinearity, parameter constancy, and residual autocorrelation tests within the STAR modelling framework

Atmospheric Administration. In particular, this index measures the difference in SST in the area of the Pacific Ocean between  $5^{\circ}\text{N} - 5^{\circ}\text{S}$  and  $170^{\circ}\text{W} - 120^{\circ}\text{W}$ , and is therefore a strong indicator of ENSO's occurrence in the tropical Pacific. The Niño 3.4 monthly measure is an average of daily values interpolated from weekly measures obtained from both satellites and actual locations around the Pacific. The SST anomaly is the deviation of the Niño 3.4 monthly measure from the average historic measure for that particular month from the period 1981 – 2010.

Primary commodity price series are collected from the World Bank and the International Monetary Fund publications, publicly available on the respective websites. The prices are spot prices and are indicative of world prices of the commodities. The prices are further deflated using the U.S. producer price index (PPI), collected from the U.S. Bureau of Labor website.

## 4 Results and Discussion

I use Akaike Information Criteria (AIC) to select optimal lag length of the autoregressive process, as well as the lag length of the exogenous variable – ENSO in the price equations. The latter is done in conjunction with the combined nonlinearity and causality tests as described previously. Table 1 summarizes the results of the aforementioned exercises.

Figures 2 – 13 illustrate combined nonlinearity and causality test results for the selected commodities. Figures 14 – 23 illustrate estimated transition functions for the selected commodities. Finally, Figures 24 – 33 illustrate generalized impulse-response functions (GIRFs) of the selected commodities. The GIRFs are crucial in deriving the causal inferences. Put differently, GIRFs allow us to visualize if the causality is truly an underlying feature of the data, or if the null hypothesis of the combined nonlinearity and causality is rejected merely due to nonlinearities.

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## Tables

Table 1: Time Series Characteristics of the Commodity Prices

Series	p	q	d	G	AIC <sub>0</sub>	AIC <sub>l</sub>	AIC <sub>n</sub>
ENSO	5	5	3	L	-	-2.714	-2.850
WHEAT	2	0	1	L	-5.735	-5.729	-5.757
MAIZE	2	1	4	L	-5.775	-5.763	-5.841
SGHUM	2	0	4	L	-5.576	-5.570	-5.678
RICE	3	1	1	L	-5.776	-5.764	-5.902
SBEAN	2	5	2	L	-6.102	-6.066	-6.196
SMEAL	2	0	6	L	-5.885	-5.879	-5.924
SBOIL	5	0	3	L	-5.781	-5.775	-5.791
PMOIL	5	6	1	Q	-5.323	-5.281	-5.331
RSOIL	3	0	1	L	-5.002	-4.996	-5.125
SFOIL	4	0	3	Q	-5.763	-5.757	-5.779
GNOIL	6	-1	-	-	-5.871	-5.871	-
LSOIL	4	-1	-	-	-5.316	-5.316	-
CNOIL	7	2	6	L	-5.216	-5.198	-5.254
COPRA	5	5	5	L	-5.336	-5.300	-5.385
FMEAL	6	3	-	-	-6.447	-6.424	-
CHIKN	2	-1	-	-	-7.955	-7.955	-
SWINE	3	6	-	-	-4.584	-4.542	-
BEEF	3	-1	-	-	-6.608	-6.608	-
LAMB	2	-1	-	-	-6.603	-6.603	-
WOOL	6	-1	-	-	-6.042	-6.042	-
HIDES	2	-1	-	-	-5.511	-5.511	-
BNNAS	7	2	6	L	-3.736	-3.718	-3.733
ORNGS	7	0	3	L	-4.376	-4.370	-4.403
SUGAR	3	-1	-	-	-4.971	-4.971	-
ABICA	3	-1	-	-	-5.183	-5.183	-
RBSTA	2	-1	-	-	-5.347	-5.347	-
TEA	2	-1	-	-	-5.366	-5.366	-
COCOA	4	-1	-	-	-5.712	-5.712	-
TBACO	5	-1	-	-	-8.045	-8.045	-
COTTN	4	4	1	L	-5.977	-5.947	-5.995

Note: p and q are selected lag lengths of the dependent and exogenous (where applicable) variables; d is the delay factor of the transition variable,  $s_{t-d}$ , wherein in the case of ENSO equation  $s_t = e_t$  and in the case of commodity price equations  $s_t = \Delta_{12} p_t$ . G denotes selected transition function (L for logistic and Q for quadratic). Finally, AIC<sub>0</sub>, AIC<sub>l</sub>, and AIC<sub>n</sub> are Akaike Information Criteria respectively for the models without exogenous ENSO variable, linear models with ENSO variable (where applicable), and nonlinear models with ENSO variable (where applicable).

## Figures

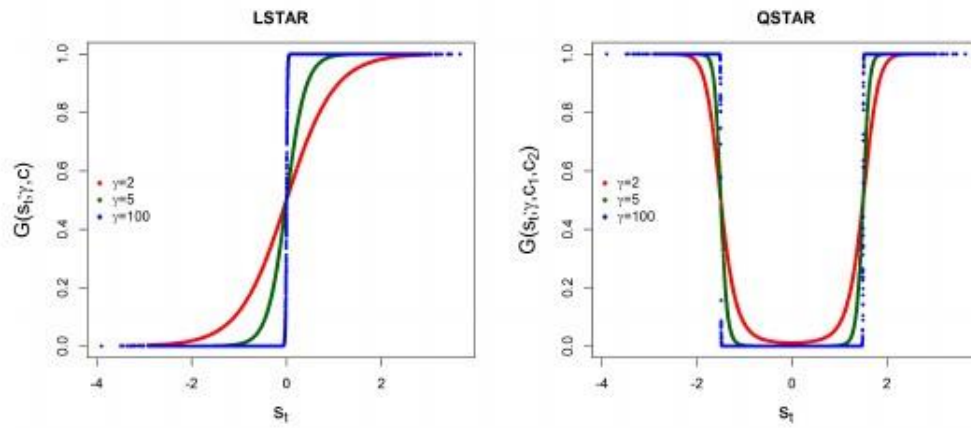


Figure 1: Sample Transition Functions

## Nonlinearity, Causality, and Nonlinear Causality

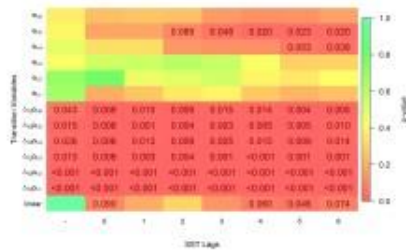


Figure 2: Wheat

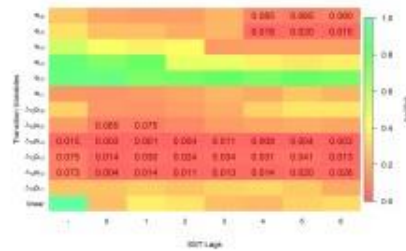


Figure 3: Maize

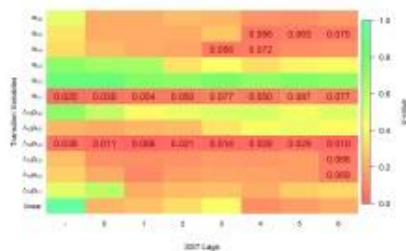


Figure 4: Sorghum

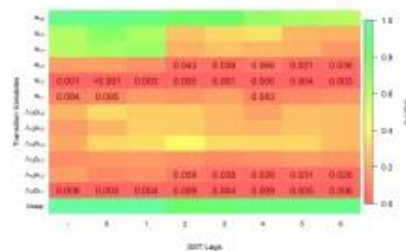


Figure 5: Rice

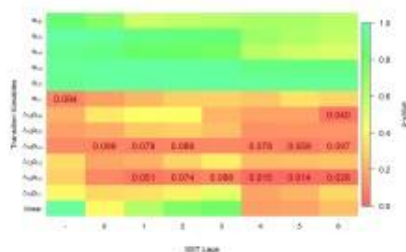


Figure 6: Soybeans

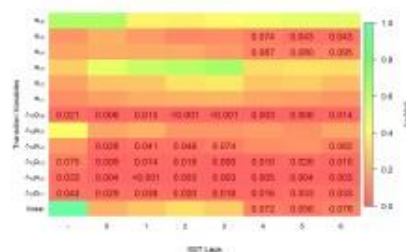


Figure 7: Soymeal



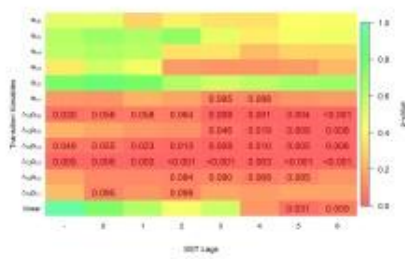


Figure 8: Soybean Oil

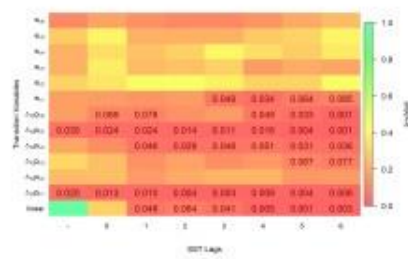


Figure 9: Palm Oil

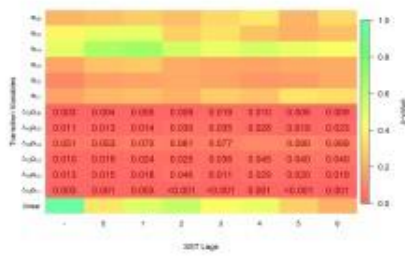


Figure 10: Rapeseed Oil

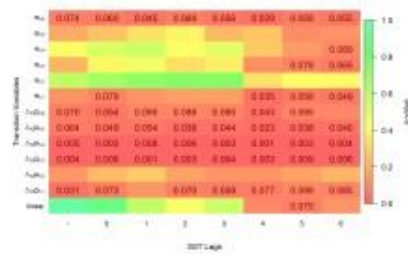


Figure 11: Sunflowerseed Oil

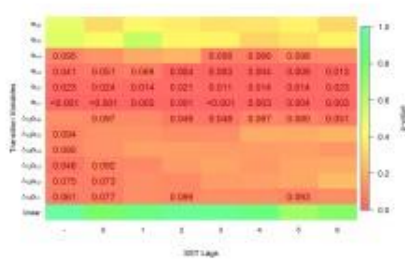


Figure 12: Groundnut Oil

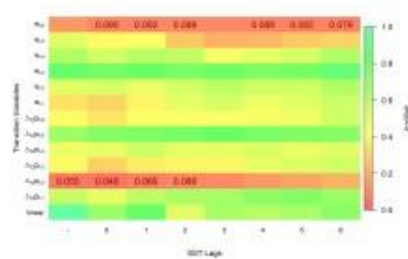


Figure 13: Linseed Oil

## Selected Transition Functions

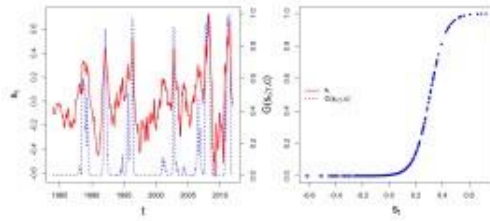


Figure 14: Wheat

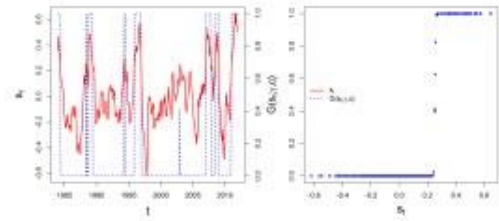


Figure 15: Maize

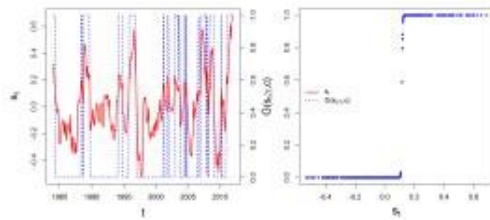


Figure 16: Sorghum

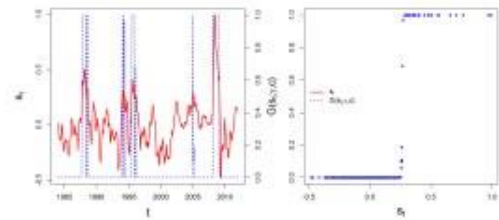


Figure 17: Rice

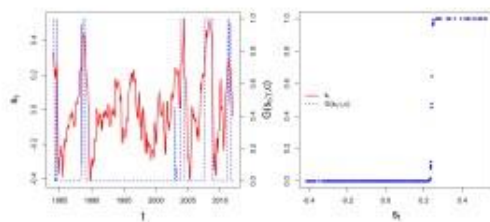


Figure 18: Soybeans

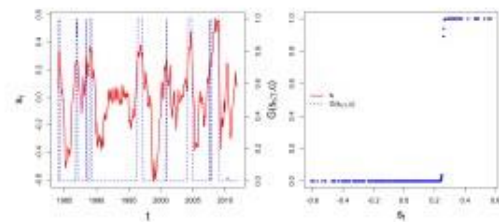


Figure 19: Soymeal

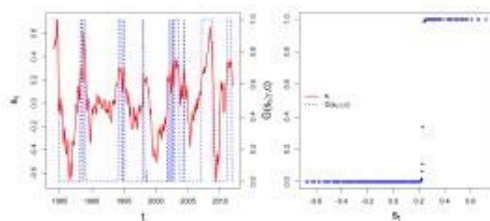


Figure 20: Soybean Oil

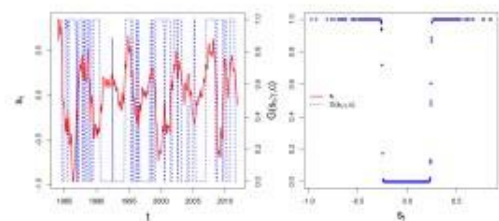


Figure 21: Palm Oil

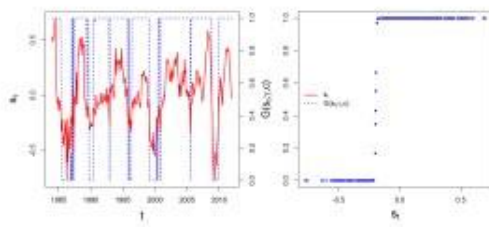


Figure 22: Rapeseed Oil

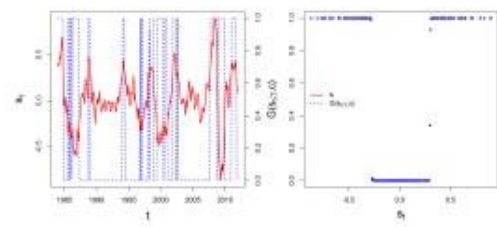


Figure 23: Sunflowerseed Oil

## Bootstrapped Impulse-Response Functions

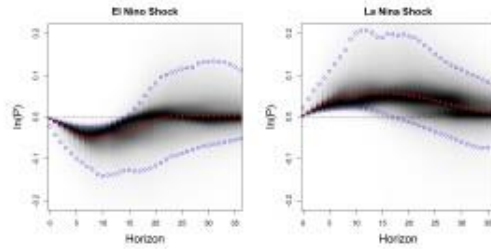


Figure 24: Wheat

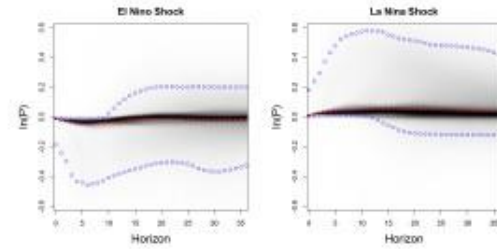


Figure 25: Maize

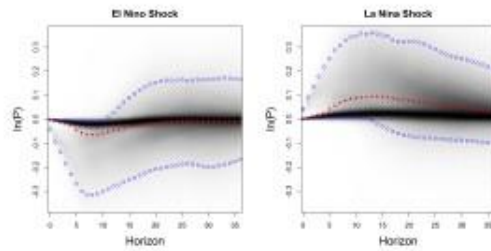


Figure 26: Sorghum

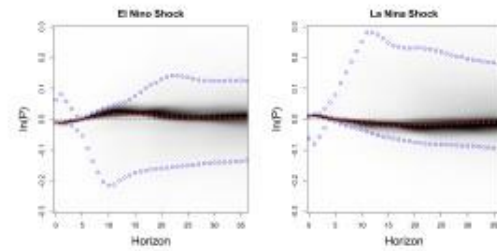


Figure 27: Rice

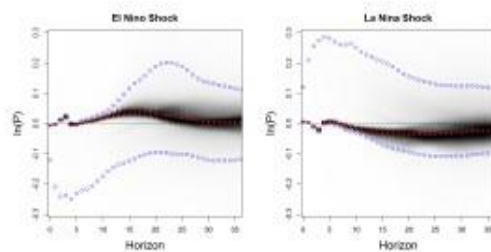


Figure 28: Soybeans

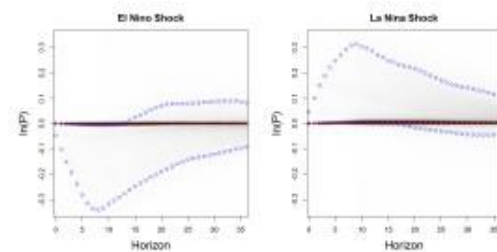


Figure 29: Soymeal

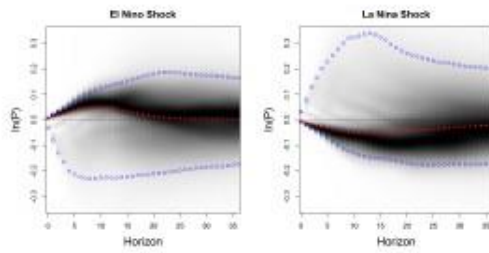


Figure 30: Soybean Oil

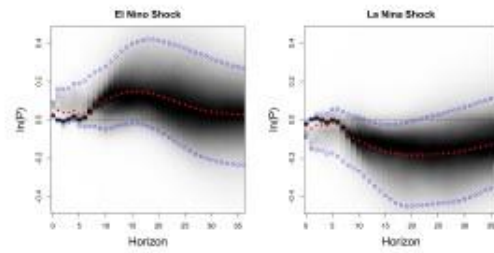


Figure 31: Palm Oil

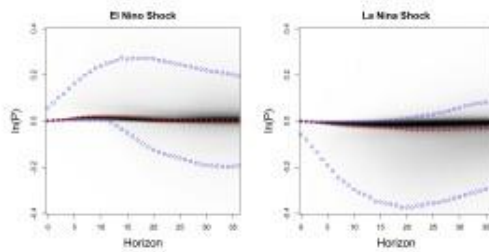


Figure 32: Rapeseed Oil

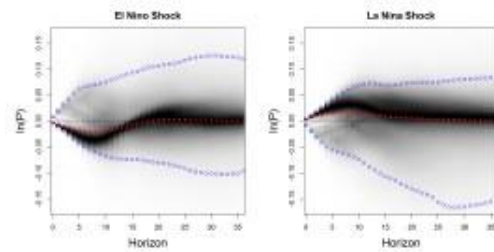


Figure 33: Sunflowerseed Oil