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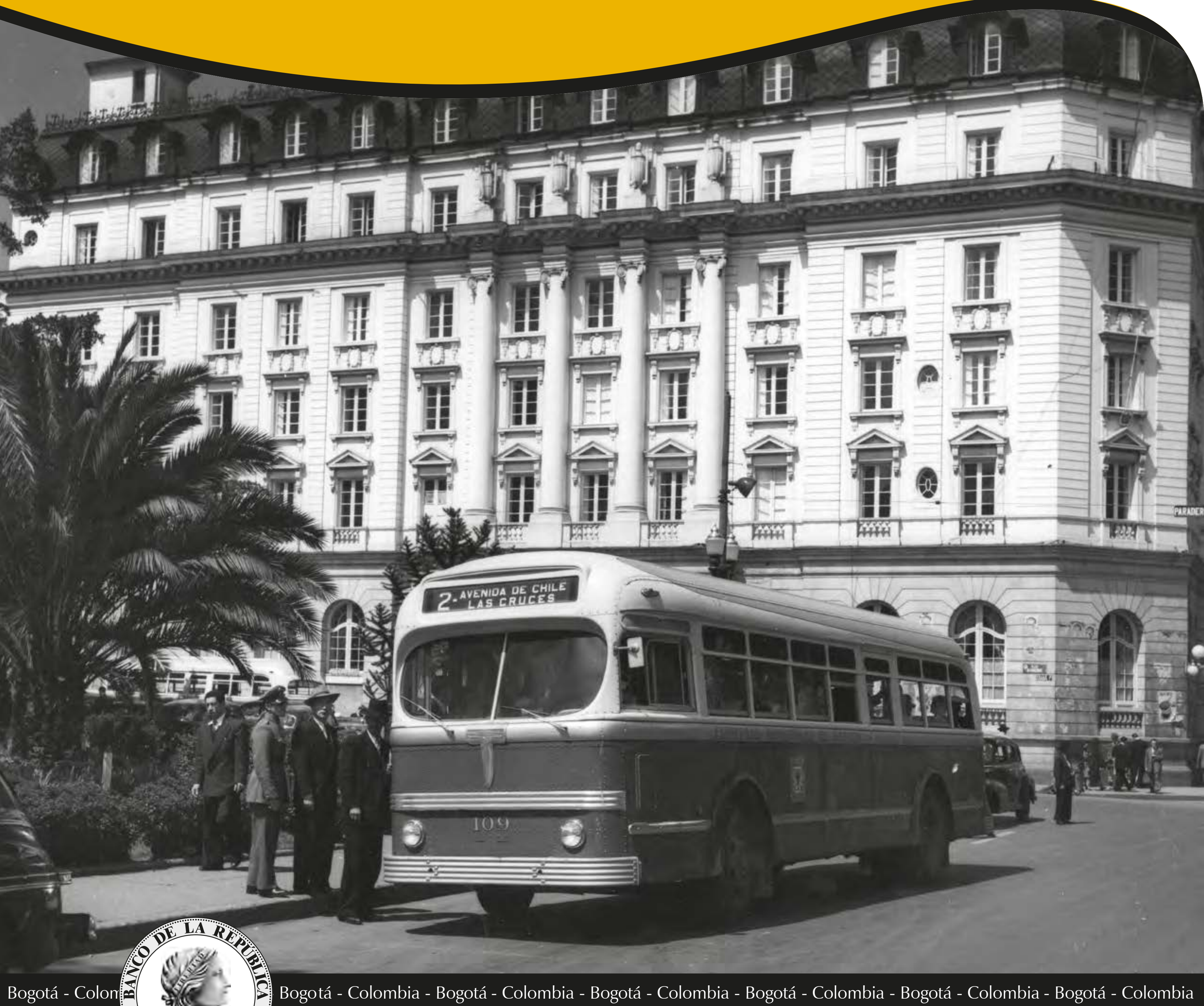

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Abstract

Extreme weather events, like a strong *El Niño* (ENSO), affect society in many different ways especially in the context of recent globe warming. In the Colombian case, ENSO had a significant impact on consumer food prices during the strongest event in 2015-16. Our research evaluates the relationship between ENSO and Colombian food inflation growth by using a smooth transition non-linear model. We estimate the impacts of a strong ENSO on food inflation growth by adopting Generalized Impulse Response Functions (GIRFs) and the results suggest that the weather shocks are transitory and asymmetric on inflation. A strong *El Niño* shock has a significate effect on the food inflation growth from six to nine months after the shock and the accumulated elasticity is close to 465 basic points. We build the GIRFs for eight different episodes associated with a strong *El Niño* in the period corresponding from March 1962 to December 2018 and there is no evidence of changes in the size of Colombian food inflation growth responses over time.

*JEL code.*C32, C50, E31.

Key words. El Niño Southern Oscillation (ENSO), non-linear smooth transition models, inflation.

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Relaciones no lineales entre el fenómeno climático El Niño y los precios de los alimentos en Colombia

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Resumen

Eventos extremos del clima como El Niño (ENSO) fuerte afectan la sociedad de diferentes maneras en especial en el reciente contexto de calentamiento global. En 2015-16, se observó el evento de El Niño más fuerte en los últimos cien años el cual presentó un impacto significativo sobre los precios de alimentos al consumidor en el caso colombiano. El presente trabajo de investigación evalúa la relación entre ENSO y el crecimiento de la inflación de alimentos para el consumidor en Colombia usando un modelo no lineal de transición suave y estimando funciones de impulso respuesta generalizadas (GIRFs). Los resultados sugieren que dichos choques climáticos son transitorios y asimétricos sobre la inflación. Así, El Niño fuerte tiene un impacto significativo sobre el crecimiento de la inflación de alimentos entre seis y nueve meses después del choque climático y la elasticidad acumulada es 465 puntos básicos. Adicionalmente, se construyeron GIRFs para ocho diferentes episodios de tiempo asociados con un fenómeno de El Niño fuerte que se observaron entre marzo de 1962 y diciembre de 2018 y se encontró que no hay evidencia estadística de cambios en el tamaño de las respuestas del crecimiento de la inflación de alimentos en Colombia a través del tiempo.

Clasificación JEL: C32, C50, E31.

Palabras clave: El Niño-Oscilación del Sur, modelos no lineales de transición suave, inflación.

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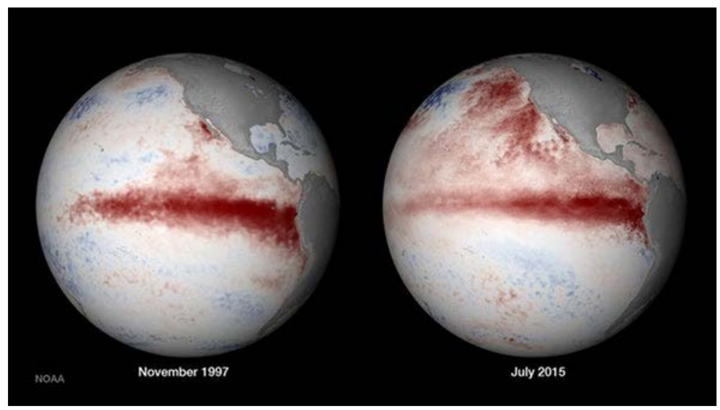
1 Introduction

Although the average surface temperature on the Earth has risen close to 1.6 degrees Fahrenheit since the 20th century according to Global Climate Change Indicators made by *NASA* and *NOAA*[1], the warming process has materialized over the last 30 years. Indeed, in 2016 we witnessed the warmest year on record since 1850, as well as another five of the warmest years on record happening since 2010. Simultaneously, other *regular* weather phenomena have also changed regarding their intensities, duration and unprecedented frequencies. In particular, *El Niño* Southern Oscillation (ENSO) changes the global atmospheric circulation and affects sea-level pressure and sea-surface temperature (SST). Otherwise, it could change patterns in rainfalls and air flow current around the world.

ENSO is a natural feature of the global climate cycle which oscillates between extreme events named *El Niño* and *La Niña*. According to NOAA, the ENSO cycle occurs on average every two to seven years and *El Niño* arises more frequently than *La Niña*. Those weather anomalies have a significant impact on agricultural production and food prices which has been documented in the economic literature (Tol, 2009 and Dell, Jones, and Olken, 2014). For example, in some countries there are high temperatures and low precipitations anomalies under a phenomena *El Niño* which are linked with lower agricultural production growth rates and an increase in prices. Thus, ENSO dynamics and agriculture are essentially connected through different channels which can affect macroeconomic growth and inflation (Brunner, 2002, Berry and Okulicz-Kozaryn, 2008, Cashin, Mohaddes, and Raissi, 2017), commodity prices (Chimeli et al., 2008, (Ubilava, 2012b; Ubilava, 2012a), Castro Campos, 2019), impact human health (Grove and Chappell, 2000, Andalón et al., 2016) and explain social-economic conflicts (Davis, 2002, Hsiang, Meng, and Cane, 2011).

Understanding relationship between climate and economy and how it affects our welfare is a relevant topic in the agenda of policy makers around the world. Even more, in recent years significant strong *El Niño* in the global warming context have occurred. Modeling and estimating those weather changes allows us to design accurate and effective macroeconomic policies and enable us to forecast both occurrence probabilities and how future changes in weather affect economic activity. Although there is wide literature on linkages between ENSO and economic variables, most of them include all the possible faces of ENSO such as neutral, moderate and strong cases in *El Niño* and *La Niña* which could lead to an underestimation of the results. On the other hand, the macroeconomic effects on inflation at an aggregate level of the most recent strong *El Niño* event of 2015/16 are understudied, even when many emerging countries with monetary policy based on inflation targeting schemes failed to control their inflation targets due to this shock. Thus, in this article we pay special attention to strong *El Niño* phenomenon and its impacts on consumer prices at a macroeconomic aggregate level in an emerging country like Colombia and contribute to weather economic literature by using information of those extreme events. For instance, the two strongest phenomena *El Niño* were in 1997/98 and 2015/16 (Figure 1). Moreover, we include the eight episodes of the strong *El Niño* since 1960 which are described in Table 1 and Figure 6.

Figure 1: *The two strongest phenomena* El Niño



Source: NOAA

Another technical modeling aspect that we should highlight is the evidence of asymmetries in ENSO behaviour. There have been various theories in the climatology literature to explain the underlying physics of strong *El Niño* events that explain nonlinear features of ENSO such as oceanic nonlinear advection (Timmermann, Jin, and Abshagen, 2003), nonlinear convective response to Sea Surface Temperatures (Ohba and Ueda, 2009, Dommenget, Bayr, and Frauen, 2013 and Choi, Vecchi, and Wittenberg, 2013) and state dependent noise acting under *El Niño* favorable conditions (Lengaigne et al., 2004 and Jin et al., 2007). On the economic framework, Hall, Skalin, and Teräsvirta, 2001 identify disparities in the autocorrelation functions patterns which reflect ENSO asymmetries between *El Niño* and *La Niña* phases. Supporting this idea, Ubilava and Holt, 2013 state an improvement in performance modeling of commodity price forecasts by using nonlinear smooth

[1]NASA: National Aeronautics and Space Administration, NOAA: National Oceanic and Atmospheric Administration.

transition models compared to the traditional lineal models.

Our research contributes to the growing literature in the economics of weather changes by modeling the presence of a relationship between ENSO and Colombian food inflation growth which has a nonlinear and asymmetric feature over time. We estimate a nonlinear smooth transition regression model (STR) and calculate generalized impulse response functions (GIRFs) which show a significate effect on the food inflation growth from six to nine months after the shock. Thus, a strong *El Niño* produces an increment of 209 basic points (b.p), 148 b.p, 75 b.p and 33 b.p for each month and the accumulated impact is 465 b.p on the Colombian food inflation growth. Another interesting exercise suggests that there is no evidence of significant changes in the size of Colombian food inflation growth responses in the period corresponding from March 1962 to December 2018.

The article is structured as follows. In the next section we show empirical evidence from Colombian data and its linkages with weather phenomena like *El Niño*. In section 3 we introduce the methodology and test for fit accuracy. In section 4 we present the results based on our estimated model and compare Colombian food inflation responses in different moments of time when a strong *El Niño* has been observed. Finally, in last section we provide concluding remarks.

2 ENSO and its relationship with the Colombian economy

According to Restrepo and Kjerfve, 2000 ENSO significantly affects the Colombian environment and its hydrological cycle through changes in precipitation pattern that is consistent with the ENSO behaviour. Esquivel et al., 2018 developed a statistical climate forecast model for colombian precipitation using Canonical Correlation Analysis (CCA) with SST data and its teleconnections as proxy of ENSO. They evaluate different models for rainfall forecast and their forecast evaluation performance on the three major staple crops in Colombia (rice, maize, and beans). They find models that capture the pattern consistent with negative precipitation anomalies during *El Niño* and positive precipitation anomalies during *La Niña* which also is described by Poveda et al., 2001 in the Colombian case. Puertas and Carvajal, 2008 characterize *El Niño* in Colombia linking an increment in SST with a reduction in precipitation levels and an increase in temperature, mainly in the Central, Northern and Western regions of the country. Furthermore, they show evidence that ENSO has a greater impact on those weather variables in the quarter corresponding to December, January and February (DJF). However, those patterns can change depending on Colombia's region. For example, Pabón et al., 2001 find two regimes associated with *EL Niño* and low pluviosity: i) bimodal in the Central region in quarters DJF and JJA and ii) unimodal in the east zone during DJF. In other regions they show there is no conclusive evidence to define those regimes. A strong *El Niño* episode has an average duration of 15 months but really five of those months reach critical temperatures (Table 1).

Colombia has an agricultural sector that represents 6.3% of the national GDP which is highly sensitive to changes in weather as well as is remarkably disparate due to Colombia's heterogenic geography. In addition, although many colombian crops could be considered less important than others in terms of international trade, they could have a great significance at a local level. In this context, farmers face uncertainty that affects income, employment and production which in turn are reflected at macroeconomic level. To be more specific, during the strong *El Niño* in $1997-1998$ Colombia suffered a severe drought over 90% of its territory. In this event, many rivers presented important decreased in their flows compared with historical records of the last 50 years (CAF, 2000).

In Colombia, most farms are medium and small businesses, thus many of them do not keep reports and their ability to assess the consequences of weather changes on their crops is limited. Loboguerrero et al., 2018 show the benefits of Local Technical Agroclimatic Committees (LTACs) system promoted by the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). It has established an organization for creating dialogue between researchers and farmers that would provide farmers with options in the face of both short and long term variations in climate in two regions of Colombia. As mentioned by them, although the limitations for the country continue, the colombian farmers community responded positively in the early stages of the project. They suggested that it should be promoted by government agencies as public policy which would allow farmers to improve on the response to weather and climate shocks.

Recently, the strong *El Niño* in $2015-2016$ had similar magnitude compared to that observed in the nineties and its effects on colombian economy was estimated close to 3.1 billion pesos (930 million in US dollars)

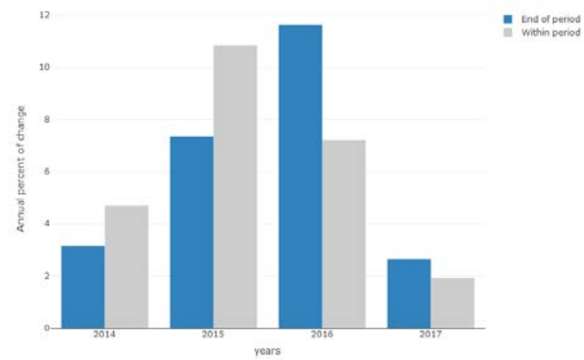
(Melo et al., 2017). In addition, Colombian agricultural economic authorities estimated a reduction of 5% in agricultural production caused by *El Niño* shocks (MinAgricultura, 2006). Some fishing and agricultural goods are adversely affected by the *El Niño* such as tilapia, livestock, sugarcane, rice, plantain, maize, potato, flowers and bananas (Blanco, Barandica, and Viloria, 2007 and Loboguerrero et al., 2018). However, a few other goods can benefit from *El Niño* conditions. For example, the increasing temperatures and sunlight and decreasing rainfalls prompt coffee plants growth which has a beneficial influence (Ubilava, 2012a and Bastianin, Lanza, and Manera, 2018). As reported by Ubilava, 2013, *El Niño* reduces wheat, corn and soybeans prices in the international market and those goods are imported by Colombia which could help reduce inflationary pressures during a strong *El Niño*.

Although *El Niño* can affect the agricultural prices in different and opposing ways, Colombia's central bank states that the strong *El Niño* has significant impacts on consumer food prices[2] and the weather shocks can explain between 30% and 40% the variability of the total national Consumer Price Index (CPI) during *El Niño* episodes (Caicedo, 2007). Abril, Melo-Velandia, and Parra-Amado, 2016 estimate the impacts of weather conditions on Colombian food inflation growth by using a smooth transition non-linear model that includes food inflation and SST data. They show that weather shocks are transitory and asymmetric both in *El Niño* and *La Niña* phases. The authors find an increment, on average, in the food inflation CPI close to 172.5 b.p during a strong *El Niño* and 116 b.p in the course of a moderate *El Niño*. They make the food inflation response elasticities over all the sample periods[3] taking the observed average value of SST greater than 1 and 1.5 as proxy of weather shocks. We also find that responses to ENSO shocks are asymmetric over the whole sample and we make impulse response over the specific strong *El Niño* periods including the two strongest observed at the end of the nineties and in the $2015-2016$. The motivation for this research arises when the monetary authorities were concerned about the effect of the last strong *El Niño* shock on inflation expectations due to the significant increase in food prices in Colombia (Figure 2). In particular, Colombian households were affected in their income when the food inflation went from 4.7% in December 2014 to the maximum value observed which was close to 15.7% in July 2016.

[2] Total National Consumer Price Index.

[3] The data contains information from the monthly period between June 1955 and May 2015.

Figure 2: *Colombian food inflation 2014-2017*



End of period (blue) corresponds to the inflation in December and within period (gray) is defined as the inflation's average between January and December.

3 Methodology and Data

In this section we outline the econometric approach used to explore nonlinear dynamic relationships between ENSO and Colombian food inflation. Following Teräsvirta, 1994 and Teräsvirta, 1998, we consider a nonlinear smooth transition regression model (STR) which is widely applied in the literature of weather effects on agricultural prices (Hall, Skalin, and Teräsvirta, 2001, Ubilava, 2012b; Ubilava, 2012a; Ubilava, 2013 and Castro Campos, 2019). The STR-type models enable us to analyze asymmetries within and between both ENSO and Colombian inflation for consumer food prices, and estimate changes in regimes linked with ENSO phases (*El Niño and La Niña*); although our analysis only aimed our attention over periods where a strong *El Niño* happened.

3.1 Smooth Transition model

Teräsvirta, 1994 proposes the following nonlineal model:

$$y_t = \phi_1' \mathbf{x_t}[1 - G(s_t;\gamma,\mathbf{c})] + \phi_2' \mathbf{x_t} G(s_t;\gamma,\mathbf{c}) + \varepsilon_t \quad (1)$$

where y_t is a dependent variable; $\mathbf{x_t} = (1, y_{t-1}, \ldots, y_{t-p}, z_{1,t}, \ldots, z_{m,t})'$ is a vector of explanatory variables which can be composed of both lagged variables of y_t and contemporaneous and lagged exogenous variables. In this article the endogenous variable is the Colombian food inflation growth (DINF) and ENSO is an exogenous variable. ϕ_1 and ϕ_2 are vectors of coefficients to estimate. $G(s_t;\gamma,\mathbf{c})$ is known as the transition function, by definition bound between 0 and 1, and where s_t is a transition variable and

γ and $\mathbf{c}$ are smoothness and location parameters, respectively. The error term is assumed to be white noise, $\varepsilon_t \sim iid(0, \sigma^2)$. The equation (1) can be specified as:

$$y_t = \varphi_1' \mathbf{x_t} + \varphi_2' \mathbf{x_t} G(s_t; \gamma, \mathbf{c}) + \varepsilon_t \quad (2)$$

where $\varphi_1 = \phi_1$ y $\varphi_2 = \phi_2 - \phi_1$. In the econometric framework there are different ways to model the transition function (Teräsvirta, 1994, Teräsvirta, 1998 y Hall, Skalin, and Teräsvirta, 2001) but the logistic and exponential transition functions are the two most common. These can be written as:

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

$$G(s_t; \gamma, \mathbf{c}) = 1 - \exp\left[-\left(\frac{\gamma}{\sigma_{s_t}^2}\right)(s_t - \mathbf{c})^2\right], \quad (4)$$

where σ_{s_t} is transition variable's standard deviation. Logistic STR (LSTR) and exponential STR (ESTR) models can be estimated by combining the equations (2) with (3) or (4), respectively.

3.2 Nonlinear test (LM) and model selection criteria

To identify regime-dependent nonlinearities, we use a third-order Taylor series expansion over the transition function which is the standard method in the testing framework of Luukkonen, Saikkonen, and Teräsvirta, 1988[4]. Then, we use an auxiliary regression which can be specified as:

$$y_t = \phi_1' \mathbf{x}_t + \sum_{j=1}^{p} \phi_{21j}' \mathbf{x}_t s_t + \sum_{j=1}^{p} \phi_{22j}' \mathbf{x}_t s_t^2 + \sum_{j=1}^{p} \phi_{23j}' \mathbf{x}_t s_t^3 + \varepsilon_t \quad (5)$$

Under the null hypothesis, we evaluate the following statistics:

$$H_{01} : \phi_{21j}' = \phi_{22j}' = \phi_{23j}' = 0 \quad \text{para} \quad j = 1, \ldots, p \quad (6)$$

$$LM = \frac{(SSR_0 - SSR_1)/(k_1 - k_0)}{(SSR_0)/(T - k_1)} \quad (7)$$

where SRR_0 is the residual sum of squares calculated using the equation (5) under the null hypothesis and SRR_1 is the residual sum of squares using the whole auxiliary regression. Then, under the null hypothesis follows a lineal model and the alternative a STR model. The LM test has a F-distribution with $k_1 - k_0$ y $T - k_1$ freedom degrees as proposed by Dijk, Teräsvirta, and Franses, 2002.[5] In addition, the LM test enables us to evaluate the selection of the transition function due to the LSTR and ESTR models are also embedded in the testing framework. Thus, when the null hypothesis is rejected Teräsvirta, 1994 suggest the following procedure through a sequence of tests:

- $H_{04} : \phi_{23j}' = 0 \qquad j = 1, \ldots, p$
- $H_{03} : \phi_{22j}' = 0 | \phi_{23j}' = 0 \qquad j = 1, \ldots, p$
- $H_{02} : \phi_{21j}' = 0 | \phi_{22j}' = \phi_{23j}' = 0 \qquad j = 1, \ldots, p$

In the case of the p-value under the hypothesis H_{03} being the lowest in comparison to the other hypothesis (H_{02}, H_{04}), then we should select the ESTR model. Otherwise, we can select the LSTR model. Furthermore, we evaluate the appropriate specification using a set of statistical tests presented in Appendix B (Dijk, Teräsvirta, and Franses, 2002).

4 Empirical results

Data and estimation: We employ a set of monthly data for ENSO anomaly and Colombian consumer food inflation (INF) that contain 682 observations for each variable corresponding to the months from March 1962 to December 2018. The INF variable is defined as the monthly percent change of the Colombian Food Price Index from a year ago which is measured by the National Administrative Department of Statistics of Colombia (DANE). The ENSO variable is measured by using SST departures from average in the Niño 3.4 region which can be downloaded from the NOAA web page (Figure 3).[6] The sample covers different phases and intensities of the ENSO (Figure 6). Although the focus of the analysis is on the strong *El Niño* periods, we use the whole data to recover the nonlinear dynamics of ENSO, and then, we construct the generalized impulse response functions using only a strong *El Niño* shocks in the following procedure.

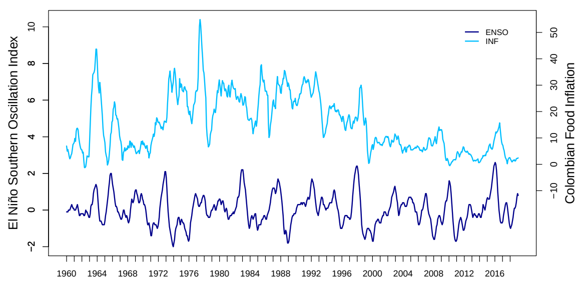
In the first step, we identified the integration degree of both the ENSO and the INF series, therefore, we used non-linear unit root tests proposed by Enders and Ludlow, 2002, Kapetanios, Shin, and Snell, 2003 and Sollis, Leybourne, and Newbold, 1999. As a result, the ENSO is stationary in levels while the INF series has a unit root (Table 2). Thus, we transform the INF series using the first difference which can be interpreted as food inflation growth (DINF). In the next step, we fixed a set of transition variables between $ENSO_t$ and $ENSO_{t-5}$, then we estimated STR models for ENSO

[4] Luukkonen, Saikkonen, and Teräsvirta, 1988. solve the nuisance parameters identification problems mentioned by Davies, 1987. For instance, when $\gamma = 0$ or the whole coefficients φ_2 are zero.

[5] k_0 y k_1 are the number of variables included in both the under the null hypothesis and the whole equation regressions, respectively.

[6] We use the measure SST (ERSST.v5) as proxy of ENSO. This SST methodology is described in Huang, 2017.

Figure 3: *ENSO and Colombian food inflation 1960-2018*



and DINF by using the consecutive candidate of this set of transition variables and the choice is presented in Appendix B (Table 3 and 8). As the following step, we estimate a system that links ENSO and DINF assuming SST anomaly is weakly exogenous:

$$ENSO_t = \phi_{10} + \sum_{i=1}^{p1} \phi_{1i} ENSO_{t-i} + G_1(ENSO_{t-d_1}; \gamma_1, c_1) \left(\phi_{20} + \sum_{i=1}^{p1} \phi_{2i} ENSO_{t-i} \right) + \epsilon_t \quad (8)$$

$$DINF_t = \varphi_{10} + \sum_{i=1}^{p2} \varphi_{1i} DINF_{t-i} + \sum_{i=0}^{p3} \psi_{1i} ENSO_{t-i} + G_2(ENSO_{t-d_2}; \gamma_2, c_2) \left(\varphi_{20} + \sum_{i=1}^{p2} \varphi_{2i} DINF_{t-i} + \sum_{i=0}^{p3} \psi_{2i} ENSO_{t-i} \right) + \varepsilon_t \quad (9)$$

where $p_1 = 5$, $p_2 = 24$ y $p_3 = 5$ are the maximum lags used by ENSO and DINF in the system of equations. The resulting models are presented in the Table 4 and 9. The ENSO shocks and DINF innovations are uncorrelated ($cov(\epsilon_t, \varepsilon_t) = 0$) which is coherent with the exogeneity assumption and provides an identification condition in the bivariate system of equations (8) and (9). In both cases, the chosen transition variable is $ENSO_{t-3}$ and we select a LSTR specification for the ENSO transition function in (8) and a ESTR specification for the DINF transition function in (9). Figure 7 shows the estimated transition functions associated with nonlinear model for DINF where the smoothness parameter and the point of inflection are $\hat{\gamma} = 9.679$ and $\hat{c} = 1.993$. The latter suggests that the most important change in the DINF behaviour occurs when ENSO dynamics reaches on strong intensity of *El Niño*. Likewise, the modulus of the transition function illustrate a explosive behaviour associated with a strong *El Niño* (Table 13) which is modeled by our estimation. Finally, there are no evidence of residual correlation nor parameter instability in the ENSO and the DINF equations. Moreover, we find evidence of no remaining nonlinearities (Table 5 and 10). The residual diagnostic tests are presented in Table 6, 7, 11 and 12.

As mentioned by Ubilava, 2017, the estimated parameters cannot be interpreted and should not be used for constructing a regular impulse responses function due to the presence of nonlinearities maybe producing biased over them.[7] One strategic way to solve this problem is discussed next.

Impulse response functions: To illustrate the nonlinear impacts of ENSO shocks on Colombian food inflation growth, we use a generalized impulse response function (GIRF) proposed by Koop, Pesaran, and Potter, 1996. The GIRF for a given shock ($\varepsilon_t = \delta$), a specific history (ω_{t-1}) and a forecast horizon determined ($h = 0, 1, 2, \ldots$) can be defined as:

$$GIFR_y(h, \delta, \omega_{t-1}) = E[y_{t+h} | \varepsilon_t = \delta, \omega_{t-1}] - E[y_{t+h} | \omega_{t-1}] \quad (10)$$

where $\omega_{t-1} \in \Omega_{t-1}$ denotes the history, that is, available information at a time when a forecast is made. To extent that δ and ω_{t-1} are realizations of the random variables ε_t and Ω_{t-1} we define the $GIRF_y(h, \delta, \omega_{t-1})$ as:

$$GIFR_y(h, \varepsilon_t, \Omega_{t-1}) = E[y_{t+h} | \varepsilon_t = \delta, \Omega_{t-1}] - E[y_{t+h} | \Omega_{t-1}] \quad (11)$$

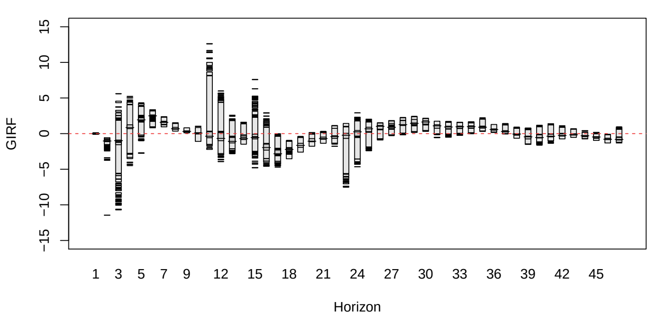
In this article, Ω_{t-1} contains every history from strong *El Niño* episodes which are described in the table. We take realizations of ε_t between 1.5 to 2.6 which are the values observed in the SST anomalies series for all the strong *El Niño* episodes. For a randomly-sampled history from each month of these episodes (Table 1), 100 bootstrap projections of ENSO equation are computed with and without shocks at initial moment ($h = 0$). Then, we incorporate those shocks and make a similar process into the DINF equation (9). An advantage of this procedure is that it enables us to obtain nonlinearities in the DINF autoregression process and its GIRFs may have an asymmetric or multimodal form by using a distribution of shocks both ENSO and DINF. Also, we can construct high density regions (HDRs) of the GIRFs at different horizons ($h = 0, \ldots, 48$) which display bands of confidence 50% (darker shade) and

[7] The author states: "that the estimated parameters of a nonlinear model, other than those of a transition function, cannot be interpreted directly. This is because nonlinear models are not invariant to idiosyncratic shocks that may alter the underlying dynamics of a stochastic process. This also implies that the so-called naive extrapolation, which is used in linear models to generate impulse response functions at horizons greater than one, yields biased results, and is not valid in the case of nonlinear models."

95% (lighter shade) in the Figure 4, 5 and 8.

The analysis, as expected, indicates that ENSO has an economically important and statistically significant effect on Colombian food inflation growth. In particular, it is affected after five months of shock occurrence. Figure 4 shows evidence of the transitory nature of *El Niño* on food prices in Colombia. It illustrates that the responses of DINF are significant between six and nine months after ENSO shock and then are statistically null. Thus, when ENSO shocks have a strong intensity, the Colombian food inflation growth increase by 209 b.p, 148 b.p, 75 b.p and 33 b.p for each month.[8] The accumulated impact is close to 465 b.p. There are two types of asymmetries in our results: i) the GIRFs after a positive shock (*El Niño*) are not mirror images of the GIRFs after a negative shock (*La Niña*), but we do not present them because we focus on *El Niño* and ii) the responses of food inflation growth is nonlinear depending on the size of ENSO shocks. For instance, when an ENSO shock is doubled, the response in food prices does not necessarily double (Figure 8). According to the result of Table 13 and Figure 7, most of time the process is stationary; however, when the process is located in a strong *El Niño* regime, it generates an explosive behaviour of DINF. An important implication is that a relatively large ENSO shock, such as a strong *El Niño*, will likely cause a regimen switch which produces different paths in comparison to a scenario without shocks.

Figure 4: *GIRF for DINF including all the strong El Niño episodes*



Bands of confidence are 50% *(darker shade) and* 95% *(lighter shade) and the median is the black horizontal line. The GIRF is associated with a strong* El Niño *shock.*

Another interesting exercise, that this methodology enables us to do, is running the bootstrap simulation of GIRF over a specific history by using the STR model. Figure 5 exhibits the same shocks associated with a strong *El Niño* over each episode. The HDRs overlap for different periods which imply that the responses do not change statistically over time. We highlight the following aspects about the results. A curious and counterintuitive feature is observed at the end of nineties where the responses of food inflation growth did not have statistical significance in a strong *El Niño* shock. Before the twenty-first century, the responses of Colombian food inflation growth showed a great amplitude of HDRs which could be associated with more volatile behaviour of food prices. It is important to mention that Colombia had double-digit inflation in last decades, but after the nineties, it fell and has been located close to the target range of the Colombian central bank for total inflation when there have been no climate shocks. Some economic reasons for those changes might be: i) access to international markets of agricultural goods and the grade of openness trade, ii) diversification of agricultural goods and iii) anchoring of inflation expectations and Central Bank credibility. In the last strong *El Niño* during 2015 – 2016, Colombian food inflation growth had a significant impact between six and nine months after the shock and the accumulated effect was 465 b.p which is similar to the observed changes of food prices (Figure 2).

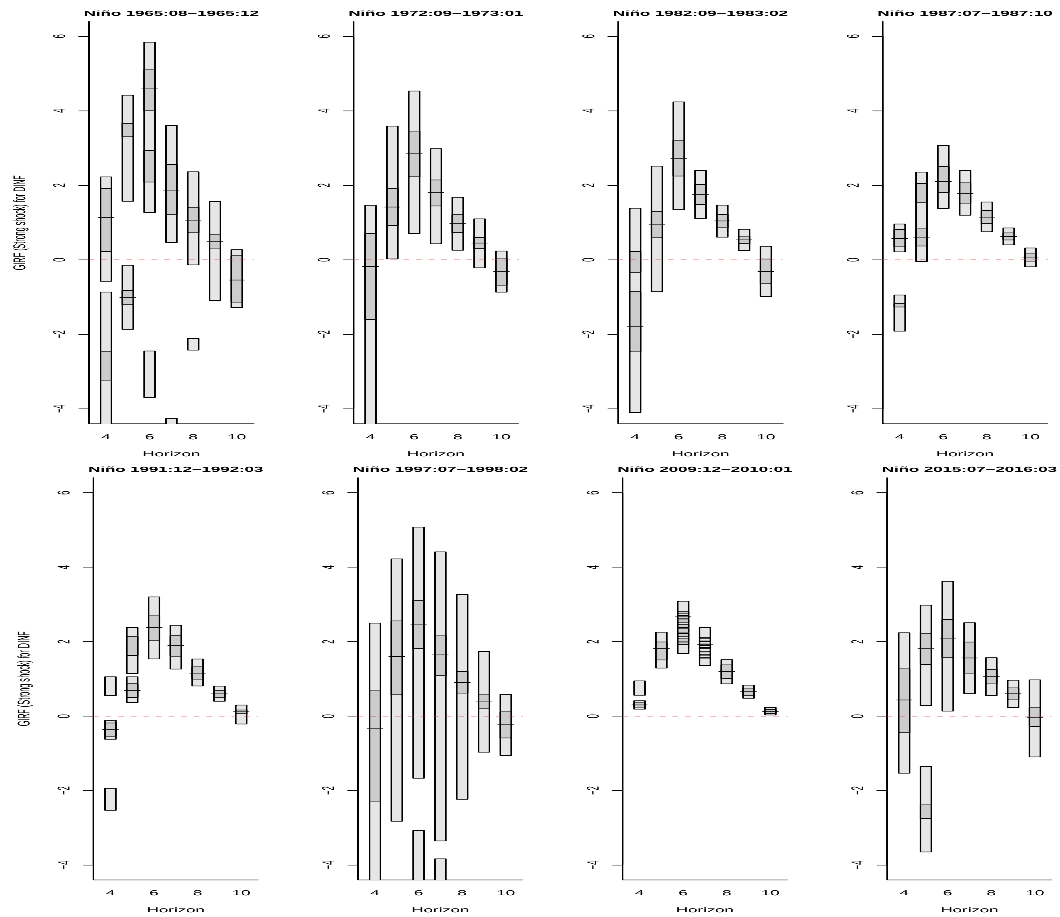
5 Discussion and conclusions

Although there is growing literature about the weather and economic relationships, extreme agroclimatic events and their relationship with food prices establish a under-researched area in developing countries such as Colombia. In this article we contributed to the empirical literature by examining the linkages between extreme weather shocks like a strong *El Niño* and Colombian food prices. In the recent global warming process, understanding these relationships will become increasingly relevant in terms of policy design and development looking to reduce their consequences. Also food markets could have consequences on macroeconomy and microeconomic levels in terms of household wellfare and income of farmers, the main challenge for economic authorities is related to the identification of the exogenous changes in weather and their impacts on food prices.

As we expected, weather shocks like ENSO affect the Colombian food prices. We find that the dynamics of the SST anomalies, as proxy of ENSO, and its relationship with Colombian food inflation growth are best characterized by a nonlinear modeling framework. Thus, there is evidence that support the election of STR specifications for each variable which is consistent

[8] These values correspond to the median for each response which are the black horizontal line in the graphs within the HDRs.

Figure 5: *Comparing GIRF for DINF over different periods*



Bands of confidence are 50% *(darker shade) and* 95% *(lighter shade) and the median is the black horizontal line. The GIRFs are associated with a strong* El Niño *shock.*

with earlier literature findings. We use the exogenous feature of ENSO over colombian food inflation to model how his variations over time changes according different regimes like a strong *El Niño* on inflation. The estimated model shows evidence of asymmetries on this relationship. However, contrary to our expectations, there is no evidence of changes in the size of Colombian food inflation growth responses over time. The results indicate a significant responses of food inflation growth between five to nine months after a strong ENSO shock. The maximum impact is reached in the six month where the effect is calculated in 209 b.p. In addition, the accumulated elasticity of food prices to ENSO shock is close to 465 b.p.

Our findings have many policy implications and our model can be useful in different ways. First, the model can be used as an input for the design of public policies to mitigate the effects of weather changes. For example, given the recent advances in climate modeling that allow forecasting strong ENSO events (Zhang et al., 2017 and Chen, Smith, and Kessler, 2018), our model enables to forecast price paths as well as to understand the propagation mechanism of weather shocks. Second, on the macroeconomic policy side, the government should have programs that encourage farmers to invest in irrigation systems as well as building more efficient food value chains. Furthermore, trade policies can be adjusted temporarily which allows changes in import policies which help to bolster agricultural production in low rainfall *El Niño* years. Headey and Fan, 2010 propose the reformulation of grain reserve arrangements and the global trade system in order to moderate future food crises.

Third, on the monetary policy side, in regimes like *El Niño* when consumer inflation increases, the identification of these weather shocks allows central banks not to overreact by tightening the monetary stance, even if there are second-round effects that could arise (Cashin, Mohaddes, and Raissi, 2017 and González, Jalil, and Romero, 2010), thus our model can be a tool to help anchor inflation expectations by explaining the transitory nature of this phenomenon and quantifying the impact on food prices in basic points as well as the number of months that those impacts will occur. Finally, the lower social-economic population is forced to behave in ways such as risk-avoidance, risk-diversification, and informal risk-sharing practices, especially against catastrophes related to the weather. This is due to low accessibility of affordable financial services (Ligon, Thomas, and Worrall, 2002 and Dubois, Jullien, and Magnac, 2008). The study by Miranda and Vedenov, 2001 found that if a developing country can utilize index-based insurance contracts, it would, in turn, let the government create agricultural insurance suited to the country in question. This allows it to transfer a non-diversifiable component of that risk to the global market at a significantly lower cost.

Other mechanism that could be used is financial guarantees that allow farmers and companies to access credit for investing in labor capital and productive technology. Moreover, Cano, 2014 aims to improve the agricultural production by developing new genetic materials resistant to drought and tolerant to both salinity and acidity of the land and promoting the development of a second generation of bio-fuels that do not compete with resources for human consumption.

Our research improves understanding of ENSO implications on consumer prices which seeks to promote the discussion of the economic effects of weather shocks by adding new insights in the empirical literature of those events. As we mentioned before, ENSO can affect the well-being of citizens in Colombia as well as other emerging countries by reducing income of farmers and welfare of households, therefore our investigation makes a call about concern in mitigating those adverse consequences in terms of communication and education on weather effects. Indeed, Colombia and other similar countries should develop public policies oriented to implement better cropping patterns and rainwater irrigation systems, develop quicker and more resistant seeds and improve the food grain inventories to avoid supply restriction due to *El Niño* events.

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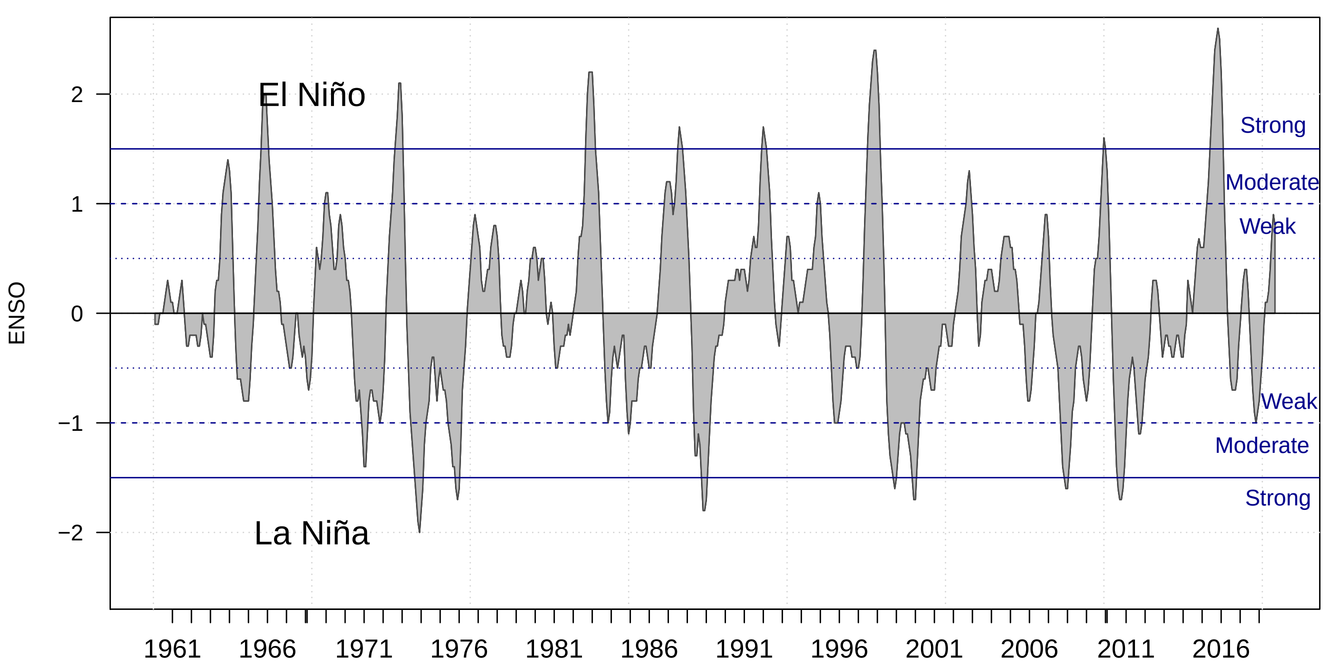
A Characteristics of the strong El Niño phenomena

Table 1: *Episodes of strong El Niño phenomena according to NOAA*

Episodes	Whole period				Period of time with strong intensity				Food Inflation***
	Dates		Duration*	ENSO**	Dates		Duration*	ENSO**	
1	may-95	abr-66	12	1.33	ago-65	dic-65	5	1.82	21.23%
2	may-72	mar-73	11	1.38	sep-72	ene-73	5	1.88	19.35%
3	abr-82	jun-83	15	1.37	sep-82	feb-83	6	2.02	30.43%
4	sep-86	feb-88	18	1.14	jul-87	oct-87	4	1.58	51.64%
5	may-91	jun-92	14	1.03	dic-91	mar-92	4	1.58	35.29%
6	may-97	may-98	13	1.67	jul-97	feb-98	8	2.10	29.18%
7	jul-09	mar-10	9	1.03	dic-09	ene-10	2	1.55	1.03%
8	nov-14	may-16	19	1.41	jul-15	mar-16	9	2.14	19.67%
Average	-	-	15	1.26	-	-	5.2	1.82	26.00%

*Number of months
**The values of ENSO correspond to the average values of SST variable.
*** Colombian consumer food price increment for whole period of each episode.

Figure 6: *ENSO phases and evolution according to NOAA (1960-2018)*



B Diagnostic test and estimation results

Table 2: *Unit root tests*

	Enders and Ludlow, 2002 F_{all}	F_{trig}	c	cr	Kapetanios et al. [2003]	Sollis et al. [1999]
ENSO	33.09	13.78	-7.53	57.63	-6.97	-8.46
INF	5.68	6.90	-1.81	3.39	-2.30	-3.01
DINF	23.86	9.11	-7.14	51.67	-3.52	-10.17
Critical Values at 5%	(7.12)	(8.03)	(-2.58)	(9.14)	(-2.22)	(-4.97)
Critical Values at 1%	(8.67)	(9.73)	(-2.93)	(13.73)	(-2.82)	(-5.53)

Null hypothesis indicates unit root.

Table 3: *Non-linearity LM test for ENSO*

s_t	H_{01}	H_{04}	H_{03}	H_{02}	Model
$ENSO_{t-1}$	0.014893	0.551998	0.314269	0.001570	LSTR
$ENSO_{t-2}$	0.007620	0.300522	0.406748	0.001038	LSTR
$ENSO_{t-3}$	**0.004048**	**0.073543**	**0.383095**	**0.002722**	**LSTR**
$ENSO_{t-4}$	0.007378	0.105819	0.327655	0.004996	LSTR
$ENSO_{t-5}$	0.017671	0.224378	0.300543	0.007637	LSTR

Bold values indicate the lag with minimum p-Value in the LM test.

Table 4: *STR estimation for ENSO*

Dependent Variable: $ENSO$
Transition Variable: $ENSO_{t-3}$

	Coef.	STD	Z	p-value
γ	28.628	32.673	0.876	0.381
c	0.676	0.086	7.840	0.000

Linear Component	Coef.	STD	Z	p-value	Non Linear Component	Coef.	STD	Z	p-value
Constant	0.012	0.006	2.224	0.026	Constant	0.024	0.040	0.600	0.548
$ENSO_{t-1}$	1.821	0.035	51.672	0.000	$ENSO_{t-1}$	0.089	0.026	3.495	0.000
$ENSO_{t-2}$	-1.009	0.052	-19.487	0.000	$ENSO_{t-3}$	-0.146	0.034	-4.277	0.000
$ENSO_{t-4}$	0.341	0.051	6.660	0.000					
$ENSO_{t-5}$	-0.186	0.033	-5.574	0.000					

Inverse of the STD of ENSO	1.1868	R-squared	0.9811
Sum of squared residuals (SSR)	9.4364	Standard error of residuals	0.1165
Log Likelihood	9.4331	Var(Nolin)/Var(Lin)	0.9645
AIC	11.5115		
BIC	33.2514		

Table 5: *No remaining non-linearity test for residuals of ENSO model*

Test	Num	Den	F-Stat	P-Value
Eitrheim and Teräsvirta (1996)	6	687	0.6662	0.6771

Ho: No remaining non-linearity.

Table 6: *Autocorrelation test for residuals of ENSO model*

Lags	F-Stat	P-Value
36	1.4431	0.0473
48	1.2351	0.1381
60	1.1185	0.2586
72	1.0819	0.3092

Ho: No autocorrelation.

Table 7: *Constant parameters test for ENSO model*

Test	Num	Den	F-Stat	P-Value
LM1	6	689	0.8188	0.5554
LM2	12	683	0.8753	0.5722
LM3	18	677	0.9161	0.5588

Ho: All parameters are constant.

Table 8: *Non-linearity LM test for DINF*

s_t	H_0	H_{04}	H_{03}	H_{02}	Model
$ENSO_t$	0.830231	0.791764	0.719204	0.478734	LSTR
$ENSO_{t-1}$	0.442937	0.281109	0.433201	0.568725	LSTR
$ENSO_{t-2}$	0.053617	0.087759	0.035769	0.675368	ESTR
$ENSO_{t-3}$	**0.001594**	**0.014837**	**0.001171**	**0.827043**	**ESTR**
$ENSO_{t-4}$	0.002894	0.133811	0.000217	0.803582	ESTR
$ENSO_{t-5}$	0.013847	0.639871	0.000344	0.620531	ESTR

Bold values indicate the lag with minimum p-Value in the LM test.

Table 9: *STR estimation for the first difference of food inflation (DINF)*

Dependent Variable: first difference of Food Inflation (DINF) Transition Variable: $ENSO_{t-3}$									
	Coef.	STD	Z	p-value					
γ	9.679	2.200	4.400	0.000					
c	1.993	0.041	48.199	0.000					
Linear Component					Non-Linear Component				
	Coef.	STD	Z	p-value		Coef.	STD	Z	p-value
Constant	-3.654	4.310	-0.848	0.397	Constant	3.642	4.314	0.844	0.399
$DINF_{t-1}$	0.488	0.033	14.580	0.000	$DINF_{t-4}$	-0.076	0.036	-2.129	0.033
$DINF_{t-5}$	0.065	0.035	1.837	0.066	$DINF_{t-8}$	1.625	0.830	1.959	0.050
$DINF_{t-8}$	-1.594	0.828	-1.926	0.054	$DINF_{t-10}$	-2.077	0.561	-3.703	0.000
$DINF_{t-10}$	2.063	0.561	3.679	0.000	$DINF_{t-11}$	0.077	0.038	2.012	0.044
$DINF_{t-14}$	-0.799	0.320	-2.500	0.012	$DINF_{t-12}$	-0.732	0.039	-18.533	0.000
$DINF_{t-15}$	0.059	0.033	1.787	0.074	$DINF_{t-13}$	0.293	0.046	6.434	0.000
$DINF_{t-17}$	1.041	0.298	3.498	0.000	$DINF_{t-14}$	0.757	0.321	2.357	0.018
$DINF_{t-20}$	-1.454	0.501	-2.902	0.004	$DINF_{t-16}$	-0.129	0.039	-3.328	0.001
$DINF_{t-23}$	-0.519	0.247	-2.098	0.036	$DINF_{t-17}$	-1.034	0.300	-3.441	0.001
$ENSO_{t-2}$	-12.479	3.273	-3.813	0.000	$DINF_{t-20}$	1.483	0.503	2.950	0.003
$ENSO_{t-3}$	24.030	6.370	3.772	0.000	$DINF_{t-23}$	0.601	0.250	2.406	0.016
$ENSO_{t-4}$	-8.517	3.955	-2.153	0.031	$DINF_{t-24}$	-0.392	0.040	-9.811	0.000
$ENSO_{t-5}$	-1.007	0.406	-2.478	0.013	$DINF_{t-25}$	0.114	0.038	2.985	0.003
					$ENSO_{t-2}$	12.012	3.308	3.631	0.000
					$ENSO_{t-3}$	-23.558	6.445	-3.655	0.000
					$ENSO_{t-4}$	9.511	3.960	2.402	0.016
Inverse of the STD of DINF				1.1696	R-Squared				0.5833
Sum oF squared residuals (SSR)				1010.6809	Standard error of residuals				1.2460
Log Likelihood				1007.0705	Var(Nolin)/Var(Lin)				0.9373
AIC				48.1704					
BIC				131.4721					

Table 10: *No remaining non-linearity test for residuals of DINF model*

Prueba	Num	Den	F-Stat	P-Value
Eitrheim and Teräsvirta (1996)	48	601	1.0296	0.4215

Ho: No remaining non-linearity.

Table 11: *Autocorrelation test for residuals of DINF model*

Lags	F-Stat	P-Value
36	1.2542	0.1497
48	1.1228	0.2689
60	1.2721	0.0882
72	1.1957	0.1393

Ho: No autocorrelation.

Table 12: *Constant parameters test for DINF model*

Test	Num	Den	F-Stat	P-Value
LM1	34	617	0.6910	0.9079
LM2	68	583	0.8069	0.8647
LM3	102	549	0.9322	0.6631

Ho: All parameters are constant.

Table 13: *Modulus of the characteristic polynomial dominant roots of the STR model of DINF for different regimes*

$G = 0$	$G = 0.4$	$G = 0.8$	$G = 1$
0.85	0.90	0.99	1.03
0.90	0.96	1.01	1.03
0.90	0.96	1.01	1.03
0.91	0.96	1.01	1.03

G indicates the transition function. Rows are associated with the modulus of the five most dominant roots of the characteristic polynomial of the STR model for DINF.

Figure 7: *Transition variable and transition function*

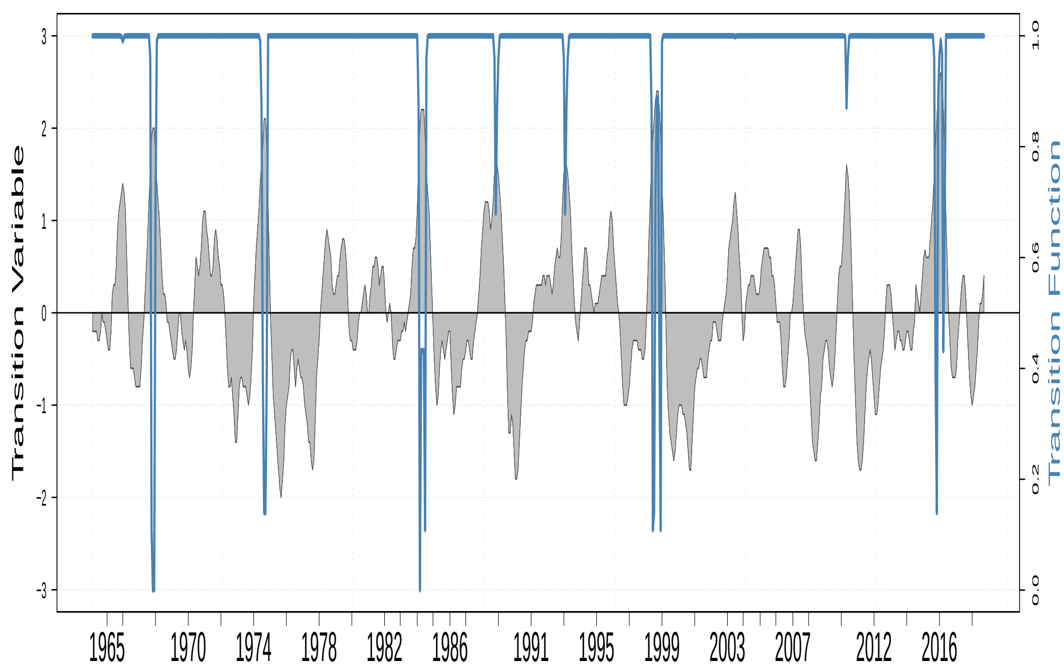
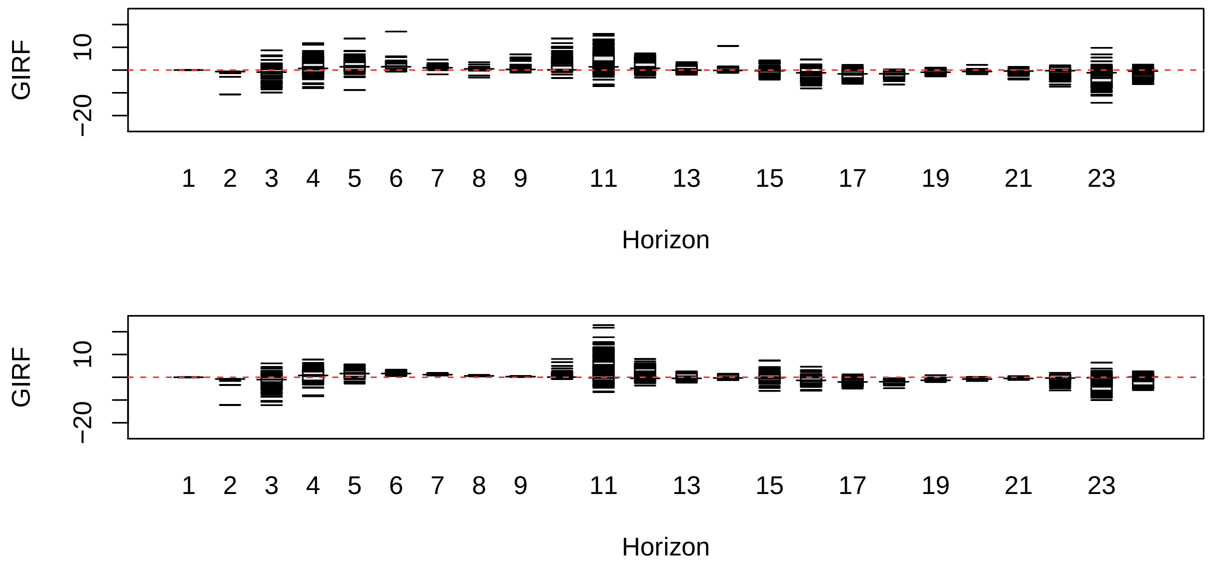


Figure 8: *GIRF with two different shocks size*



Bands of confidence are 50% *(darker shade) and* 95% *(lighter shade) and the median is the black horizontal line. The GIRFs are associated with a strong* El Niño *shock. A shock size of* 1.5 *standard deviation s.d (top panel) and* 3.0 *s.d (bottom panel).*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