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Nonlinear relationship between the weather phenomenon El niño and Colombian food prices*

Davinson Stev Abril-Salcedo, Luis Fernando Melo-Velandia and Daniel Parra-Amado†

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. Our research evaluates the relationship between ENSO and Colombian food inflation growth by using a smooth transition nonlinear model. We estimate the impacts of a strong ENSO on food inflation growth by adopting generalised impulse response functions (GIRFs). The results suggest that the weather shocks are transitory and asymmetric on inflation. A strong *El Niño* shock has a significant effect on the food inflation growth from five to nine months after the shock, and the accumulated elasticity is close to 730 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. Finally, the negative shock, associated with a strong *La Niña*, shows an ambiguous effect on food prices.

Key words: El Niño Southern Oscillation (ENSO), inflation, nonlinear smooth transition models.

1. Introduction

Despite the fact that 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 materialised significantly 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,

* The authors are, in order, Risk Director at the Fondo Nacional de Garantías (FNG), Senior Econometrician in the Econometric Unit and Research Associate in the Programming and Inflation Department at the Banco de la República(BR). The results and opinions are exclusive responsibility of the authors and those do not commit the FNG nor BR nor its board of directors. The data that support the findings of this study are available from the corresponding author upon reasonable request.

†Davinson Stev Abril-Salcedo, Luis Fernando Melo-Velandia and Daniel Parra-Amado (email: dparraa@unal.edu.co; dparraam@banrep.gov.co) are with Monetary Policy Division, Banco de la República de Colombia, Bogotá, Colombia.

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

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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 currents 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; Dell *et al.* 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. Moreover, 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 *et al.* 2017), commodity prices (Chimeli *et al.* 2008; Ubilava 2012a; Ubilava 2012b; Castro Campos 2019), impact human health (Grove and Chappell 2000; Andalón *et al.* 2016) and explain social-economic conflicts (Davis 2002; Hsiang *et al.* 2011).

Understanding relationship between climate and economy and how it affects our welfare is a relevant topic in the agenda of policymakers around the world. Even more, in recent years significant strong *El Niño* in the global warming context has occurred. Modelling and estimating those weather changes allow 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. Our research seeks to characterise the relationship between the weather phenomenon *El Niño* and the food prices for Colombian consumers. In particular, there are relevant questions that we would like to evaluate: Is there a relationship between those two variables? Is it nonlinear? Are there asymmetries in the ENSO effects on Colombian food prices? Have the impacts changed over time? Thus, our article mainly aims to provide quantitative statistical evidence and shine light on these issues.

Our research contributes to the growing literature in the economics of weather changes by modelling 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 generalised impulse response functions (GIRFs) which show a significant effect on the food inflation growth from five to nine months after the shock. For those periods, the estimation shows that a strong *El Niño* produces an increment of 209 basic points (b.p), 265 b.p, 148 b.p, 75 b.p and 33 b.p, respectively; and the accumulated impact is 730 b.p on the Colombian food inflation growth. Additional exercises show that there is no evidence of significant changes in the size of Colombian food inflation growth responses over time. We also consider a negative impact of ENSO which is linked to the *La Niña* episodes. While the *El Niño*, in general, causes an

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increase in food inflation responses, *La Niña* has an ambiguous impact on those responses which have both increases and drops in prices.

Although there is wide literature on linkages between weather and economic variables, it concentrates on long-run effects of climate change as well as weather's effects on developed countries or on specific world commodity prices. In contrast, in our approach we estimate the short-term impacts of a specific weather phenomenon on consumer aggregate prices as well as we focus on strong *El Niño* and its impacts on consumer food prices at a macroeconomic aggregate level in an emerging country like Colombia. We also contribute to weather economic literature by using information of those extreme events. An important point to note is that those effects in the most recent strong *El Niño* event of 2015/16 are understudied (Figure 1), even when many emerging countries with monetary policy based on inflation targeting schemes failed to control their inflation targets due to this shock. In our research, we include eight episodes of the strong *El Niño* since 1960 which are described in Table A1 and Figure A1.

Another technical modelling aspect that we highlight is the evidence of asymmetries in ENSO behaviour. There have been several 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 *et al.* 2003), nonlinear convective response to sea-surface temperatures (Ohba and Ueda 2009; Dommenget *et al.* 2013; Choi *et al.* 2013) and state-dependent noise acting under *El Niño* favourable conditions (Lengaigne *et al.* 2004; Jin *et al.* 2007). On the economic framework, Hall *et al.* (2001) identify disparities in the autocorrelation functions patterns which reflect ENSO asymmetries between *El Niño* and *La Niña* phases. Supporting

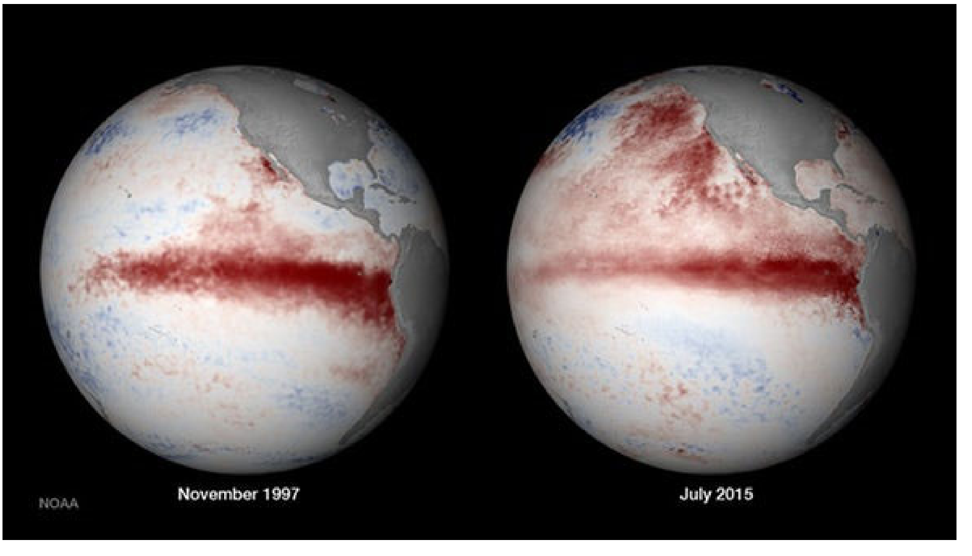

Figure 1 The two strongest *El Niño* phenomena. Source: NOAA. [Colour figure can be viewed at wileyonlinelibrary.com]

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this idea, Ubilava and Holt (2013) state an improvement in performance when modelling commodity price forecasts by using nonlinear smooth transition models compared to the traditional lineal models.

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 at 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) characterise *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 A1).

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

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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, and 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 organisation 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 were 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 *et al*. 2007; 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; Bastianin *et al*. 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*.

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 *et al*. (2016) estimate the impacts of weather conditions on Colombian food inflation growth and they 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*. On the contrary, there are reductions between 93 and 140 b.p in the *La Niña* phase. Similar to that research, we find evidence of a transitory and an asymmetric behaviour in the relationship between Colombian food prices and *El Niño* but we add impulse response functions over specific strong *El Niño* periods, including the two strongest observed at the end of the nineties and in the 2015–2016. In fact, the study of those weather extreme events was

[2] The group of food goods into the Total National Consumer Price Index.

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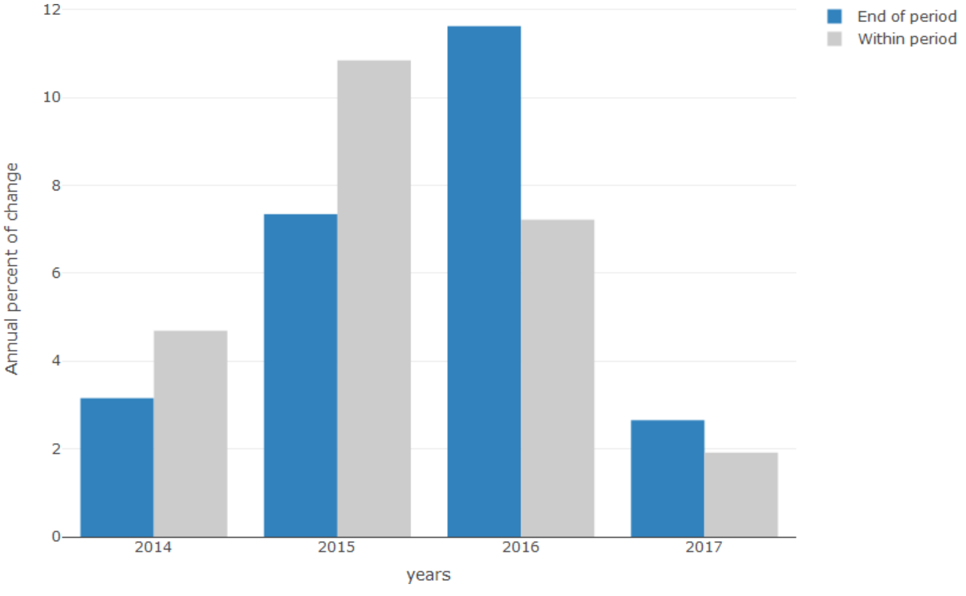

Figure 2 Colombian food inflation 2014-2017. End of period (blue) corresponds to the inflation in December and within period (grey) is defined as the inflation's average between January and December. [Colour figure can be viewed at wileyonlinelibrary.com]

relevant 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.[3] Our research quantifies the direct effect of those extreme weather conditions on Colombian food prices.

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 *et al*. 2001; Ubilava 2012b; Ubilava 2012a; Ubilava 2013; Castro Campos 2019). The STR-type models enable us to analyse 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*).

[3] There was another inflation pressure in that period which was related to significant exchange rate depreciation.

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3.1 Smooth transition model

Teräsvirta (1994) proposes the following nonlinear model:

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

where y_t is a dependent variable; $x_t = \left(1, y_{t-1}, \ldots, y_{t-p}, z_{1,t}, \ldots, z_{m,t}\right)'$ 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. $G(s_t;\gamma, c)$ is known as the transition function, by definition bound between 0 and 1, and where S_t is a transition variable, and γ and c are smoothness and location parameters, respectively. The error term is assumed to be white noise, $\varepsilon_t \sim iid\left(0, \sigma^2\right)$. The equation (1) can be specified as:

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

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; Hall *et al.* 2001) but the logistic and exponential transition functions are the two most common. These can be written as:

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

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

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 *et al.* (1988)[4]. Then, we use an auxiliary regression which can be specified as:

[4] Luukkonen *et al.* (1988). solve the nuisance parameters identification problems mentioned by Davies (1987). For instance, when γ =0 or the whole coefficients φ_2 are zero.

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$$y_t = \phi_1' x_t + \sum_{j=1}^{p} \phi_{21j}' x_t s_t + \sum_{j=1}^{p} \phi_{22j}' x_t s_t^2 + \sum_{j=1}^{p} \phi_{23j}' x_t s_t^3 + \varepsilon_t \tag{5}$$

Under the null hypothesis, we evaluate the following statistics:

$$H_{01} : \phi_{21j}' = \phi_{22j}' = \phi_{23j}' = 0\, j = 1, \ldots, p \tag{6}$$

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

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 linear 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 van Dijk *et al.* (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. When the null hypothesis is rejected Teräsvirta (1994) suggest the following procedure through a sequence of tests:

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

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 (van Dijk *et al.* 2002).

4. Empirical results

4.1 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 per cent change of the Colombian

[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.

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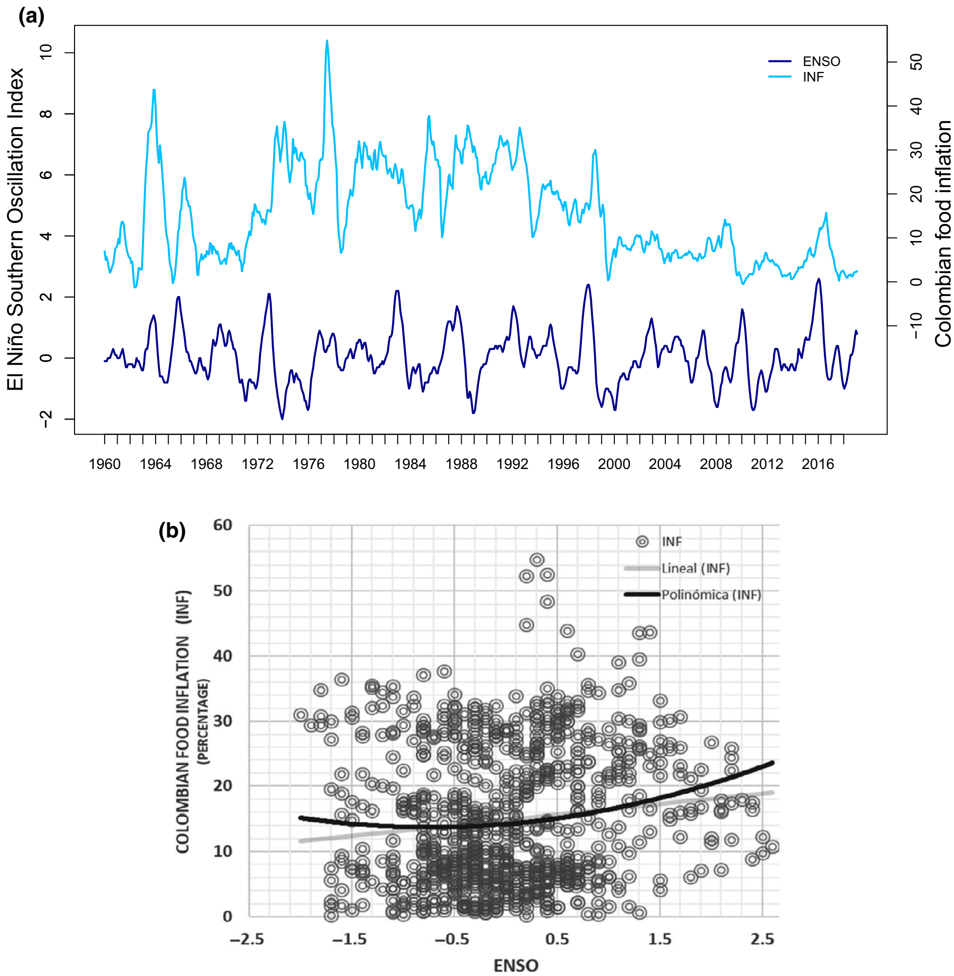

Figure 3 ENSO and Colombian food inflation 1960-2018. [Colour figure can be viewed at wileyonlinelibrary.com]

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 A1). 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.[7]

Another key feature is the observed asymmetry into ENSO-Colombian food prices relationship which will be modelled later. An initial analysis using

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

[7] We use a sample from 1962 to 2018 because it includes eight episodes of extreme events of *El Niño* as well as nonlinear models require a significant number of observations.

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the dispersion diagram (Figure 3 panel b) reflects a positive lineal trend between ENSO and INF but a *U*-shaped form when we use a polynomial trend. The *U*-shaped trend shows that *El Niño* is related to an increase of Colombian food prices regardless of the ENSO intensity level. In contrast, although *La Niña* might be associated with drops in food prices, the INF values can show an ambiguous behaviour. For instance, in some cases when the ENSO indicator took values less than -1, food prices increased or decreased according to the region of ENSO (moderate and strong *La Niña* intensities).

In the first step, we identified the order of integration of both the ENSO and the INF series, and therefore, we consider several unit root test such as Dickey and Fuller (1981), Phillips and Perron (1988), Kwiatkowski *et al.* (1992) and Elliott *et al.*(1996). These test are presented in Table B1.[8] As a result, we can conclude that the ENSO is stationary in levels while the INF series has a unit root. Thus, we transform the INF series using the first difference which can be interpreted as food inflation growth (DINF). DINF is stationary, and it is the variable used into the model STR. Taking into account that our model is nonlinear, we additionally use nonlinear unit root tests proposed by Enders and Ludlow (2002), Kapetanios *et al.* (2003) and Sollis *et al.* (1999) (Table B2). These results confirm that ENSO and DINF are stationary and FCPI and INF are non-stationary processes.

As the following step, we estimate a system that links ENSO and DINF assuming SST anomaly is weakly exogenous:

$$\begin{aligned}\mathrm{ENSO}_t = \phi_{10} + \sum_{i=1}^{p1} \phi_{1i}\mathrm{ENSO}_{t-i} + G_1(\mathrm{ENSO}_{t-d_1};\gamma_1, c_1)\\ \left(\phi_{20} + \sum_{i=1}^{p1} \phi_{2i}\mathrm{ENSO}_{t-i}\right) + \in_t\end{aligned} \tag{8}$$

$$\begin{aligned}\mathrm{DINF}_t = \varphi_{10} + \sum_{i=1}^{p2} \varphi_{1i}\mathrm{DINF}_{t-i} + \sum_{i=0}^{p3} \psi_{1i}\mathrm{ENSO}_{t-i} + G_2(\mathrm{ENSO}_{t-d_2};\gamma_2, c_2)\\ \left(\varphi_{20} + \sum_{i=1}^{p2} \varphi_{2i}\mathrm{DINF}_{t-i} + \sum_{i=0}^{p3} \psi_{2i}\mathrm{ENSO}_{t-i}\right) + \varepsilon_t\end{aligned} \tag{9}$$

where $p_1 = p_3 = 5$ and $p_2 = 24$ are the maximum lags used by ENSO and DINF in the system of equations to run different specifications and modelling seasonality patterns. However, we leave only significant values in both ENSO and DINF equations and the resulting models are presented in Table B4 and Table B9.[9] The ENSO shocks and DINF innovations are uncorrelated

[8] These tests were implemented for ENSO, Food price index (FCPI), Food inflation (INF) and Food inflation growth (DINF).

[9] The lags p_1, p_2 and p_3 were chosen according to Schwarz's Bayesian criterion.

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$(cov(\varepsilon_t, \varepsilon_t) = 0)$ which is coherent with the exogeneity assumption and provides an identification condition in the bivariate system of equations (8) and (9).

We consider a set of transition variables that include ENSO_t, ENSO_{t-1}, ENSO_{t-2}, ENSO_{t-3}, ENSO_{t-4} and ENSO_{t-5}, and we use the LM test (Luukkonen *et al.* 1988; Teräsvirta 1994) which was presented in section 3.2. The empirical results are shown in Appendix B, for ENSO equation in Table B3 and for DINF equation in Table B8. In both cases, the chosen transition variable is $ENSO_{t-3}$, and thus, we select $d_1 = d_2 = 3$ in the equations (8) and (9). In addition, we choose a LSTR specification for the ENSO transition function in (8) and an ESTR specification for the DINF transition function in (9).

As a result, the smoothness parameter and the point of inflection (threshold) are $\hat{\gamma} = 9.679$ and $\hat{c} = 1.993$ (Table B9). The γ is significant and suggests a smooth, but swift transition between regimes and the umbral $\hat{c}$ is located in the region associated with a strong *El Niño* episode. Table B13 shows the modulus of the characteristic polynomial dominant roots of the STR model of DINF. The process is stationary when the modulus is greater than one. For example, when the transition function is $G = 1$, the process is stationary since the roots are greater than one. On the contrary, when is $G = 0$, the roots are lower than one which represents an explosive behaviour. Additionally, Figure B1 shows the estimated transition function and the transition variable (ENSO_{t-3}). It suggests that the transition function takes values around zero when the transition variable stands at high and positive values, which are related to the presence of a strong *El Niño* phenomenon. This shows that when ENSO becomes high and positive, the Colombian food prices will adjust more quickly away from equilibrium as the weather conditions become more stable. In contrast, the transition function tends to one in the inner regime, which is linked to the different phases of the ENSO cycle excluding a strong *El Niño*.

By combining the Table B13 and the Figure B1, we can conclude that most of the time the process is stationary because most observations of the transition function are located around one which is linked with both the stationary process and the ENSO cycle excluding strong *El Niño* episodes. In contrast, the outer regime, for lower values of G, is associated with both the strong *El Niño* episodes and explosive behaviour.[10] An important implication is that a relatively large and positive ENSO shock, such as a strong *El Niño*, will likely cause a regimen switch which produces different paths in comparison with a scenario without shocks.

[10] As can be seen in Figure 8, the outer regime (strong *El Niño*) of DINF occurs in a few proportion of the observations (around 53 of 682 data observations). On the other hand, the transition function is grouped into values close to one in large part of the data sample which corresponds to the inner regime (remaining ENSO phases).

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A point to be careful of in the modelling process is related to the theoretical U-shaped of the exponential transition function. Given the regimes implied by the transition function of this model, it could appear economically inappropriate to assess that inflation growth (DINF) may behave differently when the ENSO measurement is around $\hat{c}$ (1.993) compared to when it is less or more than that value. However, this is not our case, a complete *U*-shaped is not feasible with our data since the observed domain of the transition variable is not far away from 1.993, this characteristic can be observed in the left panels of Figure B2.

Given this feature,[11] a plausible transition function would be the logistic one. We compare both ESTR models and LSTR models for several candidates of the transition variables. The shapes of both transition functions, ESTR and LSTR, are quite similar, as can be seen in the left panels of Figure B2.[12] In addition, the top-right and bottom-right panels in Figure B2 show that the time periods of the extreme regime are almost the same in both functions. Furthermore, both, LSRT and ESTR, transition functions have a few points in one extreme regime, this is due to the fact that both models indicate that one extreme regime is associated with a strong *El Niño* and that there are not so many observations in these episodes. Although the results of the exponential and the logistic transition functions are very similar we prefer the first ones, since the diagnostic tests of the residuals for the logistic STR model indicate that these residuals are not well behaved.

Continuing with the Exponential STR model of DINF, the residual diagnostic tests indicate that there is no model misspecification. In particular, there is no evidence of residual correlation (Table B6 and Table B12) nor parameter instability (Table B7 and Table B11) in the ENSO and the DINF equations.[13] Moreover, we find evidence of no remaining nonlinearities by using the Eitrheim and Teräsvirta, (1996) test (Table B5 and Table B10). In this test, the null hypothesis is associated with no remaining non-linearity. This test was performed for all the candidate variables which were included in the selection of the transition variable (Table B10).

As mentioned by Ubilava (2017), the estimated parameters cannot be interpreted and should not be used for constructing a regular impulse

[11] Similar results of these kinds of comparisons are given in Bessec and Fouquau (2008). They also contrast an exponential STR model with an incomplete U-Shape with a logistic STR model for studying the relationship between electricity consumption and temperature. Finally, they decide to use the exponential STR model given the features of their data.

[12] The transition variable of the logistic STR model in Figure 9 is $ENSO_{t-2}$. However, similar results are obtained when we use other lags of this variable.

[13] We use the test for parameter instability proposed by Lin and Teräsvirta (1994). We find that there is no evidence for structural change in the framework of nonlinearity models STR. Consequently, although there may be multiple regimes in our STR model, our results suggest that the estimated coefficients do not change over time.

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responses function due to the presence of nonlinearities maybe producing biased over them.[14] One strategic way to solve this problem is discussed next.

4.2 Impulse response functions

To illustrate the nonlinear impacts of ENSO shocks on Colombian food inflation growth, we use a generalised impulse response function (GIRF) proposed by Koop *et al.* (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:

$$\mathrm{GIFR}_y(h, \delta, \omega_{t-1}) = E[y_{t+h}|\varepsilon_t = \delta, \omega_{t-1}] - E[y_{t+h}|\omega_{t-1}] \tag{10}$$

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 realisations of the random variables ε_t and Ω_{t-1} we define the $\mathrm{GIRF}_y(h, \delta, \omega_{t-1})$ as:

$$\mathrm{GIFR}_y(h, \varepsilon_t, \Omega_{t-1}) = E[y_{t+h}|\varepsilon_t = \delta, \Omega_{t-1}] - E[y_{t+h}|\Omega_{t-1}] \tag{11}$$

In this article, Ω_{t-1} contains every history from strong *El Niño* episodes which are described in the table. We take realisations of ε_t between 1.5 and 2.6 which are the values observed in the SST anomalies series for all the strong *El Niño* episodes.[15] For a randomly sampled history from each month of these episodes (Table A1), 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 ($h = 0, \ldots, 24$) which display bands of confidence 50% (darker shade) and 80% (lighter shade) in Figures 4, 5 and 6.

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 five and nine months after ENSO shock and then are statistically null.

[14] 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’.

[15] we use a negative sign shock for ε_t in order to model the opposite phase of ENSO, a strong *La Niña*.

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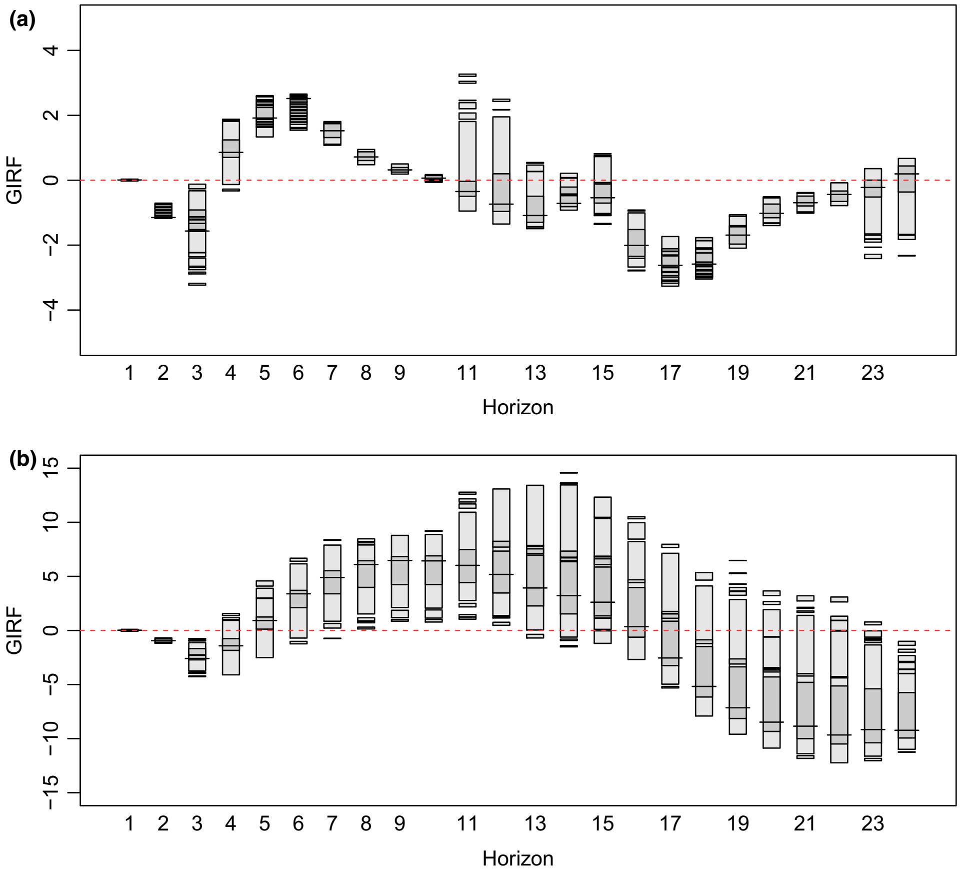

Figure 4 GIRF for DINF and INF including all the strong El Niño episodes. Upper panel corresponds to GIRF for DINF series and lower panel corresponds to GIRF for INF. Bands of confidence are 50% (darker shade) and 80% (lighter shade), and the median is the black horizontal line. The GIRF is associated with a strong El Niño shock. [Colour figure can be viewed at wileyonlinelibrary.com]

Given this shock, the Colombian food inflation growth increases by 209 b.p, 265 b.p, 148 b.p, 75 b.p and 33 b.p for each month.[16] The accumulated impact is close to 730 b.p. Although our model is implemented on DINF, some economic analysts can be concerned about inflation (INF). For this purpose, we integrated the GIRF of DINF. As can be seen in the right panel of Figure 4, the INF responses are significant one semester after the shock occurrence. In particular, the maximum impact is around 600 and 650 b.p between 8 and 9 months after the 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*

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

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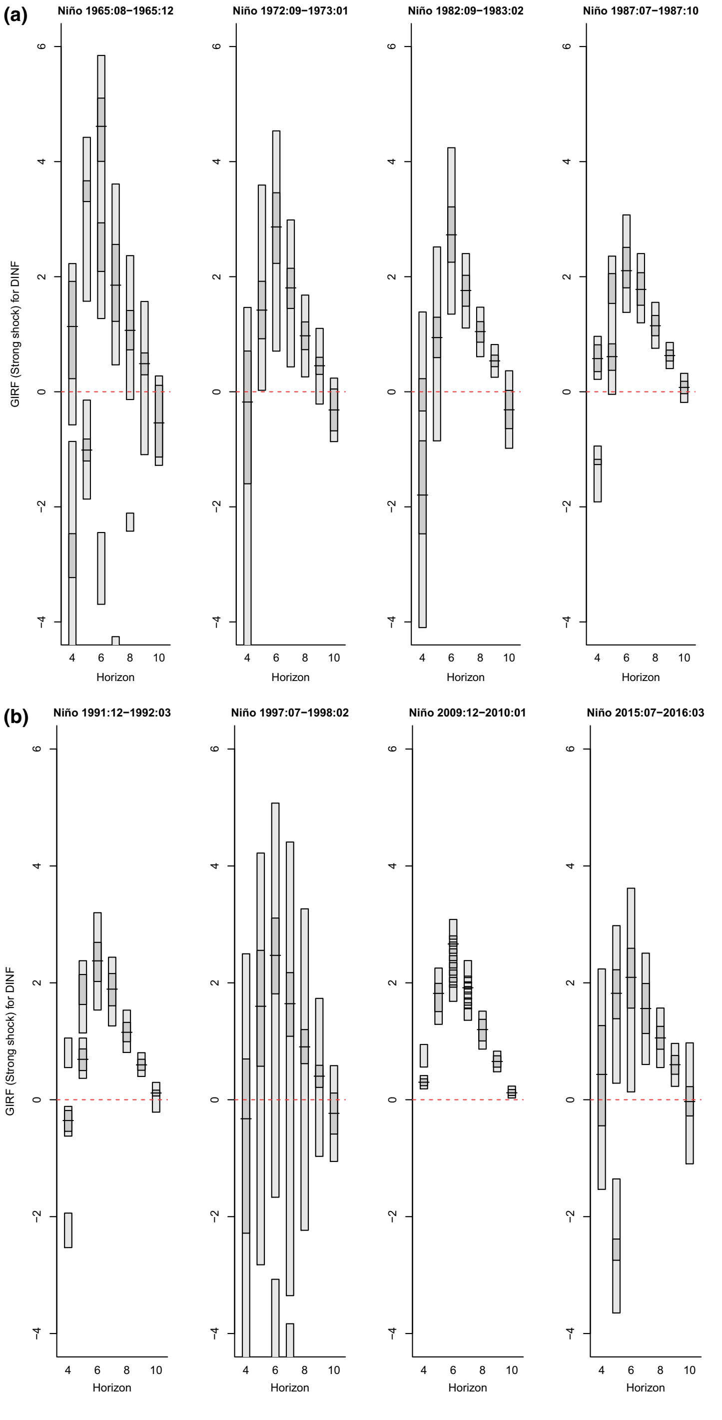

Figure 5 Comparing GIRF for DINF over different periods. Bands of confidence are 50% (darker shade) and 80% (lighter shade), and the median is the black horizontal line. The GIRF is associated with a strong El Niño shock. [Colour figure can be viewed at wileyonlinelibrary.com]

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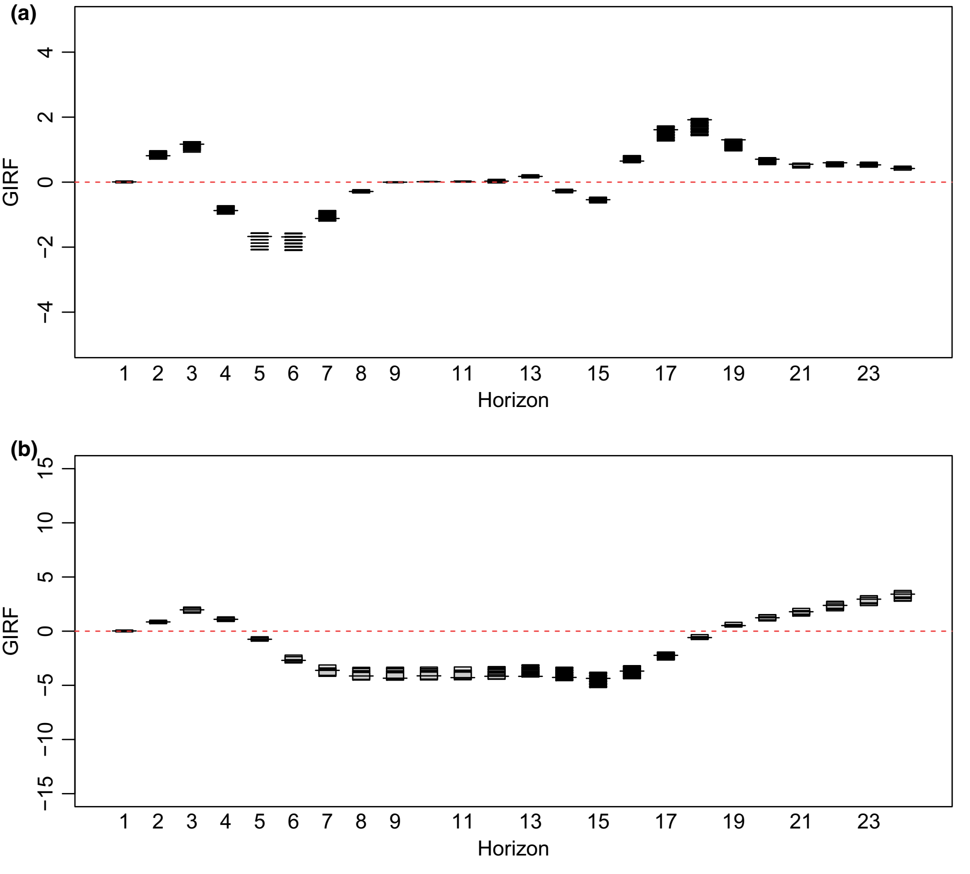

Figure 6 GIRF for DINF and INF in the opposite case (a strong La Niña). Upper panel corresponds to GIRF for DINF series and lower panel corresponds to GIRF for INF. Bands of confidence are 50% (darker shade) and 80% (lighter shade), and the median is the black horizontal line. The GIRF is associated with a strong La Niña shock. [Colour figure can be viewed at wileyonlinelibrary.com]

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

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the last strong *El Niño* during 2015-2016, Colombian food inflation growth had a significant impact between five and nine months after the shock and the accumulated effect was around 700 b.p which is similar to the observed changes of food prices (Figure 2).

Furthermore, as it is usual in nonlinear models, there are two types of potential asymmetries: i) the response 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 and ii) the GIRFs after a strong positive shock (*El Niño*) are not mirror images of the GIRFs after a strong negative shock (*La Niña*). As can be seen in GIRF responses both DINF and INF (Figures 4 and 6), the pattern during *La Niña* is completely different throughout *El Niño* in terms of the path that food prices follow over time. It is important to highlight that the magnitudes in GIRF responses of a strong *El Niño* are significantly higher than those presented in GIRF from a strong *La Niña* (in absolute values). For example, taking the INF response (in absolute value) for horizon 8, that magnitude is close to 450 b.p in the *La Niña* case while it is around 600 b.p in the *El Niño* case. However, the impacts of *La Niña* have a longer duration in the time horizon in relation to *El Niño*.

On the other hand, INF responses are significant between six and twelve months after the shock occurrence in the *El Niño* phase in comparison with *La Niña* episode where those responses are significant from the starting point to one year and half later. Other result observed in the estimated GIRFs is the ambiguity in the signs of the responses for a negative shocks associated with strong *La Niña* episodes. In this regard, there is no consensus in the literature about the final impact of a strong La Niña. For example, in the case of Rice, Iizumi *et al*. (2014) find an ambiguous effect of *La Niña* on crop yield in Brazil and Indonesia, whereas that Chen *et al*. (2008) conclude that this impact is negative for these countries and other Asian economies[17], and positive in Vietnam. This ambiguity can also be noted for wheat and maize crops in Chen and McCarl (2000).[18]

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 an 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

[17] Korea and Philippines

[18] Abdolrahimi (2016) has a survey of *El Niño* and *La Niña* impacts on yield crops for different cereal products such as maize, rice and wheat. In addition, Adams *et al*. (2003) and Travasso *et al*. (2003) are articles on this subject for other Latin American countries.

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their consequences. Also, food markets could have consequences on macroeconomy and microeconomic levels in terms of household welfare 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 is best characterised by a nonlinear modelling framework. There is evidence that support the election of STR specifications for each variable which is consistent with earlier literature findings. We use the exogenous feature of ENSO over Colombian food inflation to model how his variations over time changes according to 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 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 265 b.p. In addition, the accumulated elasticity of food prices to ENSO shock is close to 730 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 modelling that allow forecasting strong ENSO events (Zhang *et al.*2017 and Chen *et al.* 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 programmes 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 *et al.* 2017 and Gonz ez *et al.*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.

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

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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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Appendix A

Characteristics of the strong El Niño phenomena

Table A1 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.

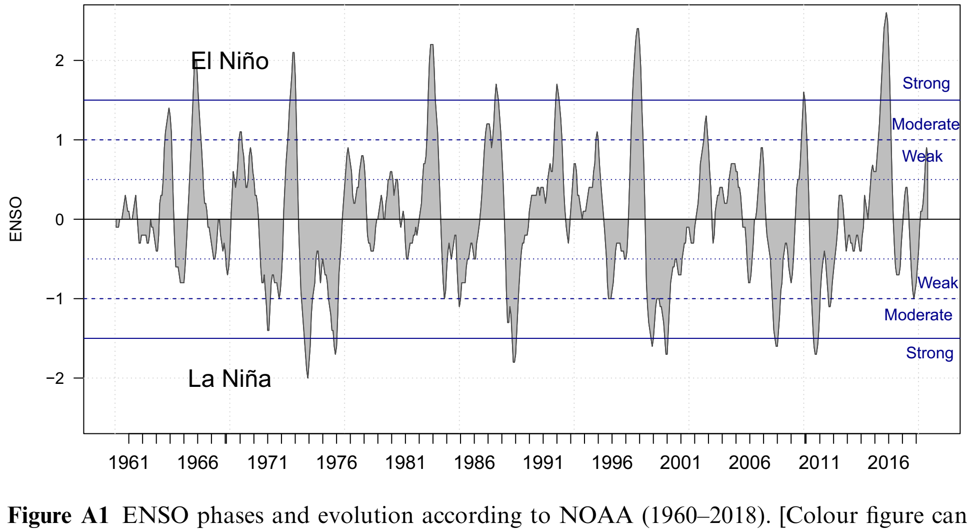

Figure A1 ENSO phases and evolution according to NOAA (1960–2018). [Colour figure can be viewed at wileyonlinelibrary.com]

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Appendix B

Diagnostic test and estimation results

Table B1 Linear unit root tests

	Augmented Dickey–Fuller (ADF)	Elliot, Rothenberg and Stock (ADF-GLS)	KPSS	Phillips and Perron (PP)
ENSO	−8.311	−8.21	0.049	−4.738
CV at 5%	(−2.86)	(−1.94)	(0.463)	(−2.866)
CV at 1%	(−3.43)	(−2.57)	(0.739)	(−3.442)
Food CPI	−0.342	−0.286	2.529	−0.209
CV at 5%	(−3.41)	(−2.89)	(0.146)	(−3.418)
CV at 1%	(−3.96)	(−3.48)	(0.216)	(−3.976)
INF	−1.784	−1.356	2.644	−3.013
CV at 5%	(−2.86)	(−1.94)	(0.463)	(−2.866)
CV at 1%	(−3.43)	(−2.57)	(0.739)	(−3.442)
DINF	−7.211	−5.32	0.035	−13.933
CV at 5%	(−2.86)	(−1.94)	(0.463)	(−2.866)
CV at 1%	(−3.43)	(−2.57)	(0.739)	(−3.442)

CV, critical values.

Table B2 Nonlinear unit root tests

	Enders and Ludlow, (2002)				Kapetanios *et al.* (2003)	Sollis *et al.* (1999)
	F_{all}	F_{trig}	c	cr		
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.

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Table B3 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 H_{01} test.

Table B4 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					Non linear component				
	Coef.	STD	*Z*	*P*-value		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 B5 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 B6 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.

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Table B7 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 B8 Non-linearity LM test for DINF

s_t	H_{01}	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 H_{01} test.

Table B9 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					Nonlinear 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

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Table B10 No remaining non-linearity test for residuals of DINF model using different candidate transition variables

Transition variable	F-Stat	*P*-Value
$ENSO_t$	0.9949	0.487
$ENSO_{t-1}$	1.0735	0.343
$ENSO_{t-2}$	1.1012	0.31
$ENSO_{t-3}$	1.1243	0.268
$ENSO_{t-4}$	1.2498	0.127
$ENSO_{t-5}$	1.3575	0.055

Eitrheim and Teräsvirta (1996).
Ho, No remaining non-linearity.

Table B11 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 B12 Autocorrelation test for residuals of DINF model

Lags	*F*-Stat	*P*-Value
1	0.0467	0.829
2	0.0540	0.947
3	0.1109	0.954
4	0.1164	0.977
5	0.0965	0.993
6	0.0814	0.998
7	0.1031	0.998
8	0.1447	0.997
9	0.2719	0.982
10	0.2462	0.991
11	0.2410	0.995
12	0.5369	0.891
36	1.2542	0.1497
48	1.1228	0.2689
60	1.2721	0.0882
72	1.1957	0.1393

Ho, No autocorrelation.

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Table B13 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 four most dominant roots of the characteristic polynomial of the STR model for DINF.

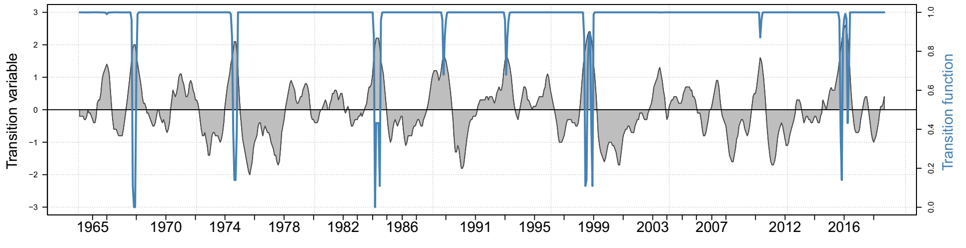

Figure B1 Transition variable and transition function. [Colour figure can be viewed at wileyonlinelibrary.com]

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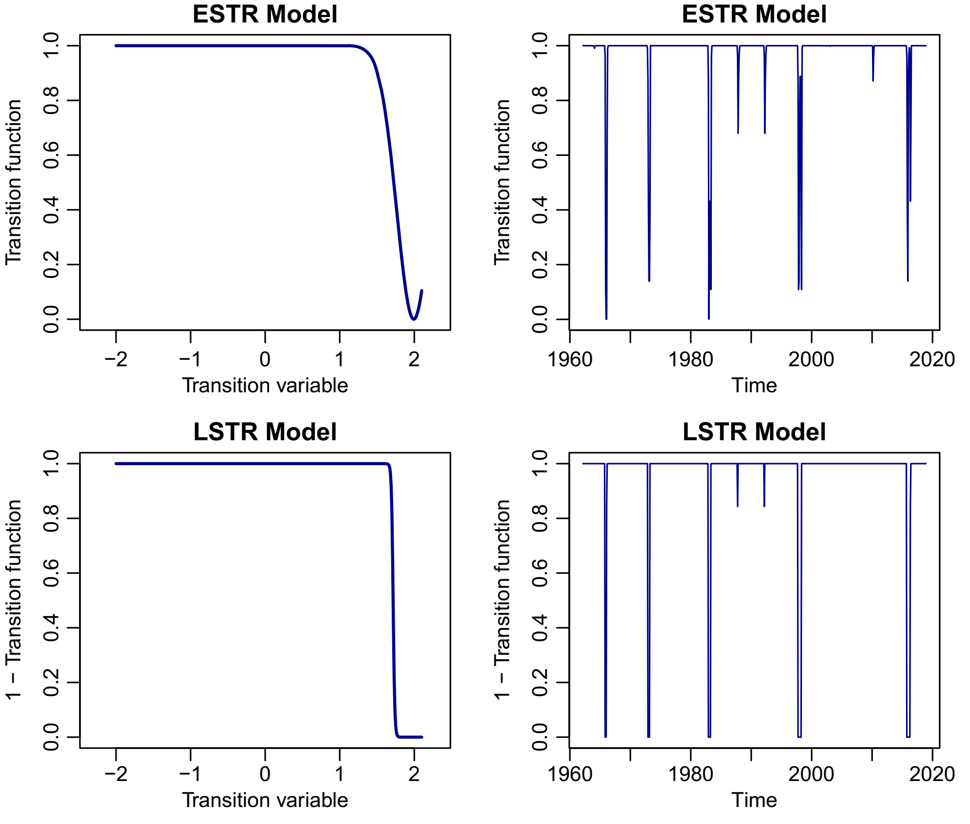

Figure B2 Comparison between ESTR and LSTR specifications. [Colour figure can be viewed at wileyonlinelibrary.com]

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