Nonlinear relationship between the weather phenomenon El Niño and Colombian food prices

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Outline

- Introduction
- Previous research
- Data and Methodology
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- Final remarks

Facts

- 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
- 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.
- According to FAO[2] more than 60 million people around the globe is affected by El Niño-related droughts, floods and extreme hot and cold weather (agriculture, food security, health and nutritional status).
- The weather changes have a lot of consequences on society in terms of food security, nutrition, health, prices and production ([Brunner, 2002], [Berry and Okulicz-Kozaryn, 2008], [Cashin et al., 2017]) and Ubilava2012a,Ubilava2012b).

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

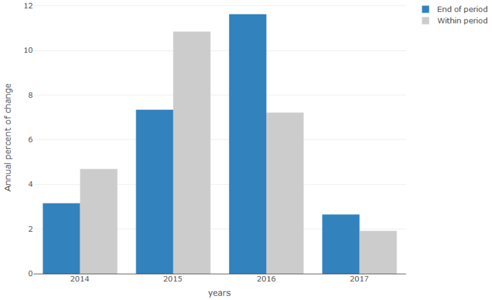
[2] FAO: Food and Agriculture Organization.

Why is this topic important for CBs?

- *El niño* has a significant impact on agricultural production and food prices ([Tol, 2009] and [Dell et al., 2014]).
- *El Niño* is linked with lower agricultural production growth rates and an increase in prices.
- In emerging countries the share of food goods in CPI is high, then *El Niño* affects significantly inflation and GDP as well as society welfare.

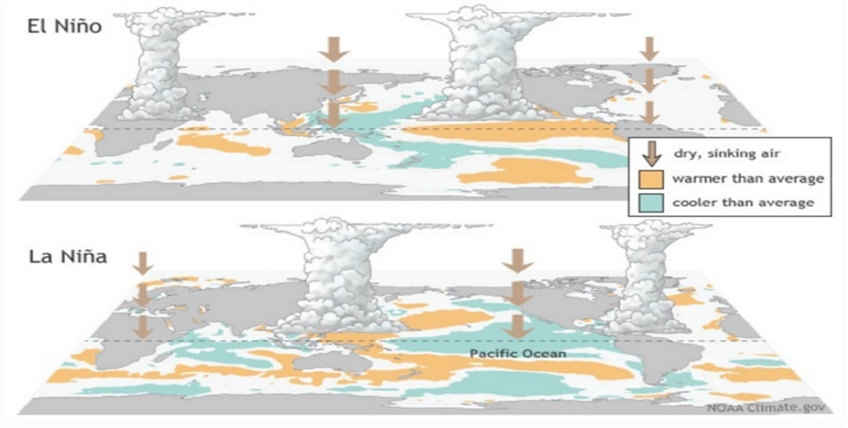
Although it is a supply shock, understanding *El Niño* allows CBs not to overreact by tightening the monetary stance.

Figura: Colombian food inflation 2014-2017



El Niño Southern Oscillation (ENSO): key features

- ENSO is a natural feature of the global climate cycle which oscillates between extreme events named *El Niño* and *La Niña*.
- ENSO occurs as a result of periodic fluctuation in atmosphere air pressure and in SEA SURFACE TEMPERATURE (SST)
- An important measure of these phenomena is: El Niño Southern Oscillation Index (ENSO), that measures SST of the central pacific ocean in the 3.4 region.



El Niño Southern Oscillation (ENSO): key features

There have been various theories in the climatology literature to explain the underlying physics of strong *El Niño* events that explain non-linear features of ENSO:

- Oceanic nonlinear advection ([Timmermann et al., 2003])
- Nonlinear convective response to SST ([Ohba and Ueda, 2009], [Dommenget et al., 2013] and [Choi et al., 2013])
- State dependent noise acting under *El Niño* favorable conditions ([Lengaigne et al., 2004] and [Jin et al., 2007])

Previous research about the relation between weather and prices

- [Hall et al., 2001] identify disparities in the autocorrelation functions patterns which reflect ENSO asymmetries between *El Niño* and *La Niña* phases.
- [Ubilava and Holt, 2013] state an improvement in performance modeling of commodity price forecasts by using nonlinear smooth transition models compared to the traditional lineal models (vegetable oil prices).
  - [Ubilava, 2012b] estimates a STAR model for coffe prices and ENSO.
  - [Ubilava, 2012a] uses a STAR model for soybean-to-corn price ratio.

Purpose of the research

- The goal of this paper is to estimate the impacts of a strong *El Niño* phenomenon on Colombian food inflation growth.
- Modeling the nonlinear relationship between ENSO and Colombian food inflation growth.
- We use generalized impulse response functions for a non-linear smooth transition model (STR) that includes food inflation and the SST index (ENSO)

Data

- Sample: from March 1962 to December 2018.
- Colombian consumer food inflation (INF): change from one year to another of Food Consumer Index (DANE)
- ENSO is measured by using SST in the *El Niño* 3,4 region (NOAA)

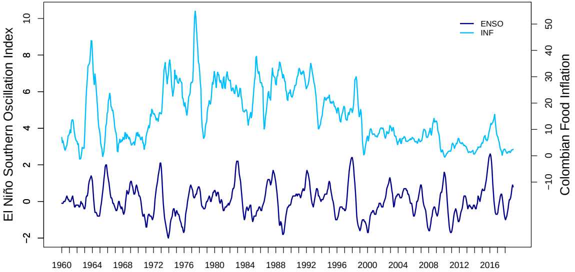
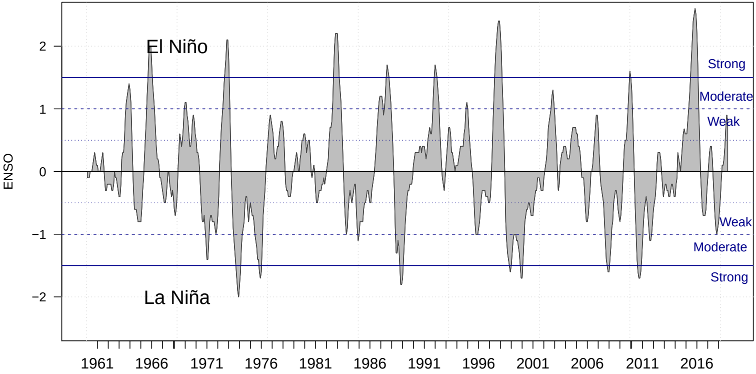


Figura: ENSO and Colombian food inflation 1960-2018

ENSO phases and evolution according to NOAA (1960-2018)



Non Linear Unit Root tests

- ENSO is stationary in levels
- INF series has a unit root.
- We transform the INF series using the first difference which can be interpreted as food inflation growth (DINF).

	[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.

Model

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

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

with

$$G_1(s_t; \gamma, \mathbf{c}) = \left[1 + \exp\left(- \left(\frac{\gamma}{\sigma_{s_t}} \right) (s_t - c) \right) \right]^{-1}, \quad (3)$$

$$G_2(s_t; \gamma, \mathbf{c}) = 1 - \exp\left[- \left(\frac{\gamma}{\sigma_{s_t}^2} \right) (s_t - \mathbf{c})^2 \right], \quad (4)$$

STR estimation for the first difference of food inflation (DINF)

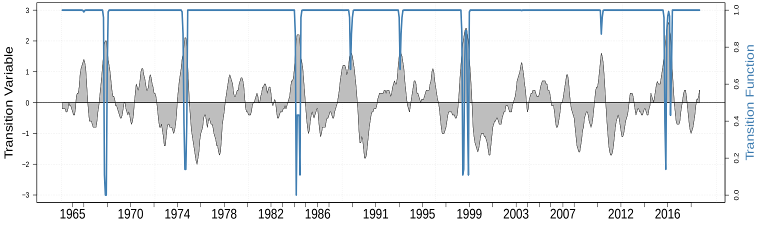
Dependent Variable: first difference of Food Inflation (DINF)				
Transition Variable: $ENSO_{t-3}$				
	Coef.	STD	Z	p-value
γ	9.679	2.200	4.400	0.000
c	1.993	0.041	48.199	0.000

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		

Some results of the STR model for DINF

Figura: Transition variable and transition function



Cuadro: 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.

Generalized impulse response function (GIRF)

- In our model, GIRF is used to quantify the dynamic response in DINF to shocks in ENSO. It is defined as:

$$GIRF(h, \delta, \omega_{t-\mathbf{1}}) = E[DINF_{t+h}|ENSO_t = \delta, \omega_{t-\mathbf{1}}] - E[DINF_{t+h}|\omega_{t-\mathbf{1}}] \quad (5)$$

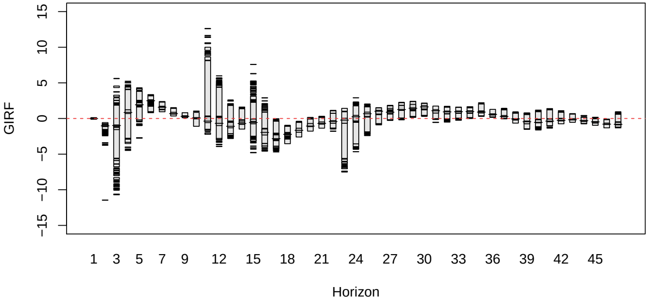
  where δ is a given shock in ENSO and ω_{t-1} is a specific history.
- This methodology incorporates the characteristic of non-linear models in the impulse response function which enables to model asymmetries in terms of sign and size of the shocks.
- It also depends on the timing of the shocks.
- Given the multi-modal behavior of the GIRF, High Density Regions (HDR) must be used instead of confidence intervals.

Shocks and histories definitions

- We take realizations of $ENSO_t = \delta$ between 1,5 to 2,6.
- For a randomly-sampled history from each month of *El Niño* episodes, 100 bootstrap projections of ENSO equation are computed with and without shocks at initial moment ($h = 0$).
- We incorporate those shocks and make a similar process into the DINF equation.
- We can construct HDRs of the GIRFs at different horizons ($h = 0, \ldots, 48$) which display bands of confidence 50 % (darker shade) and 95 % (lighter shade) in the next figures.

GIRF for DINF (all sample)

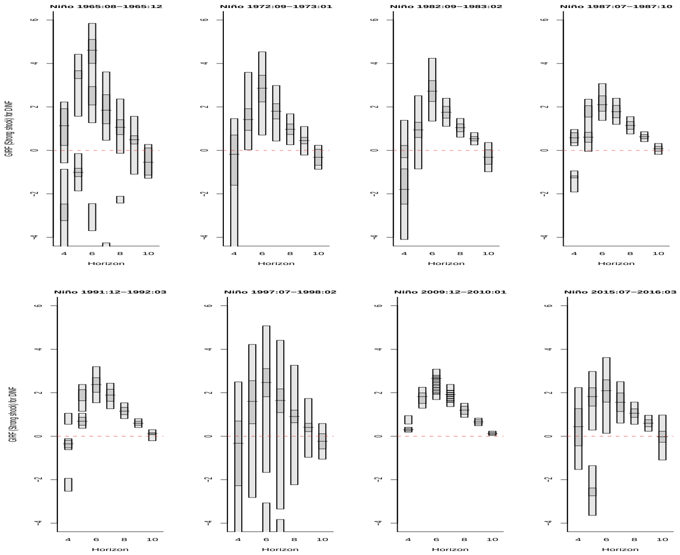
The responses of DINF are significant between six and nine months after ENSO shock. The accumulated effect was 465 b.p.



*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.

Comparing GIRF for DINF over different periods

The responses do not change statistically over time.



GIRF: General results

- As we expected, weather shocks like ENSO affect the Colombian food prices.
- We found evidence of non-linear relationship between ENSO and Colombian food prices.
- The responses of DINF are significant between six and nine months after ENSO shock.
- The ENSO shocks are transitory on inflation responses.
- The responses do not change statistically over time.

GIRF: Quantification

- Thus, the Colombian food inflation growth increase by 209 b.p, 148 b.p, 75 b.p and 33 b.p for each month.
- The maximum impact is reached in the six month where the effect is calculated in 209 b.p.
- The accumulated impact is close to 465 b.p.

GIRF Results: Asymmetries

There are two types of asymmetries in our results:

- The GIRFs after a positive shock (*El Niño*) are not mirror images of the GIRFs after a negative shock (*La Niña*). The response of DINF to *El Niño* shock is greater than *La Niña* effect.
- 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.

GIRF Results: dynamic behaviour

- 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.

Non-linearity LM test

Cuadro: Non-linearity LM test for ENSO equation

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.

Cuadro: Non-linearity LM test for DINF equation

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.

Misspecification test for DINF equation

Cuadro: 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.

Cuadro: 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.

Cuadro: 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.

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