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Extreme weather events and high Colombian food prices: A non-stationary extreme value approach

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Abstract

Given the importance of climate change and the increase of its severity under extreme weather events, we analyze the main drivers of high food prices in Colombia between 1985 and 2020 focusing on extreme weather shocks like a strong *El Niño*. We estimate a non-stationary extreme value model for Colombian food prices. Our findings suggest that perishable foods are more exposed to extreme weather conditions in comparison to processed foods. In fact, an extremely low precipitation level explains only high prices in perishable foods. The risk of high perishable food prices is significantly larger for low rainfall levels (dry seasons) compared to high precipitation levels (rainy seasons). This risk gradually results in higher perishable food prices. It is non linear and is also significantly larger than the risk related to changes in the US dollar-Colombian peso exchange rate and fuel prices. Those covariates also explain high prices for both perishable and processed foods. Finally, we find that the events associated with the strongest *El Niño* in 1988 and 2016 are expected to reoccur once every 50 years.

JEL codes: C32, C50, E31.

keywords: Extreme weather events, Extreme value theory, Food inflation, Return levels, Relative Risk ratio

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Eventos climáticos extremos y altos precios de alimentos en Colombia: Una aproximación no estacionaria de teoría de valor extremo.

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Resumen

Dada la importancia del cambio climático y su impacto sobre la ocurrencia de eventos climáticos extremos, se analizan los principales determinantes que explican altos precios de alimentos en Colombia entre 1985 y 2020 haciendo énfasis sobre los choques extremos climáticos como por ejemplo un fenómeno de *El Niño* fuerte. Se estima un modelo no estacionario de valores extremos para los precios de alimentos en Colombia y se encuentra evidencia que sugiere que aquellos bienes perecederos son los más expuestos a las condiciones climáticas en comparación con bienes de alimentos procesados. El riesgo asociado a altos precios de alimentos perecederos es significativamente más elevado para bajos niveles de precipitación (temporadas secas) comparados con altos niveles de precipitación (temporada de lluvias). Este riesgo del clima explica en buena parte los altos precios de perecederos el cual no es lineal. Adicionalmente, el riesgo asociado al factor climático es significativamente más alto a aquellos otros determinantes de altos precios como lo son la tasa de cambio peso-dólar y la dinámica de los precios de combustibles. Estas variables también explican altos precios de los alimentos tanto procesados como perecederos. Finalmente, se encuentra evidencia que sugiere que eventos como *El Niño* fuerte observados en 1988 y 2016 fueron los más extremos y las estimaciones sugieren que eventos parecidos tienen una re-ocurrencia de una vez cada 50 años.

Clasificación JEL: C32, C50, E31.

Palabras clave: Eventos climáticos extremos, Teoría de valor extremo (EVT), precios de alimentos, niveles de riesgo, razones de riesgo relativo.

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1. Introduction

One of the greatest challenges facing humanity in the 21st century will undoubtedly be the fight against climate change. It has been reflected by a significant increase in literature related to this topic in both the natural sciences and social-economic framework. In fact, climate change has become a genuinely macroeconomic anomaly due to its global nature and a recent spread in extreme weather events seen recently. In 2016 we witnessed the warmest year on record since 1850 and some weather episodes have shown greater intensity and duration. For instance, in 2015-2016, as reported by the National Oceanic and Atmospheric Administration (NOAA), mankind also faced the most severe weather phenomenon *El Niño* of the last century.

According to the Food and Agriculture Organization of the United Nations (FAO), more than 60 million people around the globe are affected by the *El Niño* Southern Oscillation (ENSO) cycle,[1] and its impact varies depending on the geographical region.[2] FAO (2016) indicates agriculture is the most influenced sector, absorbing around 84 percent of the whole economic impact. Although there is no exact estimation of the economic costs of the ENSO in 2015-16, the World Bank (WB) established that the second strongest ENSO in 1997-98 killed almost 21,000 people and caused damage to infrastructure worth US$ 36 billion.[3]

ENSO not only has a significant impact on weather conditions, but it also affects agricultural production and food prices which has been broadly evidenced in the economic literature (Laosuthi & Selover (2007), Tol (2009), Dell et al. (2014), Smith & Ubilava (2017)). In developing countries,[4] the ENSO warmer phase known as *El Niño* is associated with drops in agricultural production and increases in food prices (Cashin et al. (2017), Acevedo et al. (2020)).

WB (2015) shows how the global commodity price markets are affected by ENSO, emphasizing that its impact is highly heterogeneous across regions and types of commodities. For instance, Brunner (2002) estimates that a one-standard deviation weather shock during *El Niño* generates an increase of between 3.5% and 4% on real agricultural commodity prices. Ubilava & Holt (2013) analyze the world prices for vegetable oil and its relationship with ENSO; they report evidence of increasing prices during *El Niño*. On the contrary, Ubilava (2017) concludes that a shock of *El Niño* results in a decrease of world wheat prices, and Ubilava (2012) and Sephton (2019) find that an *El Niño* shock is linked to a reduction of coffee prices (Ubilava (2012), Sephton (2019)).

Although there is extensive literature on weather patterns and international food prices (like the previous ones), there are few studies of weather implications on local prices and local weather conditions. For instance, a stylized fact is that food inflation in developing countries rises more than in developed countries (WB (2015)), which is probably due to a larger impact of ENSO on local weather conditions in more isolated local food markets compared to those foods that could be obtained in the international markets. In fact, Brown & Kshirsagar (2015) show evidence that weather shocks tend to have a greater effect on domestic prices in a significant number of maize markets in developing countries. In particular, the authors find that around 20% of local market prices were affected by domestic weather disturbances in the short run and 9% affected by international price changes between 2008 and 2012.

On the other hand, a large range of literature suggests that in the course of the current climate change, extreme weather events are more likely to occur (Hao et al. (2013), Herring et al. (2018), Wang et al. (2019)). To model this, scientists usually use methodologies like *Extreme Value Theory* (EVT) which provides the basis for estimating the magnitude and frequency of hazardous events (Coles et al. (2001)). EVT allows to classify extreme events which can be defined by either very small or very large values and, then, it enables to model and measure those events which occur with a very small probability. Subsequently, before approaching to the empirical framework some issues must be pointed out: i) How do you define which observation is an extreme event?, ii) Which assumptions allow modeling weather patterns in a more appropriate way taking into consideration climate change context? and iii) How can risk be measured?

First, EVT consists of two fundamental methods to select a an extreme value which are Block Maxima (BM) and peak-over-threshold (POT). On the one hand, BM identifies the maximum of all recorded values in a given period. For example, for an annual block, the sample size of observations defined as extreme events is equal to the number of years of data. On the other hand, POT is used to describe extremes above a predefined threshold. In order to fit a stochastic model for those extreme observations, the former method uses the Generalized Extreme Value distribution (GEV), while the latter utilize the Generalized Pareto distribution (GP). In section 3.1, we review the main features of EVT and the type of distribution used in this article.

Second, EVT works on the assumption that events under study are independent and identically distributed which is framed within the stationarity analysis. However, this assumption has been criticized and questioned in the current climate change environment because the global warming process is not only changing the temperature and weather patterns around the world

[1] ENSO is a recurring climate pattern involving changes in the temperature of waters in the central and eastern tropical Pacific Ocean. The oscillating warming (*El Niño*) and cooling (*La Niña*) pattern, referred to as the ENSO cycle. For example, when the *El Niño* (*La Niña*) happens, the sea surface temperatures are greater than average. On the contrary, in a *La Niña* phase temperatures are lower than average.

[2] Depending on the geographical area and the phase of the climatic phenomenon (*El Niño* or *La Niña*), the countries face droughts, floods and extreme hot and cold weather. According to NOAA, The *El Niño* Southern Oscillation (ENSO) cycle is a periodic climatic phenomenon that refers to a warming of the Central and Eastern Pacific, affecting the atmosphere and weather patterns.

[3] `https://reliefweb.int/report/world/2015-2016-el-ni-o-wfp-and-fao-overview-2-february-2016`

[4] This is particularly true for countries located in the equatorial region.

(*on average*), but it is also changing the magnitude, frequency and intensity of extreme events (IPCC (2007), Malesios et al. (2020)). Milly et al. (2008) have promoted the idea of moving away from stationary models to guarantee that the changing properties of the extremes are captured. Therefore, the presence of non-stationarities must be included into the analysis when climate change is incorporated into local weather patterns. It is important to point out that the conjunction between EVT and *non-stationarities* is very useful in climatic and hydrologic fields (Cooley (2009), Cooley (2013), Salas & Obeysekera (2014) and Salas et al. (2018)).[5] In section 3.2, we present how the statistical distribution changes in both the *stationary* and *non-stationary* cases.

Third, policy makers improve their process of decision-making by assessing and mitigating risk, and incorporating critical information for policy design. These extreme values are relevant given that risk assessment is based on events located in the tails of the distribution of losses. Given climate change evolution, we expect an increase of extreme weather events in both global and local conditions which could lead to a considerable deterioration in agricultural production (losses). A very common tool is risk assessment which includes concepts such as *Value at Risk*, *Return period* or *Return level*. In section 3.3, we show the risk measures used in this article.

Our research contributes to the growing literature in the field of economics and climate by modelling the presence of a relationship between Colombian food prices and the domestic weather events measured by Colombian rainfall levels.[6]. In this context, the present study tries to shed light on the main drivers of high Colombian food prices by using the information of precipitation and other traditional drivers found in economic literature such as fuel prices (Tadesse et al. (2014), Taghizadeh-Hesary et al. (2019)) and exchange rates (Gilbert (2010), Baffes & Dennis (2013)).[7] In other words, our main objective is focusing on how extreme weather events impact Colombian food prices and quantifying a measure of risk of such events in the medium and long term. Simultaneously, we investigate the impact of several exogenous variables on high Colombian food prices. Considering the non-stationary setting of weather events in the climate change context, as it was mentioned before, another important feature to highlight regarding our contributions is that we estimate a non-stationary EVT model which helps to understand some determinants of high food prices in Colombia. We focus on two groups of local food prices: Perishable and Processed foods.

To the best of our knowledge, there are no documents that model weather variables and their impact on local food prices using a non-stationary extreme value approach,[8] neither measuring the relative risk of a high food prices caused by extreme weather events.[9] Unlike many studies, we focus our attention on local conditions in Colombia both in terms of domestic food prices and its own weather patterns which are affected by ENSO[10] and the global warming process. Overall, a lot of policy institutions not only need to understand climate change and weather patterns but they also need to assess how those changes are related to economic variables such as local food prices as well as the implications of extreme weather events over time on the economy. In section 4, we offer some findings and statistics in this field by taking Colombia as a case study.

This article is organized as follows. In the next section, we show empirical evidence from Colombian data and its links with weather conditions. In section 3, we introduce the methodology and present the measure of *Return level* which is used to assess high Colombian food prices caused specifically by extreme weather events. In section 4, we introduce the data, the model and its empirical approach, test for fit accuracy and the main results and findings. Our conclusions are drawn in the final section.

2. Weather events and Colombian economy

Although climate change has impacts on a global level,[11] there are disparities between regions with regard to the way these impacts are transmitted to the environment, which can be determined by seasonal patterns, geographic location or any other country particularity. In the Colombian case, the most common weather phenomenon is ENSO, which occurs irregularly[12] but whose presence generates significant impacts on the economy

[5]Olsen et al. (1998) introduced the approach of return period and flood risk under non-stationary conditions which could be the first attempts to extend the usual analysis of stationary risk.

[6]Statistical models that introduce precipitation are notably useful for studying issues related to those that arise with climate change (Karimi et al. (2021)) or explanations of trends in the weather patterns around the world (Moberg & Jones (2005), Alexander et al. (2006), Groisman et al. (2012))).

[7]We include other exogenous drivers such as: i) US dollar- Colombian peso exchange rate and ii) Colombian fuel prices (gasoline and others). Although there may be others drivers, we believe those are the most relevant in terms of how they affect the variability of food prices, especially on extreme events. First of all, a high proportion of the inputs used for crops are imported, such as fertilizers, which in turn are affected by the exchange rate. Secondly, the cost of transporting food between rural areas and cities also affects the food prices at country level. In order to include them, we use the fuel prices as a proxy for those costs.

[8]Most articles use EVT under the assumption of stationarity. There are few studies that blend *non-stationarities* and EVT in the economic and finance field. For example, Tiakor et al. (2017) and Dey et al. (2020) use a nonstationary extreme value approach to model crude oil prices. Other applications on stock and future prices are Romyen et al. (2019) and Zhao et al. (2020).

[9]A measure of the risk of a certain event happening in one group compared to the risk of the same event happening in another group. In the section 4.5, we will explain how we measure the relative risk in our context.

[10]Despite the fact that ENSO is a global phenomenon, throughout this article we mention it because it has a great impact on the weather patterns of Colombia's rainfall levels.

[11]It is important to note that climate change is a much more general topic than specific weather events such as *El Niño* phenomenon, but without a doubt climate change has affected and exacerbated the intensity and magnitude in which other weather events occur (hurricanes, droughts or floods). For example, Mason (2001) and Yeh et al. (2009) show evidence on the relationship between climate change and the *El Niño* phenomenon.

[12]According to the National Oceanic and Atmospheric Administration (NOAA), *El Niño* occurs roughly every 2 to 7 years, lasting from 6 to 24 months. Additionally, *El Niño* arises more frequently than *La Niña*.

and society. In fact, it has the greatest impact on the weather patterns of Colombia's rainfall levels.

ENSO shows a pattern of positive Sea Surface Temperature (SST) anomalies (anomalous warming) over the east tropical Pacific and negative SST anomalies (anomalous cooling) in the west. Regarding Climate and Colombian weather aspects, Córdoba-Machado et al. (2015) state that *El Niño* is associated with a significant decrease in rainfall over the northern, central, and western Colombia, while temperatures increase with the presence of this phenomenon. On the contrary, the cooler phase (*La Niña*) is linked with positive precipitation anomalies. In terms of physical mechanisms, there is a lot of evidence which explains how this phenomenon affects hydro-climatologic patterns in that region (Restrepo & Kjerfve (2000), Poveda et al. (2001a),Poveda et al. (2003), Tootle & Piechota (2006)). All these studies have revealed a relationship between the ENSO phenomenon and climate of Colombia, they conclude that ENSO has an earlier and stronger effect on rivers in western, northern and central Colombia, in contrast to a later and reduced effect on rivers in the eastern and southeastern regions of the country.[13]

Given the above, there are several socio-economic channels throughout ENSO which impact the Colombian economy. Droughts during *El Niño* are linked with lower agriculture production and higher food prices. Colombian agricultural economic authorities state that the *El Niño* shocks reduce agricultural production by almost 5%, which has a share of 6.5% of the Colombian Total Gross Domestic Product (GDP) (MinAgricultura (2006)). In this context, farmers face uncertainty that affects income, employment and production which in turn is reflected at a macroeconomic level. For instance, during the strong *El Niño* in 1997–1998, Colombia experienced a severe drought in over 90% of its territory and the flow of the main rivers was significantly reduced in comparison with the previous 50 years (CAF (2000)).

It is important to note that the *El Niño* in 2015–2016 was the strongest ENSO in the last century, being greater in magnitude and duration compared to that observed at the end of the nineties. In particular, Melo et al. (2017) find that Colombia might have lost around 3.1 billion pesos (930 million in US dollars) in that period. By using Colombian input-output matrices, the authors estimated an increase in the electricity prices of 4.5% and a decrease in the total GDP of approximately 0.6% caused by a 20% reduction in water flow in rivers due to *El Niño* in 2015–2016. Additionally, Martínez et al. (2017) state that the coffee crops, potatoes and rice were mainly affected due to a strong *El Niño* during 2015 and 2016. The authors noted that coffee growers lost around 90 thousand cultivated hectares which represents 18% of the total of Colombian's coffee crops. Something similar happened with the rest of the crops, as it is estimated that the loss was around 2 million hectares.

[13]Restrepo & Kjerfve (2000) conclude that ENSO explains around 64% of the variation in discharge of the Magdalena River which is the main river in Colombia.

Overall, other consequences on the Colombian economy are: i) *El Niño* leads to a drop of the national hydropower system, resulting in a rise of electricity prices and their volatility (Pantoja-Robayo (2012)), ii) an increase in SST during *El Niño* brings more warmer and drier conditions than average which weaken the behavior of fishing activities at both sea and river locations due to shifts in the salinity level of the water (Blanco et al. (2006), Blanco et al. (2007), Whitfield et al. (2019))[14] and iii) regarding health, ENSO generates an increase in several human diseases (Poveda et al. (2001b), Ordoñez-Sierra et al. (2021)).

Concerning Colombian food prices, the Central Bank (*Banco de la República*) has estimated that both the increase and volatility of the Total National Consumer Price Index (CPI) are explained between 30% and 40% by weather shocks during ENSO episodes (Caicedo (2007)). In particular, during the last strong *El Niño* between 2014 and 2016,[15] Colombian households were affected by losing part of their purchasing power when food inflation went from 3.2% in 2014 to 11.6% in 2016 (on average). Given the high share of food in the Total CPI,[16] Colombian Total inflation was over the 3% target of the Central Bank. It was 6.7% and 5.8% in December 2015 and 2016, respectively. Taking this into account, weather shocks become a risk at a macroeconomic level for the Central Bank and in this article, we try to assess the medium- and long-term risks.

Focusing on 2015 and 2016, there are a couple of empirical facts to highlight that motivate this article (Figure 1). First, international food prices known as *agriculture commodites* remained low despite the ENSO weather shock. Similarly, international crude oil prices also had a fall in 2015 and 2016 compared to 2014. Second, the Colombian fuel prices showed a drop which is closely linked to international prices. It enabled keeping transportation costs low at the local level, however, due to the fall in prices, national colombian income diminished because it depends on oil exports.

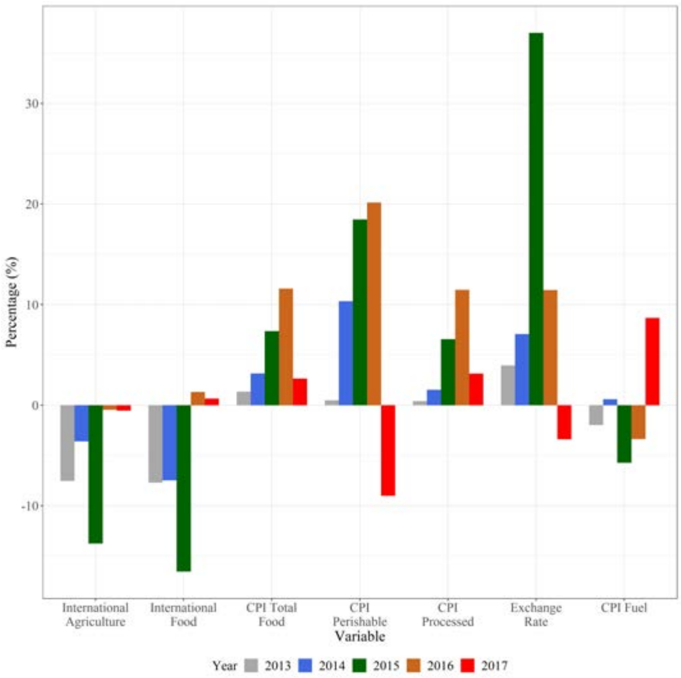
Third, lower oil revenues brought macroeconomic vulnerabilities that were reflected by an increase in country's risk premiums and later in a strong devaluation of the exchange rate. For instance, the US dollar-Colombian peso exchange rate had an average depreciation of 24% during those two years. It affected farmers through the increase in the cost of imported inputs such as fertilizers, but the evidence in this regard is scarce. As it was mentioned before, Colombian food prices rose in this

[14]Colombian Caribbean coast experienced rainfall at less than 25% of normal levels between April and October 2015, and more than 150% above normal levels from April to October 2016.

[15]According to NOAA, the El Niño started in October 2014 and ended in April 2016.

[16]In the base 2008, the share of food in Total CPI was about 30%, but this included some items called meals outside the home. In the base 2018, some items were distributed and the Food group was left in a more basic version with two groups: Perishable and Processed foods. The new classification has a share of 15% in the Total CPI. Within that Food CPI group, perishable and processed foods have a share of 20, 9% and 79, 1%, respectively.

Figure 1: Commodities food prices (IMF), Colombian fuel and food prices (CPI) and US dollar-Colombian peso exchange rate (Annual variation)



period but the interesting feature was the composition within the Colombian food CPI basket. Fourth, perishable food goods were more strongly affected than processed food goods during 2015 and 2016. For instance, Colombian consumers observed an annual increase close to 20% in those years. In other words, during that period they lost a fifth of their purchasing power related to those goods. Keeping in mind this diversity, we study the prices of both subgroups in order to understand the disparities inside food prices which might be unnoticed at an aggregate level .

Recent literature on this subject is still sparse, but it has increased the concerns of the Colombian monetary authorities about weather shocks. For instance, Abril-Salcedo et al. (2016) show evidence of transitory and asymmetric behaviour in the relationship between Colombian food prices and ENSO. The authors point out that *El Niño* has greater impacts on Colombian food prices than *La Niña*. They show impulse response functions for three ENSO's intensities: Strong, moderate and weak; they only find significance for Strong and moderate intensities. Additionally, although ENSO impacts are greater in *El Niño* episodes, the duration of weather shocks is greater in *La Niña* events. Bejarano-Salcedo et al. (2020) estimate forecasting models using both global and domestic variables of weather shocks as a proxy for ENSO.[17] They find nonlinearities between weather variables and relative food prices due to changes in the patterns of ENSO and its intensity, and they provide optimal out-sample forecasts by using different scenarios of weather variables. In this line, Abril-Salcedo et al. (2020) find nonlinearities[18], transitory and asymmetric impacts of weather shocks on food prices. They also show significant responses of Colombian food inflation growth which have an accumulated elasticity close to 730 basis points on food prices between five to nine months after a strong *El Niño* shock. Unlike this literature that estimates short-term impacts, we try to provide quantitative statistical evidence and shine light on long run risks of high Colombian food prices due to extreme weather events, local fuel prices and US dollar-Colombian peso exchange rates.

3. Methodology

In this section we explain the methodology used to analyze the impacts of extreme weather events on perishable and processed Colombian food prices. To do that, we give a brief introduction of Extreme Value Theory (EVT) in both the usual stationary and non-stationary case including covariates which help to understand the dynamics of extreme values or high values for Colombian food prices. Although weather patterns measured by Colombian rainfall level mainly explain high values of food prices, we also bring into the analysis other covariates such as US dollar-Colombian peso exchange rates and the fuel price index. Then, we present some measurements to assess risk like *Return level* and the probability of an extreme event under a non-stationary EVT approach.

3.1. Extreme Value Analysis using Block Maxima

EVT quantifies the stochastic behavior of rare events which can be considered relatively huge to the bulk of observations by fitting adequate stochastic models or probabilistic distributions to those extreme events. In this context, EVT estimates the probability of occurrence of those kinds of values that are characterized by having a low probability (Coles et al., 2001). This methodology focuses its attention on the tail of the data distribution instead of the bulk of observations.

In order to define the extreme values of a series, EVT has two main approaches: Block Maxima (BM) and Peaks Over the Threshold (POT) as we mentioned in the introduction. In this paper, we employ the former.[19] BM method splits the time series into equal time-span groups where the largest value in each of them is picked to fit a GEV distribution. Some advantages are that its implementation is simple and the series of observations

[17]The authors use the Oceanic Niño Index (ONI) measured by the National Oceanic and Atmospheric Administration (NOAA), and the Colombian rainfall level measured by the Colombian Institute of Hydrology, Meteorology and Environmental Studies (IDEAM).

[18]The authors estimate a Smooth Transition Regression model (STR) between ENSO and Colombian food inflation growth where the critical threshold corresponds to a strong *El Niño* intensity.

[19]POT method needs a larger sample size in order to adequately fit the parameters of Generalized Pareto distribution and its complexity in terms of the estimation process being than BM. Additionally, POT method often violates the *i.i.d* assumption. There a lot of studies about POT method and its comparison with BM (Engeland et al. (2004), Jarušková & Hanek (2006), Bezak et al. (2014),Szubzda & Chlebus (2020)). Although there is no consensus about which method is preferred, POT is preferable for quantile estimation, while BM is preferable for return level estimation (Bücher & Zhou (2018)).

cataloged as maximums is independent. On the contrary, its main weaknesses are related to the possible loss of information, small sample size when the data record is short, and selection of lower observations that were chosen as maximum in a period in which the time series irregularly or atypically had a behavior below the mean. There are extensive studies that acknowledge the strengths and weaknesses mentioned previously (Ferreira et al. (2015), Gomes & Guillou (2015), Rypkema & Tuljapurkar (2021)).

3.1.1. Generalized Extreme Value distribution

Let $X_1, \ldots, X_n$ be the sequence of random variables that are independent and identically distributed. So, the maximum of this process, $M_n = \max\{X_1, \ldots, X_n\}$, has the following distribution:

$$P\{(M_n - b_n)/a_n \leqslant z\} \rightarrow G(z)$$

where $\{a_n > 0\}$ and $\{b_n\}$ are sequences of normalizing constants, and G is the generalized extreme value (GEV) distribution function with the form:

$$G(z) = \exp\left\{-\left[1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{1}$$

where μ, σ, and ξ are the location, scale, and shape parameters, respectively, with $\sigma > 0$. When $\xi > 0$ the distribution is heavy-tailed Fréchet. If $\xi < 0$, the distribution is upper bounded Weibull and belongs to the Gumbel family if $\xi = 0$.

3.2. The non-stationary case

There are some cases when the extremes, $\{M_n\}$, do not follow a stationary process and change through time due to shifts in driving forces, regimes or patterns. In the non-stationary EVT context, the parameters of the GEV can be expressed as a function of covariates (Galiatsatou & Prinos (2011)). It implies that the dynamics of the series of maxima can be explained through those covariates and the equation (1) is expressed as:

$$G(z) = \exp\left\{-\left[1 + \xi\left(\frac{z-\mu(t)}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{2}$$

where:

$$\mu(t) = \mu_0 + \mathbf{X}_t\beta, \tag{3}$$

with β as $k \times 1$ coefficients vector, and $\mathbf{X}_t$ as the design matrix with the covariates data at time t.

With the purpose of understanding how the blocks are constructed for the endogenous variable and its covariates, let's assume that there are monthly data and annual blocks, therefore the endogenous variable is finally defined as the maximum value per year but the values of covariates are not necessary their annual maximum values. In fact, the observations of the covariates are those which belong to the moment t when the extreme value of the endogenous variable is observed. For instance, in a given year if the annual maximum value of endogenous variable occurred in April, the covariates values used in the estimation are those observed in April regardless of whether those are their annual maximums.

3.3. Return levels

In this article, we use the measure *Return level* in order to assess the risk of extreme weather events on Colombian food prices. In the stationary case, the return level with a T-year return period[20] usually represents an event that has a 1/ T chance of occurrence in any given year (*on average*), it is also known as the probability of exceeding (q). To be clear, given annual blocks with monthly data and a return period of five years ($l = 5$); a return level with value R implies that the endogenous variable would be greater than R once every 5 years.

The probability of exceeding some quantile is $q = P(X > x_l) = \frac{1}{l}$ where $G(x_l) = 1 - q$, x_l represents the return level, l the return period, with $0 < q < 1$. Hence, the $l-$return level can be expressed as:

$$x_l = \begin{cases} \mu + \dfrac{\sigma}{\xi}\left\{[-\ln(1-q)]^{-\xi} - 1\right\}; & \text{for } \xi \neq 0 \\ \mu + \sigma \ln\left[-ln(1-q)^{-1}\right]; & \text{for } \xi = 0 \end{cases} \tag{4}$$

The shape of the plot of the function x_l for different values of l depends on the values of ξ. Following Gilleland et al. (2016), this shape is a straight line, concave or convex when $\xi = 0$, $\xi < 0$ or $\xi > 0$, respectively.

3.3.1. The non-stationary case

As Parey et al. (2007) mention, the return levels are a sequence of values which depend on the covariates when the EVT specification is non-stationary. Those can be defined as follows:

$$x_l = \begin{cases} \mu(t) + \dfrac{\sigma}{\xi}\left\{[-\ln(1-q)]^{-\xi} - 1\right\}; & \text{for } \xi \neq 0 \\ \mu(t) + \sigma \ln\left[-ln(1-q)^{-1}\right]; & \text{for } \xi = 0 \end{cases} \tag{5}$$

Where $\mu(t)$ is given by equation (3).

Following Cheng et al. (2014) and Cheng et al. (2015) the return levels can also be estimated for specific values of the covariates. In this sense, $\mu(t)$ is fixed in a given t.

[20]This tool shows that such a significant flood or drought could occur in any year, multiple years in a row, or not at all.

3.4. *Probability of an extreme event*

Using (1) and following the methodology of Dey et al. (2020) under EVT stationary case, we can define the probability of an extreme event as:

$$P(X > x) = 1 - \exp\left\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{6}$$

where x is the extreme quantile.

Analogously, the probability of an extreme event in a non-stationary specification is given by:

$$P(X > x) = 1 - \exp\left\{-\left[1 + \xi\left(\frac{x-\tilde{\mu}}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{7}$$

where $\tilde{\mu}$ is defined by the equation (3) given some specific values of the covariates ($\mathbf{X}_t$) in a fixed period of time t.

4. Data and empirical results

4.1. *Data and empirical approach*

In a first attempt to identify some determinants of high Colombian food prices we use Colombian rainfall level, the fuel price index and US dollar-Colombian peso exchange rates as covariates. For the endogenous variables we use the monthly Consumer Prices Index of perishable and processed food prices in Colombia from June 1985 to December 2020 which are obtained from the National Statistics Department of Colombia (DANE). We use the fuel price index from the same source as the first covariate variable. We have taken the data of US dollar-peso exchange rates from the Central Bank of Colombia as the second covariate variable. Finally, the rainfall level corresponds to the third covariate variable and it was obtained from the Colombian Institute of Hydrology, Meteorology and Environmental Studies (IDEAM). All variables are measured by annual variation, with the exception of rainfall series which is expressed in millimeters (mm). Then, we use BM with a block size of 6 months in order to select the extreme values of Colombian food prices which are defined as the greatest value per semester. We called it Biannual Maximum Perishable (BMPER) and Processed (BMPRO) food prices. Taking the above into account, the values of their covariates are taken from those dates where food prices are the highest.

Regarding the empirical strategy, Maximum Likelihood Estimation (MLE) methods are used to estimate the non-stationary EVT model. Next, we assess their goodness-of-fit of the models in several ways.[21] First, in order to verify and justify the choice of the model, we compare the specification under stationary assumption and non-stationary case. Second, we run and compare many specifications of covariates in equation 3 by including different lags. Accordingly, we select the best model by using BIC values. Finally, we present some graphical statistical measures of goodness-of-fit (See Appendix A).

Figure A.5 and Figure A.6 show density and Q-Q plot for BMPER and BMPRO, respectively. Overall, Figure A.5a and Figure A.6a illustrate that both the perishable and processed food models yield a good fit and the modeled data is close to the empirical observations, therefore our models can capture the variability of the endogenous variables. On the other hand, Figure A.5b and Figure A.6b exhibit Q-Q plots that confirm our model's goodness-of-fit. At first sight, the BMPER model seems to be more suitable than the BMPRO model because its Q-Q plot is approximately a 45-degree line. Although a couple of points between observed and modeled data have small deviations from the 45-degree line, particularly for the BMPRO model.

In addition, we check the likelihood-ratio test between non-stationary (equation (2)) and stationary -restricted- models (equation (1)). In other words, we compare the EVT model under stationary and non-stationary behavior in order to assess the relevance of including covariates in the estimation. Under the null-hypothesis there is no difference between the log-likelihood values of those two specifications. The results show that there is empirical evidence to reject the null hypothesis for BMPER and BMPRO models (Table 1). These results support the inclusion of covariates in the location parameter for both BMPER and BMPRO models because covariates improve the log-likelihood value significantly. In this sense, the non-stationary models are preferred to the stationary ones.

Table 1: Likelihood-ratio test

	p - value
Perishable	0.000
Processed	0.000

This table presents the estimated p-value of the likelihood-ratio test between the restricted model of equation (1), and the non-restricted one, equation (2). The null hypothesis indicates that the likelihoods of both models are not different.

4.2. *Non-stationary EVT estimated model*

Given those extreme values and their covariates, we estimate the non-stationary EVT model of equations (2) and (3) using Maximum Likelihood (MLE). In each estimated model, the endogenous variables are BMPER or BMPRO and their covariates are rainfall levels, exchange rates and fuel prices. Regarding those covariates, we try different lags in the model specification from 0 to 6, and choose the ones with the lowest BIC. As a result, we show in Table 2 the estimated coefficients for the selected model in each group of Colombian food prices.

Viewing the results for Colombian BMPER, all the coefficients are significant and have the expected signs. Colombian rainfall level shows a negative estimated parameter which implies that we probably observe high perishable food prices in dry

[21] The data analyses are done by statistical programming language R with packages for extreme value analysis such as extRemes and evd.

Table 2: Estimated parameters of non-stationary EVT model

	μ_0	μ_{rain}	μ_{exrate}	μ_{fuel}	σ	ξ
BMPER	16.628^{***}	-1.530^{***}	0.520^{***}	0.207^{***}	9.558^{***}	-0.157^{**}
	(3.710)	(0.627)	(0.086)	(0.094)	(0.863)	(0.074)
BMPRO	-0.318	0.664^{**}	0.328^{***}	0.315^{***}	6.110^{***}	-0.318^{***}
	(1.916)	(0.320)	(0.054)	(0.064)	(0.553)	(0.071)

This table presents the estimated coefficients and their respective standard deviation in parenthesis for the non-stationary models specified in equation (2). The endogenous variables are the biannual maximum perishable and processed prices, and the covariates are the rainfall level (rain), the exchange rate (exrate), and the fuel price (fuel). Standard errors are in parenthesis, and p-values are noted as $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

seasons. Those extreme values are linked with a strong ENSO (*El Niño*, particularly) and it is consistent with the literature mentioned before where agricultural production falls and food prices rise due to weather conditions (Bejarano-Salcedo et al. (2020), Abril-Salcedo et al. (2020)). Likewise, the estimated coefficient of rainfall level indicates that a unit decrease in this variable results in an estimated increase of 1.53% in the mean level of the biannual maximum annual variation of the perishable food prices while the other covariates remain fixed. On the other hand, the extremes values of the perishable prices are influenced positively at unit increases of the exchange rate and the fuel price index. Although we do not have a structural model, we believe that a strong exchange rate depreciation makes food more expensive through two channels: i) increasing the prices of imported food and ii) increasing the costs of inputs (fertilizers) in dollars that are finally transmitted to the consumer. Similarly, fuel prices are related to transportation costs which in turn raise food prices from rural to urban areas.

In the case of Colombian BMPRO, all the parameters associated with covariates are statistically significant. Regarding the rainfall variable, the coefficient is positive which indicates that those prices could be related to *La Niña*. In particular, the maximum biannual processed food prices increase 0.664% when the rainfall level increases one unit and the other two covariates are held constant. The other covariates have the same effects sign on processed food prices. Overall, the estimated parameters of covariates in the BMPRO model have a lower magnitude in comparison to the BMPER model which is another result to highlight. Thus, the most vulnerable food prices are that of perishable food in extreme weather conditions.

4.3. Effective Return Level

We compute the effective return levels based on equation 5, which are the values expected to be exceeded on average once every $l-$years, given the values of the covariates at each biannual block. Figure 2a and Figure 2b display the observed biannual maximum perishable and processed food prices and the non-stationary return levels at 5-, 10-, 25-, and 50-year return-periods. As mentioned before, Colombian food prices are affected by ENSO -especially by a strong *El Niño*-, therefore we include the vertical gray shades to highlight previous periods of strong *El Niño* according to NOAA.

The effective return-levels let us interpret how extreme the biannual maximum values of the Colombian food prices are. To avoid misunderstandings, we should point out that although the whole black points in Figure 2a and Figure 2b were chosen as maximum values by using the Block Maxima method, those are not necessarily defined as extreme. In fact, we can classify these maximums and declare that an event is extreme and atypical when one of those values reach any return level line. For instance, perishable prices have four moments when their values are really extreme and atypical, which are: 1988-1 to 1988-2, 1992-1 to 1992-2, 2008-1 to 2008-2, and 2016-2. The extreme and atypical events for the processed food prices are only presented at the biannual ranges 1987-1 to 1988-1, which is consistent with an ENSO season, and at 1994-2 and 1995-2[22]. Overall, Figure 2a shows how there is a relationship between the annual variation of the Colombian perishable food prices and a strong ENSO. Note that in most of the cases when a strong ENSO occurs, the maximum values of the BMPER tend to increase at a later date. On the contrary, BMPRO does not show the same relationship (Figure 2b).

Focusing on the Colombian biannual maximum perishable food prices in 2016-2 after the strongest ENSO in the last century, the peak of BMPER (black line) is above the return level lines at both 5-years and 50-years (Figure 2a). It implies that the Colombian maximum perishable food prices in 1988 and 2016 were 50-year events which means those amounts of perishable food prices are expected to occur once in 50 years. Although both events share similarities such as the presence of an *El Niño* phenomenon and exchange rate depreciation, the difference can be seen in 1988 when there was a significant increase in fuel prices. Thus, if we take into account the values of all the covariates jointly, the 1988 event has a higher relative risk than the 2016 event (Table C.3 in Appendix C).[23] However, if we only compare the rainfall level while the other covariates remain constant (at 50th percentile), we find that the probability that BMPER would exceed an annual variation of 35% under 2016 weather conditions is almost twice than that those observed in 1988.

4.4. Return level scenarios and sensitivity analysis

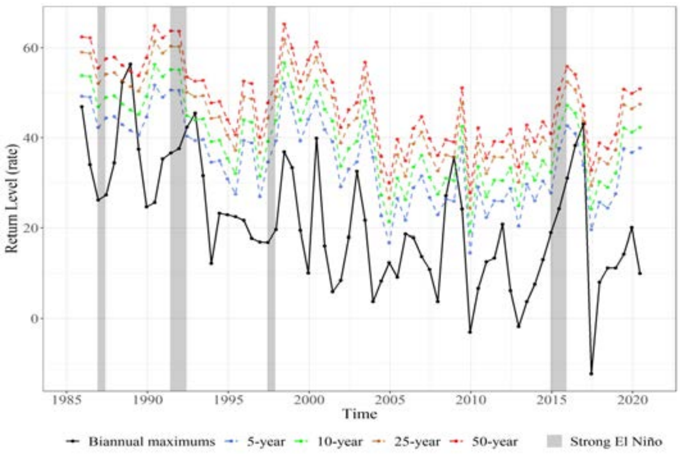
We perform a sensitivity analysis in order to study how return levels and return periods can be affected by changes in extreme precipitation while the remaining covariates hold constant. To do that, we compute return levels for different return periods by taking the percentile 50th and 95th of exchange rates and

[22]Although the weather conditions were favorable in 1995, in that year there was a depreciation of the exchange rate and a significantly high growth in fuel prices (two standard deviations with respect to its mean).

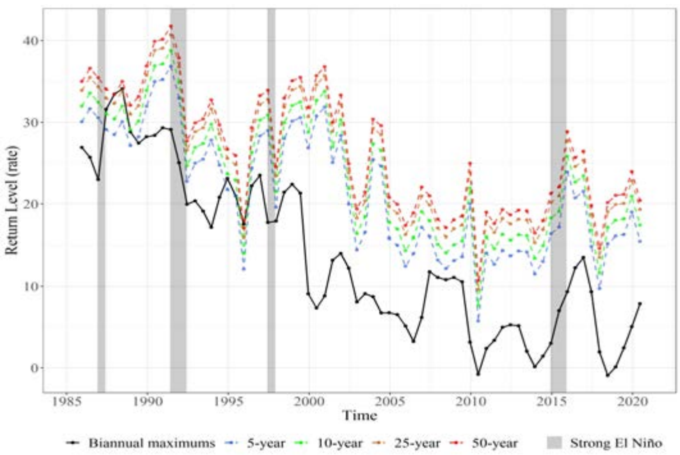
[23]The relative risk ratio is less than one, which can be seen in the last column of the Table C.3. To understand the table, let's take a particular example, in this case the sixth row associated with the probability of exceeding an annual variation of 25% in perishable food prices. Thus, when the covariates take the values observed in 2008 (fifth column linked with *La Niña*-rainy season), the probability of having values above this 25% is 12%, and that probability increases to 55% with the values observed in 2016 (fourth column linked with a *El Niño*-dry season). Then, the relative risk ratio (eighth column) is $\frac{0.55}{0.12} = 4.5$ which means 2016 was 4.5 times riskier than 2008.

Figure 2: Effective return-levels for food prices

(a) Perishable items



(b) Processed items



Notes: The black solid line represents the biannual maximum values of the annual variation of prices of each aliment group. The blue, green, brown and red dashed lines represent the non-stationary effective-return levels at 5−, 10−, 25−, and 50−year return periods, given the values of the covariates: rainfall level, fuel price index and US dollar-peso exchange rate. Gray shaded areas represent the periods of strong ENSO seasons.

fuel prices. It implies that we change the covariates values from average conditions to an extreme positive event. Speaking in the economic context, this means that we move from average conditions to a scenario in which there is high depreciation and high fuel prices, which raises the costs of imported inputs (fertilizers), food imports and transportation. As can be seen in figures 3 and B.7, the return levels of perishable and processed food prices increase for each return period when the conditions change from scenario one to scenario two, regardless of the quantiles of different rainfall levels $(0.01, 0.05, 0.1)$.[24] In other words, under a dry season when we observe high exchange rate depreciation and high fuel prices, it increases the risk of high values for food price inflation.

Focusing attention on the prices of food most exposed to weather conditions, perishable foods, in Figure 3a we consider the rate that would be exceeded once every $l-$years when the covariates exchange rate and fuel prices take the median value, and there is an extremely low rainfall level which is linked with the *El Niño* phenomenon (the most important weather pattern that affects the Colombian economy). For instance, if we take the precipitation quantile (0.01), we expect that perishable food inflation would have to reach a rate of 39.6% once every 10 years (20 semesters) or 47% once every 50 years (100 semesters). Furthermore, when we change the economic conditions through the increase of the exchange rate depreciation and fuel prices (Scenario 2 in Figure 3b), we observe that perishable food inflation would have to reach a rate of 46% once every 10 years (20 semesters) or 55% once every 50 years (100 semesters). It is important to note that those rates are higher when the rainfall level is lower which is linked to a dry season (*El Niño*).[25]

Finally, we show the non-stationary exceedance probabilities associated with perishable food prices (Figure 3c). To do that, we fix the values of covariates exchange rates and fuel prices in their monthly median and we present the quantiles 0.01 and 0.05 of the monthly rain series. The x-axis represents the value of the annual variation of the perishable food prices, while the y-axis indicates the probability of exceeding those quantiles. Under these assumptions, we find that the possible realizations of the high perishable food prices would have an observed gap between regular weather context and dry season scenarios like a strong *El Niño* which can be seen as observation below the quantile 0.01. Although the average gap is no greater than 13%, this gap is wider around 25% for values of annual price variations located between 10% and 20%.[26] For example, the probability of exceeding an annual price variation of 20% in a regular context (median values) is 27%, while that probability increases to 52% when weather conditions get worse. In other words, in this comparison there is a higher probability around 25% in which an annual variation of the prices of perishable food reaches 20% when the rainfall is located at 0.01 quantile.

Regarding processed food prices, although exchange rates and fuel prices are drivers of high prices as in the perishable case, the weather conditions are not a determinant of high prices (Figure B.7c). It is important to note that changes in the exchange rate and fuel prices affect the return levels of processed food prices more than the perishable ones. For example, taking into consideration the case of $10-$year return-levels, we see that the returns levels change on average 8.54% for the processed foods while the perishable ones change 6.62% when covariates change from scenario one to two.[27]

[24]In Figure 3a and 3b, the red, yellow, and blue lines indicate the returns that would be obtained when the covariate rainfall takes the values of the 0.01, 0.05, and 0.1 quantiles of its monthly distribution, respectively.

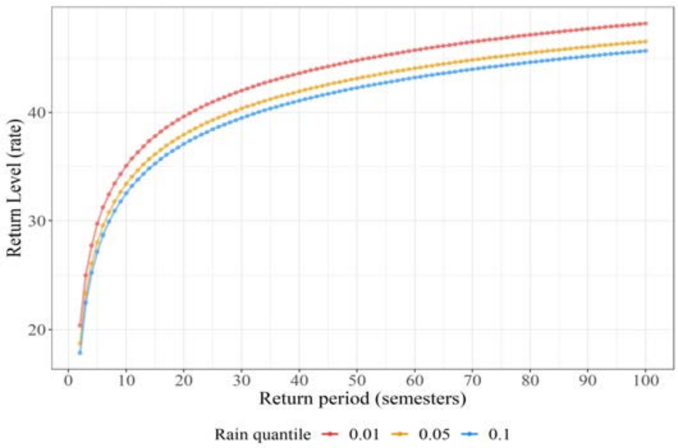
[25]The red lines have a magnitude greater than yellow and blue lines.

[26]This gap is the difference between the red and blue lines.

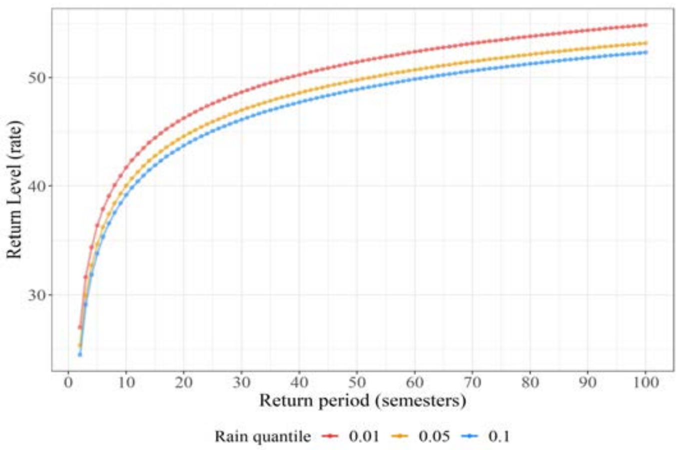
[27]Those measurements come from comparing Figure B.7a vs B.7b and Figure 3a vs 3b

Figure 3: Sensitivity analysis of rainfall level on return levels and return periods for Perishable food prices.

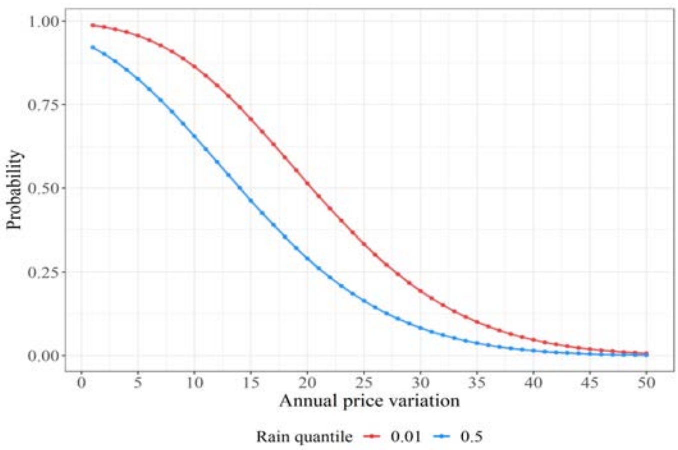
(a) Scenario 1: Remaining covariates at quantile 0.5



(b) Scenario 2: Remaining covariates at quantile 0.95



(c) Inflation quantile probabilities with remaining covariates at quantile 0.5



Notes: Figures **a** and **b** present the return-levels of the biannual maximum values of the annual variation of prices for the perishable aliment group, when the values of the covariate rainfall level are fixed at quantiles $\{0.01, 0.05, 0.1\}$ and the remaining covariates are fixed at quantile 0.5 (figure **a**). The latter assumption is changed for the quantile 0.95 in figure **b**. Figure **c** presents the exceedance probabilities for perishable food prices, with fixed covariate values at quantile 0.5.

4.5. Relative Risk Ratio for Perishable foods

Keeping in mind that climate-affected foods are mainly perishable, we focus on analyzing the Relative Risk ratio (RR) for different conditions in those food prices. In finance, the RR is traditionally used as an alternative measurement of risk. It is the ratio of the probability of an outcome in an exposed group to the probability of an outcome in an unexposed group. We use it in order to compute the probability of high perishable food prices occurrence due to changes in weather conditions. In particular, we quantify the impact of certain weather conditions on the occurrence of extreme perishable food prices by the ratio of the probability of low a precipitation level (dry season) to the probability of average weather conditions as:

$$RR(x) = \frac{\Phi_A(x)}{\Phi_B(x)} \tag{8}$$

where $\Phi_A(x) = P(X > x|t_A$-year level of exchange rate, fuel prices and Rainfall event) and $\Phi_B(x) = P(X > x|t_A$ -year level of exchange rate and fuel prices event but t_B-year level of Rainfall event). For example, t_A-year is the baseline year that implies all covariates values are the observed values in 2016 which was the year of the strongest *El Niño* and t_B-year could be any year between 1985 and 2020 where weather conditions are different from a dry season. Also, we can define t_A-year or t_B-year as the values observed in a certain quantile of variables. We compute those probabilities $\Phi_A(x)$ and $\Phi_B(x)$ by using the equation 7 when the location parameter $\mu(t_A)$ or $\mu(t_B)$ is represented by the linear function of covariates in equation 3.

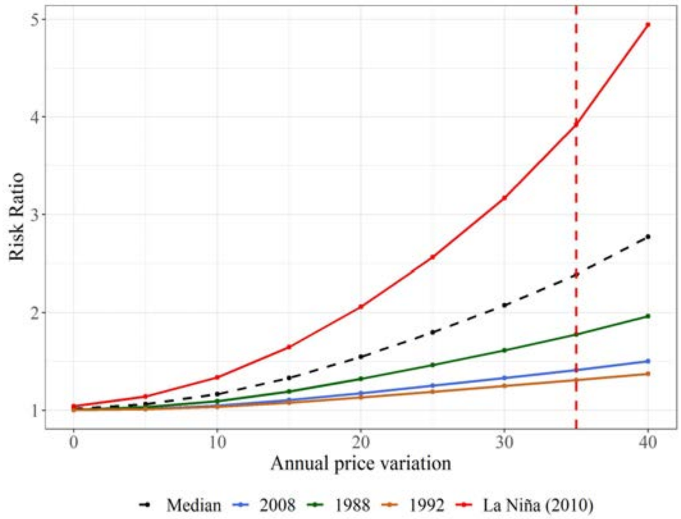
In order to show the risk sensitivity of return levels related to changes in weather conditions, in Figure 4a we compare different weather condition scenarios while exchange rate and fuel prices are fixed at their quantile 0.5 (median). To be clear, t_A-year takes the observed value of the rainfall level in 2016 and the median of the remaining covariates, then we compare it with t_B-year which takes the observed value of the rainfall level of different periods and the precipitation median between 1985 and 2020. In addition, we illustrate the relative risk of high perishable food prices due to changes in weather conditions in both extremes defined as a low precipitation level linked with a dry season and the *El Niño* phenomenon, and a high precipitation level associated with a rainy season and the *La Niña* (e.g., year 2010).

Under those scenarios and focusing our analysis on the particular case of 35% in annual variation of perishable food prices, our main findings are: i) 2016 had 2.7 times higher risk compared to the rainfall median value, ii) 2016 had 3.9 times higher risk compared to 2010 which was a year linked with a strong *La Niña*, and iii) the strongest *El Niño* in 2015-16 had less than twice the risk compared to other levels of rainfall episodes that have reached return levels from 5-year to 50-year return periods (1988, 1992, 2008). Overall, the risk gradually increases for higher annual variations.

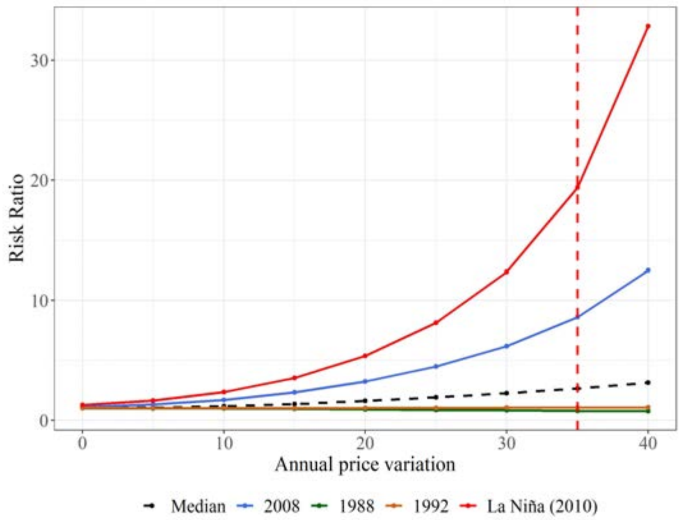
Finally, we compare the same five scenarios and we change

Figure 4: Relative risk ratio for Perishable foods (2016 baseline year)

(a) Rainfall level sensitivity with remaining covariates fixed at quantile 0.5



(b) Comparison of observed values for different periods



the values of the exchange rates and fuel prices by those actually observed in years 1988, 1992, 2008, 2010 and the baseline year 2016. As can be seen in Figure 4b, *El Niño* is significantly riskier than *La Niña* in terms of generating high perishable food prices. Taking the years 2010 (*La Niña*) and 2016 (*El Niño*) as example, 2016 has 5.37 and 19.37 times higher risk of occurring perishable annual variation of 20% and 35%, respectively, compared to 2010. The risk gradually increases for higher annual variations and its increase is not necessarily linear. A fact to underline is that 1988 was riskier than 2016; although both years share *El Niño* weather conditions, exchange rate depreciation and fuel price growth were greater in 1988 in comparison to 2016.

5. Final remarks

Climate change has affected the patterns of different weather conditions around the world, increasing the severity and periodicity of extreme weather events. Understanding the relationship between these extreme weather conditions and food prices is a relevant topic in the design of policies that reduce their consequences. In this article, we contribute to the empirical literature of weather and economics by analyzing the main drivers of high food prices in Colombia, focusing on the impacts of extreme weather shocks like a strong *El Niño*.

We use a non-stationary EVT model for perishable and processed food prices in Colombia and include exchange rate, fuel prices and rainfall levels as covariates in the econometric model. As expected, our results suggest that those covariates affect the dynamics of high Colombian prices for both perishable and processed foods. We also find that the risk of a high perishable food price is significantly larger for low rainfall levels (dry season) compared to high precipitation levels (rainy season). Although we do not have a structural model to help us explain our results, it is generally accepted that perishable foods are more exposed to the extreme weather conditions in comparison to those processed foods due to the nature and physical characteristics of those foods.

We found that in drought scenarios, perishable food price inflation could possibly reach values between 35% and 40% once every five to ten years which affects the well-being of households due to the loss of their purchasing power. Our findings also show a gap in the probability that perishable food price inflation exceeds certain values (5% to 40%) when we compare weather scenarios related to dry seasons and normal weather conditions. Although the average gap is no greater than 13%, this gap is wider around 25% for values of annual price variations between 10% and 20%. In other words, under a low precipitation level scenario (0.01 quantile), it is 25% more likely that the prices of perishable foods will have an inflation of more than 20% compared to a scenario of normal conditions.

In addition, we quantify a measure of risk of extreme events by using relative risk ratios to compare different scenarios by changing covariate values and different moments of time and their effects on annual food price variations. In particular, *El Niño* in 2016 had more than twice the risk of increasing food prices in comparison to the rainfall median value. Moreover, the results let us conclude that the risk related to changes in weather conditions has an uptrend and is not necessarily linear. This risk is also significantly larger than the one linked with changes of the US dollar-Colombian peso exchange rate and fuel prices. Given the above, ENSO can affect the well-being of citizens in Colombia by reducing the welfare of households.

Our research improves the understanding of ENSO implications on local weather conditions and consumer food prices, which can be useful in different ways. For instance, the return level and return period estimates can be used in the evaluation of agricultural risk policies by assessing the risk of extreme events.

We present a range of return levels by computing probabilities of occurrence of an event in a particular scenario (e.g., 5%, 10% or 50% quantiles), but policy makers can select the upper bound (high risk in dry seasons linked with *El Niño*) or the lower bound (low risk in rainy seasons related to *La Niña*) depending on the weather risk assessment and simulations of policy scenarios.

In addition, given that food prices play an important role in the overall inflation dynamics, Central Banks can also include scenarios with different exchange rate depreciation and fuel prices by choosing the upper bound (low risk) or the lower bound (high risk) which are other factors that explain inflationary pressures. In other words, our model can be used as an input for the design of public policies to mitigate the effects of weather changes depending on the application at hand.

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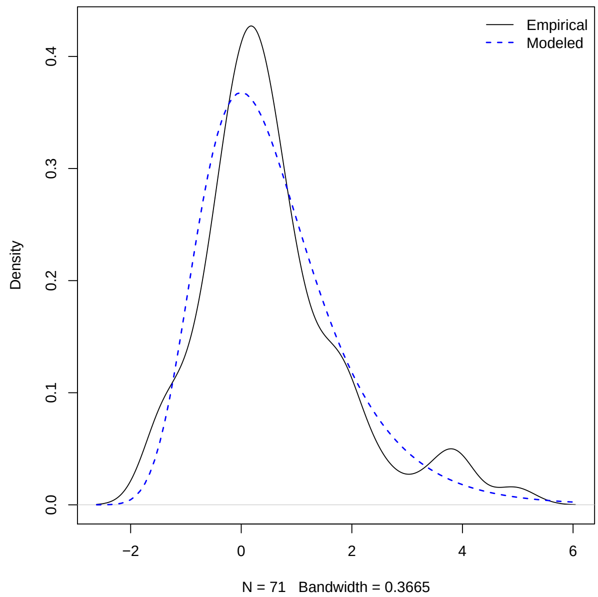
Appendix A. Diagnostic checking

Figure A.5: Density and Q-Q plots for the Perishable food prices model

(a) Density plot



(b) Q-Q plot

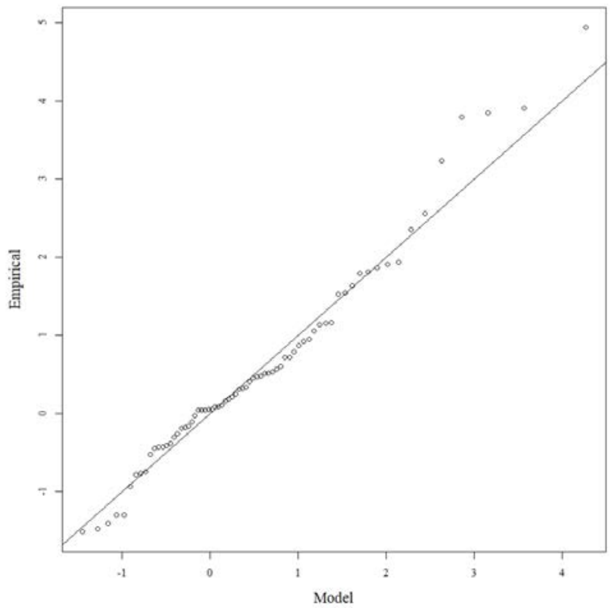
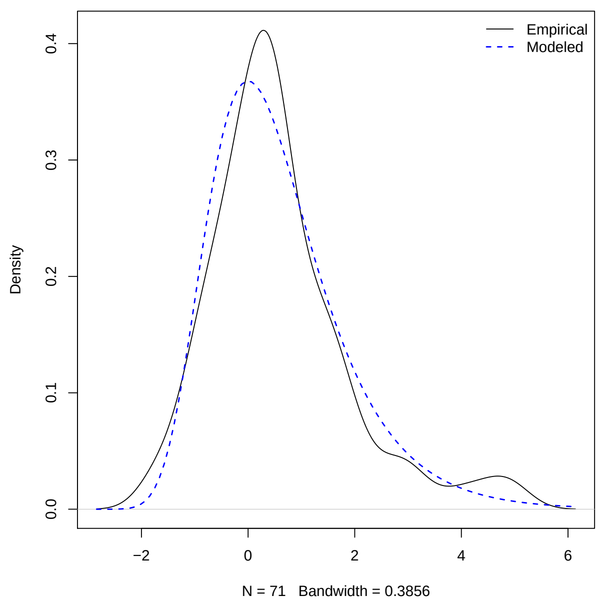
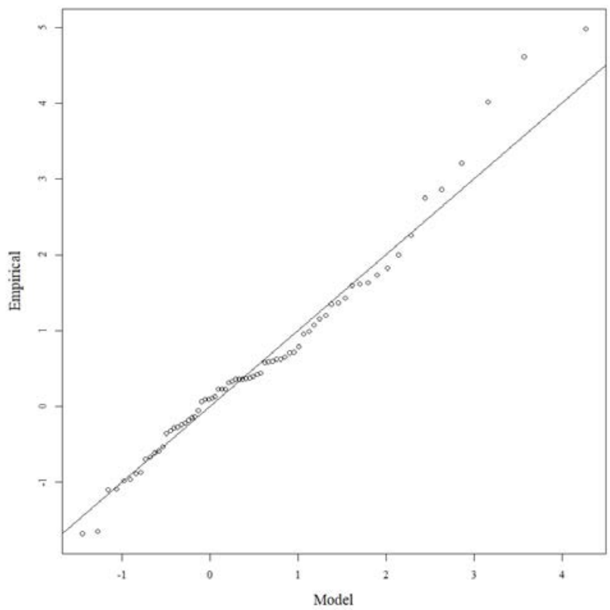


Figure A.6: Density and Q-Q plots for the Processed food prices model

(a) Density plot



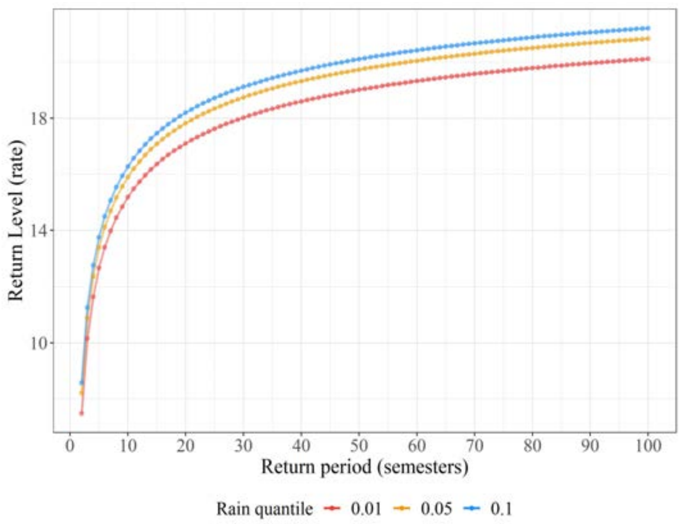
(b) Q-Q plot



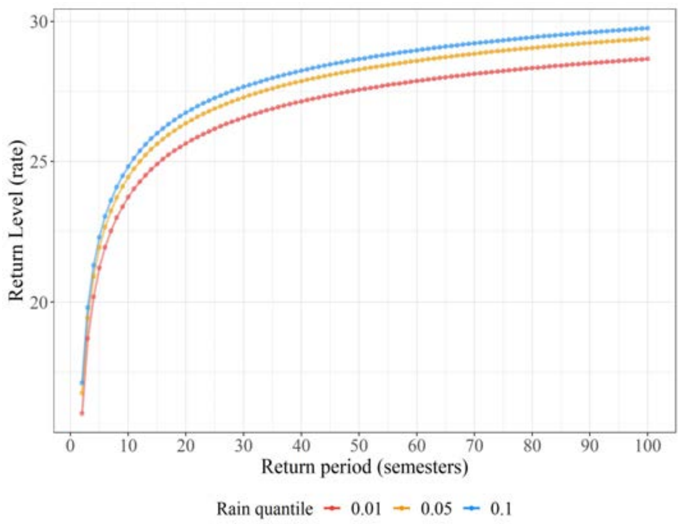
Appendix B. Return level scenarios and sensitivity analysis for Processed food prices

Figure B.7: Sensitivity analysis of rainfall level on return levels and return periods for Processed food prices.

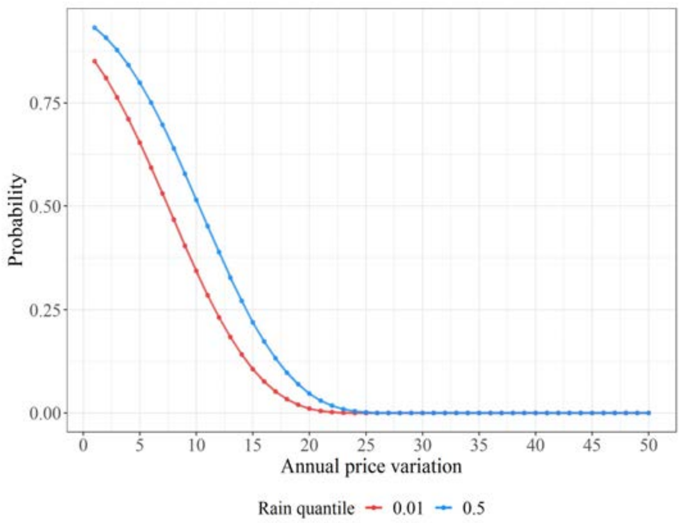
(a) Scenario 1: Remaining covariates at quantile 0.5



(b) Scenario 2: Remaining covariates at quantile 0.95



(c) Inflation quantile probabilities with remaining covariates at quantile 0.5



Appendix C. Probability of exceeding extreme quantiles and relative risk ratio(Perishable food prices)

Table C.3: Probability of exceeding extreme quantiles and relative risk ratio (Biannual maximum)

Perishable food prices									
Quantiles (Annual variation of prices)	Probability of exceeding quantiles when covariates take the values of						Relative risk ratio 2016 compared to		
	median*	2016 + median**	2016−I	2008−II	1992−I	1988−I	2008−II	1992−I	1988−I
0	0.99	1.00	1.00	0.90	0.99	1.00	1.12	1.00	1.00
5	0.93	0.99	0.99	0.75	0.99	1.00	1.32	1.00	1.00
10	0.82	0.96	0.97	0.57	0.95	0.98	1.71	1.01	0.98
15	0.65	0.86	0.88	0.38	0.87	0.92	2.34	1.02	0.96
20	0.45	0.70	0.74	0.23	0.71	0.80	3.25	1.03	0.92
25	0.28	0.51	0.55	0.12	0.52	0.62	4.50	1.04	0.88
30	0.16	0.33	0.36	0.06	0.34	0.43	6.19	1.06	0.84
35	0.08	0.19	0.21	0.02	0.19	0.27	8.61	1.07	0.80
40	0.04	0.10	0.11	0.01	0.10	0.15	12.48	1.08	0.77
45	0.01	0.05	0.05	0.00	0.04	0.07	19.72	1.10	0.73
50	0.00	0.02	0.02	0.00	0.02	0.03	36.63	1.12	0.69
Covariates conditions:									
Rainfall Level			El Niño	La Niña	El Niño	El Niño			
Exchange rate			HD	AP	LD	HD			
Fuel Prices			LP	AV	HP	HP			

* Scenario (median) means all covariates take the values of the 50−th percentile of their maximums.
** Scenario (2016+median) means that we use rainfall levels in 2016−I and remaining covariates are in their median of their maximums.
HD, LD, AP: High and Low exchange rate depreciation, and appreciation.
HP, LP, AV: High, low and average of fuel prices.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