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A NON-LINEAR ANALYSIS OF THE PHILLIPS CURVE FOR MEXICAN AGRICULTURAL PRICES UNDER DIFFERENT CLIMATIC SCENARIOS BUILT BASED ON THE ENSO CLIMATIC PATTERN

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Abstract

Extreme weather scenarios, like high and low temperature and precipitation levels, affect the economy in different ways, especially those heavily dependent on agricultural activities and that experience a lack of technological buffers against climate change. The ENSO phenomenon is considered one of the most important climatic patterns studied due to its global effects. In the Mexican case, the ENSO patterns have a significant effect on the economy. This research assesses the relationship between agricultural inflation and economic activity, specifically, an aggregate demand shock, under two different weather scenarios by using a non-linear local projection model. Significant differences in the inflation dynamic are found depending on the weather regime. In general, under abnormal weather conditions, the inflationary effect of a positive aggregate demand shock is higher than under a neutral weather regime. Namely, under an abnormal weather regime, a 1% IGAE shock generates an inflationary effect 70 bp higher than under a neutral one. The above indicates that if agricultural inflation has averaged 6% during the last years, then under adverse weather conditions agricultural inflation would be 6.7%, approximately.

Key words: Agricultural inflation, economic activity, ENSO, El Niño, La Niña, non-linear local projections.

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Chapter 1

Introduction

During the last years, climate change has become more present than ever, with the constant witness of warm record temperatures and the materialization of its consequences, like famine and migration due to droughts, floods, forest fires, hurricanes, etc. Despite climate change must be a global concern because its effects vary across regions and only a few ones get the worst consequences, not all regions have the same urgency to develop technology and knowledge that allow them to face climate change.

The most vulnerable regions to the effects of global climate change are those located closer to the Equator, those with less capacity for adaptability, and whose economies depend heavily on primary activities like agriculture for which weather it's a key component (IPCC. Stocker, 2013; IPCC. Field, 2014). The developing world that strongly depends on agricultural production faces the worst consequences of global climate change (IPCC. Stocker, 2013; IPCC. Field, 2014). Mexico is particularly vulnerable, due to its geographic position, the important economic component that agriculture represents (Statista, 2022), and the lack of technology buffers against climate change (Carr, Lopez, & Bilsborrow, 2009).

In Mexico, agricultural activity represents between 3% and 4% of the gross domestic product (GPD), according to the Mexican National Statistics Institute (INEGI). Agricultural production and exports have been growing for the last years (Statista, 2022). In this sense, agriculture represents an important activity for the economy of Mexico, not to mention that it contributes up to two-thirds of rural household income (De Janvry & Sadoulet, 2001).

Since 1960, Mexico has become warmer, facing higher summer and winter temperatures; precipitation has decreased for half a century, and the increase in hurricanes, droughts, landslides, extreme temperatures, torrential rains, floods, and fires has caused important economic and social costs (CEDRSSA, 2020). According to the World Bank and the Organization for Economic Co-operation and Development (OECD, n.d.), about 71% of Mexico's GDP is vulnerable to the consequences of climate change. An important fact to highlight is that floods represent the environmental phenomenon that causes more devastation and losses; in Mexico, they represent around 62% of total damages reported for extreme events (INECC, 2021).

This research focuses on the assessment of the economic impact of weather anomalies in Mexico. Motivated by the great participation of agriculture in Mexico's economy, its vulnerability to climate change, and the threatening high inflation context which central banks need to stabilize, not just in Mexico but globally(BIS, 2022). This research explores the short-term dynamic between agricultural prices and economic activity under two different weather scenarios in Mexico; a neutral regime or normal weather scenario and a regime where weather conditions such as El Niño or La Niña are present. Particularly, it seeks to explore a positive aggregate demand shock on agricultural inflation under these two climate regimes. For this, a non-linear Local Projection Model is employed, following Auerbach and Gorodnichenko (2012). This work aims to find significant differences in the inflation patterns depending on the weather scenarios, which helps to explain some of the agricultural prices' variability observed in Mexico. The identification of those price patterns will allow us to propose policies that help to reduce or absorb some of the negative impacts of climate change and help the central bank to control the high inflation levels.

To track weather anomalies, and therefore climate change, in Mexico, a global recurring climate pattern across the tropical Pacific is used, that is, the El Niño-Southern Oscillation (ENSO) pattern. The ENSO tracks disruptions in temperature and precipitation which cause changes in the large-scale air movements in the tropics, triggering a cascade of global side effects (NOAA, 2022a). The ENSO has two phases, the warm phase called El Niño and the cold one called La Niña. The weather conditions generated by El Niño and La Niña vary across regions but, generally, under El Niño a rise in temperatures is observed, whereas with La Niña the temperature decreases. Within Mexico there is still a variation of El Niño and La Niña's weather patterns, but, under El Niño a general rainfall decrease during summer and an increase during winter is observed. On the other hand, under La Niña there is an overall trend towards a rainfall increase during summer and a decrease during winter. Similarly, there is a general temperature increase during El Niño summers and a decrease during its winters, the opposite occurs during La Niña.

The ENSO pattern is considered a relevant climatic variable since it is one of the most important and studied phenomena on the planet (Climate, n.d.-a). ENSO tracks the weather changes caused by El Niño and La Niña which affect not only the tropics but many other regions of the world. Despite in many regions, the influence of ENSO on climate variability is small, for some regions it represents about 50% of seasonal climate variability (Climate, n.d.-b). These weather disturbances generate social and economic consequences around the globe; they can reduce agricultural output, generate inflation, reduce construction and services activities, etc.(Cashin, Mohaddes, & Raissi, 2017)

The deterioration of climatic conditions and their consequences could affect economic variables. Climate change has a significant impact on prices. In particular, it has been documented in the literature that weather anomalies have a relevant effect on agricultural production and food prices (Tol, 2009; Dell, Jones, & Olken, 2014). For Mexico, it has been reported that climate change contributes to food price volatility due to the shortage of agricultural production (SAGARPA, 2012). Particularly, the weather conditions generated by El Niño and La Niña have meaningful impacts on agricultural prices. Ubilava (2017) analyzes the ENSO–wheat price relationship for some countries and finds that overall, wheat prices tend to increase after La Niña events, and decrease after El Niño events. He also analyzes the ENSO effect on fishmeal–soya bean meal prices (Ubilava, 2014) and on other agricultural commodity prices (Ubilava, 2018).

In the Mexican case, among others, Cashin et al. (2017) finds an average increase in inflation after an El Niño shock and show that the larger the share of food in the consumer price index (CPI), the greater the increase in inflation. Later, in this section, the relationship between climate change and agricultural production and its prices will be described in more detail within the Mexican context.

A Non-Linear Local Projection Model is used as the empirical model to explore the agricultural inflation response to positive shocks in the aggregate demand under two different weather scenarios. The local projection method is adopted since it provides estimations at each period instead of extrapolating them, also, it provides appropriate individual or joint inference without requiring asymptotic approximations and adjusts easily for non-linear approximations. The Sticky-Information Phillips Curve is used as the baseline theoretical model to shape the relationship between agricultural inflation and economic activity. This model is applied since it allows for a more realistic dynamic between inflation and GDP, that is, it shows a gradual inflation response to GDP shocks unlike other models and, also, with the correct sign (positive).

Results show that there exist significant differences in the agricultural inflation behavior depending on the weather. Namely, under abnormal weather conditions caused by El Niño or La Niña phenomena, a positive 1% aggregate demand shock (higher economic activity) has a positive impact of 70 bp larger on agricultural prices than under a neutral weather scenario. In other words, if agricultural inflation has averaged 6% during the last years, then under adverse weather conditions agricultural inflation would be 6.7%, approximately. This is due to an existing shortage in the agricultural production supply caused by El Niño or La Niña, which generates a scenario with already high agricultural prices under which a positive aggregate demand shock causes higher prices. These findings represent a tool for identifying transitory monetary effects, but also highlight the relevance of considering weather variables in the monetary decisions and the income volatility that faces households that depend on agriculture.

This work is organized as follows. In the following lines literature related to the discussion is reviewed. Chapter 3 chapter presents the theoretical framework concerning the Phillips Curve.

Chapter 4 discusses the econometric approach, that is, the Local Projection Model; presents a description and analysis of the data and explains the empirical strategy. Then, results are shown in chapter 5 and, finally, chapter 6 concludes with the implications and limitations of this research.

Chapter 2

Literature Review

2.1 Identification of climate change and its relevance in the economic analysis for Mexican agriculture

Fisrtable, before choosing the ENSO pattern as the variable to track climate change in Mexico, a literature review was made to identify the relevant weather variables through which would be possible to observe climate change and its impact on agriculture. Literature related to the assessment of climate change's impact on weather patterns of Mexico and Mexican agriculture was reviewed. Some literature focuses mainly on the identification of climate change's effects on weather patterns and natural resources and only highlights some consequences on agriculture production. Liverman and O'Brien (1991) explores the effect of global warming on weather and water availability in Mexico and describe some consequences on agriculture. They use General Circulation Model's (GCM) projections on precipitation, temperature, and solar radiation to identify the impact of global warming on weather. Mendoza, Villanueva, and Adem (1997) asses, as well, the impact of global warming on water availability in Mexico. Unlike Liverman & O'Brien, they used predictions on 7 climate variables to identify climate change: air temperature, relative humidity, wind velocity, precipitation, cloudiness, clear sky surface, short-wavelength radiation, and surface albedo for wet and dry conditions. Becerril-

Pina, Mastachi-Loza, González-Sosa, Díaz-Delgado, and Bâ (2015) explore the desertification risk in the semi-arid highlands of central Mexico, what is relevant for this research is the impact of desertification on agriculture and the weather variables used to assess its increase. They used the Aridity Index (AI) as an indicator of desertification, which is made up of precipitation and potential evapotranspiration information. Magaña, Conde, Sánchez, and Gay (1997) identify and develop future regional climate change scenarios for Mexico, for this, they use GCM's simulations on temperature, precipitation, radiation, and wind velocity.

Other researches focus, specifically, on the impact of climate change on Mexico's agricultural production, the main climatic factors considered to identify weather changes are precipitation and temperature. Appendini and Liverman (1994) describe how agricultural policy and weather conditions have affected maize production. They found, based on climate model projections, that Mexico will become warmer and drier in the next decades, which will have negative repercussions on agriculture, that will be enhanced by inefficient agricultural policies. Gay, Estrada, Conde, Eakin, and Villers (2006) explore the influence of weather conditions similar to those during El Niño on coffee production in Veracruz. Gay, C. et.al found a future reduction in coffee production due to higher temperature levels. Conde et al. (1998) analyzed the impact of a potential climate change on rainfed maize crops in Mexico. They found that maize crops are highly vulnerable to climate change. Based on this brief literature review, precipitation and temperature information appear to be the most relevant and common weather variables to take into consideration for an assessment of climate change in Mexico and its impact on agriculture. Therefore, the ENSO pattern is used to identify abnormal weather scenarios in the model, since it tracks disruptions of temperature and precipitation.

2.2 ENSO's relevance in the economy and the non-linear approach

Another strand of literature related to this research is about the use of non-linear models for the assessment of climate change effects, particularly, ENSO effects. As mentioned, the main ENSO's impacts on the global economy can go from inflationary effects due to a shortage in agricultural production, to a reduced fishing production and cause obstructions in the construction and services industries (Cashin et al., 2017).

What most researchers assess is the non-linear relationship between ENSO and agricultural inflation. For instance, Dufrénot, Ginn, and Pourroy (2021) explore the impact of changing ENSO patterns on global commodities prices, including agriculture prices. Dufrénot et.al use a global factor local projections (GFALP) model to assess the differential agricultural inflation responses to ENSO shocks in each phase, through a transition function that allows to switch regimes and evaluate the impact in each one. Their results show that agricultural inflation is sensitive to ENSO shocks and that its responses to El Niño and La Niña shocks are asymmetric. Abril-Salcedo, Melo-Velandia, and Parra-Amado (2020), similarly, evaluate the non-linear relationship between ENSO and Colombian food inflation growth by using a smooth transition nonlinear model. They find that agricultural responses to ENSO shocks differ in each regime as well; there is a significant increase in inflation growth under warm temperatures and under cold temperatures the effect is ambiguous. Smith and Ubilava (2017) and (Ubilava, 2017) analyze the effect of weather anomalies on developing countries economic growth and international prices of wheat, respectively. They also find an asymmetric effect of weather anomalies on both, economic growth and international prices of wheat, that is, a regime-dependent non-linearity in the economic variables' responses to weather shocks. In the Mexican case, the ENSO impacts on agricultural and non-agricultural commodities production and prices have been analyzed, as well as on the occurrence of natural disasters and its benefits for the oil industry.(Cashin et al., 2017)

Nevertheless, this research focuses on the analysis of the non-linear relationship between agricultural inflation and economic activity under two different regimes determined by normal weather conditions and by the ENSO patterns in Mexico. In other words, this research assesses the non-linear agricultural inflation response, dependent on weather regimes, to economic activity shocks. Then, although this analysis differs from the literature related to the assessment of non-linear agricultural prices response to weather shocks, its findings are relevant for the conclusions of this research, since it shows the significant direct effect of weather patterns on agriculture prices. To be specific, in this research the non-linear relationship between agricultural inflation and economic activity is observed under two different weather regimes which affect the level of economic activity, then, a different level of economic activity is observed in each regime, therefore it is possible to identify a non-linear behavior in the price responses to economic activity shocks depending on the weather regime. However, the effect of ENSO on agricultural prices is not assessed directly. But, based on the two strands of literature reviewed, it is possible to make a direct linkage between ENSO's patterns and agricultural prices and, therefore, not only explain the price response differences among weather regimes but describe the channels through which weather conditions might influence the prices responses differences.

Concerning the discussion about the non-linearities in the inflation equation, some literature analyzes the non-linear relationship between inflation and unemployment. Doser, Nunes, Rao, and Sheremirov (2017) and Babb and Detmeister (2017) find an asymmetric inflation response to unemployment shocks depending on the existing level of unemployment. On the other hand, Pyyhtiä (1999) analyzes the relation between inflation and the output gap. He finds a clear indication of the nonlinearity of the Phillips Curve in many euro countries. Pyyhtiä argues that inflation responses are asymmetric to output gap shocks in the sense that, with a positive output gap, inflation is positive, but, with a negative output gap, the deflationary impact is small and not significant. In this regard, the present analysis is similar to Pyyhtiä's, but the ENSO variable is added.

In this sense, this work contributes to the non-linear Phillips Curve literature and to the climate change impact on prices literature by exploring the non-linearities between the Mexican agricultural inflation and economic activity while assessing the differences caused in this relationship by ENSO.

Chapter 3

Theoretical Framework: The Phillips Curve

To describe the basic agricultural inflation and economic activity dynamic in Mexico, the equation of the Phillips Curve is taken as the baseline theoretical model. The classic Phillips Curve describes the inflation and unemployment relationship. It states that inflation and unemployment have a stable and inverse relationship. Namely, economic growth generates inflation, which in turn should lead to more jobs and less unemployment. In 1970 the validity of the Phillips Curve was questioned when in the United States the high levels of unemployment did not coincide with declining inflation (Bryan, 2013). Then, economists started to look at the inflation expectations' role in the inflation dynamics, to explain the inconsistencies between theory and reality.

Important modifications and adaptations have been made to the Phillips Curve to simulate and get closer to the observed inflation dynamics. There are early researches that emphasize the role of staggered price setting by firms, based on their forward-looking expectations or forecastings, some researches are those by Fischer (1977), Taylor (1980), and Calvo (1983). In this regard, Galı and Gertler (1999) developed a Phillips Curve structural model, known as the New Keynesian Phillips Curve, which is based on a fraction of forward-looking firms which set prices optimally and a remaining fraction of firms that do not update their prices. Also, instead of using the output gap or unemployment as an indicator of economic activity, they use the real marginal cost. Nevertheless, capturing the persistence of inflation still appears to be an issue for these models (Mankiw & Reis, 2002). Some critics of the Gali & Geltler model are from Rudd and Whelan (2005), who use different econometric tools to estimate the coefficients of the New-Keynesian Phillips Curve and show that it cannot explain the relevance of both, the inflation lags and the backward-looking method and state that the forward-looking method has little importance when explaining the dynamic of inflation. On the other hand, Lindé (2005) states through a new estimation of the New-Keynesian Phillips Curve that both methods, forward and backward-looking are significant when explaining inflation dynamics.

Ramos-Francia and Torres (2008) made an empirical work where they try to describe the short-run inflation dynamics for Mexico using a hybrid New Keynesian Phillips Curve model. The model extends by assuming that a group of firms that can not change their prices and a group of firms that do change their prices exist, the latter divides into backward and forward-looking firms. Their results show that when inflation persistence (backward-looking component) and future inflation expectations (forward-looking component) are considered in the Phillips Curve, the inflation dynamic is best described. They state that the Mexican inflation dynamic is defined by three key structural components; a discount factor, the fraction of firms that can not change their prices, and the fraction of firms that use a backward-looking rule of thumb to set their prices.

One of the most recent works about the development of a new structure of the Phillips Curve, which appears to address the issues about the persistence of inflation, is from Mankiw and Reis (2002)). They built the Sticky-Information Model where macroeconomic information spread slowly through the population due to re-optimization costs or costs for acquiring information (Mankiw & Reis, 2002). Also, firms' expectations not only depend on macroeconomic information but previous experience of other firms as well. The model is based on backward-looking firms that set their prices based on updated information and another fraction of firms that set their prices based on old information. In this model the persistence of inflation is present on the dependence of firms macroeconomic expectations on the previous experience of other firms, which allows for a gradual inflation response to GDP shocks, unlike the New-Keynesian Curve (Mankiw & Reis 2002). Another relevant result of this model is the relationship shown between GDP and inflation, which is positive as it should be, unlike the New-Keynesian Model at which the beginning of the inflation response shows a negative relationship (Mankiw & Reis, 2002).

Although the version of the Phillips Curve model used by Ramos-Francia and Torres to describe Mexican inflation dynamics is different from the Sticky-Information model, both emphasize the importance of past expectations in inflation dynamics. Following the most recent literature, this research uses the dynamic inflation stated by the Sticky-Information model as the theoretical base.

The equation that describes the basic dynamic of inflation in the Sticky-Information model is as follows:

$$\pi_t = [\frac{\alpha\lambda}{1-\lambda}]y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-1-j}(\pi_t + \alpha \Delta y_t) \tag{3.1}$$

The inflation π_t depends on the output gap y (the difference between actual GDP and potential GDP) of period t weighted by the fraction of firms that update their price every period λ and by the level of importance of macroeconomic information in the formation of firms expectations α, both parameters between 1 and 0. It also depends on the past expectations of current macroeconomic conditions, the inflation and the output gap change, $E_{t-1-j}(\pi_t + \alpha\Delta y_t)$, where j determines the number of periods in the past plus one where expectations are built. Past expectations are weighted by $\lambda(1-\lambda)^j$ which gets closer to zero as j increases, that is, furthest past expectations of current macroeconomic conditions influence less on inflation. In this model, the relevant expectations are the ones generated in the past (backward-looking).

For this research, the Sticky-Information model equation is linearized, and are include control variables. The specific equation to estimate is described later, but here, the variables and the relationship that shapes the basic inflation dynamic in this research are presented.

Chapter 4

Econometric Approach

4.1 Local Projection Model

This section aims to explain the model on which this research is based, that is, the non-linear local projection approach, following Auerbach and Gorodnichenko (2012). The main idea in the Local Projection models consists in estimating the Impulse Response Functions (IRFs) by local projections at each period of interest rather than extrapolating into increasingly distant horizons (Jordà, 2005). Local projections are based on sequential regressions of the endogenous variable shifted several steps ahead estimated by simple least squares, they provide appropriate individual or joint inference without requiring asymptotic approximations, also, they easily adjust for experimentation with non-linear specifications (Jordà, 2005). For these reasons, this approach appears to be the best tool to estimate IRFs from VARS and to address the questions stated in this research.

Firstly, A Vector Autoregressive model (VAR) is used to describe the dynamic behavior of the variables and how they interact. To identify causal relationships, namely, the effects of a structural shock on a variable, a reduced-form VAR is estimated to subsequently, solve the causal identification problem by the Cholesky matrix. Finally, based on the obtained coefficients, local projections are estimated.

Consider the next reduced-form VAR as an example:

$$y_{1,t} = \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + u_{y_1 t} \tag{4.1}$$

$$y_{2,t} = \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + u_{y_2 t} \tag{4.2}$$

Where $y_{1,t}$ and $y_{2,t}$ are two covariance stationary times series and the paramaters ϕ capture the variables dynamic. The residuals are defined as a combination of structural shocks:

$$u_{y_1 t} = b_{11} \epsilon_t^{y_1} + b_{12} \epsilon_t^{y_2} \tag{4.3}$$

$$u_{y_2 t} = b_{21} \epsilon_t^{y_1} + b_{22} \epsilon_t^{y_2} \tag{4.4}$$

Where ϵ^{y_1} and ϵ^{y_2} represent the unobserved structural shocks and, B, the impact matrix.

Parameters ϕ can be estimated by OLS, where u_t will be the residuals. Nevertheless, u_t does not represent the effect of a single structural shock, therefore, the residual's structural form is used to identify the individual effects, that is, the impact matrix:

$$u_t = B\epsilon_t \tag{4.5}$$

The next relation between the covariance matrix of the reduced-form residuals $\sum_u$ and the structural shocks is employed:

$$\sum u = \mathbb{E}[u_t u_t'] = \mathbb{E}[B\epsilon_t(B\epsilon_t)'] = B\mathbb{E}(\epsilon_t \epsilon_t')B' = B \sum \epsilon B' = BB'$$

Then, the identification problem is reduced to find B that satisfies $\sum_u = BB'$. Here, a Cholesky decomposition of $\sum_u$ allows finding B, assuming that some shocks have zero contemporaneous effect on some endogenous variables, namely, $b_{12} = 0$. Once the impact matrix has been identified, local projections can be estimated.

To explain the non-linear local projection model methodology, firstly, a brief description of the linear case is presented. As in Jordà (2005), following the example and generalizing for n endogenous variables and T lags, a linear local projection for the endogenous variables Y_t is estimated as:

$$Y_{t+h} = \alpha_0 + \sum_{i=1}^{T} \phi_i Y_{t-i} + u_t, \text{for the horizon } \; h = 1, ..., H. \tag{4.6}$$

Where:

$$Y_t = \begin{bmatrix} y_{1,t} \\ \vdots \\ y_{n,t} \end{bmatrix} \alpha_0 = \begin{bmatrix} \alpha_{01} \\ \vdots \\ \alpha_{0n} \end{bmatrix} \phi = \begin{bmatrix} \phi_{11} & \dots & \phi_{1n} \\ \vdots & \ddots & \vdots \\ \phi_{n1} & \dots & \phi_{nn} \end{bmatrix} u_t = \begin{bmatrix} u_{1,t} \\ \vdots \\ u_{n,t} \end{bmatrix}$$

As mentioned, parameters ϕ_i and α_0 are estimated by an OLS model for each horizon h. An IRF can be described as the difference between two forecasts, following this definition, the IRFs from the linear local projections are:

$$I\hat{R}F_{j,h} = \phi^h_{j,1} B_j, \quad \text{for the endogenous variable } \; j \; \text{ and the horizon } \; h = 1, ..., H. \tag{4.7}$$

Where:

$$B_j = \begin{bmatrix} b_{11} \\ \vdots \\ b_{1n} \end{bmatrix}$$

B_j represents the impact coefficients of the endogenous variable j and $\phi^h_{j,1}$ only contains variable j interaction coefficients (j row).

In the non-linear case, local projections and IRFs are estimated for each regime (Auerbach & Gorodnichenko, 2012). A switching or trigger variable is used to differentiate between regimes. If the trigger variable is a dummy, a determined regime is assigned to one value. If the trigger variable is not a dummy, it can be plugged into a transition function, namely, a logistic function:

$$F(Z_t) = \frac{e^{-\gamma Z_t}}{1 + e^{-\gamma Z_t}} \in [0, 1], \text{with a parameter } \ \gamma > 0 \tag{4.8}$$

Where Z_t is the trigger variable, which can be decomposed with a Hodrick-Prescott filter. Then, the regimes can be defined as:

$$\text{Regime 1} : (1 - F(Z_{t-1})Y_{t-i}, \text{ for the lags } \ i = 1, ...T$$

$$\text{Regime 2} : (F(Z_{t-1})Y_{t-i}, \text{ for the lags } \ i = 1, ...T$$

In this sense, when the trigger variable is a dummy, regime 1 is activated when the dummy is equal to 0, and vice versa. Consequently, for the endogenous variables Y_{t+h} the model is estimated as:

$$Y_{t+h} = (1 - F(Z_{t-1})) \sum_{i=1}^{T} \phi_{i,R1}^{h} Y_{t-i} + (F(Z_{t-1})) \sum_{i=1}^{T} \phi_{i,R2}^{h} Y_{t-i} + u_t \tag{4.9}$$

for the horizon $h = 1, ..., H$, with $\phi_{1,R1}^{0} = I$ and $\phi_{1,R2}^{0} = I$

The set of parameters ϕ_i is estimated by OLS for each horizon h as well. The IRFs for each regime are then estimated as:

$$\text{IRF in regime 1: } I\hat{R}F_{j,h}^{R1} = \phi_{j,1,R1}^{h} B_j \tag{4.10}$$

$$\text{IRF in regime 2: } I\hat{R}F_{j,h}^{R2} = \phi_{j,1,R2}^{h} B_j, \tag{4.11}$$

for the endogenous variable j and the horizon $h = 1, ..., H$.

Once the local projection model theory has been described, as well as its non-linear case, the next section focuses on describing and analyzing the data used in the estimation.

4.2 Data

Our data set uses monthly data and spans the period that runs from March 2005 to October 2020 (188 observations). The variables are agricultural inflation, the Global Indicator of Economic Activity (IGAE) gap, past expectations of current inflation, past expectations of the current IGAE's changes, 91-day Cetes rate, the change in the exchange rate of the peso against the dollar – all the former are from Mexico–, the Volatility Index (VIX) and an International Agriculture Price Index (IAPI). Finally, ENSO is considered the relevant climate variable. Table 4.1. summarizes all variables.

Table 4.1: **Variable Selection**

Variable	Symbol	Source
Agricultural Inflation	π_t	SIE, Banco de México
IGAE Gap	y_t	SIE, Banco de México
Inflation Expectations	$E_{t-\delta-1}\pi_t$	SIE, Banco de México
IGAE Expectations	$E_{t-\delta-1}\Delta y_t$	ARIMA Model
91-day Cetes Rate	i	SIE, Banco de México
Exchange Rate	Δc_t	SIE, Banco de México
VIX	VIX_t	Yahoo Finance
International Agriculture Price Index	$Pagr_t$	World Bank Commodity Price Data
SOI	SOI_t	Australian Government: Bureau of Meteorology

Note: Variable selection for the non-linear local projection model. The first column shows the variable's name, the second column shows the variable's symbol used in the specification, and the tird column shows the source. Source: own elaboration.

Some economic time series are affected by seasonal behaviors, for instance, prices of some fruits that can be produced only during certain seasons, like summers, tend to rise during other seasons due to a shortage in the supply and a high level of aggregate demand, and then, decline during summer months when there are enough production to satisfy the level of demand. Hence, in this case, the price series and the aggregate demand or economic activity series would experience predictable changes that would occur every calendar year, this is called stationality. It is important to adjust for these patterns, since the cyclic behavior could bias the estimation and lead to misleading conclusions. Another reason to adjust for seasonality is to pull apart these cyclical weather events, like summer and winter seasons, from aperiodic weather events, like El Niño and La Niña, so we can avoid a deceptive analysis.

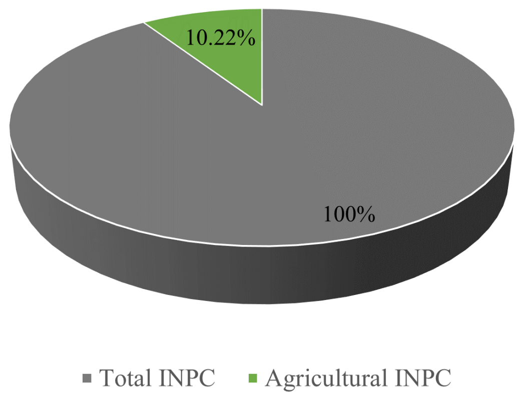
There are other causes of stationality in time series, Granger (1978) states that there are at least another three; institutional decisions, calendar effects, and economic agents' expectations. Other ways that seasonality can affect an economic analysis are, for instance, it can be the main source of variability in a time series; two series could be correlated just because of shared seasonal features, and seasonality could make it difficult to identify and understand underlying economic signals of the series. Finally, but not less important, a seasonal adjustment helps to mitigate the outliers effect on the underlying patterns of a series.

To adjust for seasonal factors, a test for seasonality was run for every variable, in particular, a X-13-ARIMA analysis. It is important to mention that all variables were adjusted in levels before to calculate year over year rates for the corresponding variables.

Agricultural inflation represents the year-over-year rate of the agricultural Price Consumer National Index (INPC, by its Spanish initials). The agricultural INPC is made up of two sections, fruits, and vegetable prices, and beef, pork, poultry, fishmeal, processed meats and dairy products prices, and it represents the 10.22% of the total INCP as figure 4.1 shows. Year-over-year rates were chosen due to they are commonly used in the economic analysis of inflation, also, they allow for cleaning any seasonality element that could be left in the series, since there is high autocorrelation in it. Figure 4.2 plots agricultural inflation and total inflation series. As it is possible to identify, agricultural year-over-year rates have more variability and a higher mean than those from total prices, this could be the consequence of several factors that affect them, like weather, other services prices, transport, electricity, and international prices as well.

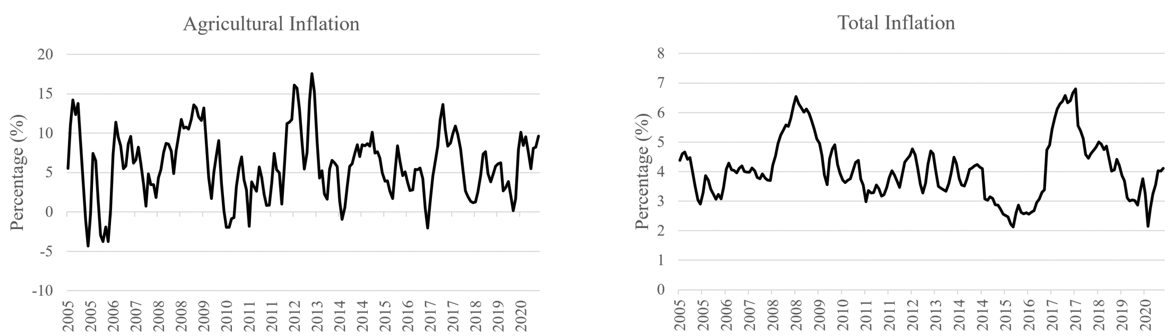
In this sense, the annual inflation of the International Agriculture Price Index (IAPI) is included in the model since Mexico is a small and open economy that is susceptible to international prices changes. The IAPI includes prices of beverages, like cocoa, coffee, and tea; of oils and meals, like coconut oil, copra, fishmeal, groundnuts, groundnut oil, and palm oil; of grains, like maize, rice, and wheat; of other food, like bananas, meat and oranges and raw material prices, like timber, cotton, and tobacco. Figure 4.3 plots year-over-year agricultural inflation and IAPI inflation. It is possible to observe that Mexican agricultural inflation has more variability than

Figure 4.1: **Agricultural INPC as a percentage of total INPC.**



Note: Agricultural INPC as a percentage of total INPC. Source: own elaboration, data from SIE, Banco de México.

Figure 4.2: **Agricultural Inflation vs Total Inflation**

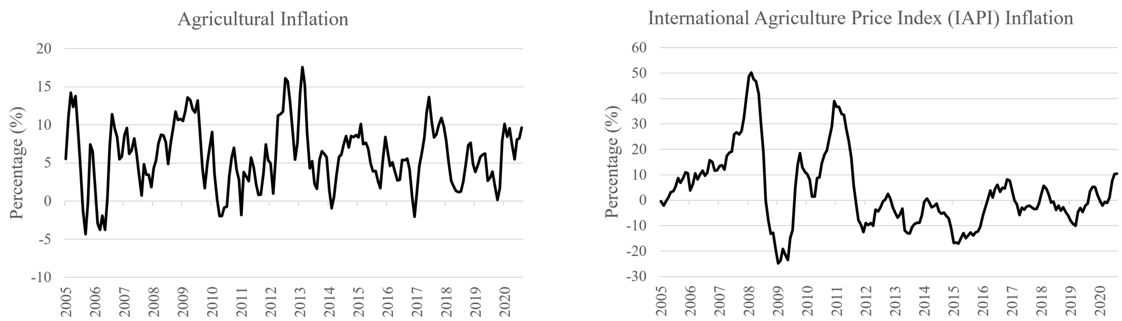


Note: Agricultural inflation (left panel) and total inflation (right panel), from March 2005 to October 2020; both are year-over-year rates. Source: own elaboration, data from SIE, Banco de México.

international agricultural inflation. In the same way, year-over-year rates of the exchange rate are included in the model to control for the effect of US import prices.

Inflation expectations are from a series of surveys collected by Banco de México (BANXICO) among national and foreign specialists on economics in the private sector, like analysis groups and consulting firms. The expectations correspond to general inflation and are expressed in percentages. This variable is included in the model since it allows for capturing the persistence of inflation, and, therefore obtaining a gradual inflation response to economic activity shocks like is observed in reality. It is important to mention that during this century, central

Figure 4.3: **Agricultural Inflation vs International Agriculture Price Index (IAPI) Inflation**



Note: Mexican agricultural inflation (left panel) and International Agriculture Price Index (IAPI) inflation (right panel), from March 2005 to October 2020; both are year-over-year rates. Source: own elaboration, data from SIE, Banco de México.

banks have adopted inflation targeting schemes, and have directed actions to achieve their targets, which has brought contexts with low and stable inflation expectations, and, therefore, inflation with stable, predictable, and low levels, including its components with a volatile nature like agricultural inflation (Bems, Caselli, Grigoli, Gruss, & Lian, 2018; Chiquiar, Noriega, & Ramos-Francia, 2010).

The IGAE is based on a physical volume index, which includes primary, secondary, and tertiary sectors. The secondary sector includes mining; generation, transmission, and distribution of electricity; water and gas services; construction and manufacturing industries. Within the tertiary sector are activities such as commerce; transport, mail, and storage; financial and insurance services; real estate services, and rental of movable and intangible assets, etc. The Hodrick-Prescott filter is applied to calculate IGAE's gap. The HP filter calculates the difference between the original IGAE series and its trend, which gives the IGAE's gap; this variable can be interpreted as an economic slack measure or an aggregate demand tightening measure.

The IGAE's growth expectations are estimated using an ARIMA model. The IGAE monthly data is collected from BANXICO, for which an appropriate ARIMA model is identified. Since the release of IGAE data on the BANXICO site is lagged by three months, monthly IGAE is forecasted (starting in March 2005) using IGAE data lagged by three months (data until November

2004, in the first forecast). Subsequently, an additional observation is added in order to forecast the next month and so on —an out of sample forecasting. The ARIMA model that best fits each data subsample is one with a first difference of the series, two lags of the stationary series, and a moving average term:

$$\hat{y}_t - y_{t-1} = \alpha + \phi_1(y_{t-1} - y_{t-2}) + \phi_2(y_{t-2} - y_{t-3}) + \theta_1 e_{t-1} \tag{4.12}$$

Year-over-year rates are calculated using the forecasts, in order to get the IGAE's growth expectations. Figure 4.4 shows the year-over-year rate of the IGAE series and the IGAE's growth expectations. The 91-day Cetes rate is included in the model to control for short-term monetary policy. The VIX is used to control for periods of high variability in the financial market like the 2008 financial crisis and the 2020 health crisis.

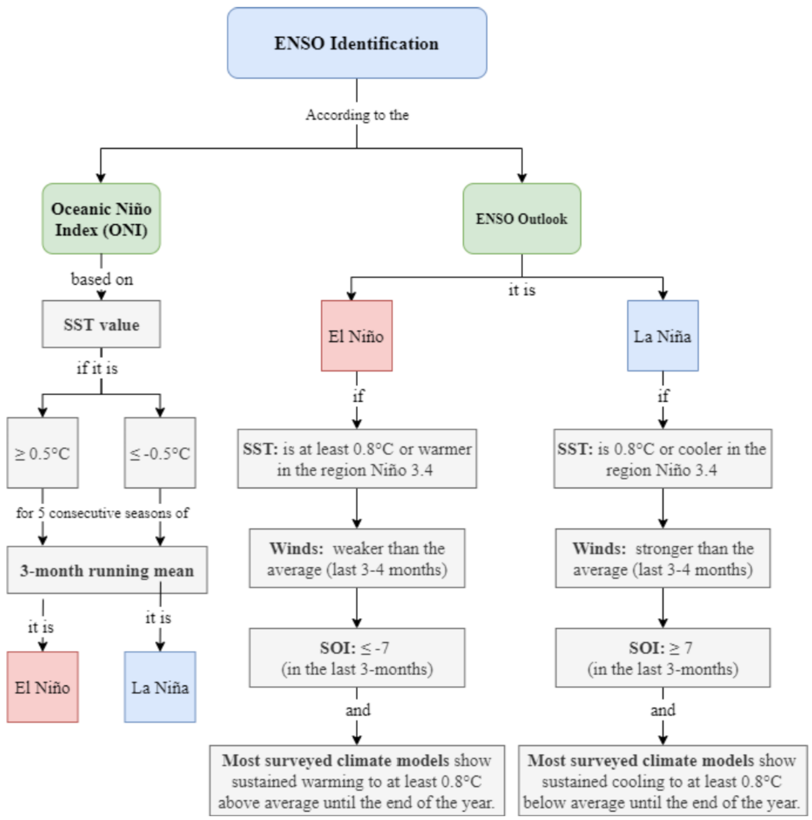
Figure 4.4: **Annual growth of the Global Indicator of Economic Activity (IGAE) and the IGAE expectations**

Note: Global Indicator of Economic Activity (IGAE) annual growth (left panel) and IGAE expectations annual growth (right panel) from March 2005 to October 2020. Source: own elaboration, data from SIE, Banco de México.

The Southern Oscillation Index (SOI) is one measure of the large-scale fluctuations in air pressure occurring between the western and eastern tropical Pacific during El Niño and La Niña episodes, therefore it is an instrument that allows to track and identify the ENSO's current state (NOAA, 2022b). Specifically, this index is based on a standardized difference of the observed values of atmospheric pressure between Tahiti and Darwin, Australia.

The SOI shows a value equal to or less than -7 in the last 3 months when an El Niño event occurs and equal or greater than 7 in the last 3-months when a La Niña event occurs (NOAA, 2009). The negative phase of the SOI represents below-normal air pressure at Tahiti and above-normal air pressure at Darwin. Figure 4.5 shows a diagram of the main ways to track the development of the ENSO cycle based on two indicators – SST refers to the Sea Surface Temperature, which changes depending on the sea sunlight exposure–.

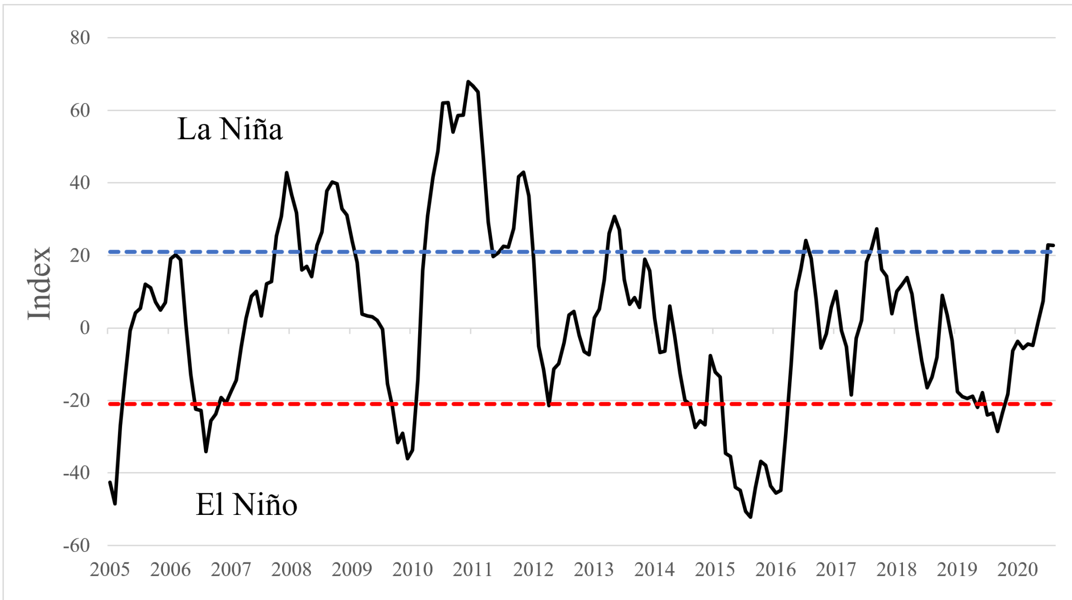
Figure 4.5: **El Niño Southern Oscillation (ENSO) identification**



Note: El Niño Southern Oscillation (ENSO) identification based on two indicators, the Oceanic Niño Index (ONI) and the Southern Oscillation INdex (SOI) – SST refers to the Sea Surface Temperature. Source: Australian Government: Bureau of Meteorology.

The SOI in the Variable Selection table refers to a dummy variable built based on a three-month moving sum of the original monthly SOI index, then, when it shows a value equal to or less than -21 or equal to or greater than 21 it takes the value 1, which means that there are abnormal weather conditions (El Niño or La Niña) and if the moving sum shows a value between 21 and -21 it takes the value 0, which indicates a normal weather scenario. The next figure illustrates how the ENSO state is identified according to the SOI three-month moving sum.

Figure 4.6: **Southern Oscillation Index (SOI)**



Note: El Niño Southern Oscillation (ENSO) state according to the Southern Oscillation Index (SOI) three-month moving sum. The blue horizontal line points out the 21 valueand the red one the -21 value, from March 2005 to October 2020. Source: own elaboration, data from Australian Government: Bureau of Meteorology.

Additionally, the SOI is lagged 12 periods, that is, the ENSO status for the current month is determined by the value of the moving sum 12 months before. A 12-period lag was chosen since the effects of climate change take time to reflect on agricultural prices due to either production reserves, technology that allows farmers to face adverse conditions, and, more importantly, due to the agricultural production cycle, since, it takes a few months since grains are cultivated, harvested and, then, sold in the markets. Table 4.2 shows the descriptive statistics of the variables.

Since the purpose of this work is to identify the effect of large-scale climatological phenomena on economic variables, a non-linear analysis was made for the agricultural inflation and the IGAE year-over-year rates depending on the weather regime. The next figures show boxplots of the agricultural inflation and IGAE's gap distributions according to the SOI index lags' classification. Specifically, there is a distribution when no La Niña or El Niño events occur and another

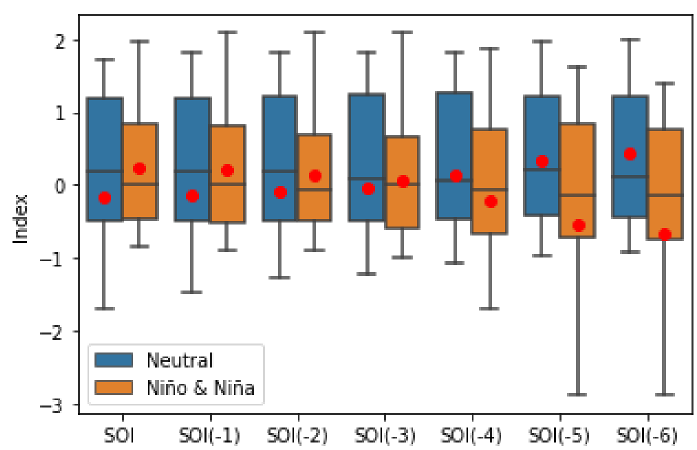
Table 4.2: **Descriptive Statistics**

Variable	Mean	Median	Minimum	Maximum	Std. Dev.
π_t	5.9158	5.6920	-4.3475	17.543	4.2292
y_t	99.330	99.078	84.562	113.65	9.1127
$E_{t-j-1}\pi_t$	0.34432	0.33653	-0.52901	1.5483	0.1655
$E_{t-j-1}\Delta y_t$	1.5725	2.4734	-32.726	8.9245	4.4869
i_t	5.7989	5.1855	2.8848	10.232	1.9492
Δc_t	4.6516	1.7158	-14.274	37.338	10.966
VIX_t	19.252	16.829	9.6800	52.187	8.4630
$Pagr_t$	3.2264	-0.19677	-24.779	50.218	14.698
SOI_t	0.39894	0.00000	0.00000	1.0000	0.4910

Note: Basic descriptive statistics of the variables' series used in the non-linear local projection model which span from March 2005 to October 2020. Source: own elaboration.

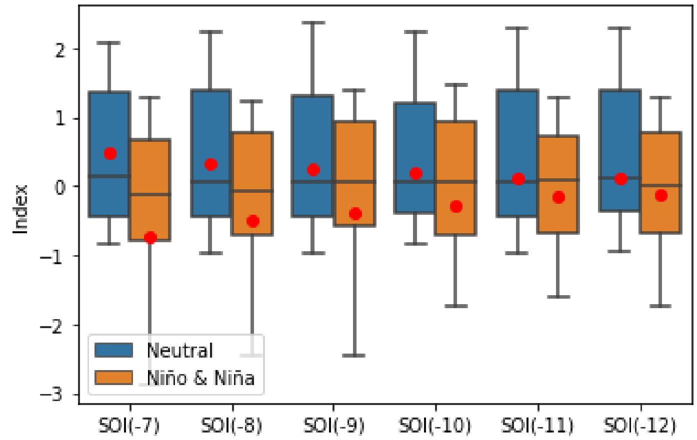
one when one of these events occur for each lag. Here, what is expected to see is the IGAE gap distributions as far away as possible for the 12 lag at least, and, consequently, agricultural inflation distributions as well. This would mean that the IGAE behaves differently depending on the weather regime, and the agricultural inflation reacts differently to weather as well since the weather regimes change the IGAE level. The agricultural inflation could change through different channels when the weather changes, here, just the economic activity channel is identified and assessed.

Figure 4.7: **IGAE gap distribution according to SOI index's lags 0 to 6 (Niña & Niño vs Neutral)**



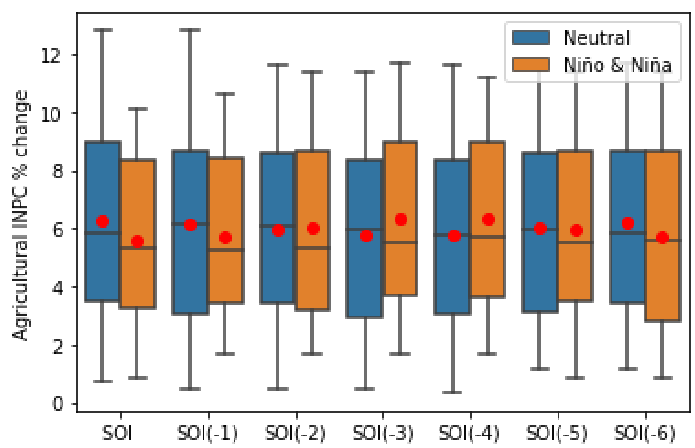
Note: Total Global Indicator of Economic Activity (IGAE) gap distribution according to the SOI index's classification (Niño or Niña vs Neutral) considering its lags 0 to 6. P(10), Q1(25), P(50), Q3(75), P(90), the mean (red circles), and the outliers (diamonds) are shown. Source: own elaboration, data from SIE, Banco de México and Australian Government: Bureau of Meterology.

Figure 4.8: **IGAE gap distribution according to SOI index's lags 7 to 12 (Niña & Niño vs Neutral)**



Note: Total Global Indicator of Economic Activity (IGAE) gap distribution according to the SOI index's classification (Niño or Niña vs Neutral) considering its lags 7 to 12. P(10), Q1(25), P(50), Q3(75), P(90), the mean (red circles), and the outliers (diamonds) are shown. Source: own elaboration, data from SIE, Banco de México and Australian Government: Bureau of Meterology.

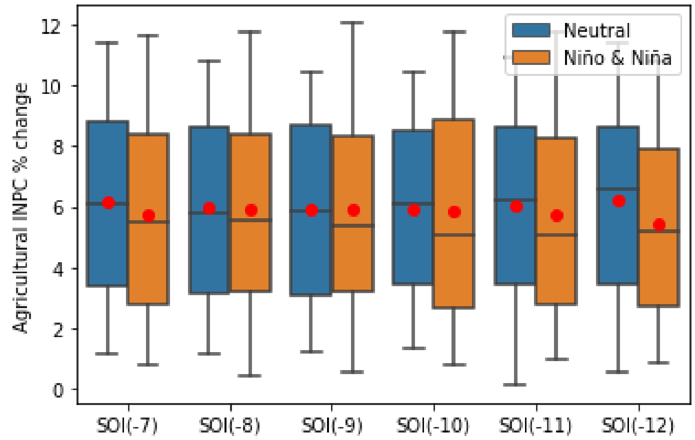
Figure 4.9: **Annual Agricultural Inflation distribution according to SOI index's lags 0 to 6 (Niña & Niño vs Neutral)**



Note: Annual agricultural inflation distribution according to the SOI index's classification (Niño or Niña vs Neutral) considering its lags 0 to 6. P(10), Q1(25), P(50), Q3(75), P(90), the mean (red circles), and the outliers (diamonds) are shown. Source: own elaboration, data from SIE, Banco de México and Australian Government: Bureau of Meterology.

Figures 4.7 and 4.8 show that one of the lags where the IGAE gap distributions are least spliced appears to be the 12 one. This follows with the fact that figures 4.9 and 4.10 show that agricultural inflation distributions are least spliced at the 12 lag. For this reason, the 12

Figure 4.10: **Annual Agricultural Inflation distribution according to SOI index's lags 7 to 12 (Niña & Niño vs Neutral)**



Note: Annual agricultural inflation distribution according to the SOI index's classification (Niño or Niña vs Neutral) considering its lags 7 to 12. P(10), Q1(25), P(50), Q3(75), P(90), the mean (red circles), and the outliers (diamonds) are shown. Source: own elaboration, data from SIE, Banco de México and Australian Government: Bureau of Meterology.

lag is chosen as the relevant one to determine the number of periods that pass until the weather conditions affect the IGAE and the agricultural inflation.

To work with series, these need to have constant variance over time, in other words, they can not show a trend. Therefore, a stationarity test is applied to the series to verify if these need adjustment or not. Once the seasonality test was executed, and the corresponding year-over-year rates were calculated, it follows the stationarity test. Phillips-Perron test is used to check for a unit root in a time series. Unlike the Dickey-Fuller test, the Phillips-Perron test considers heterogeneity in the variance of the errors, as well as weak dependence between them, for this reason, this test is used since it allows greater flexibility in the distribution of the errors of the series. Applying the Phillips-Perron test on all seasonal adjusted variables, it is found that only the IGAE needed stationary adjustment. Nevertheless, the IGAE is not adjusted since the HP filter is applied later to it, in which the difference between the original data and its trend is calculated. That is, the series is decomposed between its trend and its cycle, since the series is already seasonally adjusted, it can be stated that there is a matching move between its trend and the adjusted series; therefore, the difference between the original data and its trend is a stationary series. Table 4.3 shows the Phillips-Perron test results.

Table 4.3: **Phillips-Perron Unit Root Test**

Variable	Statistical Z_t	p-value
π_t	-4.70861	0.0001
y_t	0.810272	0.8862
$E_{t-j-1}\pi_t$	-12.0446	0.0000
$E_{t-j-1}\Delta y_t$	-3.57927	0.0071
i_t	-1.6281	0.0976
Δc_t	-2.94657	0.0034
VIX_t	-3.41087	0.0118
$Pagr_t$	-2.81165	0.0051

Note: The statistical and p-value from the Phillips-Perron unit root test for each variable used in the model. The null hypothesis indicates the presence of a unit root. Only the the IGAE required stationary adjustment.
Source: own elaboration.

It is important to mention that some tests include a deterministic term in the auxiliary regression, namely, a constant. The constant is interpreted as a trend element in the variable data generating process.

Finally, a non-linearity test is run to support the non-linear relationship between agricultural inflation and economic activity that is intended to assess. To identify regime-dependent nonlinearities in these variables' dynamics, the Regression Error Specification Test (RESET) is used. The residuals from a linear model are regressed on the explanatory variables used in the estimating equation and on the fitted values. Then, if the residuals are independent, they should not be correlated with the regressors or the fitted values. RESET's null hypothesis states linearity in the time series, namely, that the residuals are independent. The next auxiliary regression is used:

$$e_t = \delta \hat{y}_t + \alpha x_t^2 \tag{4.13}$$

where $\hat{y}_t$ are the linear model fitted values and x_t is the vector that contains the explanatory variables, including exogenous variables. The explanatory variables included are IGAE's gap, the past expectations of current inflation and igae's growth, the 91-day Cetes rate, the year-over-year rate of the exchange rate, the VIX index and the IAPI.

Table 4.4 shows the test results that support the rejection of the null hypothesis, which is to say, the agricultural inflation and explanatory variables relationship is not linear. It is important to mention that the RESET test helps determine whether a nonlinear model is appropriate but not in determining the nature of the non-linearity. In this sense, the empirical model –explained later–, assumes that agricultural inflation responses to positive shocks in the IGAE are not mirror images under different initial IGAE scenarios, that is, agricultural inflation responses are asymmetric. This could be true due to several intermediary channels, which might differ depending on the weather regime. For instance, a scenario with abnormal high or low temperatures or abnormal high or low levels of precipitation can discourage agricultural production, due to droughts, frosts or floods, then diminishing economic activity. Therefore, based on the weather regime, the initial level of economic activity could be low or high, which can change agricultural inflation responses to IGAE shocks.

Table 4.4: **RESET Test**

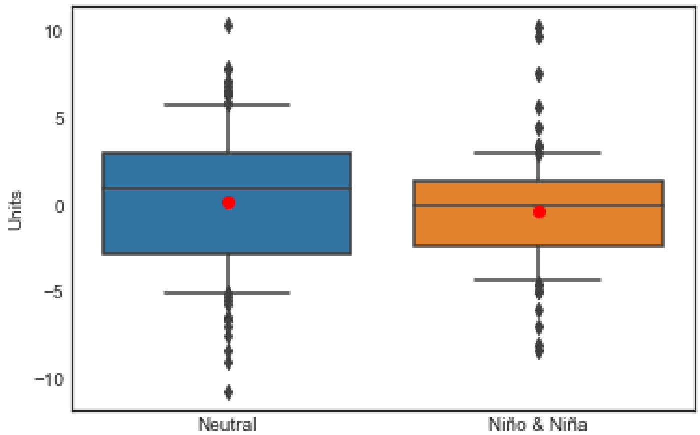
RESET	df1	df2	p-value
3.3382	7	173	0.0023

Note: Statisticals and p-value from the RESET test. RESET's null hypothesis states linearity in the series relationship. At the 1% level of significance the series relationship is non-linear. Source: own elaboration.

As a complement to the RESET test, Figure 4.11 shows the residuals' distributions of a linear regression model, that is, agricultural inflation against the explanatory variables (considering exogenous variables) according to the SOI index's 12 lag classification. It is shown that the neutral regime's residuals have a distribution with a wider range and a higher mean than the other regime.

It is important to recall that literature that assesses the direct effect of ENSO on agricultural inflation highlights the asymmetric influence of El Niño and La Niña shocks. For instance, Abril-Salcedo et al. (2020) found that an El Niño shock has an effect of 730 basis points on

Figure 4.11: **Linear Regression's Residuals distributions according to SOI index 12 lag**



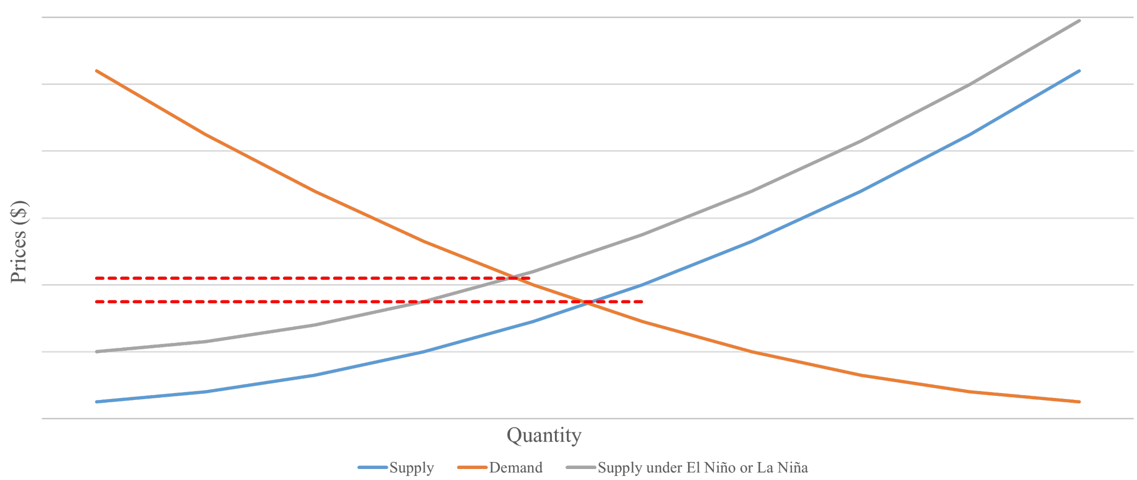
Note: Linear Regression's Residuals distributions according to the SOI index's classification (Niño or Niña vs Neutral) considering its 12 lag. P(10), Q1(25), P(50), Q3(75), P(90), the mean (red circles), and the outliers (diamonds) are shown. Source: own elaboration, data from SIE, Banco de México and Australian Government: Bureau of Meterology.

Colombian food inflation, while a La Niña shock has an ambiguous effect. Smith and Ubilava (2017) found that an El Niño event results in one to two percent annual growth reduction in developing countries, while a La Niña event has no effect. Ubilava (2017) found more amplified (persistent) wheat prices responses after (during) La Niña events for the United States, Canada, the European Union, Argentina, and Australia.

This research tests the hypothesis that some high inflation periods are generated or empowered by a supply shortage due to a production reduction in the agricultural sector caused by abnormally high or low temperatures and precipitation levels. Better say, it is intended to identify differences in the inflation behavior depending on the weather regime. But, it is important to mention that EL Niño and La Niña conditions are not treated as shocks but as global scenarios that can generate a context of a shortage supply of agricultural products. The hypothesis is tested indirectly through a shock of economic activity (a positive aggregate demand shock) on agricultural inflation analyzed under a neutral and an abnormal weather scenario. Namely, based on the literature reviewed related to climate change's impact on Mexican agriculture, it is expected to see that, under abnormal weather, a positive aggregate demand shock will generate a higher increase in inflation or the largest number of periods with positive inflation impacts, than under neutral periods, due to droughts, frosts or floods.

To explain the economic intuition better, Figure 4.12 shows a diagram of the aggregate demand and supply under a neutral weather scenario vs the aggregate supply under an El Niño or La Niña scenario. It is possible to see that under abnormal weather conditions the aggregate supply would be contracted to generate, then, higher prices. In this sense, a positive aggregate demand shock (higher economic activity) would cause higher prices under an abnormal weather scenario than under a neutral one.

Figure 4.12: **Aggregate demand and supply**



Note: Agricultural inflation and IGAE series for Mexico from March 2005 to October 2020. Blue lines indicate neutral regimes and orange lines indicate El Niño or La Niña regimes. Source: own elaboration.

4.3 Empirical Strategy

In this section, the empirical approach used to explore Mexican agricultural inflation and economic activity dynamics under two different weather scenarios (El Niño or La Niña vs neutral weather) is described. Following Jordà (2005) and Auerbach and Gorodnichenko (2012) a Non-Linear Local Projection Model is considered to study all endogenous and exogenous variables' dynamics. As mentioned, the Local Projection approach is considered to fit better with the intended analysis since it easily accommodates non-linear specifications, also it is robust to misspecification of the data generating process (DGP) and projections are easily calculated but still show consistent estimates of the IRFs coefficients, in contrast with direct forecasting where only an optimal multistep forecast is pursued (Jordà, 2005). The Non-Linear model, through the estimation of impulse response functions, allows analyzing agricultural inflation response to a positive aggregate demand shock in Mexican economic activity under two different scenarios.

The local projection equation for agricultural inflation can be specified as:

$$\begin{aligned} \pi_{t+h} = \beta_0 + (1 - Z_{t-1})(\sum_{i=0}^{4} \phi_{i,N}^h x_{t-i} + \gamma_{i,N}^h \sum_{i=0}^{1} z_{t-i}) + \\ (Z_{t-1})(\sum_{i=0}^{4} \phi_{i,A}^h x_{t-i} + \sum_{i=0}^{1} \gamma_{i,A}^h z_{t-i}) + u_t \end{aligned} \tag{4.14}$$

for the horizon $h = 1, ..., 12$, with $\phi_{1,N}^0 = I$ and $\phi_{1,A}^0 = I$.

Where:

$$x_t = (\pi_t, y_t, E_{t-\delta-1}\pi_t, E_{t-\delta-1}\Delta y_t, i, \Delta c_t)$$

$$z_t = (VIX_t, Pagr_t)$$

N indicates the neutral/normal regime and A indicates the El Niño or La Niña regime. The trigger variable, Z_t, corresponds, as explained, to SOI(-12). When SOI(-12) takes the value of 0, the neutral regime is activated and when it takes the value of 1, El Niño or La Niña regime is activated. x_t represents the endogenous variables vector and z_t the exogenous one. Matrix ϕ_i^h and γ_i^h contains the interaction coefficients for endogenous and exogenous variables, respectively. Also, a constant β_0, for each horizon, is included since the mean of some series is different from zero.

As mentioned, the Sticky-Information model is used to shape the inflation dynamics, particularly, agricultural inflation in Mexico. Then, among the endogenous variables, besides agricultural inflation, IGAE's gap and the respective expectations are included as the theory states. However, other control variables are incorporated among the endogenous variables and exogenous as well. As explained, the 91-day Cetes rate is included to control for short-term monetary policy. The exchange rate controls the level of imports and exports, and the effect of US prices. Among the exogenous variables is the VIX, which is used to control for periods of high variability in the financial market like the 2008 financial crisis and the 2020 health crisis. Finally, the IAPI adds the international agricultural prices dynamic to the model, which could be affected by international supply chain interruptions, environmental disasters, foreign policies, etc.

Lag selection for both endogenous and exogenous variables is made based on the Bayesian information criterion (BIC). The Akaike information criterion (AIC) and the Hannan–Quinn information criterion (HQC) were also consulted, however the BIC criterion was considered the best. One lagg was applied to the endogenous variables and one lag for the exogenous ones.

The IRF of agricultural inflation to a positive aggregate demand shock would be:

$$\text{IRF in neutral regime: } I\hat{R}F^{N}_{\pi,h} = \phi^{h}_{\pi,1,N} B_{\pi} \tag{4.15}$$

$$\text{IRF in El Niño or La Niña regime: } I\hat{R}F^{A}_{\pi,h} = \phi^{h}_{\pi,1,A} B_{\pi}, \tag{4.16}$$

for the endogenous variable π and the horizon $h = 1, ..., H$.

Where $\phi^{h}_{\pi,1}$ is the interaction coefficients matrix and B_{π} is the impact coefficient matrix both for agricultural inflation.

Chapter 5

Results

Before showing the estimation results, it is important to describe the dynamic between inflation and economic activity. A positive economic activity shock, namely, an aggregate demand shock can come from a fiscal stimulus, a monetary stimulus, foreign capital inflow, an international demand increase for national products or services, etc. In this sense, companies anticipating increased demand or revenues will respond by expanding production and hiring more workers. This increase in production and hiring could lead to an increase in the aggregate demand and, therefore, in consumption. This, in turn, will lead to higher prices. Then, the relationship between inflation and economic activity, namely, a positive aggregate demand shock, is expected to be positive.

As demonstrated in last sections, the former relationship appears to have a nonlinear behavior. That is, agricultural inflation response to changes in the economic activity could differ depending on the initial level of the latter. The level of economic activity could be affected by several channels as mentioned. In Mexico, agricultural production represents a relevant part of the GDP and is an important economic activity for many Mexican households. Then, a generalized disruption in agricultural product supply could lead to a reduction in Mexican economic activity and vice versa. A shortage supply of agricultural products can be the consequence of adverse weather like abnormally high or low temperatures which could cause droughts and frosts, respectively. Also, abnormally high or low precipitation levels could decrease agricultural production due to floods and droughts, respectively. Therefore, the weather scenario, namely, El Niño and La Niña scenarios, are considered as instruments that can alter the initial level of economic activity and, at the same time, be able to analyze the weather influence on the agricultural inflation dynamics. It is important to recall that EL Niño and La Niña conditions are not treated as shocks but as global scenarios that generate disruptions in the agricultural production.

As explained, in a context with a shortage supply of agricultural products, a positive aggregate demand shock could lead to higher prices. Then, this analysis intends to discover how El Niño and La Niña contexts can affect agricultural inflation response to economic activity shocks compared to a normal o neutral context.

Table 5.1 presents the change in agricultural inflation in percentage points (pp) caused by a 1% increase in the IGAE (a positive aggregate demand shock) for both regimes and for 2 to 12 months after the shock. In the neutral regime, months 7 to 12 present a significant response, and in the El Niño or La Niña regime the impact in months 5 to 12 is significant. The accumulated effect is bigger in the El Niño or La Niña regime. That is, under abnormal weather conditions, namely, abnormal temperature and precipitation levels, agricultural inflation responds earlier, at the 5th month, in contrast with the neutral regime, where the effect appears until the 7th month, and the total impact under the El Niño or La Niña regime is 70 bp bigger than under the neutral one. The above indicates that if agricultural inflation has averaged 6% during the last years, then under adverse weather conditions agricultural inflation would be 6.7%, approximately.

Figure 5.1 shows the IRFs for both regimes. IRFs are graphed with a 10% confidence interval, nevertheless, with a 5% or 1% confidence interval the significance of most of the periods remains. Both IRFs are similar, they both have a soft demeanor and have significant periods from the 5th month onwards. Nevertheless, as explained, the agricultural inflation responses under the El Niño or La Niña regime have a larger magnitude, reaching the highest at the 9th month, in contrast with the neutral regime where the highest response of agricultural inflation is at the 10th month and of a smaller magnitude.

Table 5.1: **Agricultural Inflation response to a 1% IGAE shock under the neutral vs the El Niño or La Niña regimes**

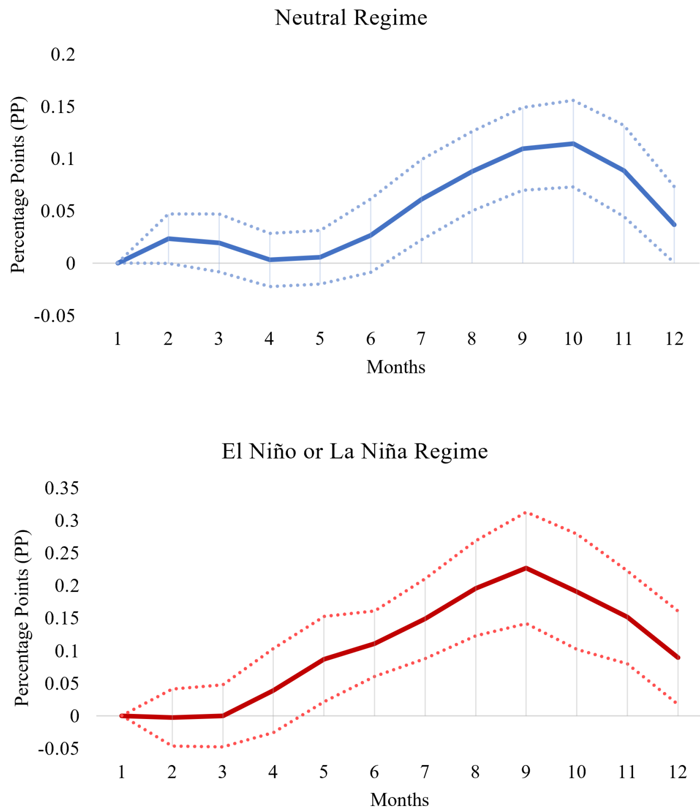
	Regime	
Horizon	Neutral	El Niño or La Niña
2	0.023	-0.003
3	0.019	0.000
4	0.003	0.039
5	0.006	0.087**
6	0.027	0.111***
7	0.061**	0.149***
8	0.088***	0.196***
9	0.109***	0.227***
10	0.114***	0.191***
11	0.088***	0.151***
12	0.037*	0.090*
Accumulated Effect	0.4972	1.2011

Note: Agricultural inflation response in percentage changes to a 1% IGAE shock (a positive aggregate demand shock) for 2 to 12 months after the shock, under neutral versus El Niño or La Niña regime. Statistical significance: * $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$. Source: own elaboration.

It was expected that under the abnormal weather conditions of El Niño and La Niña, agricultural inflation response would be higher, due to a greater existing shortage supply in agricultural production, as explained in figure 4.11, we do see that the accumulated impact is larger, appears early, and keeps significant for more periods. These results suggest that both climatic phenomena could generate a scenario of a relevant shortage of agricultural production and, therefore, have a positive effect on its prices. In other words, the abnormal high temperatures and lower precipitation levels brought by El Niño and the abnormal low temperatures and high precipitation levels brought by La Niña could importantly block agricultural production and generate a scenario with higher agricultural prices under which a positive economic activity shock will generate even higher prices.

Specifically, agricultural production can be affected by the droughts during El Niño summers caused by the decreasing levels of precipitation and higher temperatures. Also, during El Niño winters some unexpected frosts can appear due to the increasing levels of precipitation and lower temperatures. In the same way, general lower temperatures during La Niña events can reduce

Figure 5.1: **Agricultural Inflation Response to a 1% IGAE shock under neutral vs El Niño or La Niña regimes**



Note: Impulse response functions (IRFs) of agricultural inflation to a 1% IGAE's shock (a positive aggregate deman shock) for 1 to 12 months after the shock. The top panel corresponds to a neutral regime and the bottom one to a El Niño or La Niña regime. The dotted lines indicates the 10% confidence interval. Source: own elaboration.

agricultural production due to frosts and the general abnormally high levels of rainfall during La Niña events could importantly reduce agricultural production due to floods in regions where the soil has lost its ability to absorb water due to agricultural misuse.

The time differences identification in the inflation response is an important result since it allows monetary policy authorities to expect a certain inflation behavior depending on the weather regime. In particular, to be prepared for a fast and larger inflation response under abnormal weather and a more retarded and smaller one under normal weather. Furthermore, the identification of this agricultural inflation dynamic allows the central bank to recognize transitory effects under both regimes and, therefore, not to overreact by tightening the monetary stance. In this sense, this model can be used as a tool to anchor inflation expectations by explaining the transitory nature of this phenomena. Nevertheless, the magnitude of these effects suggests that agricultural inflation should be considered a phenomenon that can turn on a red light for intervention. In the same way, the differences in the inflation dynamic between regimes suggest that weather should be an element to be considered in the inflation targeting schemes.

These results also show the great uncertainty to which farmers are exposed since agricultural inflation's responses vary across the weather scenarios. An increase in agricultural prices affects farmers' income, employment, and production, which in the end are reflected at the macroeconomic level (Abril-Salcedo et al., 2020). In this sense, the model can be used to design public policies to mitigate high inflation levels depending on the highest inflation regime. That is, under abnormal weather, the government could encourage programs that provide training and tools for the implementation of drainage systems or greenhouses to improve production. Also, improving trade policies and storage capacity would be effective in smoothing supply, and, consequently, agricultural prices. Programs focused on reducing income volatility (like stabilization funds) or smooth household consumption via a food subsidy program also is a way to reduce the households' vulnerability to agricultural prices. This weather regime-dependent variability in the Mexican agricultural prices represents a food security issue in the short run, that could become a long-term problem if the consequences on health and development are taken into consideration. The data sets, tests and results' codes can be found in the following link `https://github.com/AnnKari/The-Phillips-Curve-and-ENSO-`.

Chapter 6

Concluding Remarks

We assess the non-linear relationship between Mexican agricultural prices and economic activity, specifically, a demand shock, under two different weather scenarios by the estimation of IRFs using a Non-Linear Local Projection approach. The Sticky-Information model by Mankiw and Reis (2002) is used to stablish the basic theoretical relationship between inflation and economic activity. It is found that agricultural inflation responses to a 1% shock of the IGAE differ according to the weather regime. In general, under the abnormal weather regime, built based on the El Niño and La Niña conditions, the accumulated effect on inflation is 70 bp higher than under the neutral regime. In other words, if agricultural inflation has averaged 6% during the last years, then under adverse weather conditions agricultural inflation would be 6.7%, approximately. This suggests that droughts, frosts and floods could have an important negative impact on agricultural production which would cause an agricultural price rising. Then, under this context, a positive shock of the aggregate demand will generate higher agricultural prices. IRFs of both regimes have a similar demeanor, but under the abnormal weather regime, the agricultural inflation response arrives two months earlier, there are more periods of significant impacts and the impact's magnitudes are larger.

These findings are an important tool to monetary policy, since they allow to identify inflation patterns depending on the economic and weather context, understand sources of prices changes, and also important, to know the temporary nature of these phenomena. In this sense, mecanisms to anchor inflation expectations and increase credibility on the central bank are important to consider in order to keep monetary stability under these scenarios and limit the consequences of inflationary effects linked to climatic variations. These results show some of the different challenges placed by climate change as well, and highlight the importance of considering weather variables into the inflation targeting schemes. "Overlooking the effects of changing weather patterns has on future inflation could potentially move inflation away from central bank's target" (Dufrénot et al., 2021, p.1062). In the same way, the inflationary effect's magnitude suggests that agricultural inflation should be subject to policy intervention and do not wait until second hand effects on other sectors.

Policies that absorb or reduce income volatility for households dependent on agriculture production and agriculture consumption, that provides food security and access to technological buffers against climate change, like good storage conditions, irrigation and water retention systems, adaptation of groundwater pumping strategies, greenhouses tools, etc, would help to mitigate the climate change effect on agricultural inflation and the wellness of families. As discussed earlier, these income and food security problems could bring long-term consequences to the health and productivity of the Mexican people, as well as to the central bank's credibility if they are not addressed pertinently.

An analysis that assesses the direct effect of climate change on agricultural prices in Mexico could complement this research and shed light on the impacts of weather under a normal economic context, that is, without the presence of a positive aggregate demand shock, but just with a temperature or precipitation shock. This would allow us to observe the influence of weather patterns on agricultural inflation without the economic activity effect combined. In this sense, another way to expand this research would be the addition of a third regime in the model, so the El Niño or La Niña regime can be separated, allowing for a more deep comparison analysis. However, the results presented here are sufficient to identify the relevance of climatic variables in the Mexican economic context and pertinent policies to absorb negative effects.

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