EL COLEGIO DE MÉXICO
CENTRO DE ESTUDIOS ECONÓMICOS

MAESTRÍA EN ECONOMÍA

TRABAJO DE INVESTIGACIÓN PARA OBTENER EL GRADO DE MAESTRO EN ECONOMÍA

THE IMPACT OF EXTREME WEATHER EVENTS ON AGRICULTURAL PRICES: EVIDENCE FROM GRAIN AND LEGUME WHOLESALE MARKETS IN MEXICO

EDILBERTO DAVID MATÍAS GARCÍA

PROMOCIÓN 2020-2022

ASESOR:

GERARDO ESQUIVEL HERNÁNDEZ

AGOSTO, 2022

Acknowledgments

I am highly grateful for the guidance, comments, and suggestions from my advisor Gerardo Esquivel Hernández. Gerardo's support and thoughtful example have been crucial in my path to and through my bachelor's and master's studies. Thank you for your guidance and patience.

I am deeply grateful for the very insightful teaching, support, and advice from my professors, Aurora Ramírez, David Cantala, Raymundo Campos, Arturo Herrera, Santiago Bazdresch, and Laura Juárez. Thank you all for developing and maintaining a satisfying and intellectually compelling setting for economic studies and research in the Colegio de México.

I would like to extend my sincere gratitude to David López Soto. His mentorship and advice have been essential to my development as an economist. Conversations with David about this work were an important input into how I think about the purpose of this thesis.

Throughout my time in the Colegio de México, I have enjoyed and benefitted from the friendship, advice, and support of many people, including Atzin Chiguil, Marcos García, and Dario Pazos. I couldn't have done it without you guys; thank you for sharing with me your passion for economics.

I greatly appreciate the generous financial support provided by CONACYT. Thanks to the Mexican government's support, I could devote full time to my master's studies for two years.

I am indebted to my family for their continuous support. Above all else, I am grateful to my parents Micaela García and Edilberto Matías, and to my brothers, Estefania Matías and Elias Matías. I love them profoundly and thank you for believing in me.

Contents

I. Introduction

Increasing studies and climate data indicate that the rise in the global temperature has resulted in more frequent and severe extreme weather events. The Intergovernmental Panel on Climate Change estimates a further increase in the variability and frequency of extreme weather events, such as windstorms and droughts (IPCC 2011). This situation will cause substantial damage to most economies and reduce the economic growth potential in some countries (Drudi et al. 2021; S. M. Hsiang and Jina 2014). Agriculture will be the most affected sector because of the decline in production that will result from agriculture's dependence on meteorological conditions, such as temperature and precipitation (Auffhammer and Schlenker 2014; Carleton and Hsiang 2016). The literature suggests that developing countries are projected to suffer most because of their high dependence on the agricultural sector and because of the large share of household expenditures allocated to food consumption.

The economic literature considers broader consequences of extreme weather; in Mexico, for example, the literature suggests effects on economic growth, poverty, employment, prices, and agricultural output (Arceo-Gómez, Hernández-Cortés, and López-Feldman 2020; Feng, Krueger, and Oppenheimer 2010; Guerrero Compeán 2013; Murray-Tortarolo and Jaramillo 2019). The literature on the effect on prices has focused on the impact of increases in temperature and extreme weather events on general price indices and, in some cases, food prices (BANXICO 2021; De Winne and Peersman 2021; Guerrero Compeán 2013; Mukherjee and Ouattara 2021; Parker 2017). This thesis contributes to the literature on the effect of extreme weather events on increases in food prices, particularly in grain and legumes prices. More specifically, this article makes the following two key contributions. First, unlike most studies that use times-series methods or panel data estimation to identify the effects of natural disasters on prices, we analyzed the short-run impact on prices of a particular context: the extreme weather events of 2011. The paper's second contribution is the identification of the medium-term effects of price increases.

Grain prices are especially relevant because they are a major driver of food prices, serving as the main determinants of meat, poultry, and dairy product prices. In addition, legumes and grains constitute humans' primary food products (Dale, Hendrik, and John 1974). Also, food volatility has been one of the biggest challenges for policymakers, primarily because families with incomes below the poverty level disburse a significant percentage of their income on food (Banerjee and Duflo 2007). On the other hand, monetary policy should consider extreme weather shocks, especially the range and durability of the effect on prices. In addition, shocks to one sector may impact relative prices (Faccia, Parker, and Stracca 2021).

The extreme weather events of 2011 involved an intense frost that affected Mexico's northern region. Later that year, Mexico suffered the largest drought registered in the previous seven decades. It affected more than 80% of the Mexican territory; the most affected regions were the northern and central states of the country. These extreme weather events broadly impacted the planted area and the yield of the agricultural products in which Sinaloa specializes (white corn and some legumes) in the autumn/winter cycle.

Our approach exploited the exogeneity of the extreme weather events of 2011, identifying the immediate effect of these events on agricultural prices. This approach provided relevant insights concerning how the production shocks caused by extreme weather may affect prices. We focused on white corn and the most important legumes; such as beans and chickpeas. These products are highly relevant to rural production and to the Mexican diet. For instance, corn comprises about 25% of the national planted area, and the annual per capita consumption is more than 300 kilograms.

We applied the regression discontinuity in time (RDiT) framework to explore the short-run effects of extreme weather events on white corn and some legumes. Our results provide evidence that the extreme weather events of 2011 had an important impact on white corn prices: the estimated increases ranged from 30%–35%. Our findings remained unaltered by various robustness checks. The results show impacts not only on the main supplying entities but also on the rest of the country. On the other hand, the effect on the prices of legumes, such as small chickpeas, large chickpeas, and Peruvian beans, was around 20%–25%.

Furthermore, we used the synthetic control method to identify the effects on prices in the medium term. The weather shock produced significant price increases over time, and they persisted in the medium-term. An asymmetric price transmission was observed; initially, the prices rose quickly, but the downward price adjustment process lasted three to four years.

Finally, our findings contribute to broader research on supply-side shocks in the commodities markets. The results are relevant from a policy maker's perspective, as they help to understand and to predict price deviation due to production shock generated by extreme weather events. Consequently, they will support policy makers in designing and implementing the most appropriate and efficient public policy to limit the short- and medium-term effects of extreme weather events on grain and legume prices.

This thesis is organized as follows. The following chapter presents a review of the literature that analyzes the impact of extreme weather on economic outputs. Chapter III describes the data, illustrates the grain industry in Mexico, and shows the dynamics of the natural experiment. Chapter IV provides the empirical estimates of the effect of the extreme weather event on grain and legume prices and presents some robustness tests, and Chapter V presents the medium-term estimates. Finally, Chapter VI concludes the thesis.

II. Background

II.A. The relevance of climate change

The evidence shows that human development has warmed the atmosphere, ocean, and land (IPCC, 2021). Economic growth has been gone along with the emission of carbon dioxide (CO2) and other greenhouse gases that have affected the atmosphere's balance. The results have been changes in temperature worldwide and an increase in extreme weather events, such as droughts, frosts, floods, cyclones, sea-level increases, and other natural phenomena in places where they did not occur before. The temperature increases have been more relevant and significant since the late nineteenth century; almost every place on Earth has presented an upward temperature trend during the last century (Hayhoe et al. 2017; S. Hsiang and E. Kopp 2018). For instance, Muller et al. (2013) estimated that from 1950 to the 2000s, the land temperature increased by about 0.90 ± 0.05 degrees Celsius, mainly due to anthropogenic causes. The increase in temperature levels and changes in precipitation patterns due to climate change has altered the frequency and intensity of extreme moisture conditions, i.e., droughts and floods (S. Hsiang and E. Kopp 2018).

In the northern region of Mexico, precipitation has reduced in intensity, and the temperature has increased. This is relevant because water scarcity will become a more concerning issue for the agricultural sector as the demand for water increases. Cavazos et al. (2020) discovered significant decreases in precipitation (15% per decade) and increases in the temperature ($0.35°C$ per decade) in parts of northwestern Mexico in the period 1980–2010. Other studies suggest significant and relevant increases in the frequency and intensity of days marked by extreme heat and the frequency of those marked by extreme cold (García-Cueto et al. 2019; IPPC 2021, Montero-Martínez et al. 2018; Murray-Tortarolo 2021). Shifts in rainfall patterns are likely to increase the need for irrigation. However, irrigation may not be enough to prevent damage to crops from heat waves in some regions. Moreover, the availability of water obtained through river abstraction and from groundwater is limited and has been decreasing due to increased demand from agriculture, energy, industry, and households, which is potentially problematic (Andersson, Morgan, and Baccianti 2021). A drought is a natural phenomenon that Mexico has used to experience before. Nevertheless, these phenomena are predicted to become more severe in the coming decades in response to climate change (Neelin et al. 2006; Dobler-Morales and Bocco 2021). Because of the relevance of these extreme weather events, multiple studies have investigated the impact of droughts on several socioeconomic variables

II.B. Climate change´s impact on economic variables

Evidence has demonstrated that extreme weather events have significant and meaningful economic effects on economic growth, poverty, employment, and agricultural output.

A negative correlation between economic growth and extreme weather events has been found in several studies. Dell, Jones, and Olken (2012) show that more elevated temperatures may reduce growth rates and output in emerging countries and, to a lesser degree, in rich countries. In addition, the authors indicate that higher temperatures and low precipitation rates affect the agricultural output and the output of other sectors, such as industrial output. Damania, Desbureaux, and Zaveri (2020) use a sample of 82 countries to identify the effect of rainfall on economic activity. The authors report an increasing and concave relationship between rainfall and gross domestic product (GDP) growth; the marginal economic return of an extra drop of precipitation was loftiest in dry areas and gradually decreased as the weather improved. The authors suggest that most of the effects of rainfall on GDP growth may be attributed to the impact on agriculture.

De Bandt, Jacolin, and Lemaire (2021) uses panel data of 126 poor and emerging economies from 1960-2017, uncovering that a sustained one centigrade temperature increase reduces by $0.7 - 1.5$ percentage points the real GDP per capita annual growth. Juárez-Torres and Puigvert (2021) explore the impacts of tropical cyclones on the economic activities of firms in the manufacturing and service sectors in Mexico. They highlight that manufacturing establishments experienced a short-term and small negative effect on production growth after a tropical cyclone. In contrast, service firms experienced a small and adverse effect on revenue growth and a positive impact on the growth of operative expenditures. Albert, Bustos, and Ponticelli (2021) analyze the economic effect of extreme temperatures in Brazil in the period from 2000 to 2020. The authors analyze fluctuations in agricultural output, credits, and deposits, and migration flows. They find a sharp reduction in population and employment in the affected areas, concentrated in agriculture and services.

Hernández Solano (2015) uses a general equilibrium model to study the effects of climate change on the rural economy in Mexico; in particular, he identifies the possible direct and indirect effects of a reduction in corn yields due to climate change. The author finds that the impact on households will be heterogeneous; households in the south-southeast, center-west, and northeast regions would be the most affected. The main effects will be the reduction of crops (mainly corn) planted by rural households and reductions in their real income. The present work complements the work of Hernández; we explore the dynamics of the market prices of agricultural products in the face of climate change. Both studies help understand the possible consequences of extreme weather events in Mexico.

Feng, Krueger, and Oppenheimer (2010) examines the relationship between crop yields and migration using state-level data from Mexico and find that climate-driven changes in crop yields had a significant effect on the rate of emigration to the United States. Murray-Tortarolo and Jaramillo (2019) evaluate the impact of the 2011–2012 drought in Mexico on livestock populations. They show that cattle and goat stock decreased by 3% due to the drought. Using data for all Mexican municipalities over the period 1980-2010, Guerrero Compeán (2013) finds that only if a temperature shock occurs during the farming growing cycle the effects on output, prices, and yields are extensive and meaningful. In summary, studies suggest significant effects of extreme weather on economic growth, and agricultural output, especially for developing countries.

Climate change is expected to increase the number of individuals at risk of experiencing hunger and exacerbating poverty. Particularly, rural towns tend to be more sensitive to climate shocks because of their dependence on the agricultural sector and the lack of a protective infrastructure. Arceo-Gómez, Hernández-Cortés, and López-Feldman (2020) find that rural households that experienced the 2011–2012 drought in Mexico had lower incomes and were nearly 5% more likely to be poor in comparison of households that weren't affected by the drought. Jessoe, Manning, and Taylor (2018) use a 28-year panel data to show that years with higher temperatures relative to the average in Mexico decrease rural employment, especially for wage work and non-farm labor.

Other studies in the Mexican context have established negative effects of elevated temperatures on health (Cohen and Dechezleprêtre 2020), and loan defaults (Aguilar-Gomez et al. 2021). The previously mentioned literature refers to the effects of climate change on several variables. Nevertheless, interest in investigating the effect that droughts have on food prices is growing.

II.C. How do extreme weather events affect prices?

The equilibrium market price of agricultural products is the market clearing price at which food demand (consumption and exports) equals supply (imports and production) at the beginning of the period minus the change in stock.

Supply Side

Crop price volatility in the short run is related directly to the supply side, particularly production shocks (Berry, Roberts, and Schlenker 2014; Dehn, Gilbert, and Varangis 2005). Production shocks depend on changes in crop yields and planting areas (Mukherjee and Ouattara 2021; Hendricks, Janzen, and Smith 2015). The main drivers of production shocks are temperature shocks because agriculture is highly dependent on and sensitive to rainfall, temperature, and soil conditions (Berry, Roberts, and Schlenker 2014; Kornher and Kalkuhl 2013; Mall, Gupta, and Sonkar 2017). Consequently, extreme weather events, such as droughts, cyclones, and floods, potentially affect prices and inflation by decreasing agricultural output. This study was intended to analyze the effects that extreme weather events have on prices due to their effect on the supply of agricultural outputs.

Production is the result of crop yield times planted area. Temperature shocks affect the planted area and productivity. (Hendricks, Janzen, and Smith 2015; Kornher and Kalkuhl 2013; Mukherjee and Ouattara 2021). This situation causes grain production to be innately volatile throughout the year; nevertheless, the impact varies, depending on whether the extreme weather event occurs during the planting, growing, or harvesting season. However, supply is guaranteed throughout the year because the agricultural outputs can be traded and stored (Kornher and Kalkuhl 2013). Serra and Gil (2013) mention that the impact on stock is relevant and significant in the short run. In addition, they show that the marginal impact of stock decreases with stock levels.

Food prices will increase due to changes in production if the demand exceeds the supply. The magnitudes of the impact on prices rely on the dimension of the supply elasticity comparative to the demand elasticity. Michael J. and Wolfram (2010) uncovered that supply is more elastic than demand. On the other hand, demand for food is inelastic, implying that price shocks do not decrease demand to bring equilibrium prices down (Kornher and Kalkuhl 2013).

A significant number of studies have explored the link between natural disasters and prices. Mukherjee and Ouattara (2021) use a panel-VAR model and a sample of developing and developed economies during 1961–2014 and find that climate shocks led to inflationary pressures. In particular, the effects on developing countries persisted for several years after the initial shock. Heinen, Khadan, and Strobl (2019) examine how extreme weather events can push short-term price upsurges in the Caribbean. They find hurricanes and floods have the largest impact on food prices.

Parker (2017) finds a significant and last-lasting effect on prices of extreme weather events in developing economies and an insignificant effect in advanced economies. Furthermore, the impact of catastrophes differs by type of disaster. For instance, droughts boost food price inflation, potentially for multiple years after the event starts. De Winne and Peersman (2021) use a panel of 75 economies and demonstrate that raises in global agricultural prices due by harvest or weather disturbances significantly shrink economic activity. Faccia, Parker, and Stracca (2021) study the relationship between climate change and medium-term inflation, finding that season affected matters; the largest and most durable impact is from hot summers. In addition, supply shortages due a negative effect hot summers on food production is the main cause of food price inflation.

Finally, BANXICO (2021) analyzes the relationship between white corn and bean prices and low precipitation from 2001 to 2020. The findings highlight that the impact of low rainfall in the main supplying entities has induced upward pressure on the prices of the national markets for white corn and beans. Guerrero Compeán (2013) finds that extreme weather increases agricultural prices; in particular, events affecting the growing season and hot temperatures are the factors that exacerbate prices most. He finds that an extra degree day above 30°C is related to an increase of 7 percent in crop prices. The nature of the extreme weather events of 2011 affected the harvest and planted area.

Demand side

Demand side shocks are driven by population growth and changes in personal income, but these are considered long-run factors (Kornher and Kalkuhl 2013; Gilbert 2010). The effect of population growth has been small in developed countries, but of relevance for developing countries (Dale, Hendrik, and John 1974).Conversely, the relevance of personal income depends on the income elasticity for food. In the case of poor countries and rich countries, the demand side represents the extremely low-price elasticity of demand for food in the aggregate. This generates a situation in which a moderate reduction in the supply of food causes sharp price increases (Dale, Hendrik, and John 1974).

III. Data and natural experiment

The main sources of the data were publicly available from the National Information and Market Integration System of the Ministry of Economy[1], the Agrifood and Fisheries Information of the Ministry of Agriculture and Rural Development[2] (SAGARPA), and the Mexico Drought Monitor (MSM) of the National Metereological Service[3] for the years 2009-2015. The data include wholesale agricultural prices, drought index, production, planted, harvested, and damaged area information. All data were presented monthly. Price data were collected from 43 local markets across the country. We used the monthly Mexican Consumer Price Index (CPI) for all grain and legume prices to convert nominal to real values, setting the base period to February 2010.

The data published by SAGARPA allows for a better analysis of corn production to identify the effects of drought; the institution presents monthly data related to the production cycle. This level of detail is not available for other interest crops affected by the extreme events of 2011, so this research emphasizes the effects of extreme weather events on the price of corn, particularly white corn.

III.A. Corn industry

Agriculture is directly related to the seasons of the year and the growing season of crops. In Mexico, the vegetative periods of crops are spring/summer, autumn/winter, and perennial cycles. The first two periods are cyclical productive periods; the process lasts a year and consists of sowing, cultivating, and harvesting. On the other hand, perennial cycles are long-cycle crops; their vegetative period extends beyond the year, and usually, several harvests are obtained once the plantation is established. The sowing period of the spring/summer season starts in March and lasts until September, and the autumn/winter cycles extend from October to February. The harvests of the spring/summer cycle begin in June and conclude in March of the following year. The collecting period of the autumn/winter cycle in Mexico begins in April and ends in August.

---

[1] http://www.economia-sniim.gob.mx/Nuevo/Home.aspx

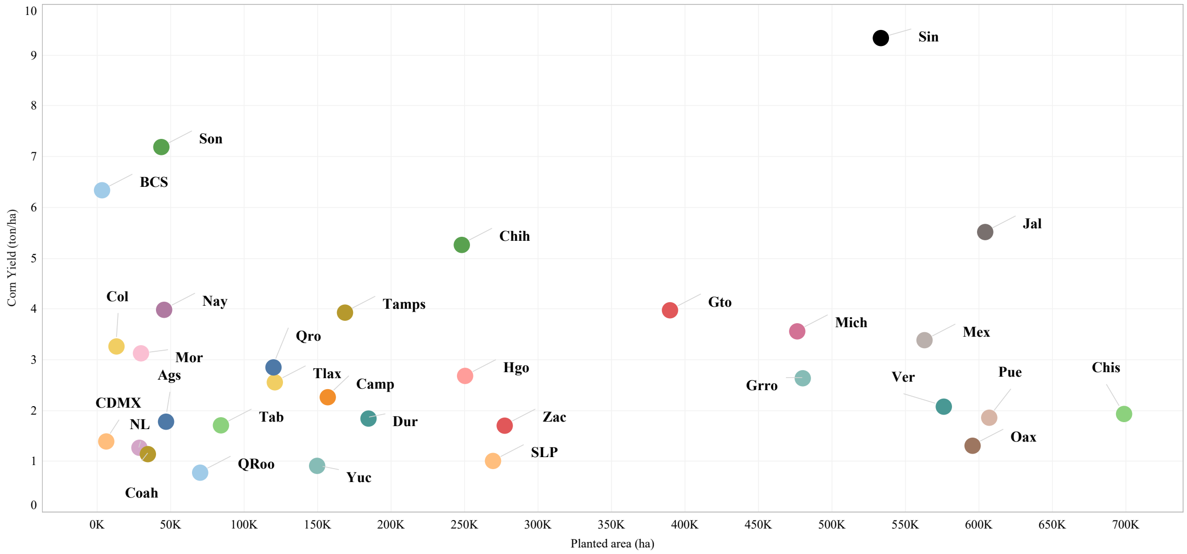
[2] https://nube.siap.gob.mx/avance_agricola/

[3] https://smn.conagua.gob.mx/es/climatologia/monitor-de-sequia/monitor-de-sequia-en-mexico

Corn is Mexico's most representative grain because of its economic, social, nutritional, and cultural importance. Corn is the largest crop industry in Mexico, with an average cultivated area of 7.8 million hectares per year in the last 20 years, accounting for 36% of the total planted area. In addition, Mexico has produced 23 million metric tons per year on average from 2000 to 2020.

Corn cultivation occurs mainly in two varieties of corn: white and yellow. White corn is produced primarily for human consumption because of its high nutritional content. Mexico primarily produces white corn (represents about 90% of production), used to elaborate tortillas and other corn-based foods for direct human consumption. Annual per capita consumption of white corn is around 200 kilograms (SAGARPA 2020). On the other hand, yellow corn is used for industrial processing and animal feed. Both are produced in two productive cycles: spring/summer and autumn/winter.

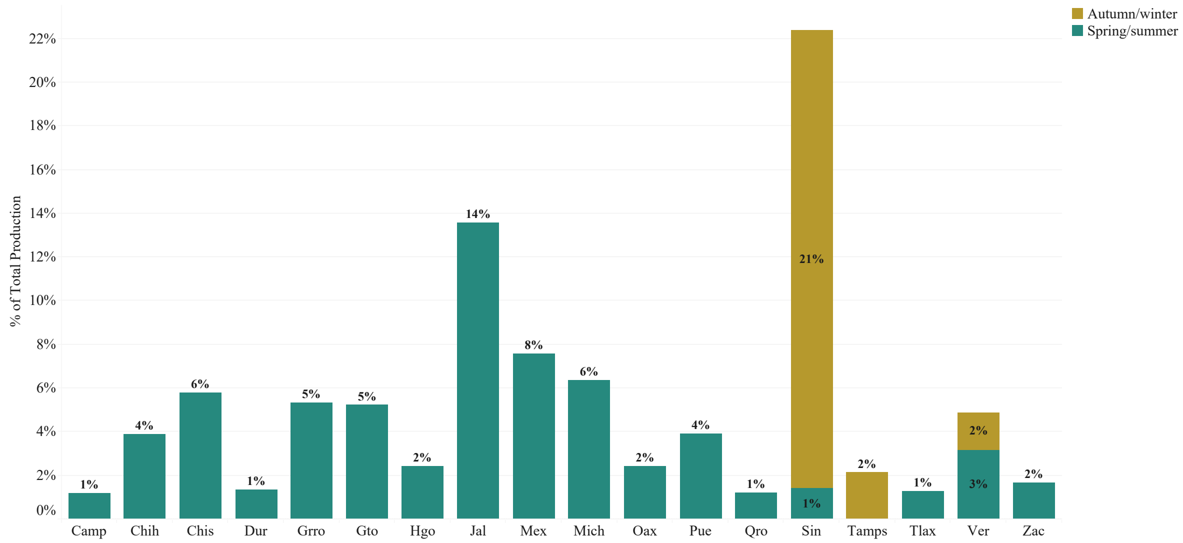
The variable production stands for the product of crop yield times planted area (harvested areas). Figure 1 presents the planted area plotted against the corn yield for each state. Sinaloa and Jalisco are majorly relevant entities in corn production because of their high crop yield and planted area. On the other hand, states such as Oaxaca, Chiapas, Puebla, and Veracruz have the largest planted area, but their yield is much lower because their farms are small in size, and most of their production is concentrated on auto consumption.



Source: Ministry of Agriculture and Rural Development

Figure 1: Corn planted area and yield, 2010

The 32 states produce white corn; nevertheless, 10 States account for 90 percent of national production. Figure 2 shows the percentage of production by state and agricultural cycle in 2006-2010. Sinaloa and Jalisco account for over 35 percent of the national production; on the one hand Sinaloa cultivates white corn during the fall-winter cycle and depends largely on irrigation. On the other hand, Jalisco grows white corn in the spring-summer cycle, with most of its production rainfed. Seventy-five percent of Mexico's yellow corn production is planted in the spring-summer season, and approximately 70 percent is irrigated.



Source: Ministry of Agriculture and Rural Development

Figure 2: Average production 2006-2010

According to the United States Department of Agriculture (2019), The main reason Mexican yield is inferior compared to the United States is the corn farm dimensions. The average size of a corn farm is 3.6 hectares in Mexico, and the American farm is about 101 hectares. Large U.S. farms reach greater land and labor efficiencies via more cost-effective technologies when used at a large scale. On the other hand, these technologies in Mexican smaller farms stay out of reach, causing lower yields.

Grains, along with legumes and some fruits, have been the mainstay of food in Mexican households. In the present work, in addition to white corn, we include the impact on prices of some types of legumes for four main reasons: 1) the main state (Sinaloa) affected by the 2011 weather events is one of the primary producers of legumes, 2) they are a rich source of protein and aminoacids for Mexican diet, for example, the per capita consumption of beans in 2021 was 9 kilos according to SAGARPA. 3) a large part of rural households cultivate legumes; for example, 38.5% of rural households grow beans (Cedrssa 2014), and 4) to show that the effect of the prices observed in corn was not unique, other crops showed a similar dynamics.

III.B. Natural experiment

In 2011, a large drought and frost affected planted areas and crop yields in the country; the events can be defined as exogenous and somewhat random. First, an intense frost affected the country's north region in February 2011. In the first days of February, a mass of cold air that accompanied a frontal system interacted with the upper jet stream and with a mid-level trough, giving rise to a winter storm, which caused notable drops in temperature and snowfall from Canada and the United States to northern Mexico (Ramírez Reynaldo and Albanil Encarnación 2011). The frost affected corn crops in Sinaloa, the country's main producer of the grain in the autumn/winter cycle.

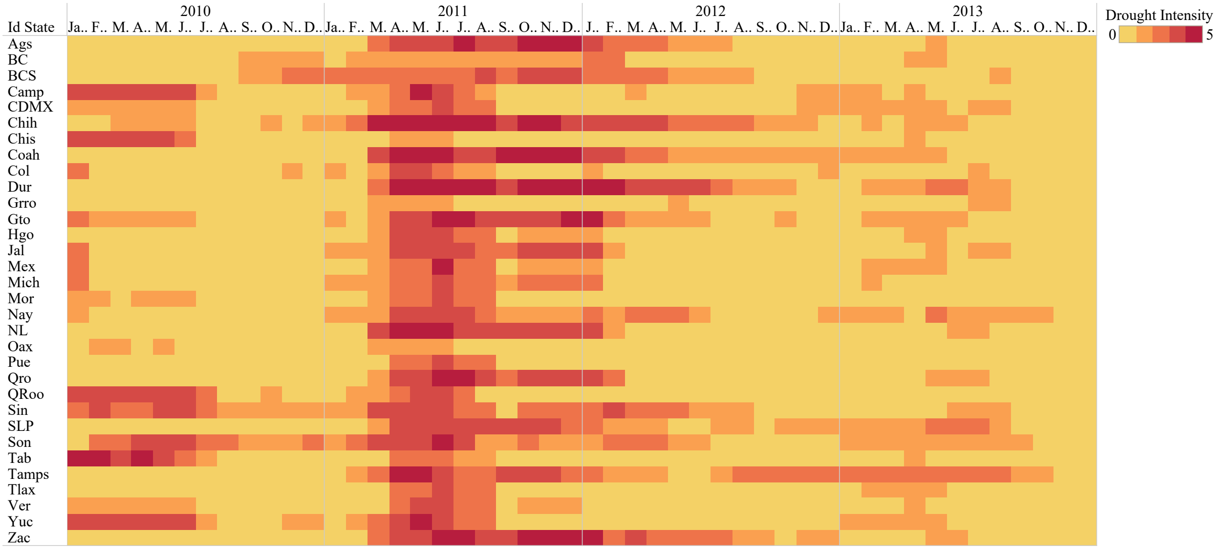
Furthermore, 2011 was the thirteenth year with less rain since 1941, with 697.2 mm, 10.47% below the historical average of 779 mm, and the least rainy of the previous fourteen years. In nine of the twelve months of the year, rainfall levels were below average. Only June, July, and November experienced normal to above normal rainfalls. Also, the average annual temperature was greater than 1°C above the average temperature presented from 1971 to 2010 (Ramírez Reynaldo and Albanil Encarnación 2011).

Various newspapers (Espinosa 2011; Expansion 2011; Notimex 2012) pointed out that 2011 was the driest year in decades, affecting half of the municipalities and crushing the corn and bean harvest.

"Because of the drought, 80% of bean production has been lost, 50% of corn and wheat production has also been lost. It hasn't rained in the last 16 months, but not all the damage has been due to drought; we have also suffered frosts and floods," said the National Association of Farm Products Marketing Companies president (Camarena 2012).

After the frost affected the crops planted in Sinaloa in February, the area planted and the yield were greatly affected by the lack of rain, impacting corn production. The combination of the frost and drought largely affected the supply of corn production during the autumn/winter season. In addition, the drought significantly affected the spring/summer cycle, the cycle in which the largest amount of corn is harvested in Mexico.

The North American Drought Monitor (NADM) developed a drought index; this index is the most precise and compiled indicator for studying droughts in Mexico. The measure incorporates various indices, such as the standardized precipitation index (SPI), the average temperature anomaly, and the percentage of water availability in the country's dams, among other indicators. The drought index shows the following levels of drought: abnormally dry (D0), moderate drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4). Figure 3 shows the drought index from the period 2010–2013. The heat map indicates that the 2011 drought began in February and March in most states. Notably, the state of Sinaloa was affected by severe drought starting in March.



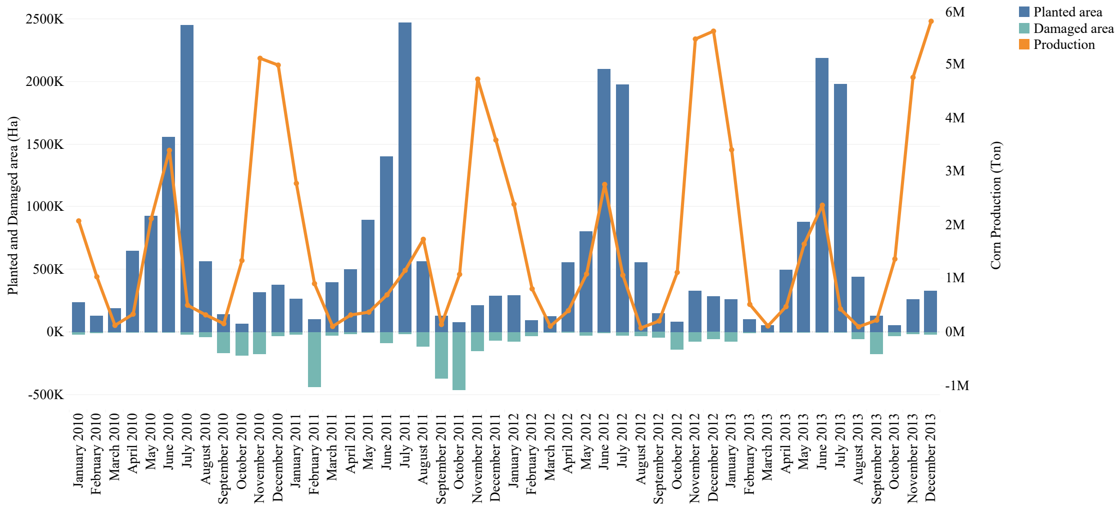
Notes: No drought (0), abnormally dry (1), moderate drought (2), severe drought (3), extreme drought (4), and exceptional drought (5). The state indices were created by weighting the area planted of corn at the municipal level.

Source: Drought Monitor in Mexico, CONAGUA.

Figure 3: Monthly drought index, 2010-2013

Corn

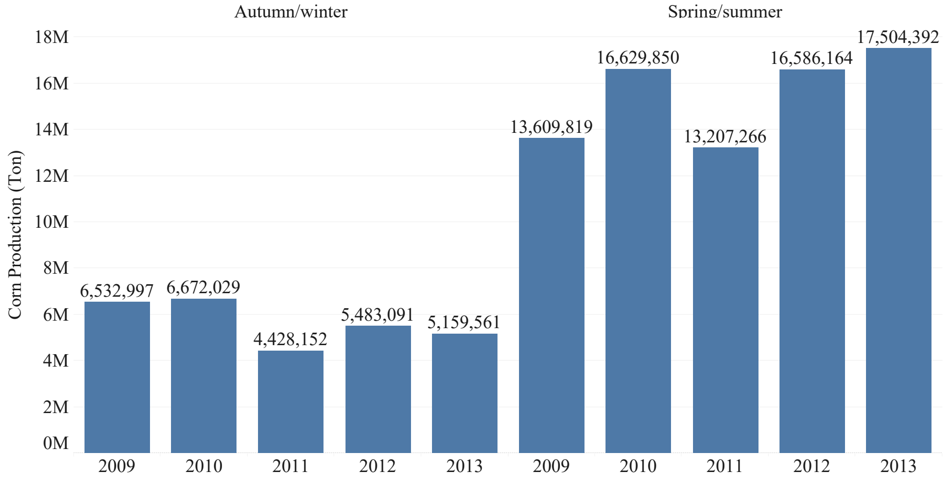
The months of February and March are relevant for identifying short-term effects on corn prices. The frost occurred during these months, and the great drought of 2011 began, which affected the largest corn-producing state in the fall/winter cycle. Specifically, it affected the growing season of the plants, so much of the production potential was lost. Figure 4 shows the monthly planted and damaged areas and production. The extreme weather events affected the cultivated area in February of 2011; this situation reduced the supply of corn in the autumn/winter cycle. In addition, the drought affected the spring/summer season; consequently, the yearly agricultural cycle was impacted. In 2012, the weather improved, and the production increased to pre-event levels in the case of fall/winter cycle. The interruption of the food supply chain caused by the extreme temperature events was expected to result in higher food prices that could exacerbate food insecurity concerns.



Source: Ministry of Agriculture and Rural Development

Figure 4: Planted, damaged area, and production of corn, 2010-2013

Figure 5 presents the effects on production. Production fell by -34 percent in the autumn/winter cycle in 2011 compared to the previous year, while agricultural output in the spring/summer cycle decreased by 21 percent. Notably, the spring/summer cycle recovered the production levels of 2010 in the following year. Still, the autumn/winter cycle remained at low levels, even though weather conditions improved.



Source: Ministry of Agriculture and Rural Development

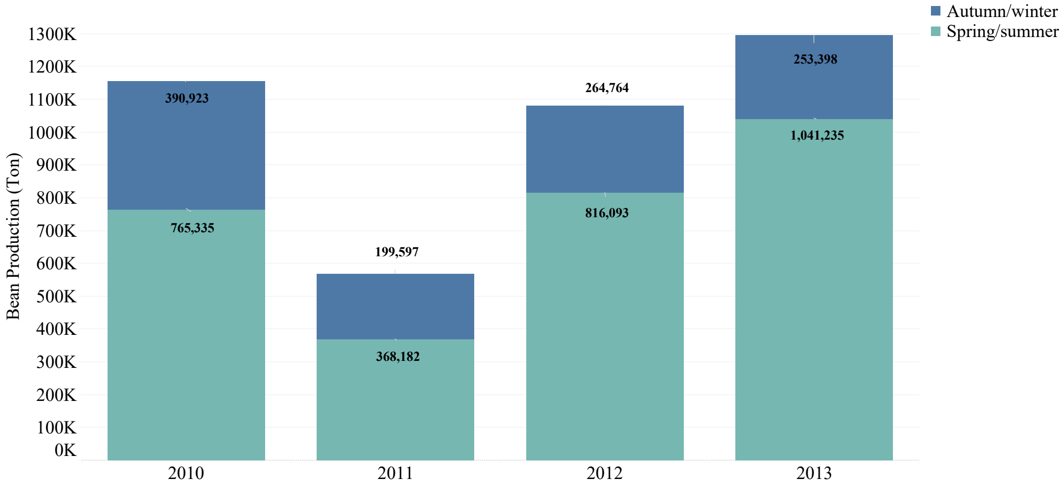
Figure 5: National corn production, spring/summer and autumn/winter cycles 2009-2013

Our analysis considers the assumption that the relevant effects on prices in 2011 were due to the extreme weather events of 2011 that affected mainly the supply side, and the influence on demand was low; thus, the demand factors are irrelevant to the observed sharp increase in prices.

Legumes

The most important agricultural products produced in Sinaloa are corn, chickpeas, tomatoes, beans, wheat, and cucumber. Their production values in 2012 were \$ 1.1 billion, \$ 149 million, \$ 139 million, \$ 236 million, \$ 28.9 million, and \$ 43 million of US dollar, respectively (World Bank, CIAT, and CATIE 2014). In particular, grains such as beans and chickpeas take on relevance given their relevance to Mexican households. The annual per capita consumption of beans is 9 kilograms; the consumption needs are supplied by local production (SAGARPA 2017). The varieties of black, pinto, and sulfur/Peruvian beans are the most relevant to national production, with shares of 35.3, 26.1, and 15.3 percent, respectively (FIRA 2019). The main bean producers are Zacatecas, Sinaloa, Durango and Chihuahua.

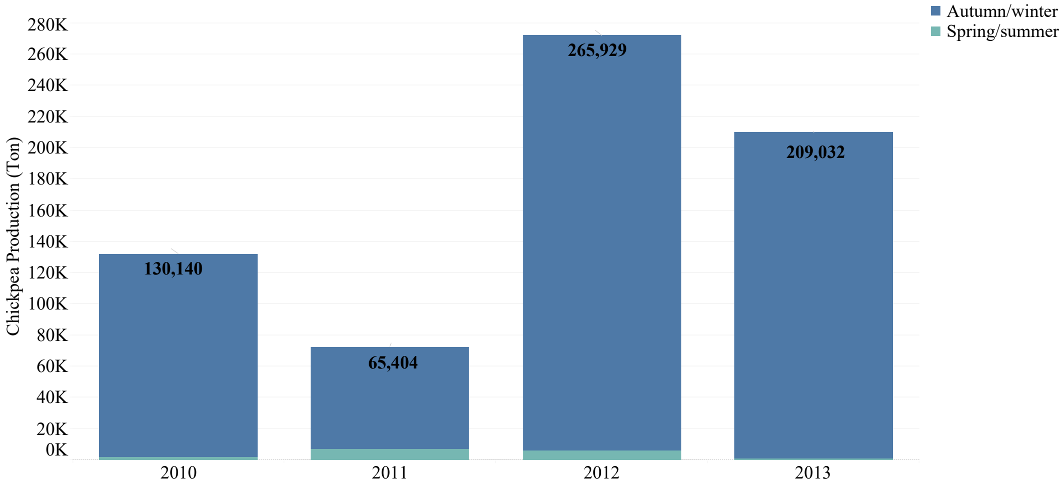
Figure 6 shows the effects on bean production caused by the extreme weather events of 2011. Autumn/winter and spring/summer cycles were widely affected; the bean output of both cycles decreased by around 50 percent in 2011 compared to last year. However, the spring/summer cycle recovered its production in 2011, but the autumn/winter cycle did not recover its pre-event levels.



Source: Ministry of Agriculture and Rural Development

Figure 6: National bean production, 2010-2013

The chickpea grain is a dry legume whose participation in the national production of dry legumes is around 20 percent. The annual per capita consumption is around 274 grams (SAGARPA 2017). There are two types of chickpea varieties, the large ones, and the small ones. The main producers are Sinaloa, Sonora, and Michoacan. Almost all chickpeas are produced in the Autumn/Winter season, as shown in figure 7. The weather events of 2011 affected production in this season by around 50 percent. However, production recovered during 2012.



Source: Ministry of Agriculture and Rural Development

Figure 7: National chickpea production, 2010-2013

IV. Short-run impacts

IV.A. Identification strategy

We use the Regression Discontinuity in Time (RDiT) framework to exploit the sharp increase in prices observed on the date when extreme weather events in 2011. In the RDiT model, the running variable is time T, and treatment status is defined as:

$$D_{ct} : \begin{cases} 1 \quad if \qquad T \geq \tau \\ 0 \quad if \qquad T < \tau \end{cases} \tag{1}$$

where $D_{c,t}$ is a dummy for the period after the climate events, τ is a cutoff (March 2011)[4], and c and t indicate city and time, respectively. The main identification assumption is that if the weather were good and there were not affected planted area, the wholesales prices would have followed a smooth trend and the extreme weather events explain the changes of prices on march 2011. All the wholesale markets across the country were affected by 2011s extreme weather events. The most affected state was Sinaloa; however, this state is the leading and only relevant product in the autumn/winter season, which is why it supplies the national territory. The identification strategy is inspired by the work of Ruan, Cai, and Jin (2021). The authors use the RDiT method to identify the causal effect of the strict lockdown policy on cabbage prices in China. The authors observe an increase of 45.9 – 47.7% in cabbage prices immediately after the quarantine policies.

First, the parametric RDiT specification to estimate the causal effects of extreme weather events on wholesales prices is as follows:

$$ln(Price_{c,t}) = \alpha + \beta_1 D_{c,t} + \gamma f(Z_{c,t}) + \theta D_{c,t} * f(Z_{c,t}) + \lambda_i + \tau_c + \epsilon_{c,t} \tag{2}$$

where β_1 is the coefficient of interest that measures the causal effect of extreme weather events. $ln(Price_{c,t})$ is logarithm of white corn price in wholesale market c at time t; λ_i and τ_c display market and year fixed effects, respectively. Furthermore, we include the interaction term between market and year FE. $Z_{c,t}$ is a polynomial function of the running variable T and the interaction term $D_{c,t} * f(Z_{c,t})$ is included to permit the time trend in grain price to vary on either side of the

---

[4] I exclude February from the analysis because the impact on prices happened between February and March. Including month 2 in the analysis results in similar estimates, but the effect is lower.

event date.

Market FE incorporates the time-invariant, market-specific factors: agriculture production trends, climatic conditions, and geographic location. Yearly time FE seizes time-related factors such as agricultural seasons and nationwide trends in the wholesales price. The interaction term between year FE and market FE would account for the intra-annual market-specific factors. We use cluster-robust standard errors at the market level to control for within-cluster serial autocorrelation. Lee and Lemieux (2010) suggest to use nonparametric and parametric estimation to verify that results are stable and robust across alternative specifications.

Second, nonparametric RDiT model is used to estimate discontinuity in the conditional expectation $E[P_{ct}|Z_{ct}]$ at the cutoff. We employ a triangular kernel function with a mean squared error (MSE) optimal bandwidth, yielding a point estimator with optimal properties. Subsequently, we selected the bandwidth using a non-parametric method that minimizes the mean squared error of the local polynomial RDiT point estimator, given our selection of polynomial kernel and order.

IV.B. Results

Before the extreme weather events, the real prices followed a decreasing trend, however, after the cut-point, there was a significant sharp increase in real corn prices. Figure 8 shows the logarithm of real wholesale prices of white corn against the running variable. This plot presents the non-parametric RDit model; the circles in the figure represent mean values for each one-month bin in the case of the left and the two-month bin for the right. On the other hand, the lines have been fitted through a local linear regression with a fourth-order polynomial of time, including the optimal bandwidth. Figure 8 is visual evidence that the jump may be attributive to the impact of extreme weather events that affected the corn planted area between February and March.

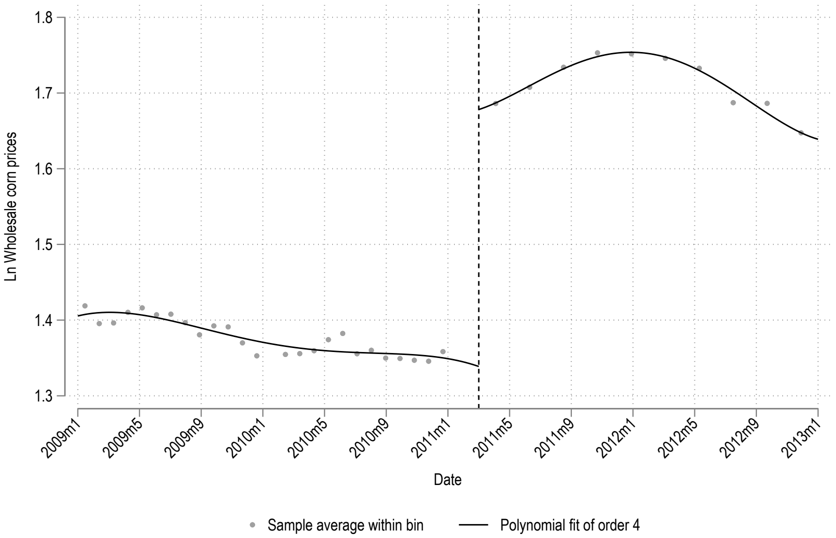


Figure 8: “Fourth-order polynomial RDit”

Table 1 shows the parametric regressions results for the impact of extreme weather events on the price of white corn. In each estimation, a different order of the variable time were included into the model to check for the robustness of the result. Additionally, each regression is estimated using the best bandwidth according to the MSE-optimal bandwidth selector and the standard errors are clustered at the market level. The results indicate that immediate effect on white corn prices was around 32%. The coefficient of interest is highly significant using the different order polynomials and including fixed effects and cluster-robust standard errors at the market level.

Table 1: Impacts of extreme weather events on white corn price: Parametric RDit estimates

	(1)	(2)	(3)	(4)
Extreme weather event	0.32***	0.32***	0.32***	0.34***
	(0.02)	(0.02)	(0.03)	(0.05)
Market FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Market×Year FE	Y	Y	Y	Y
Best bandwidth	6.32	9.53	9.82	11.97
Polynomial Order	1	2	3	4
Effective N	335	490	490	592
adj. R2	0.92	0.73	0.73	0.72

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2 presents the estimation results of the local polynomial regression discontinuity estimators. The results suggest estimated coefficient similar that those estimated with parametric methods. The estimated effect ranges from 31 to 32%, verifying the results of the parametric estimates and suggesting the presence of minimum bias.

Table 2: Impacts of extreme weather events on white corn price: Non-Parametric RDit estimates

	(1)	(2)	(3)	(4)
Conventional	0.32***	0.32***	0.31***	0.31***
	(0.03)	(0.03)	(0.05)	(0.07)
Bias-corrected	0.32***	0.31***	0.31***	0.32***
	(0.03)	(0.03)	(0.05)	(0.07)
Robust	0.32***	0.31***	0.31***	0.32***
	(0.03)	(0.04)	(0.06)	(0.08)
Order est. (p)	1	2	3	4
Order bias (q)	2	3	4	5
Number of obs	646	646	646	646
Kernel	Triangular	Triangular	Triangular	Triangular
BW type	mserd	mserd	mserd	mserd

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

IV.C. Robustness tests

There are four challenges in considering an unbiased treatment effect using the RDiT framework, especially in applications where time is the running variable. The challenges are; the selection of the cutoff, some international events that may have affected the local prices, the optimal bandwidth selection, and the autoregression nature of the time series. This section describes these challenges in detail and shows the robustness of our main findings.

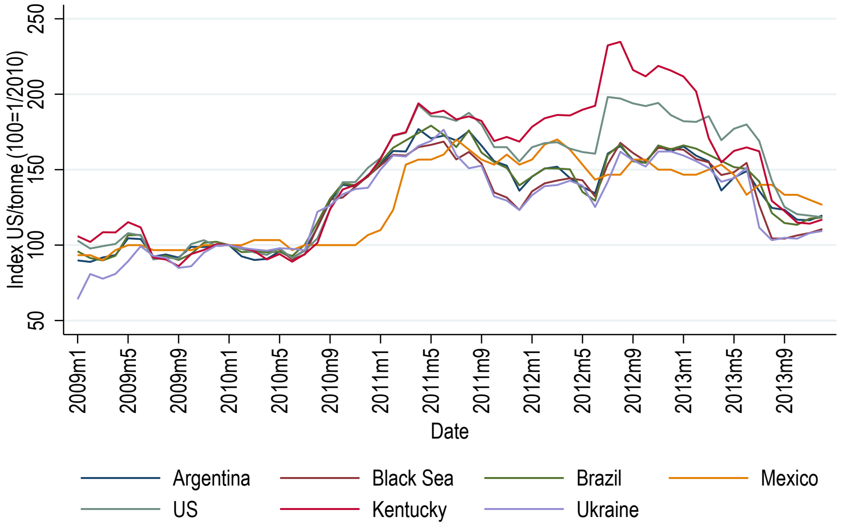
Hausman and Rapson (2018) suggest when using RDiT framework to incorporate alternative event dates as a placebo test. Two alternative event dates are incorporated into the analysis; half-year earlier than the extreme weather events of 2011 and 6 months after this event. The assumption, in this case, is that in the absence of extreme weather on those two placebo dates, the prices must be smooth across the cutoff. The first placebo test results are reported in columns 1 and 2, and the second placebo test in columns 3 and 4. The RDiT is employed with order 1 and order 4 in columns 1 and 2, respectively. The results are illustrated in table 3. As expected, we find no positive and statistically meaningful effect for either of the two placebo dates. These previous results are evidence that our study measures the impact of the extreme weather events of 2011.

Table 3: Placebo test using alternative dates.

	(1)	(2)	(3)	(4)
Conventional	-0.07***	-0.03	0	0.07
	(0.03)	(0.13)	(0.03)	(0.12)
Bias-corrected	-0.08***	-0.05	0.03	0.08
	(0.03)	(0.13)	(0.03)	(0.12)
Robust	-0.08***	-0.05	0.03	0.08
	(0.03)	(0.15)	(0.04)	(0.14)
Order est. (p)	1	4	1	4
Order bias (q)	2	5	2	5
Number of obs	1228	1228	1228	1228

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

International prices of agricultural commodities such as futures and export prices serve as reference prices for domestic markets. Generally, prices of tradable commodities are determined by global prices, and non-traded commodities are defined primarily by regional supply and demand (Minot 2011).



Note: Argentina Maize (Up River, f.o.b.), Black Sea (Maize feed), Brazil (Maize feed), Kentucky (Maize US No. 2, White)
US (Maize No. 2, Yellow), Ukraine (Maize offer, f.o.b.)
Source: FAO Global Information and Early Warning System (GIEWS)

Figure 9: "International prices of corn"

Figure 9 presents additional evidence of the causal interpretation of the sharp increases in prices. It shows the most important international prices of corn; the behavior of these prices illustrates that all markets except Mexico had a significant increase during the end of 2011.

Mexican white corn may have different price dynamics, mainly because the grain is a local product. The supply of white corn in 2010 was composed of 10% local stock, 88% national production, and 2% imports. On the other hand, demand was equal to 29% auto consumption, 50% local consumption, 7% livestock consumption, 10% final stock, 1% seeds, and 3% losses. The configuration of demand and supply of white corn generates that the local prices may have a not strong correlation with international prices. Ortiz Arango, Nelly, and Guzmán (2016) analyses the relationship between US#2-grade yellow corn and Mexican white corn during 2007-2012. They find a weak integration between the future price of corn and the prices of white corn reported in some local markets in Mexico.

However, Jaramillo-Villanueva, Yunez-Naude, and Cote (2016) suggest that since the implementation of NAFTA, there has been a cointegration or long-term relationship between the price of Mexican and US corn, and this relationship operates with lags over many periods. These results could be a concern to our identification strategy. Nonetheless, we believe that the sharp increase in white corn prices responds to extreme weather events for two reasons. First, the increase in white corn prices occurs in the immediate months after the extreme weather events. Second, although there is a long-term relationship, the price adjustment in the study period seems to be conducted and accelerated by the climatological events that occurred during February and March in Mexico.

Hausman and Rapson (2018) point out the relevance to check whether the estimates are sensitive to the optimal bandwidth selection. In some cases, the time series sample is too small for estimation as the bandwidth narrows around the threshold, and expanding the bandwidth could lead to bias resulting from unobservable confounders. Hausman and Rapson (2018) suggest showing robustness to polynomial order and alternative local linear bandwidths. Therefore, we employ alternative bandwidths from $h^* - 10$ to $h^* + 10$. Estimates using those alternative bandwidths are plotted in Figure 10. The estimated coefficients estimates are highly robust and remain similar to the previous reported, suggesting that a particular bandwidth does not drive the results.

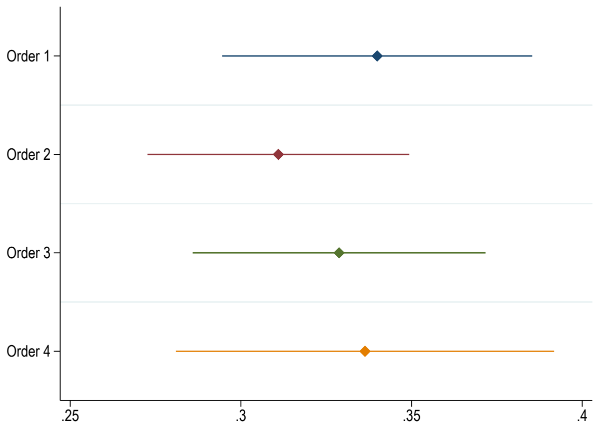


Figure 10: “Parametric RDiT estimates with different bandwidth”

A potential concern with the RDiT method is its use of time-series data, which are possible to show serial dependence. Hausman and Rapson (2018) mentions that unless the nature of autoregression is comprehended, the effects computed may approximate the short-run or long-run estimates, or neither, thus they recommend including the lagged dependent variable as a regressor to mitigate concerns about autoregression. Table 4 presents the results of the parametric estimation when including the lagged dependent variable. The estimates of the extreme weather effect are statistically significant at 1%, which is consistent with the RDiT results. However, the magnitude of the effects is significative lower when applied AR(1), but, overall, the magnitude of the price surge remains large.

Table 4: Placebo test using lagged dependent variable

	(1)	(2)	(3)	(4)
Extreme weather event	0.17***	0.12***	0.16***	0.19***
	(0.03)	(0.03)	(0.04)	(0.05)
Ln(prices(-1))	0.43***	0.54***	0.54***	0.58***
	(0.08)	(0.05)	(0.05)	(0.06)
Market FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Market×Year FE	Y	Y	Y	Y
Best bandwidth	6.32	9.53	9.82	11.97
Polynomial Order	1	2	3	4
Effective N	335	490	490	592
adj. R2	0.90	0.92	0.92	0.95

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

IV.D. Legumes

To comprehend how the 2011's extreme weather event impacted grain prices, not only the white corn, we examine the effects of legumes produced in the Autumn/winter season that resulted affected in the same manner as the white corn. Table 5[5] reports parametric results for the effects on small and large chickpea, peruvian bean, and a grain index[6] We report the estimates with different polynomial orders. In general, all estimates are highly significant at the 1% level. The effects on small chickpeas were around 16-25 percent, large chickpeas 22-25 percent, Peruvian bean 18-24 percent, and grain index around 37-40 percent.

The results provide insights that the impact of extreme weather on the planted area and crop yield on prices was similar for legumes. The impact was much less in chickpeas and beans, even though a greater product was lost compared to white corn; this could implicitly indicate that white corn is more sensitive to this type of weather shock.

---

[5] It is important to note that the observations were different for each product given the availability of information.

[6] The grain index is created using a weighted average of the prices of chickpeas, Peruvian beans and white corn.

Table 5: Effects of extreme weather events on agricultural prices (Parametric RDiT estimates)

	Small chickpea	Large chickpea	Peruvian bean	Grain index
Order 1	0.25***	0.25***	0.24***	0.4***
	(0.04)	(0.03)	(0.03)	(0.04)
Order 2	0.24***	0.22***	0.2***	0.36***
	(0.05)	(0.03)	(0.03)	(0.05)
Order 3	0.17***	0.25***	0.19***	0.35***
	(0.06)	(0.04)	(0.03)	(0.06)
Order 4	0.16***	0.25***	0.18***	0.37***
	(0.05)	(0.05)	(0.03)	(0.07)
Market FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Market×Year FE	Y	Y	Y	Y
Markets	17	30	29	12

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

V. Medium-run impacts

In this section, we employ the synthetic control method to show the robustness of the RDiT estimates and to identify the medium-run effects of extreme weather events.

V.A. Identification strategy

As previously mentioned, the extreme climate events of 2011 affected the prices of white corn and some legumes. The affected products were those grown in those areas damaged by the frost and drought. This means that unaffected agricultural products may be a comparison group of impacted agricultural prices, that could be compared to a grain index of affected crops to identify the effect of the extreme events. An assumption is that the comparison groups are neither substitutes nor complements for crops such as white corn. Therefore we estimate the effects of the extreme weather by comparing the prices of affected grains, which we refer to collectively as treatment group or grain index[7], to the prices of unaffected grains/legumes or the control group.

For this purpose, we employ the synthetic control method (SCM) designed by Abadie, Diamond, and Hainmueller (2015), and Abadie, Diamond, and Hainmueller (2010) . We construct a synthetic control group that replicates the behavior of affected white corn and some legume prices before the extreme weather events employing the linear convex combination of agricultural products (legumes and grains) that were not influenced directly by these phenomena. Then, we compare the prices of the synthetic grain index to the actual grain index for the period 2011–2015.

Let the periods of interest be $T = T_B + T_C$, where T consist of all the period ranging from March 2011 to January 2015, T_B are the periods before the climate events, and T_C are periods afterward. The number of comparison groups is P. Let Y_1 be the Tx1 vector of prices for the grain index and Y_0 the T x P matrix of prices of unaffected products. Y_{1B} be the vector of affected grain prices before march 2011 and Y_{1C} the vector of prices post-event. Similarly, Y_{0B} is the T x P matrix of control group prices before the extreme events, and Y_{0C} is the matrix including periods post-event. Finally, W is a Px1 vector of weights. The synthetic control method consists in creating a synthetic treatment group that matches the trajectory of the pre-intervention periods. Therefore, the synthetic grain index is created by choosing the values of W to solve $min(Y_{1B} - Y_{0B}W)'V(Y_{1B} - Y_{0B})$ subject to the elements of W sum to one and be non-negative. The matrix V is diagonal and non-negative and

---

[7] The grain index is created using a weighted average of the prices of chickpeas, Peruvian beans and white corn.

may weigh more on some observations than others. According to Grogger (2016), the estimated treatment effect is given by $TE = \frac{1}{T_C}\sum_{T_B+1}^{T}(Y_{1Ct} - Y^*_{1Ct})$, where Y_{1Ct} is a typical element of Y_{1C}, Y^*_{1Ct} is a typical element of $Y^*_{1C} = Y_{0A}W^*$, and W^* is the solution to the minimization problem. This estimated treatment effect is a special case of the original control synthetic method. Similar to Grogger (2016), we lack variables that may predict the outcome in the treatment unit. Thus, we restrict to pre-event prices of the comparison goods for the construction of the synthetic.

V.B. Results

The synthetic control results are shown in figure 11. Panel A presents the grain index and synthetic grain index trends in the period of interest. In the pre-event period, the trajectory is similar between the grain index and its synthetic; the estimated RMSPE is .97. The synthetic control group is formed from grain and legume varieties that were not affected by climatic events. The elements with more relevant weights are Morelos polished rice, general variety of polished rice, small lentils, kidney bean and large lentils.

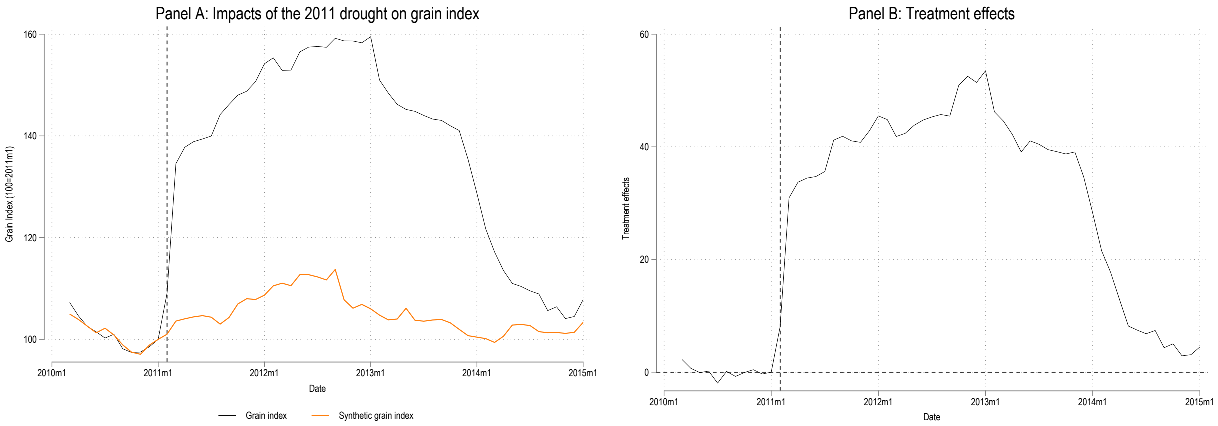


Figure 11: "Synthetic control method results, 2010–2015"

Panel B shows the difference between the grain index and its synthetic. Due to the price indexes equaling 100 in January 2011, the estimates are the proportionate change in price caused by the extreme weather. It can be seen that the effect on prices increased as the drought-affected most of the states. This phenomenon lasted the rest of 2011 and the beginning of 2012, as shown in Figure 3, continued to affect the Autumn/Winter cycle of 2012. This situation provides evidence that the effect on prices is primarily related to weather conditions. The treatment effect is estimated at around 30 percent initially and reaches up to 60 percent in the later months. The results are very similar to the RDiT estimates, so the synthetic control results suggest that the short-term results are robust. As the drought ended and the weather conditions were again favorable, the price of grains began to decline. However, the price adjustment process lasted around 3 to 4 years. An asymmetric price transmission is observed; at first, the prices rose quickly, but the adjustment process took much longer.

V.C. Robustness Tests

We construct a placebo test where extreme weather effects are reassigned to other grains/legumes other than the ones on the grain index to identify the effect on prices in a hypothetical scenario. The placebo test identifies the effect on prices, assuming that grains that weren't affected by the extreme weather events (donor pool) behave as if they were affected. If the placebo test identifies price increases proximate to the one estimated for the grain index, the estimation interpretation does not show meaningful evidence of the positive impact of extreme weather events on grain prices. On the other hand, if the placebo test presents that the price increases calculated for the grain index are large relative to the grains that weren't affected by the frost and drought, then the test provides significant evidence of a positive impact of extreme weather events on the grain index.

Figure 12 shows the results of the placebo test. The gray lines illustrate the effect related to each of the tests. It shows the difference in price between each grain price in the donor pool and its respective synthetic group. The black line indicates the effect estimated for the grain index. Figure 12 displays that before March 2011, the grain index and its synthetic control gap were smaller than the gap calculated for most placebo tests. On the other hand, the estimated impact on the grain index between the March 2011 and January 2015 is large relative to the effects on the agricultural products in the donor pool. Accordingly, we may infer that there is considerable evidence of a positive impact of extreme weather events on prices. As discussed in the literature review, the results align with previous studies analyzing the impact of weather shocks on prices.

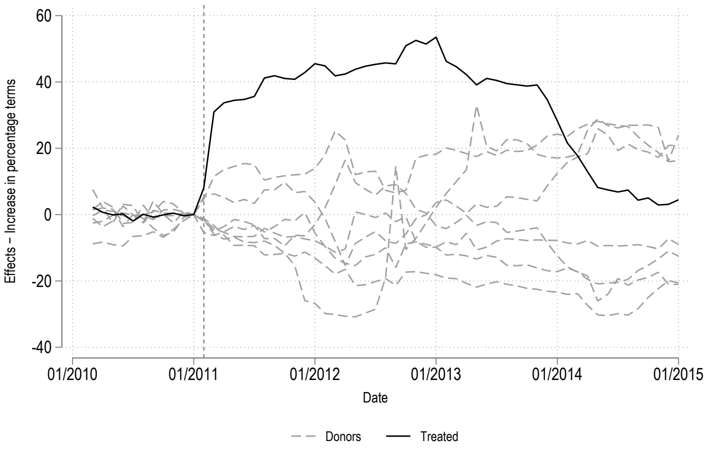


Figure 12: “Placebo test for grain index, 2010–2015”

Second, we calculate the pseudo-p-values to assess whether the estimated post-treatment effects are driven by chance. This placebo test calculates the p-value for each post-treatment effect and finds if the placebo effects are as significant as the main effect. If multiple placebo effects are as significant as the principal effect, the p-values will be large. In this situation, the main effect was likely to be observed by chance. Figure 13 shows estimates of the p-values of standardized effects. We find that the p-values on whether the results are estimated at random are close to zero in most of the post-intervention period. Thirty-six months after the events of extreme weather events of February and March in 2011, the p-values indicate a marked and gradual upsurge, indicating the transient nature of the event. The effect faded after three years. We interpret these results as evidence that the effects weren't driven by chance.

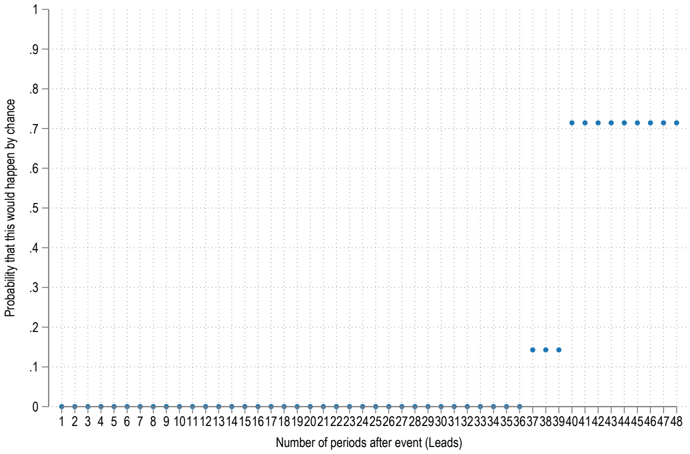


Figure 13: “Inference for effects in Post-treatment years”

VI. Conclusions

Extreme weather events such as droughts represent Mexico's economic and social concern and may increase in frequency and intensity. Climatological research studies suggest that Mexico's north region has experienced increasing temperatures, on average, and decreased rainfall levels in the last fifty years. In 2020–2021, Mexico experienced the second-largest drought within the previous twenty years, just slightly less intense than the 2011 drought. In this sense, a research agenda has begun to identify the effects of this climate phenomenon on poverty, employment, prices, migration, and so forth. This thesis intends to contribute to the literature by providing insights into how extreme weather events affect prices, especially agricultural prices. Agricultural prices are relevant for three reasons: 1) food expenses constitute more than 50% of the Mexican family budget, 2) food prices are linked to the prices of other products, and 3) food price increases are a key component of inflation.

This work focuses on the frost and drought that affected white corn and some legumes in the autumn/winter season during 2011 in northern Mexico. The planted area and crop yield especially in the northern part of the country were affected; for example, Sinaloa lost about half of the planted area of white corn that season. Similarly, legumes were affected, such as chickpeas and some varieties of beans. The results suggest important effects on prices. First, we used the regression discontinuity in time (RDiT) framework to estimate the short-run impact on prices. The results suggest a 30% to 35% price increase for white corn. Our findings remained unaltered by various robustness checks. The results show impacts not only on the main affected entities but also on the rest of the country. On the other hand, the effect on legumes, such as small chickpeas, large chickpeas, and Peruvian beans, was around 20%–25%.

Our findings contribute to understanding how supply shocks caused by extreme weather events affect prices. Understanding the duration and reach of this shock is crucial to implementing public policies. Our results suggest that the impact of the extreme events of 2011 on agricultural prices was persistent and long-lasting. An asymmetric price transmission was observed; initially, the prices rose quickly, but the downward price adjustment process lasted three to four years.

The findings indicate that policymakers should implement measures to support the income of the poorest Mexican households in the presence of these extreme events because of the large impact on agricultural prices. In addition, the results inform a better comprehension of setting monetary policy in the immediate aftermath of a climate shock. However, policy makers should also consider the states' heterogeneity. The impact may be distinct for each drought. For example, the 2011 events heavily affected Sinaloa, one of the main supply entities, but price increases should not be of the same magnitude for a drought that affects states with low production levels.

Moreover, future work can also investigate the impact of higher prices caused by climate events on the income and welfare of households, the income of small farmers, and the mechanism of price increases[8]. Our work suggests that the main mechanisms are the reduction of crop yield and planted areas. Nevertheless, we did not test this hypothesis. Finally, studies are needed on the estimation of the pass-through of the increase of these prices on overall inflation.

---

[8] For instance Hernández Solano (2015).

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association* 105 (490): 493–505. https://doi.org/10.1198/jasa.2009.ap08746.

———. 2015. "Comparative Politics and the Synthetic Control Method." *American Journal of Political Science* 59 (2): 495–510. https://doi.org/https://doi.org/10.1111/ajps.12116.

Aguilar-Gomez, Sandra, Emilio Gutierrez, David Heres, David Jaume, and Martín Tobal. 2021. "Extreme Temperatures and Loan Defaults: Evidence from Bank-Firm Level Data in Mexico." *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.3934688.

Albert, Christoph, Paula Bustos, and Jacopo Ponticelli. 2021. "The Effects of Climate Change on Labor and Capital Reallocation." *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.3875822.

Andersson, Malin, Julian Morgan, and Claudio Baccianti. 2021. "Climate Change and the Macro Economy." *SSRN Electronic Journal*, no. 243. https://doi.org/10.2139/ssrn.3632832.

Arceo-Gómez, Eva O., Danae Hernández-Cortés, and Alejandro López-Feldman. 2020. "Droughts and rural households' wellbeing: evidence from Mexico." *Climatic Change* 162 (3): 1197–1212. https://doi.org/10.1007/s10584-020-02869-1.

Banerjee, Abhijit V., and Esther Duflo. 2007. "The Economic Lives of the Poor." *Journal of Economic Perspectives* 21 (1): 141–68. https://doi.org/10.1257/JEP.21.1.141.

BANXICO. 2021. "El Efecto de la Baja Precipitación en el Precio del Maíz Blanco y del Frijol." In *Reporte Sobre Las Economías Regionales Abril - Junio 2021*, 57–60.

Berry, Steven T., Michael J. Roberts, and Wolfram Schlenker. 2014. "Corn Production Shocks in 2012 and Beyond: Implications for Harvest Volatility." *The Economics of Food Price Volatility*, no. October: 59–81.

Camarena, Salvador. 2012. "La sequía abrasa México | Internacional | EL PAÍS." https://elpais.com/internacional/2012/01/20/actualidad/1327098885_729925.html.

Cavazos, Tereza, Rosa Luna-Niño, Ruth Cerezo-Mota, Ramón Fuentes-Franco, Matías Méndez, Luis Felipe Pineda Martínez, and Ernesto Valenzuela. 2020. "Climatic trends and regional climate models intercomparison over the CORDEX-CAM (Central America, Caribbean, and Mexico) domain." *International Journal of Climatology* 40 (3): 1396–1420. https://doi.org/10.1002/joc.6276.

Cohen, François, and Antoine Dechezleprêtre. 2020. "Mortality, temperature, and public health provision: evidence from Mexico" 5709 (305). www.cccep.ac.uk.

Dale, Hathaway, Houthakker Hendrik, and Schnittker John. 1974. "Food Prices and Inflation." *Brookings Papers on Economic Activity* No. 1-197: 63–116.

Damania, R., S. Desbureaux, and E. Zaveri. 2020. "Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014)." *Journal of Environmental Economics and Management* 102 (July): 102335. https://doi.org/10.1016/J.JEEM.2020.102335.

De Bandt, Olivier, Luc Jacolin, and Thibault Lemaire. 2021. "Climate Change in Developing Countries: Global Warming Effects, Transmission Channels and Adaptation Policies." *Banque de France Working Paper*, no. 822.

De Winne, Jasmien, and Gert Peersman Peersman. 2021. "The Adverse Consequences Of Global Harvest And Weather Disruptions On Economic Activity." *Nature Climate Change* 11 (8): 665–72. https://ideas.repec.org/p/rug/rugwps/21-1012.html.

Dehn, J., C. L. Gilbert, and P. Varangis. 2005. "Agricultural Commodity Price Volatility." In *Managing Economic Volatility and Crise*, 137–85. Cambridge University Press, Cambridge.

Dell, By Melissa, Benjamin F Jones, and Benjamin A Olken. 2012. "Temperature shocks and economic growth. Evidence from the last half century" 4 (3): 66–95.

Dobler-Morales, Carlos, and Gerardo Bocco. 2021. "Social and environmental dimensions of drought in Mexico: An integrative review." *International Journal of Disaster Risk Reduction* 55 (March): 102067. https://doi.org/10.1016/J.IJDRR.2021.102067.

Drudi, Francesco, Emanuel Moench, Cornelia Holthausen, Pierre-François Weber, Gianluigi Ferrucci, Ralph Setzer, Bernardino Adao, Stéphane Dées, Spyros Alogoskoufis, and Mar Delgad Téllez. 2021. "Climate change and monetary policy in the euro area." Occasional Paper Series 271. European Central Bank. https://ideas.repec.org/p/ecb/ecbops/2021271.html.

Espinosa, Verónica. 2011. "Pedirá CNC declarar zona de desastre en 15 entidades - Proceso." https://www.proceso.com.mx/nacional/2011/6/20/pedira-cnc-declarar-zona-de-desastre-en-15-entidades-88403.html.

Expansion. 2011. “México enfrenta peor sequía en 70 años.” https://expansion.mx/economia/2011/11/24/mexico-enfrenta-peor-sequia-en-70-anos.

Faccia, Donata, Miles Parker, and Livio Stracca. 2021. “Temperatures and price stability.” *ECB Working Paper Series* 2626.

Feng, Shuaizhang, Alan B. Krueger, and Michael Oppenheimer. 2010. “Linkages among climate change, crop yields and Mexico-US cross-border migration.” *Proceedings of the National Academy of Sciences of the United States of America* 107 (32): 14257–62. https://doi.org/10.1073/PNAS.1002632107/SUPPL_FILE/SAPP.PDF.

FIRA. 2019. “Panorama agrolimentario - Frijol 2019.” FIRA. https://www.inforural.com.mx/wp-content/uploads/2020/01/Panorama-Agroalimentario-Frijol-2019.pdf.

García-Cueto, O. Rafael, Néstor Santillán-Soto, Ernesto López-Velázquez, Jaime Reyes-López, Samantha Cruz-Sotelo, and Sara Ojeda-Benítez. 2019. “Trends of climate change indices in some Mexican cities from 1980 to 2010.” *Theoretical and Applied Climatology* 137 (1-2): 775–90. https://doi.org/10.1007/s00704-018-2620-4.

Gilbert, Christopher L. 2010. “How to Understand High Food Prices.” *Journal of Agricultural Economics* 61 (2): 398–425. https://doi.org/10.1111/J.1477-9552.2010.00248.X.

Grogger, Jeffrey. 2016. “Soda Taxes and the Prices of Sodas and Other Drinks: Evidence from Mexico.” *IZA DP* No. 9682.

Guerrero Compeán, Roberto. 2013. “Weather and Welfare : Health and Agricultural Impacts of Climate Extremes, Evidence from Mexico.” *IDB Working Paper Series; 391. Inter-American Development Bank*, no. February.

Hausman, Catherine, and David S. Rapson. 2018. “Regression discontinuity in time: considerations for empirical applications.” *Ann. Rev. Resour. Econ.* 10 (1): 533–52.

Hayhoe, K., J. Edmonds, R. E. Kopp, A. N. LeGrande, B. M. Sanderson, M. F. Wehner, and D. J. Wuebbles. 2017. “Climate Models, Scenarios, and Projections.” In *Climate Science Special Report: Fourth National Climate Assessment*, edited by D. J. Wuebbles, D. W. Fahey, K. A. Hibbard, D. J. Dokken, B. C. Stewart, and T. K. Maycock. Vol. I. Washington, DC USA: U.S. Global Change Research Program; U.S. Global Change Research Program. https://doi.org/10.7930/J0WH2N54.

Heinen, Andréas, Jeetendra Khadan, and Eric Strobl. 2019. "The Price Impact of Extreme Weather in Developing Countries." *The Economic Journal* 129 (619): 1327–42. https://doi.org/10.1111/ECOJ.12581.

Hendricks, Nathan P., Joseph P. Janzen, and Aaron Smith. 2015. "Futures prices in supply analysis: Are instrumental variables necessary?" *American Journal of Agricultural Economics* 97 (1): 22–39. https://doi.org/10.1093/ajae/aau062.

Hernández Solano, Alan Martín. 2015. "Pobreza Y Cambio Climático El Caso De Mexico." In *[Doctoral Thesis], El Colegio de méxico, CEE, Promoción 2012-2015*. https://colmex.userservices.exlibrisgroup.com/view/delivery/52COLMEX_INST/1265002460002716.

Hsiang, Solomon M, and Amir S Jina. 2014. "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones." Working Paper 20352. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w20352.

Hsiang, Solomon, and Robert E. Kopp. 2018. "An Economist's Guide to Climate Change Science." *The Journal of Economic Perspectives* 32 (4): 3–32.

Jaramillo-Villanueva, Jose, Antonio Yunez-Naude, and Valeria Cote. 2016. "Spatial Integration of Mexico-U.S. Grain Markets: The Case of Maize, Wheat and Sorghum." *EconoQuantum* 12 (January): 57. https://doi.org/10.18381/eq.v12i1.4853.

Jessoe, Katrina, Dale T. Manning, and J. Edward Taylor. 2018. "Climate Change and Labour Allocation in Rural Mexico: Evidence from Annual Fluctuations in Weather." *The Economic Journal* 128 (608): 230–61. https://doi.org/10.1111/ECOJ.12448.

Juárez-Torres, Miriam, and Jonathan Puigvert. 2021. "The effect of tropical cyclones on economic activities: micro level evidence from Mexico for secondary and tertiary activities." *Working Paper Banco de México*, no. 24.

Kornher, Lukas, and Matthias Kalkuhl. 2013. "Food Price Volatility in Developing Countries and its Determinants." *Quarterly Journal of International Agriculture* 52 (4): 277–308. https://ageconsearch.umn.edu/record/173649?ln=en.

Lee, David S., and Thomas Lemieux. 2010. "Regression Discontinuity Designs in Economics." *Journal of Economic Literature* 48 (2): 281–355. https://doi.org/10.1257/JEL.48.2.281.

Mall, R K, A Gupta, and G Sonkar. 2017. "2 - Effect of Climate Change on Agricultural Crops."

Current Developments in Biotechnology and Bioengineering, 23–46. https://doi.org/10.1016/B978-0-444-63661-4.00002-5.

Michael J., Roberts, and Schlenker Wolfram. 2010. "Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate." *NBER Working Paper No. 15921.*

Minot, Nicholas. 2011. "Transmission of world food price changes to markets in Sub-Saharan Africa." *Discussion Papers 1059. International Food Policy Research Institute (IFPRI), Washington, D.C.* https://ebrary.ifpri.org/digital/collection/p15738coll2/id/124886.

Montero-Martínez, Martín José, Julio Sergio Santana-Sepúlveda, Naydú Isabel Pérez-Ortiz, Óscar Pita-Díaz, and Salvador Castillo-Liñan. 2018. "Comparing climate change indices between a northern (arid) and a southern (humid) basin in Mexico during the last decades." *Advances in Science and Research* 15 (2014): 231–37. https://doi.org/10.5194/asr-15-231-2018.

Mukherjee, K., and B. Ouattara. 2021. "Climate and monetary policy: do temperature shocks lead to inflationary pressures?" *Climatic Change* 167 (3-4): 1–21. https://doi.org/10.1007/s10584-021-03149-2.

Muller, Richard, Robert Rohde, Robert Jacobsen, Elizabeth Muller, and Charlotte Wickham. 2013. "A New Estimate of the Average Earth Surface Land Temperature Spanning 1753 to 2011." *Geoinformatics & Geostatistics: An Overview* 01 (01): 1–7. https://doi.org/10.4172/2327-4581.1000101.

Murray-Tortarolo, Guillermo N. 2021. "Seven decades of climate change across Mexico." *Atmósfera* 34 (2): 217–26. https://doi.org/10.20937/ATM.52803.

Murray-Tortarolo, Guillermo N., and Víctor J. Jaramillo. 2019. "The impact of extreme weather events on livestock populations: the case of the 2011 drought in Mexico." *Climatic Change* 153 (1-2): 79–89. https://doi.org/10.1007/s10584-019-02373-1.

Neelin, J. D., M. Münnich, H. Su, J. E. Meyerson, and C. E. Holloway. 2006. "Tropical drying trends in global warming models and observations." *Proceedings of the National Academy of Sciences of the United States of America* 103 (16): 6110–15. https://doi.org/10.1073/PNAS.0601798103/SUPPL_FILE/01798FIG10.PDF.

Notimex. 2012. "Sequía afecta a más de 1,200 municipios en 2011." https://www.eleconomista.com.mx/politica/Sequia-afecta-a-mas-de-1200-municipios-en-2011-20120123-0036.html.

Ortiz Arango, Francisco, Alma Nelly, and Montiel Guzmán. 2016. “Transmisión de precios futuros de maíz del Chicago Board of Trade al mercado spot mexicano.” *Contaduría y Administración* 62 (3): 924–40. https://doi.org/10.1016/J.CYA.2016.01.004.

Parker, Miles. 2017. “The Impact of Disasters on Inflation.” *Economics of Disasters and Climate Change 2017 2:1* 2 (1): 21–48. https://doi.org/10.1007/S41885-017-0017-Y.

Ramírez Reynaldo, Pascual, and Adelina Albanil Encarnación. 2011. “Reporte Anual del clima en México.” CONAGUA.

Ruan, Jianqing, Qingwen Cai, and Songqing Jin. 2021. “Impact of COVID-19 and Nationwide Lockdowns on Vegetable Prices: Evidence from Wholesale Markets in China.” *American Journal of Agricultural Economics* 103 (5): 1574–94. https://doi.org/10.1111/ajae.12211.

SAGARPA. 2017. “Planeación Agrícola Nacional 2017 - 2030.” Secretaría de Agricultura y Desarrollo Rural. https://www.gob.mx/agricultura/documentos/planeacion-agricola-nacional-2017-2030?state=published.

Serra, Teresa, and José M. Gil. 2013. “Price volatility in food markets: can stock building mitigate price fluctuations?” *European Review of Agricultural Economics* 40 (3): 507–28. https://doi.org/10.1093/ERAE/JBS041.

World Bank, CIAT, and CATIE. 2014. “Climate-Smart Agriculture in Sinaloa, Mexico.” CSA Country Profiles for Latin America Series. Washington, DC: The World Bank Group.

Zahniser, Steven, Nicolás Fernando López López, Mesbah Motamed, Zully Yazmin Silva Vargas, and Tom Capehart. 2019. “The Growing Corn Economies of Mexico and the United States.” United States Department of Agriculture. www.ers.usda.gov.