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The price effect of weather shocks: the case of staple crops in Mexico El efecto de choques climáticos en los precios: el caso de cultivos básicos en México

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Abstract

This paper investigates the effect of weather shocks on agricultural prices focusing on Mexico and its two major staple crops: white corn and dry beans. Mexico provides a relevant case study due to its high exposure to climatic variability. Given the importance of white corn and dry beans in both consumption and production, weather-induced supply shocks may have significant economic and welfare implications. The analysis relies on the estimation of fixed-effects models using a 20-year long panel of monthly prices at the market level, linked to weather shocks experienced by the main supplier states of each market. To identify these suppliers, a relevance index is constructed combining information on production levels, geographical distance, and commercialization patterns, allowing for a more accurate representation of the relationship between weather conditions in producing areas and observed prices in the consumer markets. Our results show that positive temperature and negative precipitation shocks of at least 0.5 standard deviations relative to the climate normal have immediate and lagged effects on the price of these crops. The immediate effect is about 2%, while the lagged effect is between 1% and 2.5%, depending on the timing of the shock within the crop's growing period. These results are consistent with the detrimental effect that weather shocks have on crop productivity that has been largely documented in related literature. Overall, these findings suggest that weather shocks may generate upward pressures on agricultural prices with potential implications for food inflation under increasing climate variability.

Keywords: Food Inflation, Weather Shocks, Staple Prices, Local Markets

JEL Clasification: E31, Q15, Q54

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 Resumen

En este artículo se investiga el efecto de los choques climáticos en los precios agrícolas para el caso de México y sus dos principales cultivos básicos: maíz blanco y frijol. México constituye un caso de estudio relevante debido a su elevada variabilidad climática. Dada la importancia del maíz blanco y el frijol tanto en el consumo como en la producción, los choques de oferta inducidos por el clima podrían tener implicaciones económicas y de bienestar significativas. El análisis se basa en la estimación de modelos de efectos fijos utilizando un panel de 20 años de precios mensuales a nivel de mercado, vinculado a los choques climáticos experimentados por los principales estados proveedores de cada mercado. Para identificar a estos proveedores, se construye un índice de relevancia que combina información sobre los niveles de producción, la distancia geográfica y los patrones de comercialización, lo que permite una representación más precisa de la relación entre las condiciones climáticas en las zonas productoras y los precios observados en los mercados de consumo. Nuestros resultados muestran que choques positivos de temperatura y choques negativos de precipitación de al menos 0.5 desviaciones estándar con respecto a la normal climática tienen efectos inmediatos y rezagados en el precio de estos cultivos. El efecto inmediato es de aproximadamente el 2%, mientras que el efecto rezagado oscila entre el 1% y el 2.5%, dependiendo del momento en que se produzca el choque dentro del ciclo de crecimiento del cultivo. Estos resultados son consistentes con el efecto perjudicial que los choques climáticos tienen sobre la productividad agrícola, ampliamente documentado en literatura relacionada. En general, estos hallazgos sugieren que los choques climáticos podrían generar presiones al alza sobre los precios agrícolas, con posibles implicaciones para la inflación de los alimentos ante una creciente variabilidad climática.

Palabras Clave: Inflación en Alimentos, Choques Climáticos, Precio de Cultivos Básicos, Mercados Locales

Clasificación JEL: E31, Q15, Q54

1. Introduction

A large body of empirical evidence documents a strong and robust relationship between weather and agricultural yields (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016; Moore and Lobell, 2014; Mérel and Gammans, 2021). The general finding is that heat and water stress are associated with diminished crop yields (Ortiz-Bobea *et al.*, 2019). If sufficiently large, the productivity damages caused by weather shocks could translate into higher prices, particularly if they hit an important producing area highly connected with the domestic market through commercialization. Crop prices could increase due to updated expectations about the current and future availability of the crop in the market (Letta *et al.*, 2022). While this mechanism is apparently obvious, empirical evidence linking weather shocks and agricultural prices directly is still rare.

In this paper, we estimate the effect of weather shocks on crop prices in the context of Mexico, a country that is particularly vulnerable to climatic variability. Mexico's weather is highly influenced by *El Niño-Southern Oscillation* (ENSO), a recurring climate phenomenon that significantly modulates global weather patterns. The warming phase of ENSO, commonly

referred to as *El Niño*, is often associated with warmer and drier conditions in most of Mexico, often resulting in prolonged and geographically extensive droughts. Conversely, the cooling phase of ENSO, *La Niña*, is typically characterized by wetter conditions, frequently linked to episodes of intense rainfall and flooding across the country (Magaña *et al.*, 1999). ENSO also influences the level hurricane activity affecting Mexico through both the Pacific and Atlantic Oceans. These ENSO-related extreme weather events constitute a persistent threat to agricultural production in Mexico, a vulnerability that is projected to increase with climate change (Cai *et al.*, 2015).

The analysis centers on two crops of great importance in Mexico in terms of consumption and production: white corn and dry beans.¹ From a consumption perspective, these crops are important staple foods with the average Mexican household allocating nearly 9% of its food budget to the purchase of white corn and dry beans related-products meaning that price increases caused by weather disturbances may have significant welfare implications. On the production side, white corn and dry beans are widely cultivated across different climates in Mexico and exposed to different kinds of weather shocks, offering a valuable context to evaluate their impact on prices. Importantly, most of the production of these crops is obtained under rainfed conditions rendering them highly susceptible to precipitation variability. Furthermore, the majority of the domestic supply of these crops is met with local production with imports accounting for a small fraction only. While international *price* benchmarks influence the domestic price, the fact that most of the production of white corn and dry beans is destined for domestic consumption makes their domestic prices temporarily sensitive to weather shocks in the country.

For the estimation, we rely on monthly panel data of prices for each crop at the market level for the period 2001-2020. Our price data is combined with information about the commercialization patterns of these crops among producing and purchasing states. This information allows us to identify the supplier states of each market. We examine the weather (temperature and precipitation) in the two main state suppliers and construct variables identifying weather deviations below and above its long-run average. We define a weather shock as weather deviations in supplier states larger than 0.5, 1.0 or 2.0 standard deviations (s.d.).² Then, using a fixed effects model, we estimate how these weather shocks, experienced in producing areas, affect the prices of white corn and dry beans in the markets where they are sold. Our fixed effects model includes present and lagged realizations of weather shocks for a time window equivalent to a growing period of each crop.

There are four main results. First, temperatures below normal (*i. e.*, average) increase the price of white corn. When temperatures are at least 0.5 s.d. below normal, the price of white corn increases by 1.2-1.6%, depending on the timing of the shock. The estimated impact rises to 1.6-2.2% when temperatures are at least 1.0 s.d. below normal. Second, temperatures above

¹ We focus in white corn (*Zea mays*) because it is the most cultivated variety across the country. In 2020, white corn was produced in 94% of the municipalities and accounted for 92.4% of the total area planted with corn and for 90.0% of total corn production (SADER-SIAP, 2021a). In Mexico, white corn is mainly devoted to human consumption as opposed to yellow corn which is used mainly by the processed-food industry and for livestock feed (Nuñez and Sempere, 2016).

² For reference, a 1.0 s.d. of the monthly temperature and precipitation normal roughly equals, on average, 1°C and 3.7cm, respectively.

normal increase the price of white corn and dry beans. According to our estimates, temperatures of at least 0.5 s.d. above normal increase the price of these crops by 1.8-2.6% and 1.0-1.6%, respectively. Larger temperature shocks are associated with larger price increases, although estimates are less precise. Third, episodes of scarce precipitation are associated with higher white corn and dry beans prices. For both crops, the estimated effect is between 1.1% and 1.7% depending on the timing of the shock. As the severity of the negative precipitation shock increases, the estimated impact also increases, particularly in the case of dry beans whose price increases up to 8.1% when precipitation is at least 2.0 s.d. below normal. Fourth, positive precipitation shocks are beneficial for white corn prices. When precipitation is at least 0.5 s.d. above its normal level, the price of white corn decreases by 1.4-1.7%, depending on the timing of the shock. The sensitivity of white corn and dry beans prices to past weather shocks could be explained by the productivity damages they cause at different stages of their growing period, which have been largely documented in the literature (Ortiz-Bobea and Just, 2013, Ortiz-Bobea *et al.*, 2019; Schlenker and Roberts, 2009; Burke and Emerick, 2016) or by updated price expectations due to markets anticipating a potentially reduced supply (Letta *et al.*, 2022).

This paper adds to the scarce empirical evidence regarding the effects of weather on agricultural prices using panel data (Letta *et al.*, 2022). Most of the empirical evidence available is based on time series techniques that rely on variation over time of aggregated measures of prices and weather (Abril-Salcedo *et al.*, 2020; Ubilava, 2018; Ubilava and Holt, 2013; Ubilava, 2012; Bastianin *et al.*, 2018). In contrast, this paper relies on time and spatial variation of weather and prices at more disaggregated levels. In general, the effect of weather shocks is first experienced at local levels affecting local production and prices. Then, it gets disseminated to the rest of the market through commercialization. Thus, by relying on local variation of weather and prices, we get closer to the process that originates the joint evolution of these two variables.

The findings of this paper suggest that weather shocks could create upward pressures in the price of these crops and have significant inflation consequences given their importance in the Consumer Price Index (CPI).³ Of particular interest are our estimates of the price increases associated to positive temperature shocks and negative precipitation shocks since their frequency has increased dramatically over the course of our sample period. If such trend continues, our estimates anticipate further upward pressures on the price of these crops resulting from future weather shocks.

The article is organized as follows. Section 2 presents an overview of the existing literature on linking weather, agricultural productivity and prices. In section 3 we provide the overall context of staple production in Mexico highlighting its seasonality and high concentration in few producing states at certain times of the year. Sections 4 and 5 describe the empirical strategy and the data used in the analysis, respectively. Section 6 presents the results. Finally, section 7 offers conclusions and policy implications derived from the article.

³ White-corn-related products (tortillas, masa, corn flour, tostadas) represent 11.7% of the total weight of the *Food, beverages and tobacco* category of the CPI, a core inflation component. Similarly, dry beans represent 9.9% of the total weight of the *Fruits and Vegetables* category of the CPI, a non-core inflation component.

2. Literature review

The general finding of the literature documenting the relationship between weather and agricultural yields is that heat and water stress are associated with diminished crop yields (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016; Tack *et al.*, 2017; Mérel and Gammans, 2021; Ortiz-Bobea *et al.*, 2019). For example, Schlenker and Roberts (2009) find that corn yields in the U.S. decrease sharply once temperature surpasses 29°C (a similar result is also found in Burke and Emerick, 2016). They also find a statistically significant inverted U-shaped relationship between corn yields and growing season precipitation. Ortiz-Bobea *et al.* (2019) find that the sensitivity of corn yields to high temperatures and water stress is larger in the middle portion of the growing season, which can irreversibly affect crop development at key stages such as the flowering and grain-filling periods. They also find that dry conditions toward the end of the growing season are beneficial for corn yields because they facilitate the harvest. Other studies have also confirmed the strong association between weather and corn yields in non-US contexts (Welch *et al.*, 2010; Demeke *et al.*, 2011; Moore and Lobell, 2014; Taraz, 2017 and 2018; Chen *et al.*, 2016).

If sufficiently large, the productivity damage caused by weather shocks could reduce the availability of the crop in the market and create upward pressures on its price. Most of the empirical evidence available directly relating weather shocks and agricultural prices comes from studies that rely on time series techniques applied to aggregate measures of prices and weather aggregated to country-year or country-month levels. For example, using a smooth transition non-linear model, Abril-Salcedo *et al.* (2020) find that positive temperature anomalies (deviations from the historical mean) linked to strong *El Niño* (ENSO) events increase food inflation growth in Colombia. Applying similar techniques, Ubilava (2018) and Ubilava and Holt (2013) also find that positive *El Niño* temperature anomalies increase the price of agricultural commodities like coffee, vegetable oils, oilseeds, fishmeal and salmon. Using a structural vector autoregression (SVAR), Bastianin *et al.* (2018) show that positive temperature ENSO anomalies are beneficial for Colombian production and exports and decrease the price of Colombian coffee because higher temperatures stimulate production (see also Ubilava, 2012). Finally, Cashin *et al.* (2017) estimate a Global VAR and find that the 21 countries/regions included in their sample experience short-run inflationary pressures after positive temperature anomalies linked to ENSO due, in part, to increased prices of agricultural raw materials.

As these studies have proved, aggregated weather variation can affect the aggregate evolution of prices. However, weather varies a lot at local levels and the effect of weather shocks on agriculture is first felt locally. Frosts, heat waves and cyclones are highly localized. Droughts also have a large regional component. Thus, the aggregation of weather shocks to, say, the national level, could obscure the effect that they have on price formation because such effect is first felt in local production and prices. Then, the effect gets disseminated to the rest of the market through commercial exchanges.

To identify the effect of weather shocks on prices, this paper relies on panel data. The identifying variation in panel data comes from weather anomalies experienced locally in producing areas. Panel data allows to better represent the relationship between weather and

prices and to control for unobserved factors potentially correlated with weather using fixed effects (Dell *et al.*, 2014; Blanc and Schlenker, 2017). Using this approach, Maystadt and Ecker (2014) estimate the effect of drought on livestock prices in Somalia. Their results indicate that drought increases the likelihood of conflict, and that the main mechanism exacerbating civil unrest is the direct effect of drought on local livestock prices as herders are forced to sell low-quality animals at low prices which depresses local income. In turn, this lowers the opportunity cost of engaging in conflict-related activities. Letta *et al.* (2022) investigate the effect of weather anomalies on the local price of corn, rice, and wheat in India also relying on panel data. Their results indicate that drought conditions increase the price of these crops during the growing season, even before the supply shock is materialized in the form of lost production. This result suggests that weather shocks may impact crop prices through an expectations channel in which markets anticipate a reduced availability of the crop and adjust prices accordingly.

Our paper is closer to the literature that relies on panel data to investigate the direct effect of weather on prices. Importantly, besides relying on local variation of weather and prices we also link weather shocks in producing areas with prices in final markets which are often distant from each other. The works of Maystadt and Ecker (2014) and Letta *et al.* (2022) estimate the effect of local weather on local prices but omit the additional effect that weather shocks may have on markets located beyond subnational boundaries and not necessarily close to the producing areas. Consider, for example, large cities whose supply of agricultural products depends on producing areas, some of them located nearby but some located further away. Agricultural prices in these cities are also expected to vary with weather shocks that impact the production of the areas that supply them. Our analysis considers all the markets in the country and their links to producing areas through commercialization.

3. The context of staple crops production in Mexico

White corn and dry beans are the two most important staple crops in Mexico in terms of production and consumption. Their production is widely spread across the country. In 2020, they were produced in 94.0% and 71.8% of the municipalities, respectively.⁴ Together, they represented 60.4% of the total area planted with annual crops and 34.6% of the total gross value (SADER-SIAP, 2021a). The average household devotes 8.7% of its total food budget to the purchase of white corn- and dry bean-related products (Garza-Montoya *et al.*, 2017) such as tortillas (a thin, circular flat bread made of white corn) which alone represent 6.7% of the total food budget.

In Mexico, white corn and dry beans are produced in two different growing seasons: the Spring-Summer or rainy season which runs from April to September, and the Fall-Winter or dry season which runs from October to March. Most of the production of these crops is obtained under rainfed conditions during the Spring-Summer season which makes it highly susceptible to precipitation shocks.⁵ The rest is produced under irrigated conditions mainly during the Fall-

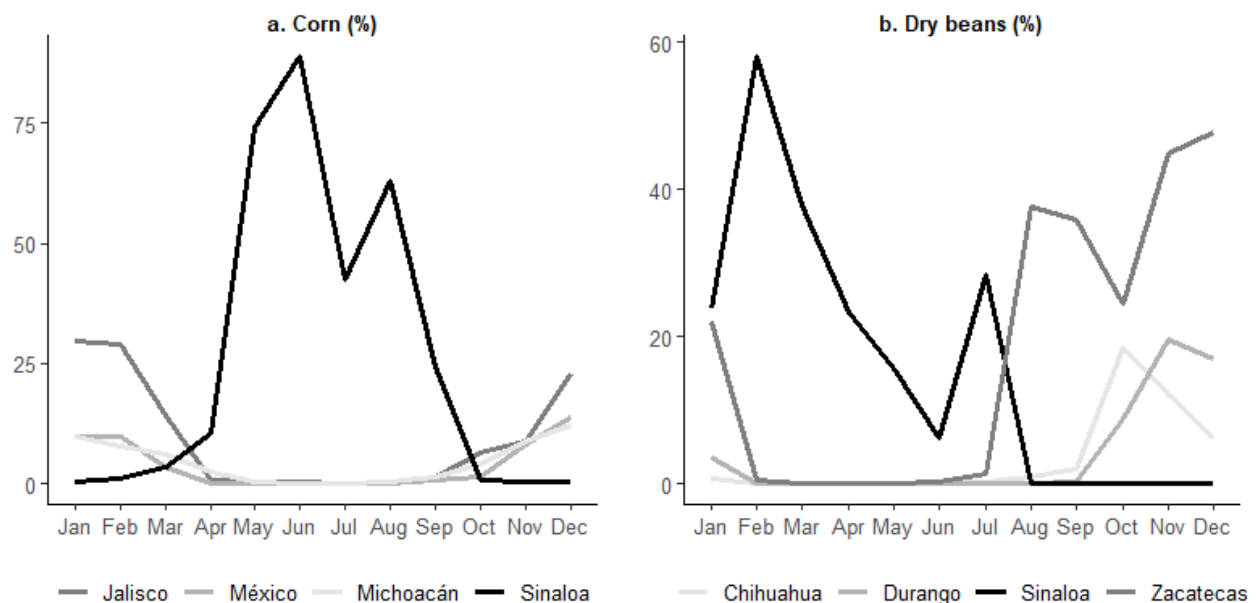
⁴ The municipality is the lowest level of disaggregation of federal administrative units. As of 2020, Mexico had 2,469 municipalities.

⁵ In 2020, 51.9% and 68.5% of white corn and dry beans production was rainfed with more than 80% of it obtained during the Spring-Summer season (SADER-SIAP, 2021a).

Winter season. Geographically, rainfed production is concentrated in the humid central and southern regions of Mexico while irrigated production takes place mostly in the arid north. Although the production of these crops is widespread across the country, some states are particularly important at producing them in specific months of the year as the production cycle transitions from one season to the other.

Figure 1 plots the average share of the top four producers of each crop in monthly production for the period 2004-2020 (SADER-SIAP, 2021b).⁶ Sinaloa, a state located in northern Mexico, is a major producer of both white corn and dry beans. Its production is mostly irrigated, cultivated in the Fall-Winter season, and harvested during the late winter months (in the case of dry beans) or at the beginning of the Spring-Summer season (in the case of corn). During this period, the domestic market of white corn and dry beans heavily depends on the production of this single state. For example, in June, Sinaloa accounts for about 80% of domestic corn production. Sinaloa also accounts for about 60% of domestic dry beans production in February. As Spring-Summer production takes place, Sinaloa's production is replaced by states relying mostly on rainfed production. In the case of white corn, the states of Jalisco, México and Michoacán, all located in central Mexico, account for about 50% of production toward the end of the year. In the case of dry beans, the states of Zacatecas, Chihuahua and Durango, all located in northern Mexico, concentrate about 70% of production at the end of the year.

Figure 1. Average share of the top 4 state producers on historical monthly production, 2004-2020



Note: Figure 1 plots the average share of the top four producers of each crop in monthly production for the period 2004-2020. Source: Own elaboration using monthly production data from SADER-SIAP (2021b).

⁶ For every year, we compute the share that each state represents in total monthly production and then take the average of these shares across years. Monthly production data for white corn is not available. Because of this, the average corn shares presented in Figure 1 were calculated using monthly production data for aggregated corn which includes white and yellow corn (SADER-SIAP, 2021b).

The sensitivity of white corn and dry beans prices to weather shock also depends on the ability of the domestic market to substitute production deficits with imports. However, imports of white corn and dry beans represent a small percentage of the domestic supply (see Figure A1 in the Appendix). Because most of the domestic supply of white corn and dry beans is generated domestically, their domestic price is susceptible to the influence of domestic weather shocks, at least temporarily while imports adjust in order to stabilize supply.

4. Empirical Strategy

To identify the effect of weather shocks on white corn and dry beans prices, this paper deploys a fixed effects model applied to panel data of prices at the market/city level. For each crop (white corn or dry beans), we estimate the following equation:

$$\ln P_{it} = \sum_{l=0}^L \varphi_l T_{t-l}^- + \sum_{l=0}^L \gamma_l T_{t-l}^+ + \sum_{l=0}^L \alpha_l Pr_{t-l}^- + \sum_{l=0}^L \vartheta_l Pr_{t-l}^+ + \mu_i + \tau_t + \epsilon_{it} \quad (1),$$

where $\ln P_{it}$ represents the logarithm of the price of each crop in market/city i in year-month t . T^- , T^+ , Pr^- , Pr^+ , are state-level dummy variables that identify weather shocks in at least one of the two main supplier states of city/market i . The two main state suppliers are identified using a relevance index constructed using commercialization patterns and production data. This relevance index varies by month j which means that the two main supplier states of a city/market could also change by month according to the production cycle of white corn and dry beans throughout the year (see Figure 1). In such a way, the estimation considers the weather shocks of the relevant producing states at different points of the production cycle. Details about the data used to identify commercialization patterns and construct the relevance index are given later in the text (see section 5.2.1).

To construct our weather shocks variables, we followed three steps. First, we calculated temperature and precipitation normals for the supplier states using monthly weather data for the period 1980-2019.⁷ Second, we compared observed temperature and precipitation with their normal and constructed: T^- which identifies months in which average monthly temperature is at least 0.5 standard deviations (s.d.) below its normal; T^+ which identifies months in which average monthly temperature is at least 0.5 s.d. above its normal; Pr^- which identifies months in which total monthly precipitation is at least 0.5 s.d. below its normal and; Pr^+ which identifies months in which total monthly precipitation is at least 0.5 s.d. above its normal.⁸ In the third and final step, the prices observed in each of the cities/markets in our sample were linked with the weather shocks identified in their two main state suppliers.

Our model includes up to L lags of the weather shock variables limiting their impact on crop prices to the duration of their phenological cycle, which on average is 6 months for white corn and 4 months for dry beans (Ruiz *et al.*, 2013). As a result, $L=5$ when the model is applied to

⁷ Climate normals are used to represent the long-term weather pattern of a particular area. They describe the typical meteorological conditions and provide a comparison point for weather variations

⁸ A similar approach is adopted by Skoufias and Vinha (2012 and 2013) when analyzing weather variability in Mexico and its consequences on rural welfare.

white corn prices and $L=3$ when the model is applied to dry beans prices. The coefficients φ_l , γ_l , α_l and ϑ_l provide the estimated impact of a weather shock in year-month $t-l$ with $(l = 0, \dots, L)$ on prices observed in year-month t . The estimation includes market/city fixed effects (μ_i) and year-month fixed effects (τ_t). Market/city fixed effects control for all the common time-invariant factors at the city level explaining crop prices. Year-month fixed effects flexibly control for all the common time-varying factors influencing crop prices across markets/cities within the same month, such as the seasonality of production and existing inventories. The identifying assumption is that conditional on μ_i and τ_t , contemporaneous and lagged realizations of weather shocks are not correlated with the rest of unobserved determinants of crop prices (ϵ_{it}). In this estimation, standard errors are clustered at the market/city and state-year levels. In additional regressions, we test the robustness of our results to more stringent definitions of weather shocks in which the threshold to identify them is set to 1.0 s.d. and 2.0 s.d.

5. Data

5.1 Price data

Price data come from two different sources. White corn prices are obtained from the National System of Market Information and Integration (SE-SNIIM by its Spanish acronym) administered by the Ministry of Economics. SNIIM reports the price of a large number of agricultural products quoted at wholesale markets located throughout the country (SE-SNIIM, 2021). White corn prices are available for 39 wholesale markets distributed across 30 Mexican states. Our main variable is constructed by calculating a market-specific monthly average of white corn prices for the period January 2001 to December 2020. We chose to use white corn prices from wholesale markets because they refer to the grain actually used in the preparation of *tortillas*, a staple food that represents the main form of human consumption of white corn in Mexico. CPI series for corn exist at the city level but they mix white corn with other varieties or subspecies of corn such as the ones used to make *pozole* and popcorns (INEGI, 2024).⁹ While the consumption of these other forms of corn is popular in Mexico, we want to exclusively focus on white corn, the most widespread crop in the country and the most important in terms of caloric intake for the average Mexican. Besides, other varieties tend to be more expensive than regular white corn.

Dry beans prices at the city level are generated using monthly CPI series obtained from the National Institute of Statistics and Geography (INEGI by its acronym in Spanish), the institution in charge of measuring and releasing inflation data in Mexico. The current base period of the CPI series provided by INEGI is July 2018 (INEGI, 2024). We construct dry beans prices for each city and for the period January 2001 to December 2020 by retro-projecting and projecting observed prices in July 2018 using the dry beans CPI with the following calculation:

$$P_{it} = \frac{CPI_{it}}{CPI_{i, July 2018}} * Price_{i, July 2018} \quad (2),$$

⁹ Pozole, is a traditional stew in Mexican cuisine prepared with an old heirloom variety of white corn originated in Mexico called *Cacahuazintle*. The corn subspecies used to make popcorns is *Zea mays everta*.

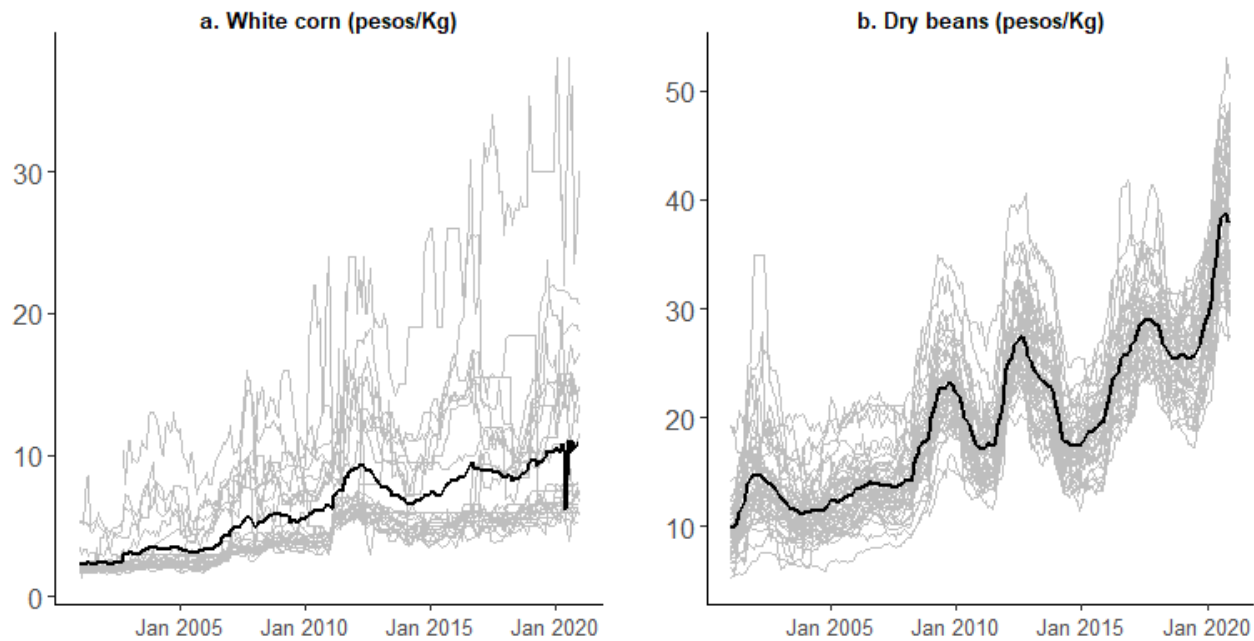
where the subscripts i and t refer to city and year-months, respectively. We use prices for July 2018 as baseline because they coincide with the base period of the CPI series. Dry beans prices before July 2018 are not available. By retro-projecting and projecting July 2018 prices we are able to recreate longer dry beans price series for each city using city-specific variation in the dry beans' CPI. This procedure implicitly assumes that the CPI accurately reflects actual price volatility. In practice, the CPI results from the aggregation of prices of sampled products at selected locations. This aggregation may hide part of the variability that weather shocks may cause on prices which is extremely valuable for our fixed-effects estimation. If such is the case, the estimated impact may be attenuated (biased toward zero).

We exclude markets and cities with less than 85% of the 240 monthly observations of the sample period. As a result, our final sample consists of a panel of prices that includes 26 markets in the case of white corn and 45 cities in the case of dry beans.¹⁰ Figure A2 (in the Appendix) displays the location of the markets and cities included in the sample. Our white corn prices come from wholesale markets whereas our dry beans prices refer to retail markets. Thus, the interpretation given to the results presented in this paper should consider the different nature of the prices used in each case.

Figure 2 shows the evolution of white corn and dry beans prices during the sample period. The black lines refer to the national average while the grey lines represent the price series for each of the markets (white corn) and cities (dry beans) in the sample. The price of both crops increased since 2001. They also vary substantially at the market or city level. For example, toward the end of 2020, white corn prices ranged from 5 to 40 pesos per kilogram. Dry beans prices ranged from 20 to 55 pesos per kilogram. Table A1 (in the Appendix) presents summary statistics.

¹⁰ In our white corn sample, we exclude a total of 13 wholesale markets. On average, these excluded markets have price data for about half of the 240 months contained in our sample period. In our dry beans sample, we exclude 9 cities because CPI information is not available before July 2018.

Figure 2. Evolution of white corn and dry beans prices, 2001-2020



Note: The black line refers to the national average while the gray lines represent the price series of each of the markets (white corn) and cities (dry beans) in the sample. Source: Own elaboration with price information from INEGI (2021) and SE-SNIIM (2021).

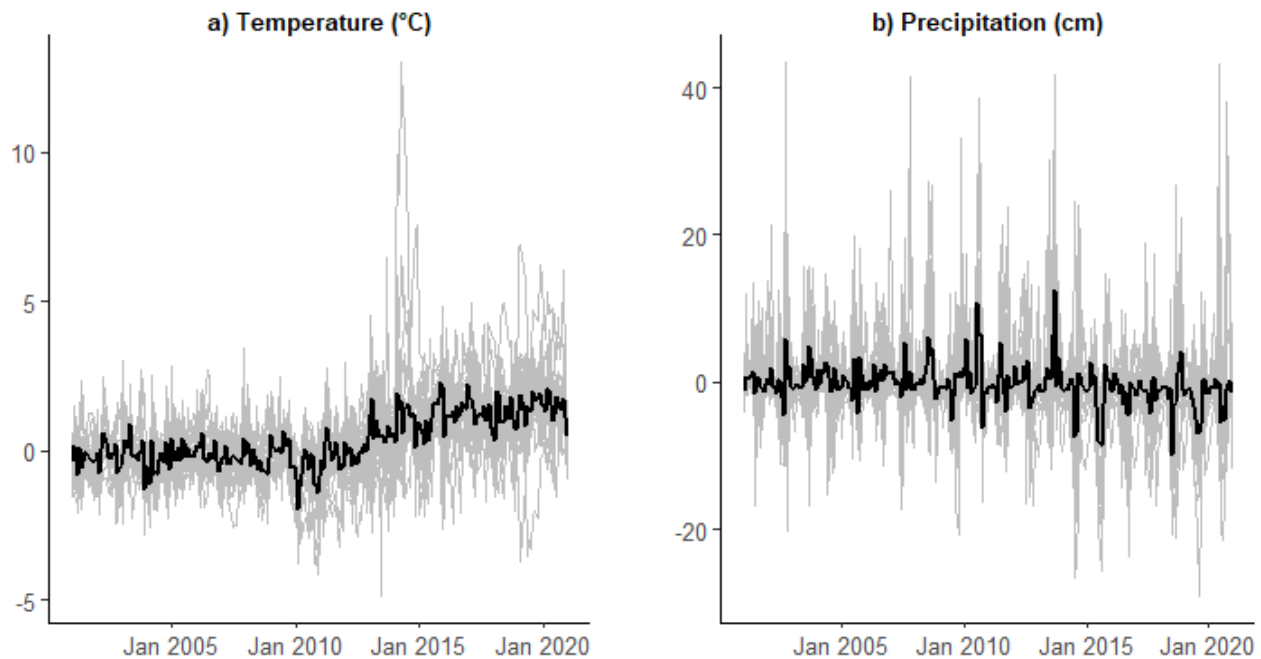
5.2 Weather data

Monthly weather data come from DAYMET (Thornton *et al.*, 2020), a gridded dataset that provides estimates of maximum and minimum temperature as well as accumulated precipitation. The data is available at a spatial resolution of 1 km². Monthly average temperature results from averaging monthly maximum and minimum temperatures. We first create weather variables for each grid point and then aggregate them to the state level by averaging grid cell values over agricultural land according to an agricultural land use map generated by the Mexican Ministry of Agriculture (SADER-SIAP, 2021c).¹¹ Figure 3 presents the weather anomalies observed in the sample calculated as deviations from the 40-year climate normal¹². Black lines identify the national average deviation whereas gray lines identify the average deviation in each of the 32 Mexican states. Climate normals at the state level were calculated as the average of monthly weather between 1980 and 2019 (40 years). Most of the temperature deviations lie within a 2.5°C band (panel a). Larger deviations are observed in the sample, particularly in the last decade of the sample period. Precipitation deviations (panel b) vary substantially across states, but episodes of precipitation deficits have also become more frequent in the last decade.

¹¹ The monthly temperature and precipitation series can be seen in Figure A3.

¹² In our setting, monthly 40-year climate normals for temperature and precipitation for each state were generated by averaging monthly temperature and precipitation from 1980 to 2019.

Figure 3. Temperature and precipitation deviations from the climate normal, 2001-2020



Note: The black lines identify the regional average deviation. Gray lines identify the average deviation in each of the 32 Mexican states. Source: Own elaboration based on Thornton *et al.* (2020) and SADER-SIAP (2021c).

5.2.1 Weather in relevant state suppliers

White corn and dry beans are produced and consumed extensively across Mexico. Local production is consumed locally or elsewhere by trading white corn and dry beans across states. If most of the local supply of these crops comes from local production, then the relevant weather shocks to explain price movements at the local level are those experienced by local producers. On the other hand, if most of the local supply of these crops is not produced locally, then, price movements at the local level are tied to weather shocks experienced by non-local producers.

When produced elsewhere, weather shocks affecting the most important state suppliers of a market/city are the most relevant. We focus on the two main state suppliers of each market/city. To identify them, we first elicit commercialization patterns among Mexican states using SNIIM monthly commercialization data for white corn and dry beans for the period 2004-2020. Data identify the origin (producer state) and destination (purchasing state) of each transaction. For each crop and month, we identify a commercialization pattern between a pair of states if white corn or dry beans were sold and bought among said states in at least 9 years out of the 21 years contained in the data (about 40 % of the time). This procedure allows us to identify the likely state suppliers of each crop for every state every month. Diagrams of the commercialization patterns identified for each crop for the whole 2004-2020 period can be seen in Figure A4 (in the Appendix).

The relevance index of the n th supplier of state m in calendar month j is calculated with the following formula:

$$s_{mnj}^k = \frac{\frac{1}{\sqrt{d_{mn}}} * shprod_{nj}^k}{\sum_{r=1}^N \frac{1}{\sqrt{d_{mr}}} * shprod_{rj}^k} \quad (3),$$

where N is the total number of suppliers of state m , d_{mn} is the distance (in kilometers) between state m and its n th supplier and $shprod_{nj}^k$ is the share of the n th state supplier in the historic production (2004-2020) of crop k (white corn, dry beans) in calendar month j at the national level.^{13,14} The production component increases the weight of producing states that have specialized at producing crop k in calendar month j over time. The inverse of the square root of the distance increases the weight of producing states located close to state m as it is more likely that markets/cities in state m purchase white corn or dry beans from states nearby.¹⁵ The two main state suppliers of a market/city located in state m are those with the two highest index values. Implicitly, we assume that the relative importance of the two main state suppliers is the same. This is an assumption we must make because our commercialization data does not include the volume of white corn and dry beans sold among states. If we had this information, we could in fact rank the N suppliers of each city/market based on supplied volume. With the relevance index we combine production data and commercialization networks to approximate the relative importance of each supplier state. This approach has been previously applied by Arellano-González *et al.* (2023).

The relevance index given by equation (3) includes the share of locally produced white corn and dry beans in state m . Thus, a given state could end up being a supplier of itself if its relevance index is large enough. Because we take local production into account, the relevance index also reflects internal sources of weather variation. So, whenever local production is large, weather variation in our weather shocks variables will come from internal sources: weather shocks experienced locally. If local production is small, then, weather variation will come from external sources: weather shocks experienced in other states. So, internal or external sources of weather variations will be used whenever one is more relevant than the other.

¹³ Monthly production data for white corn is not available. Because of this, the corn shares used in equation (3) were calculated using monthly production data for aggregated corn which includes white and yellow corn.

¹⁴ The production data used to calculate the relevance index includes auto-consumption which is the part of production devoted to family consumption. Ideally, auto-consumption would be excluded from the analysis because it is not sold in the market and thus, it is not expected to impact the market price. If this was possible, the share of production included in the calculation of the relevance index would reflect the participation of producer states in terms of marketed production. Unfortunately, the production data that we use (SADER-SIAP, 2021b) does not distinguish auto-consumption, so, we are unable to exclude it from the analysis. We note, however, that states who devote a large fraction of their production to auto-consumption are less likely to appear in the commercialization data that we use to identify state suppliers (SE-SNIIM, 2021). Thus, by definition, the relevance index is only calculated for the states that actively participate in the commercialization of white corn and dry beans. This minimizes the risk of incorrectly classifying a state with a high share of auto-consumption as the main supplier of a city/market.

¹⁵ The inverse of the square root of the distance has been used as weighting factor in other empirical work to generate weather variables for a location of interest using nearby locations (Jessoe *et al.*, 2018).

Figure 4 exemplifies this procedure for the case of corn sold in Mexico City during January. Panel a) shows the share of every Mexican state in the total historic production of corn during the calendar month of January (2004-2020). The state of Jalisco accounts for 29.7% of the total historic production of corn in that calendar month. Panel b) shows that between 2004 and 2020, Mexico City bought white corn from 5 producing states in January. Most of these states are in the vicinity of Mexico City except Sinaloa, which is located 1,200 km away. Panel c) shows the final relevance index assigned to each producing state after combining panels a) and b) according to equation (3). The State of Mexico and Puebla have the two highest indexes and are thus identified as the two main state suppliers to Mexico City market in January. Weather shocks affecting corn production in these two states could have an important influence in Mexico City's white corn prices in January. The relevance indexes shown on panel c) vary over time as the production cycle of white corn evolves over the course of the year, particularly when switching from the Spring-Summer to the Fall-Winter agricultural season. This dynamic evolution of the index reflects the changing structure of supply and of weather at the most relevant producing states for each market at different points of the production cycle.

We compare the weather in each of the two main state suppliers of each market/city against its climate normal to construct the weather shocks variables included in our price estimation, T^- , T^+ , Pr^- , Pr^+ . When weather deviations from the climate normal in at least one of the two main state suppliers of a market/city are larger than 0.5 s.d, these variables take the value of 1. Figure 5 shows the annual frequency of weather shocks. For both white corn and dry beans, the frequency of positive temperature shocks and negative precipitation shocks increased dramatically since 2012. At the same time, the frequency of negative temperature shocks and positive precipitation shocks decreased. This result is in line with the temperature and precipitation deviations trends shown in Figure 3 and suggests that towards the end of our sample period, white corn and dry beans were cultivated in hotter and drier conditions. Figure A5 and A6 (in the Appendix) show the frequency of weather shocks observed in the sample when the threshold is set to 1.0 and 2.0 standard deviations, respectively. Also, Table A1 (in the Appendix) offers detailed summary statistics of these variables.

Figure 4. *Relevance index example: white corn sold in Mexico City in January*
a) *Historic production shares by state, 2004-2020 (percentages)*



b) Mexico City's state providers and distances (thousands of kms)

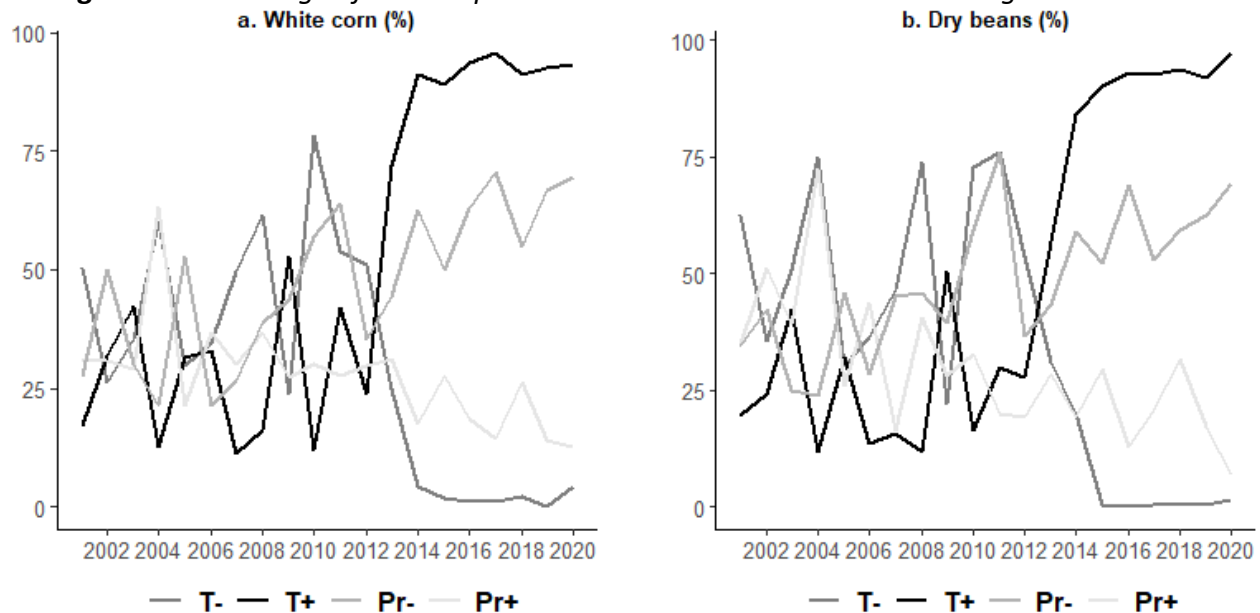


c) Relevance index of Mexico City's state providers (percentages)



Source: Own elaboration based on data from SE-SNIIM (2021) and SADER-SIAP (2021b).

Figure 5. Percentage of the sample observations with weather shocks larger than 0.5 s.d.



Source: Own elaboration based on Thornton *et al.* (2020), SADER-SIAP (2021b and 2021c), and SE-SNIIM (2021).

6. The effect of weather shocks on white corn and dry beans prices

Table 1 displays the parameter estimates for equation (1). Each column shows the results obtained when equation (1) is estimated using different thresholds to define a weather shock. For example, columns 1 and 4 show the results obtained when observed weather (temperature or precipitation) in one of the two main state suppliers of a city/market in a given month is 0.5 standard deviations (s.d.) below or above their 40-year climate normal. As we move to the right of the table, the severity of the weather shock scenario increases to 1 s.d. (columns 2 and 5) and 2 s.d. (columns 3 and 6). There are four general results.

First, temperatures below normal increase the price of white corn. In columns (1) and (2), most of the estimated coefficients for the T^- variables are positive and statistically significant. In the 0.5 s.d. scenario, the estimated effects range from 1.2% to 1.6%, depending on the timing of the shock. In the 1.0 s.d. scenario, the magnitude of the effect increases to a range of 1.6% to 2.2%. Estimates in the 2.0 s.d. scenario are less precisely estimated due to the lower frequency with which this scenario is observed in the sample (see Figures A5, A6, and Table A1). These findings are consistent with episodes of upward pressures in the price of this crop due to the damaging effects of extremely low temperatures in white corn production (USDA, 2011a and 2011b).

Second, temperatures above normal increase the price of white corn and dry beans. In column 1, all of the estimated coefficients for the T^+ variables are statistically significant. Positive temperature shocks of at least 0.5 s.d. are associated with white corn price increases between 1.8% and 2.6%, depending on the timing of the shock. For dry beans, all of the estimated coefficients are positive but only the contemporaneous and first lag estimates are statistically significant. The estimated effect is 1.6% and 1.0%, respectively. In the case of white corn, as we move to the right of the table, toward more severe positive temperature shocks, the estimated coefficients for the T^+ variables remain positive and become larger, although the precision of the estimates decreases. In the case of dry beans, the size of the estimates decreases. Again, the low frequency of the 1.5 s.d. and 2.0 s.d. scenarios might be the cause of noisier estimates.

Third, dry conditions in one of the two main state suppliers of a city/market increase the price of white corn and dry beans. Most of the estimated parameters for the P^- variables are statistically significant in the 0.5 s.d. scenario (columns 1 and 4). For both crops, the estimated effect is between 1.0% and 2.0% depending on the timing of the shock. In general, as the severity of the negative precipitation shock increases and we move from the 0.5 s.d. scenario to the 1.0 s.d. and 2.0 s.d. scenarios the estimated effects also increase, although in the case of white corn estimates are less precisely estimated. For example, the current price of white corn increases 1.4% if the negative precipitation shock is in the 0.5 s.d. scenario (column 1, lag 0). This effect increases to 5.4% in the 1 s.d. scenario (column 2, lag 0). For dry beans, the estimated effect in the third lag in the 0.5 s.d. scenario is 1.5% and it increases to 2.0% and 8.1% in the 1.0 s.d. and 2.0 s.d. scenarios (columns 5 and 6, lag 3), respectively. The magnitude of these estimates reveals the large sensitivity of white corn and dry beans prices to episodes of scarce precipitation.

Fourth, the price of white corn decreases when precipitation is above normal. All of the estimated coefficients in column (1) for the P^+ variables are negative and half of them are statistically significant. White corn prices decrease between 1.4% and 1.8%, depending on the

timing of the shock. Again, results in column (2) and (3) are noisier due to the lower frequency with which the 1.0 s.d. and 2.0 s.d. scenarios are observed in the sample (see Figures A5 and A6 and Table A1).

Table A2 (in the Appendix) displays the results obtained when we modify the calculation of the production shares used in the weighting procedure to generate our relevance index. Specifically, instead of calculating the shares using monthly production from 2004 to 2020, we use monthly production information for 2004 to 2007, the first three years for which monthly production information by state is available. We keep shares constant at the 2004-2007 level to avoid the potential endogeneity that arises by the influence of weather and price movements on the production shares. Our main findings are robust to this change in the weighting procedure albeit slight differences in the statistical significance for some of the parameter estimates. Table A3 (in the Appendix) shows that results are robust to inclusion of region-by-month fixed effects which conditions the identification of the parameters to rely on weather variation over time and across cities within the same region and month, which might better capture seasonality at the regional level.

Table 1. Panel estimates of the effect of weather shocks on the price of white corn and dry beans

	White corn			Dry beans		
	(1) 0.5 s.d.	(2) 1.0 s.d.	(3) 2.0 s.d.	(4) 0.5 s.d.	(5) 1.0 s.d.	(6) 2.0 s.d.
T_{t-0}	0.0055 (0.0077)	0.0046 (0.0104)	0.0232 (0.0411)	0.0067 (0.0059)	-0.0164 (0.0102)	-0.0115 (0.0159)
T_{t-1}	0.0135* (0.0067)	0.0192* (0.0095)	0.0204 (0.0356)	0.0063 (0.0049)	-0.0075 (0.0083)	-0.0152 (0.0171)
T_{t-2}	0.0144** (0.0067)	0.0216* (0.0123)	0.0186 (0.0291)	0.0083 (0.0060)	-0.0099 (0.0086)	-0.0174 (0.0181)
T_{t-3}	0.0153** (0.0067)	0.0173* (0.0100)	0.0185 (0.0254)	0.0074 (0.0063)	-0.0095 (0.0097)	-0.0129 (0.0220)
T_{t-4}	0.0121* (0.0064)	0.0164* (0.0090)	0.0171 (0.0291)			
T_{t-5}	0.0155* (0.0076)	0.0196* (0.0101)	0.0143 (0.0328)			
T^+_{t-0}	0.0176* (0.0098)	0.0245 (0.0173)	0.0265 (0.0193)	0.0157** (0.0065)	0.0082 (0.0057)	0.0053 (0.0103)
T^+_{t-1}	0.0224** (0.0087)	0.0222 (0.0154)	0.0398 (0.0302)	0.0103* (0.0058)	0.0052 (0.0057)	0.0041 (0.0103)
T^+_{t-2}	0.0259** (0.0101)	0.0261* (0.0129)	0.0495 (0.0310)	0.0087 (0.0055)	0.0024 (0.0056)	0.0006 (0.0113)
T^+_{t-3}	0.0218* (0.0112)	0.0216 (0.0143)	0.0423 (0.0299)	0.0070 (0.0060)	0.0008 (0.0064)	-0.0037 (0.0125)
T^+_{t-4}	0.0220* (0.0107)	0.0226 (0.0165)	0.0550 (0.0356)			
T^+_{t-5}	0.0223* (0.0125)	0.0316 (0.0195)	0.0512 (0.0393)			
P_{t-0}	0.0137** (0.0061)	0.0539* (0.0267)	0.0495 (0.0566)	0.0074 (0.0063)	0.0161** (0.0078)	0.0743* (0.0395)
P_{t-1}	0.0148** (0.0064)	0.0356 (0.0209)	0.0414 (0.0458)	0.0111* (0.0062)	0.0171*** (0.0063)	0.0704* (0.0419)
P_{t-2}	0.0171** (0.0073)	0.0308 (0.0191)	0.0383 (0.0514)	0.0117* (0.0062)	0.0161** (0.0065)	0.0663 (0.0395)
P_{t-3}	0.0093 (0.0060)	0.0288 (0.0173)	-0.0227 (0.0268)	0.0148** (0.0067)	0.0200** (0.0081)	0.0806** (0.0357)
P_{t-4}	0.0091 (0.0058)	0.0291* (0.0147)	0.0061 (0.0256)			

P_{t-5}	0.0117* (0.0061)	0.0335* (0.0190)	-0.0567 (0.0386)			
P_{t-0}^+	-0.0177** (0.0082)	-0.0037 (0.0067)	0.0041 (0.0099)	-0.0013 (0.0053)	0.0037 (0.0079)	0.0038 (0.0114)
P_{t-1}^+	-0.0175* (0.0098)	-0.0018 (0.0078)	0.0025 (0.0082)	-0.0040 (0.0054)	0.0002 (0.0080)	-0.0027 (0.0110)
P_{t-2}^+	-0.0163 (0.0105)	-0.0026 (0.0087)	0.0018 (0.0093)	0.0002 (0.0053)	0.0035 (0.0080)	0.0050 (0.0106)
P_{t-3}^+	-0.0144 (0.0086)	-0.0033 (0.0094)	0.0048 (0.0091)	0.0021 (0.0059)	0.0036 (0.0093)	0.0119 (0.0112)
P_{t-4}^+	-0.0118 (0.0076)	-0.0064 (0.0073)	0.0122 (0.0115)			
P_{t-5}^+	-0.0139** (0.0067)	-0.0099 (0.0065)	0.0138 (0.0117)			
R^2	0.9036	0.9052	0.9039	0.9268	0.9269	0.9265
N	6,009	6,009	6,009	10,800	10,800	10,800

Note: White corn (dry beans) regressions are weighted by the share of each state (city) on the national CPI. Market/city and year-month fixed effects are included in all the regressions. Standard errors (in parenthesis) clustered at the city and state-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Own elaboration based on data from INEGI (2021), SE-SNIIM (2021), SADER-SIAP (2021b and 2021c), and Thornton *et al.* (2020).

Table 2 shows the accumulated effect of temperature and precipitation shocks over the growing period which is obtained by adding up the estimated parameters of the T_- , T_+ , P_- and P_+ variables in Table 1. This estimate summarizes the total effect on prices if below or above normal weather conditions persist in the producing areas over the whole growing period. Results suggest that white corn prices would increase between 7.6% and 9.9%, depending on the scenario, if sustained below-normal temperatures are present over the growing period. Results also suggest that above-normal temperatures could increase the price of white corn and dry beans by 13.2% and 4.2% in the 0.5 s.d. scenario. While temperature anomalies do not tend to persist over time, particularly over several months, dry conditions do. Droughts could in fact last for several months or years. Prolonged episodes with above-the-normal precipitation are feasible too. The accumulated effect of negative precipitation shocks (P_-) indicates that severe drier-than-normal conditions over the growing period could increase the price of white corn and dry beans by as much as 21.2% and 29.2%, respectively. The large magnitude of the estimated effect is consistent with the fact that more than half of the production of these crops is obtained under rainfed conditions. For white corn, the accumulated effect of positive precipitation shocks (P_+) under the 0.5 s.d. scenario (column 1) indicates that above-normal precipitation during the growing period could decrease white corn prices by 9.2%.

The price increases triggered by positive temperature and negative precipitation shocks could be associated to productivity damages of heat and water stress at different stages of crop development largely documented in related literature (Fageria *et al.*, 2006; Barnabás *et al.*, 2008; Ortiz-Bobea and Just 2013; Carter *et al.*, 2016; Jin *et al.*, 2016; Ortiz-Bobea *et al.*, 2019) or by markets updating their price expectations because of the expected supply shortfalls caused by the weather shocks (Letta *et al.*, 2022).

Table 2. *Accumulated effect of weather shocks over the growing period*

	White corn (6 months)			Dry beans (4 months)		
	(1) 0.5 s.d.	(2) 1.0 s.d.	(3) 2.0 s.d.	(4) 0.5 s.d.	(5) 1.0 s.d.	(6) 2.0 s.d.
Accumulated T ⁻	0.0764** (0.0376)	0.0986* (0.0564)	0.1120 (0.1820)	0.0287 (0.0220)	-0.0433 (0.0353)	-0.0570 (0.0694)
Accumulated T ⁺	0.1321** (0.0604)	0.1486 (0.0917)	0.2644 (0.1819)	0.0417* (0.0226)	0.0166 (0.0220)	0.0063 (0.0429)
Accumulated P ⁻	0.0756** (0.0343)	0.2118* (0.1145)	0.0559 (0.1936)	0.0451* (0.0249)	0.0693** (0.0279)	0.2916* (0.1536)
Accumulated P ⁺	-0.0916* (0.0488)	-0.0277 (0.0427)	0.0392 (0.0498)	-0.0031 (0.0211)	0.0110 (0.0323)	0.0180 (0.0422)
N	6,009	6,009	6,009	10,800	10,800	10,800

Note: Standard errors (in parenthesis) calculated using the delta method. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Own elaboration based on data from INEGI (2021), SE-SNIIM (2021), SADER-SIAP (2021b and 2021c), and Thornton *et al.* (2020).

7. Conclusions

In this paper, we estimate the effect of weather shocks on the price of white corn and dry beans, the most important staple crops in Mexico. We rely on panel data techniques that reduce the threat of omitted variable bias by controlling for unobserved determinants of prices with the use of fixed effects. For our price estimation, we utilize 20 years of monthly panel data at the market/city level and focus on the effects of weather shocks experienced in the producing areas that supply each market/city.

Our results indicate that positive temperature shocks and negative precipitation shocks increase the price of white corn and dry beans. Depending on the timing of the shock, monthly prices increase between 1% and 2% if monthly temperature (precipitation) is at least one of the two main state suppliers of a market/city is at least 0.5 standard deviations above (below) its normal. We also find similar effects of negative temperature shocks on white corn prices. While temperature anomalies tend to be short-lasting, precipitation anomalies tend to persist over time. Dry spells could in fact last for several weeks or months affecting the entirety of the growing period of the crop. Continued drier-than-normal conditions over the growing period of white corn and dry beans could increase their prices by as much as 21.2% and 29.2%, respectively, depending on the severity of precipitation scarcity. The contemporaneous and lagged effects that weather shocks have on prices indicate that markets anticipate present and future supply imbalances and adjust prices to equilibrate supply and demand.

Our results may inform the making of policies seeking to mitigate the adverse effects of extreme weather events on food inflation. Such policies could include the timely programming of imports to substitute lost production or lower yields right after an extreme weather event, especially if it hits an important producing area. Typically, when weather shocks impact agricultural production, imports of the affected products tend to increase facilitated by the elimination of tariffs and quotas. Due the importance of these two crops in Mexican agriculture,

an agile coordination between local producers and the public sector right after a weather shock is necessary in order to provide markets with accurate information about expected losses in production, the specific policies designed to alleviate supply imbalances, including the volume of imports necessary to replace lost production and the amount of time it will take to get those imports in the domestic market. The timely provision of such information could mitigate the uncertainty formed around their prices and drive down upward pressures.

White corn and dry beans are storable crops. A caveat of our analysis is our inability to directly control for their existing inventories which could cushion the effect of extreme weather events on prices. A large inventory would attenuate expectations on their current and future availability in the market, thus attenuating the effect of extreme weather events on their prices, as opposed to small inventories which would leave their prices unprotected. Unfortunately, monthly data on inventories of white corn and dry beans disaggregated at the state level are not available. We argue, however, that our year-month fixed effects flexibly control for them, up to some extent. Storage capacity in Mexico is largely heterogenous and is sufficient to meet storage demand mostly in states located in the north and center north regions, but insufficient in several states located in the center and south regions (García Salazar *et al.*, 2020). Thus, another avenue for policy making is to build up storage capacity in states that need it. This could decrease the sensitivity of local prices to the adverse effects of extreme weather events.

The findings of this paper demonstrate that weather shocks are among the factors creating upward pressures in the price of these two crops. Given the importance they have on the CPI, weather shocks could also have important inflation consequences, especially for low-income households who devoted a larger fraction of their income to the purchase of white-corn- and dry-beans-related products. In our data, the frequency of heat waves and dry spells has increased over time which could be associated with the long-term trends in temperature and precipitation caused by climate change. Thus, in the future, upward pressures on prices associated with weather shocks could become larger and more frequent (Perkins-Kirkpatrick and Lewis, 2020; Diffenbaugh, 2020). The diffusion of technologies seeking to improve the resilience of these crops to extreme weather events, such as heat and drought tolerant varieties, could reduce the sensibility of yields and prices to weather shocks.

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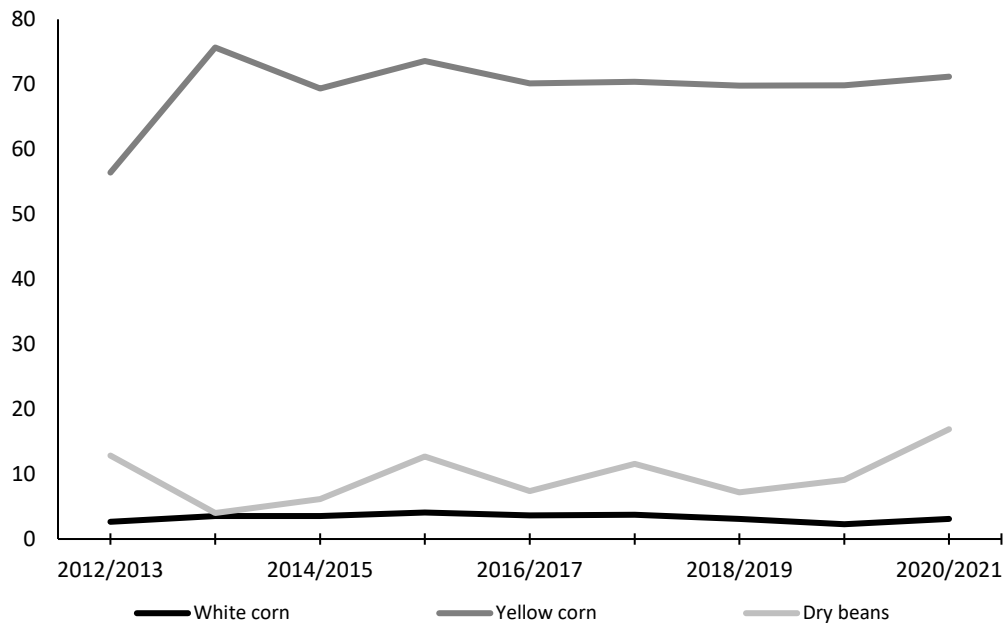
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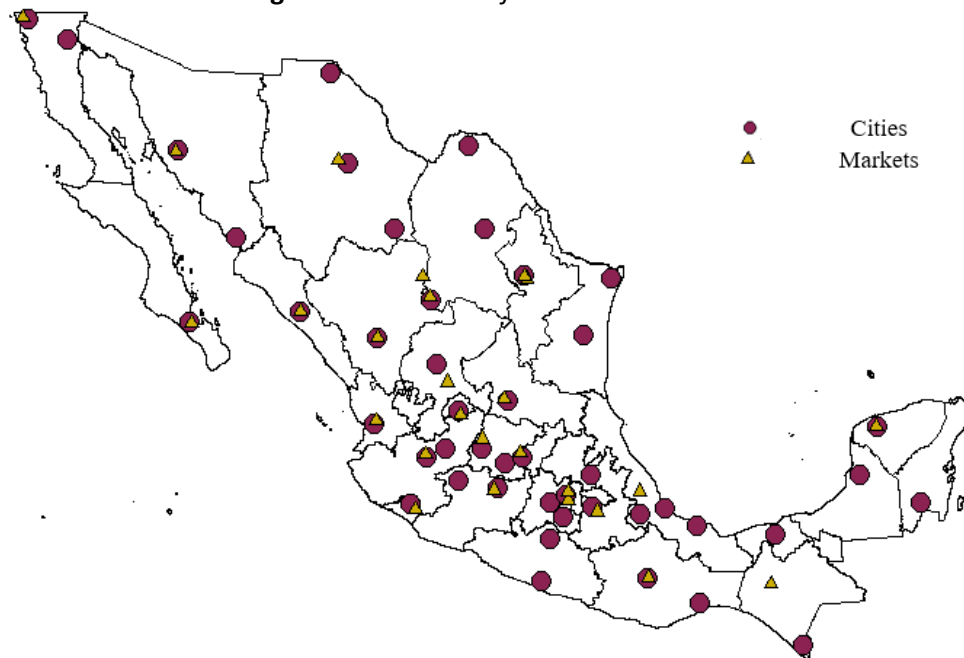
Appendix

Figure A1. *Share of imports in domestic supply (%)*



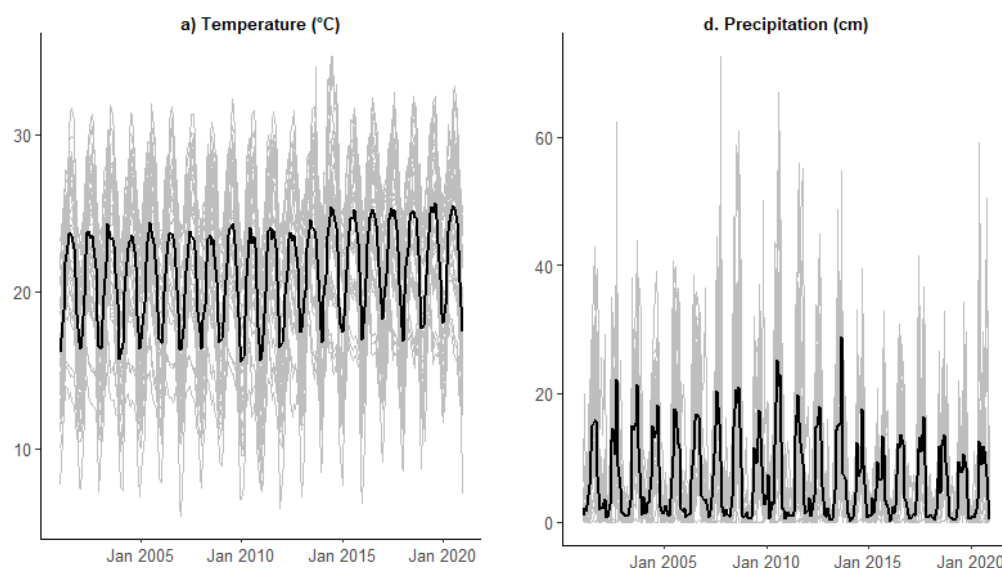
Note: The figure plots the share that imports represent in domestic total supply which is defined as the sum of inventories, production and imports. Statistics are presented for the agricultural year, which runs from October to September of the following year. The average for the period 2012-2021 is 3% for white corn, 10% for dry beans and 70% for yellow corn. Source: Own elaboration using data from SADER-SIAP (2019, 2020, 2021, 2022a, 2022b).

Figure A2. *Location of markets and cities*



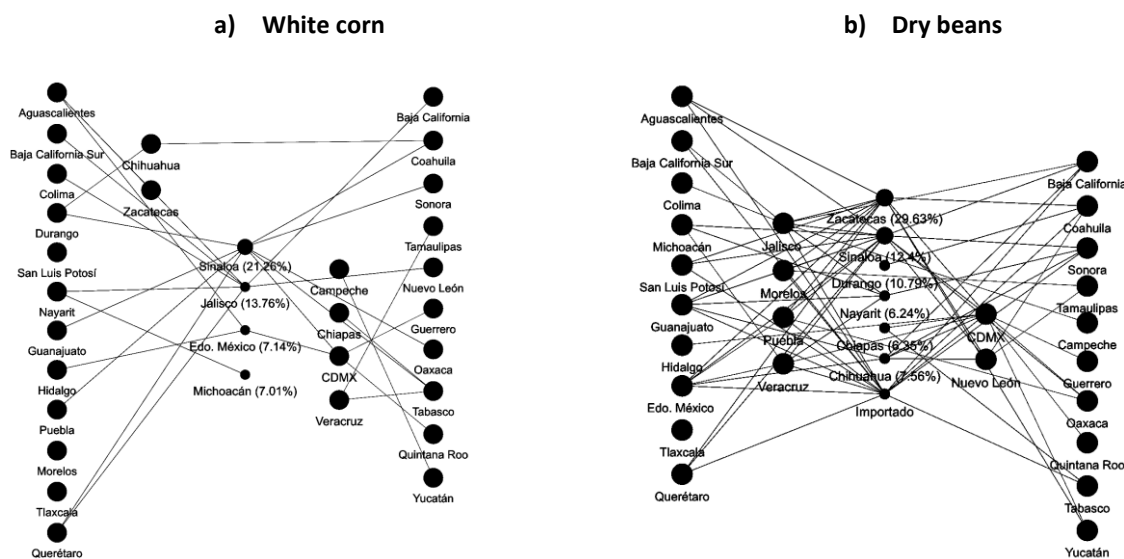
Note: The map shows the location of the 26 markets (white corn) and 45 cities (dry beans) contained in the sample. Source: Own elaboration based on data from INEGI and SE-SNIIM (2021).

Figure A3. Monthly temperature and precipitation series by state, 2001-2020



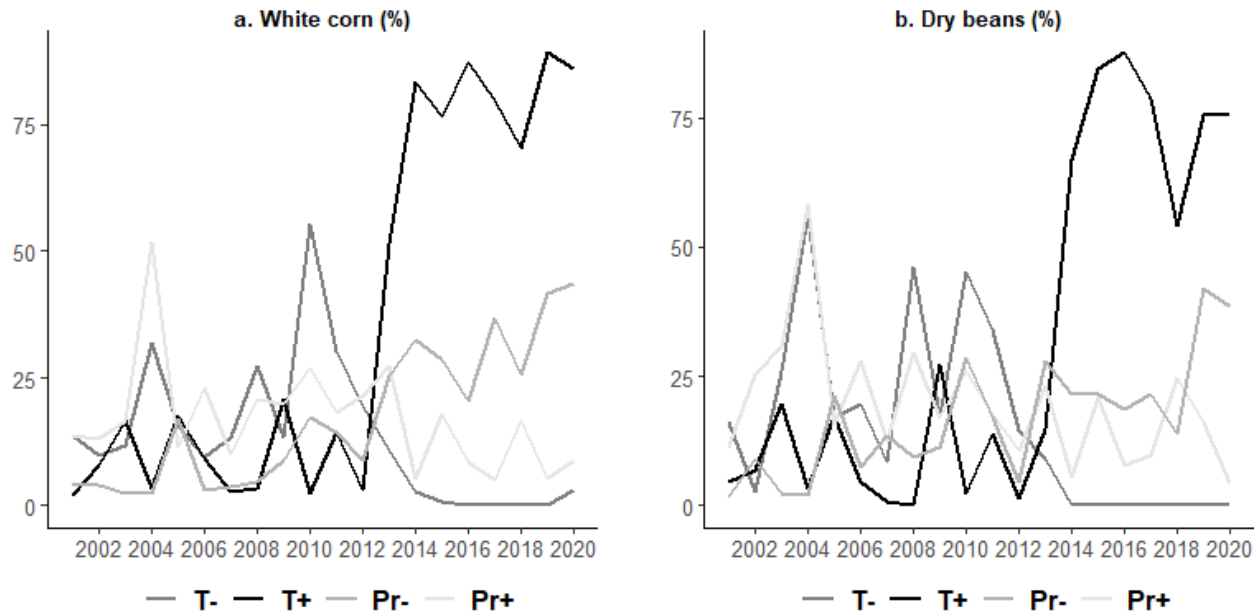
Note: Black lines identify the national average. Gray lines identify the average for each of the 31 Mexican states.
Source: Own elaboration based on Thornton *et al.* (2020) and SADER-SIAP (2021c).

Figure A4. Commercialization patterns among Mexican states



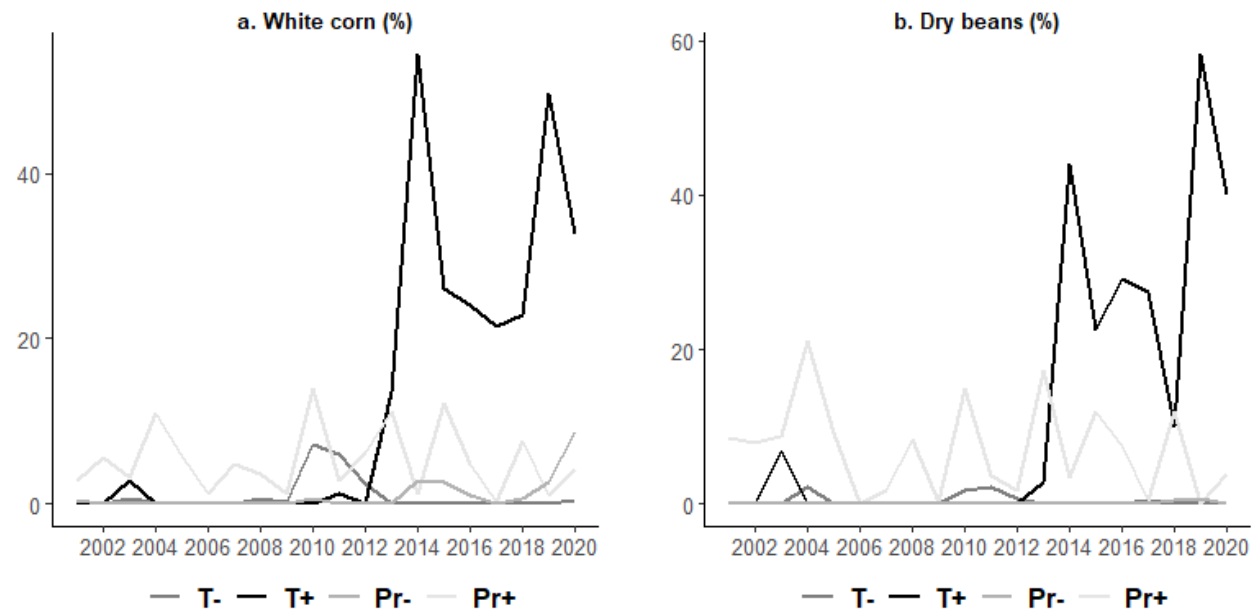
Note: The figure shows the commercialization patterns of white corn and dry beans among Mexican states. Dots at the center identify producing states that concentrate at least 60% of historic production during the period 2004-2020. In the case of white corn these are Sinaloa, Jalisco, State of Mexico and Michoacán. In the case of dry beans these are Zacatecas, Sinaloa, Durango, Nayarit, Chiapas and Chihuahua. The size of each dot is proportional to the share of each producing state in total historic production (in parenthesis). Intermediate dots represent intermediary states. For white corn these are Chihuahua, Zacatecas, Campeche, Chiapas, Mexico City and Veracruz. For dry beans these are Jalisco, Morelos, Puebla, Veracruz, Mexico City and Nuevo León. Lines connecting states indicate that a commercialization link exists between them. Source: Own elaboration based on data from SADER-SIAP (2021b) and SE-SNIIM (2021).

Figure A5. Sample observations with weather shocks larger than 1.0 s.d.



Source: Own elaboration based on Thornton *et al.* (2020), SIAP (2021b and 2021c), and SE-SNIIM (2021).

Figure A6. Sample observations with weather shocks larger than 2.0 s.d.



Source: Own elaboration based on Thornton *et al.* (2020), SIAP (2021b and 2021c), and SE-SNIIM (2021).

Table A1. Summary statistics of the variables used in the price regressions (mean values)

	(1) White corn	(2) Dry beans
Price (\$/kg)	6.301	19.72
T^-		
0.5 s.d.	0.2974	0.3442
1.0 s.d.	0.1356	0.1564
2.0 s.d.	0.0092	0.0036
T^+		
0.5 s.d.	0.5229	0.4971
1.0 s.d.	0.3646	0.3199
2.0 s.d.	0.1246	0.1205
Pr^-		
0.5 s.d.	0.4753	0.4844
1.0 s.d.	0.1731	0.1667
2.0 s.d.	0.0093	0.0007
Pr^+		
0.5 s.d.	0.2782	0.2949
1.0 s.d.	0.1717	0.1973
2.0 s.d.	0.0528	0.0710
Observations	6,009	10,800

Source: Own elaboration based on data from INEGI (2021), SE-SNIIM (2021), SIAP (2021b and 2021c) and Thornton *et al.* (2020).

Table A2. Panel estimates of the effect of weather shocks on the price of white corn and dry beans with an alternative procedure to generate the relevance index

	White corn			Dry beans		
	(1)	(2)	(3)	(4)	(5)	(6)
	0.5 s.d.	1.0 s.d.	2.0 s.d.	0.5 s.d.	1.0 s.d.	2.0 s.d.
T_{t-0}	0.0037 (0.0067)	0.0010 (0.0101)	0.0059 (0.0305)	-0.0031 (0.0052)	-0.0211* (0.0105)	-0.0039 (0.0149)
T_{t-1}	0.0101 (0.0061)	0.0172* (0.0097)	0.0055 (0.0250)	-0.0032 (0.0046)	-0.0168** (0.0082)	-0.0055 (0.0147)
T_{t-2}	0.0103* (0.0054)	0.0145 (0.0131)	0.0083 (0.0231)	-0.0014 (0.0053)	-0.0203** (0.0096)	-0.0108 (0.0150)
T_{t-3}	0.0150** (0.0061)	0.0121 (0.0112)	0.0060 (0.0185)	-0.0018 (0.0059)	-0.0201* (0.0100)	-0.0074 (0.0191)
T_{t-4}	0.0097 (0.0058)	0.0165* (0.0096)	0.0065 (0.0231)			
T_{t-5}	0.0146* (0.0073)	0.0209* (0.0111)	-0.0014 (0.0240)			
T^+_{t-0}	0.0174 (0.0122)	0.0207 (0.0185)	0.0322 (0.0193)	0.0149* (0.0084)	0.0140** (0.0069)	0.0182** (0.0081)
T^+_{t-1}	0.0199* (0.0102)	0.0164 (0.0147)	0.0501 (0.0328)	0.0109 (0.0076)	0.0118* (0.0066)	0.0138 (0.0083)
T^+_{t-2}	0.0206* (0.0113)	0.0209* (0.0122)	0.0578* (0.0338)	0.0098 (0.0075)	0.0076 (0.0070)	0.0120 (0.0088)
T^+_{t-3}	0.0212 (0.0125)	0.0219 (0.0147)	0.0552 (0.0338)	0.0058 (0.0078)	0.0052 (0.0083)	0.0097 (0.0099)
T^+_{t-4}	0.0175	0.0181	0.0647			

	(0.0123)	(0.0169)	(0.0404)			
T ⁺ _{t-5}	0.0173	0.0222	0.0579			
	(0.0150)	(0.0211)	(0.0431)			
P ⁺ _{t-0}	0.0161**	0.0634**	0.0546	0.0142**	0.0191**	0.0690*
	(0.0060)	(0.0291)	(0.0552)	(0.0059)	(0.0087)	(0.0386)
P ⁺ _{t-1}	0.0145**	0.0399*	0.0524	0.0159***	0.0201***	0.0674*
	(0.0066)	(0.0232)	(0.0467)	(0.0059)	(0.0073)	(0.0397)
P ⁺ _{t-2}	0.0181**	0.0329	0.0408	0.0158**	0.0204**	0.0604
	(0.0073)	(0.0209)	(0.0504)	(0.0062)	(0.0078)	(0.0386)
P ⁺ _{t-3}	0.0147**	0.0291	-0.0209	0.0189***	0.0258***	0.0673*
	(0.0069)	(0.0174)	(0.0247)	(0.0064)	(0.0090)	(0.0374)
P ⁺ _{t-4}	0.0140**	0.0338**	0.0072			
	(0.0066)	(0.0154)	(0.0254)			
P ⁺ _{t-5}	0.0177**	0.0412*	-0.0579			
	(0.0077)	(0.0204)	(0.0355)			
P ⁺ _{t-0}	-0.0191**	-0.0058	0.0007	0.0003	0.0041	0.0059
	(0.0082)	(0.0070)	(0.0097)	(0.0052)	(0.0069)	(0.0127)
P ⁺ _{t-1}	-0.0162	-0.0016	-0.0002	-0.0010	0.0027	0.0039
	(0.0099)	(0.0073)	(0.0082)	(0.0053)	(0.0070)	(0.0122)
P ⁺ _{t-2}	-0.0134	-0.0033	0.0012	0.0009	0.0055	0.0067
	(0.0108)	(0.0084)	(0.0107)	(0.0055)	(0.0070)	(0.0119)
P ⁺ _{t-3}	-0.0083	-0.0016	0.0058	0.0023	0.0053	0.0108
	(0.0099)	(0.0093)	(0.0102)	(0.0057)	(0.0080)	(0.0115)
P ⁺ _{t-4}	-0.0089	-0.0069	0.0106			
	(0.0090)	(0.0075)	(0.0122)			
P ⁺ _{t-5}	-0.0151*	-0.0115	0.0146			
	(0.0077)	(0.0083)	(0.0136)			
R ²	0.9037	0.9054	0.9045	0.9270	0.9274	0.9265
N	5,873	5,873	5,873	10,800	10,800	10,800

Note: White corn (dry beans) regressions are weighted by the share of each state (city) on the national CPI. Market/city and year-by-month fixed effects are included in all the regressions. Standard errors (in parenthesis) clustered at the city and state-year level. * p<0.10, ** p<0.05, *** p<0.01. Source: Own elaboration based on data from INEGI (2021), SE-SNIIM (2021), SIAP (2021b and 2021c), and Thornton *et al.* (2020).

Table A3. Panel estimates of the effect of weather shocks on the price of white corn and dry beans with region-by-month fixed effects included

	White corn			Dry beans		
	(1)	(2)	(3)	(4)	(5)	(6)
	0.5 s.d.	1.0 s.d.	2.0 s.d.	0.5 s.d.	1.0 s.d.	2.0 s.d.
T _{t-0}	0.0059	0.0043	0.0267	0.0070	-0.0163	-0.0100
	(0.0075)	(0.0104)	(0.0410)	(0.0060)	(0.0102)	(0.0164)
T _{t-1}	0.0117	0.0188*	0.0212	0.0065	-0.0069	-0.0139
	(0.0071)	(0.0100)	(0.0363)	(0.0048)	(0.0082)	(0.0171)
T _{t-2}	0.0127*	0.0193	0.0200	0.0088	-0.0091	-0.0158
	(0.0072)	(0.0126)	(0.0294)	(0.0059)	(0.0085)	(0.0179)
T _{t-3}	0.0134*	0.0141	0.0170	0.0076	-0.0090	-0.0129
	(0.0071)	(0.0099)	(0.0258)	(0.0063)	(0.0096)	(0.0217)
T _{t-4}	0.0106	0.0159*	0.0154			
	(0.0067)	(0.0093)	(0.0293)			
T _{t-5}	0.0134*	0.0185*	0.0165			
	(0.0075)	(0.0100)	(0.0335)			
T ⁺ _{t-0}	0.0178*	0.0256	0.0283	0.0165**	0.0081	0.0055
	(0.0099)	(0.0181)	(0.0198)	(0.0065)	(0.0060)	(0.0104)
T ⁺ _{t-1}	0.0221**	0.0223	0.0402	0.0112*	0.0057	0.0043
	(0.0091)	(0.0159)	(0.0309)	(0.0057)	(0.0058)	(0.0103)
T ⁺ _{t-2}	0.0244**	0.0253*	0.0475	0.0095*	0.0032	0.0004
	(0.0099)	(0.0134)	(0.0301)	(0.0053)	(0.0055)	(0.0113)
T ⁺ _{t-3}	0.0203*	0.0189	0.0406	0.0077	0.0015	-0.0039
	(0.0108)	(0.0138)	(0.0297)	(0.0059)	(0.0062)	(0.0126)
T ⁺ _{t-4}	0.0213*	0.0212	0.0535			
	(0.0107)	(0.0164)	(0.0351)			

T ⁺ _{t-5}	0.0206 (0.0121)	0.0299 (0.0183)	0.0513 (0.0395)			
P ⁺ _{t-0}	0.0160** (0.0066)	0.0576** (0.0252)	0.0525 (0.0543)	0.0075 (0.0066)	0.0176** (0.0084)	0.0802* (0.0399)
P ⁺ _{t-1}	0.0171** (0.0068)	0.0405* (0.0209)	0.0449 (0.0464)	0.0113* (0.0065)	0.0182** (0.0069)	0.0742* (0.0427)
P ⁺ _{t-2}	0.0176** (0.0083)	0.0338 (0.0199)	0.0382 (0.0505)	0.0117* (0.0064)	0.0166** (0.0070)	0.0648 (0.0399)
P ⁺ _{t-3}	0.0093 (0.0067)	0.0310 (0.0183)	-0.0237 (0.0269)	0.0149** (0.0068)	0.0203** (0.0084)	0.0773** (0.0359)
P ⁺ _{t-4}	0.0076 (0.0063)	0.0276* (0.0158)	0.0067 (0.0255)			
P ⁺ _{t-5}	0.0112* (0.0063)	0.0323 (0.0204)	-0.0595 (0.0387)			
P ⁺ _{t-0}	-0.0161* (0.0079)	-0.0033 (0.0072)	0.0054 (0.0097)	-0.0004 (0.0054)	0.0046 (0.0080)	0.0039 (0.0115)
P ⁺ _{t-1}	-0.0161 (0.0098)	-0.0003 (0.0081)	0.0036 (0.0085)	-0.0034 (0.0055)	0.0012 (0.0082)	-0.0025 (0.0112)
P ⁺ _{t-2}	-0.0159 (0.0101)	-0.0020 (0.0086)	0.0027 (0.0097)	0.0013 (0.0055)	0.0046 (0.0083)	0.0045 (0.0105)
P ⁺ _{t-3}	-0.0145* (0.0081)	-0.0024 (0.0094)	0.0037 (0.0091)	0.0026 (0.0061)	0.0039 (0.0096)	0.0115 (0.0111)
P ⁺ _{t-4}	-0.0123* (0.0071)	-0.0062 (0.0070)	0.0103 (0.0113)			
P ⁺ _{t-5}	-0.0144** (0.0065)	-0.0107 (0.0063)	0.0133 (0.0117)			
R ²	0.9039	0.9056	0.9042	0.9269	0.9270	0.9266
N	6,009	6,009	6,009	10,800	10,800	10,800

Note: White corn (dry beans) regressions are weighted by the share of each state (city) on the national CPI. Market/city, year-month and region-by-month fixed effects are included in all the regressions. Standard errors (in parenthesis) clustered at the city and state-year level. * p<0.10, ** p<0.05, *** p<0.01. Source: Own elaboration based on data from INEGI (2021), SE-SNIIM (2021), SIAP (2021b and 2021c), and Thornton *et al.* (2020).