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Weather shocks, prices and productivity: Evidence from staples in Mexico

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Abstract: In this paper, we investigate the effect of weather shocks on the price of two crops of great importance in Mexican agriculture: white corn and dry beans. We rely on panel data techniques applied to a 20-year long panel of prices at the market/city level. 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 positive effects on the price of these crops. The immediate effect is about 2.0%, while the lagged effect is between 1.0% and 2.5%, depending on the timing of the shock within the crop's growing period. We also show that one of the mechanisms explaining the effect of weather shocks on the price of these crops is their detrimental effect on productivity, especially for rainfed production.
Keywords: Food Inflation, Weather Shocks, Staple Prices, Local Markets
JEL Classification: E31, Q15, Q54

Resumen: En este artículo se investiga el efecto de choques climáticos en el precio de dos cultivos de gran importancia en la agricultura mexicana: el maíz blanco y el frijol. Se utilizan técnicas para datos en panel que se aplican a un panel de 20 años de precios a nivel de mercado/ciudad. Los resultados muestran que choques positivos y negativos de temperatura y precipitación de al menos 0.5 desviación estándar con respecto a la normal climatológica tienen efectos positivos inmediatos y rezagados en el precio de estos cultivos. El efecto inmediato es de alrededor de 2.0%, mientras que el efecto rezagado es de entre 1.0% y 2.5%, dependiendo del momento en el que sucede el choque dentro del periodo de crecimiento del cultivo. También se muestra que uno de los mecanismos que explica el efecto de los choques climáticos en el precio de estos cultivos es el efecto negativo que tienen en su productividad, particularmente en la producción de temporal.
Palabras Clave: Inflación en Alimentos, Choques Climáticos, Precio de Cultivos Básicos, Mercados Locales

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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; Mérrel and Gammans, 2021). The general finding is that heat and water stress are associated with diminished crop yields (Ortiz-Bobea et al., 2019). The productivity damages caused by weather shocks could have consequences beyond a reduced supply. If weather shocks hit an important producing area highly connected with the domestic markets through commercialization, crop prices could increase due to updated expectations about the current and future availability of the crop in the market. While this mechanism is apparently obvious, empirical evidence linking weather and prices directly is still rare (Letta et al., 2022).

In this paper, we investigate the effect of weather shocks on the price of two crops of great importance in Mexico in terms of production and consumption: white corn and dry beans.[1] Together, these two crops represent, on average, about two thirds of the total planted area with annual crops. Most of the supply of these crops is generated domestically, thus, weather shocks experienced internally could influence their productivity and their prices. We rely on monthly panel data of prices for each crop at the market/city level for the period 2001-2020. Data of white corn prices at the market level come from the National System of Market Information and Integration (SNIIM by its Spanish acronym) administered by the Ministry of Economics. Data of dry beans prices at the city level come from the National Institute of Statistics and Geography (INEGI by its Spanish acronym). 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.

[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 (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).

We combine our price data with a unique dataset that contains the commercialization patterns of these crops among producing and purchasing states. This information allows us to identify the supplier states of each city/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, or climate normal, calculated using monthly weather data for the period 1980-2019. We define a weather shock as weather deviations larger than 0.5, 1.0 or 2.0 standard deviations (s.d.).[2] For example, a supplier state experiences a negative precipitation shock of more than one standard deviation if precipitation in a given month is at least one standard deviation below the 1980-2019 average for that month. This approach has been previously used by other authors also analyzing the consequences of weather variability in welfare outcomes in rural Mexico (Skoufias and Vinha, 2012, 2013). By defining weather shocks in terms of standard deviations we consider the historical variability of climate in each of the producing areas contained in our sample. 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 cities/markets where these crops are sold. Our fixed effects model includes present and lagged realizations of weather shocks. Lagged weather shocks are included in the model to control for lagged effects of weather shocks happening at any point during the growing period of white corn and dry beans (6 and 4 months, respectively). This allows us to estimate different price sensitivities directly tied to the timing of the weather shock.

There are four main results. First, temperatures below normal increase the price of white corn, with the increase becoming larger with the severity of the negative temperature shock. 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 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%,

[2] For reference, a 1.0 s.d. of the monthly temperature and precipitation normal is, on average, roughly equal to 1ºC and 3.7cm, respectively.

respectively. More severe positive temperature shocks are associated with larger price increases in white corn, although estimates are less precisely estimated. 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 1.4-1.8%, depending on the timing of the shock.

Overall, our results indicate that current and past weather shocks in at least one of the two main state suppliers of a market/city impact the price of white corn and dry beans. 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. So, in recent years, white corn and dry beans have been cultivated in hotter and drier conditions. If such trend continues, our estimates anticipate further upward pressures on the price of these crops resulting from weather shocks.

In the article, we also suggest that one of the mechanisms driving the effect of weather shocks on prices is the detrimental effect they have on crop productivity. We arrive to such conclusion by estimating auxiliary fixed effect models that relate crop yields and weather at the municipal level. The parameter estimates of these models are then used to simulate the effect of weather shocks on yields. We find that the yield of white corn and dry beans decreases after positive (negative) temperature (precipitation) shocks when produced under rainfed conditions. We also find that the yield of irrigated white corn decreases after negative temperature shocks. Thus, weather shocks impact the productivity of white corn and dry beans. If the impact on yields is negative, the current and future supply shortfalls caused by weather shocks may ultimately lead to increased prices. 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 the growing period of the crop (Ortiz-Bobea and Just, 2013, Ortiz-

Bobea et al., 2019) or by the expectations formed by markets who anticipate the damages and adjust prices accordingly (Letta et al., 2022).

The contribution of this paper is threefold. First, 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., 2019; Ubilava, 2018; Ubilava and Holt, 2013; Ubilava, 2012; Bastiani et al., 2018). In contrast, this paper relies on time and spatial variation of weather and prices at more disaggregated levels. Spatially, our price series vary at the market/city level while our weather variables vary at the state level. Over time, our information varies monthly and spans two decades. In general, the effect of weather shocks is first experienced at local levels affecting local productions 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.

Second, the findings of this research complement the abundant empirical evidence regarding the effect of weather on staple crops around the world (Schlenker and Roberts, 2009, Burke and Emerick, 2016; Ortiz-Bobea et al., 2019; Welch et al., 2010; Tack et al., 2017). Our findings for white corn confirm what has been previously found in related literature, i.e. corn yields are highly sensitive to temperature shocks. We also study dry beans, a crop that so far has been ignored in the literature but that is extremely important in terms of consumption and production in Mexico and other Latin American countries. Most of the domestic supply of white corn and dry beans in Mexico is internally grown . As a result, weather shocks affecting domestic production might have important food security implications for the country. Importantly, this paper represents an addition to the scarce empirical evidence that exists for developing countries regarding the relationship between weather and agricultural productivity using panel data (Guiteras 2009; Welch et al., 2010; Taraz, 2017 and 2018; Chen et al., 2016; Birhanu Demeke et al., 2011).

Third, the findings of this paper suggest that weather is a driving factor of food price fluctuations. This result is of particular importance for countries where the share of food in their CPI baskets is high. In Mexico and other developing countries, this share is larger than 20% (Cashin, 2017). White corn and dry beans are of particular importance because these crops are essential components of the Mexican diet. The average Mexican household devotes 8.7% of its total food expenditures to buy corn- and dry-beans-related products. *Tortillas* are the main form of human consumption of white corn in Mexico and they alone represent, on average, 6.7% of the total food expenditures, which is almost twice the share they represented in the mid 1980´s (Garza-Montoya et al., 2017). 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. This research shows that weather shocks could create upward pressures in the price of these crops and have important inflation consequences given their importance in the CPI, particularly for low-income households who more likely devote a larger share of their expenditure to these staples.

The organization of this paper is as follows. In section 2, we provide a review of the existing literature analyzing the relationship between weather, prices and productivity. In section 3, we provide some context about the production of white corn and dry beans in Mexico. In section 4, we lay out our empirical specification. In section 5, we describe the price and weather data used and the methodology applied to identify the main supplier states of each market/city. In section 6, we present the estimated effect of weather shocks on prices. In section 7, we present our results about the effect of weather shock on the yields of these crops. We conclude in section 8 by providing some insights on the relevance of these results for policy making.

2. Literature review

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; Mérrel and Gammans, 2021; Ortiz-Bobea et al., 2019). Most of the existing evidence focuses on the case of grains (corn, wheat, rice) mainly due to their widespread cultivation around the world and their importance in human caloric intake. The general finding of this literature is that heat and water stress are associated with diminished crop yields. For example, Schlenker and Roberts (2009) find that corn yields in the U.S. decrease sharply once temperature surpasses 29ºC (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 with a maximum yield achieved at around 63.5 cm. It follows that precipitation levels below or above this optimum are associated with lower corn yields. 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. Rather than using precipitation to represent the yield-water relationship, the authors use soil moisture which better reflects the changing balance of water inflows (precipitation, irrigation) and outflows (runoff, percolation, evapotranspiration) and thus, captures the complex hydrological processes that determine the availability of water for crop absorption. Other studies have also confirmed the strong association between weather and corn yields in non-US contexts (Moore and Lobell, 2014; Taraz, 2018; Chen et al., 2016).

If sufficiently large, the productivity damages, 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), Bastianini 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. Similarly, droughts tend to have a large regional component. Thus, the aggregation of weather shocks to, say, the national level, could obscure the causal effect that they have on price formation because such effect is first felt in local production and prices. Then, it gets disseminated to the rest of the market through commercial exchanges.

To identify the causal effect of weather shocks on prices, this paper relies on panel data. The identifying variation in panel data comes from weather anomalies experienced at the local level. Panel data allows to better represent the causal 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). The panel approach has been rarely used to investigate the direct effect of weather on prices. Maystadt and Ecker (2014) estimate the effect of drought on livestock prices and the probability of civil conflict in Somalia using monthly panel data for administrative regions. The authors proxy drought with variables that identify region-specific temperature and precipitation anomalies. 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 relying on monthly panel data at the district level. The authors proxy for abnormal weather using a drought index that jointly considers precipitation, evaporation, and temperature. 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 propose a method to 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 urban centers 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 (wholesale and retail markets for white corn and dry beans, respectively) and their links to producing areas through commercialization which allows us to estimate the effect of weather shocks on the price of white corn and dry beans considering the whole domestic market.

3. The context of staple crops production in Mexico

White corn and dry beans are the two most important staple crops in Mexico. Their production is widely spread across the country. In 2020, they were produced in 94.0% and 71.8% of the municipalities, respectively (SIAP, 2021a).[3] Together, they represented 60.4% of the total area planted with annual crops and 34.6% of the total gross value (SIAP, 2021a). The average household devotes 8.7% of its total food budget to the purchase of white corn

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

and dry beans related products (Garza-Montoya et al., 2017) such as tortillas (a thin, circular flat bread made out 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.[4] The rest is produced under irrigated conditions mainly during the Fall-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. While 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.

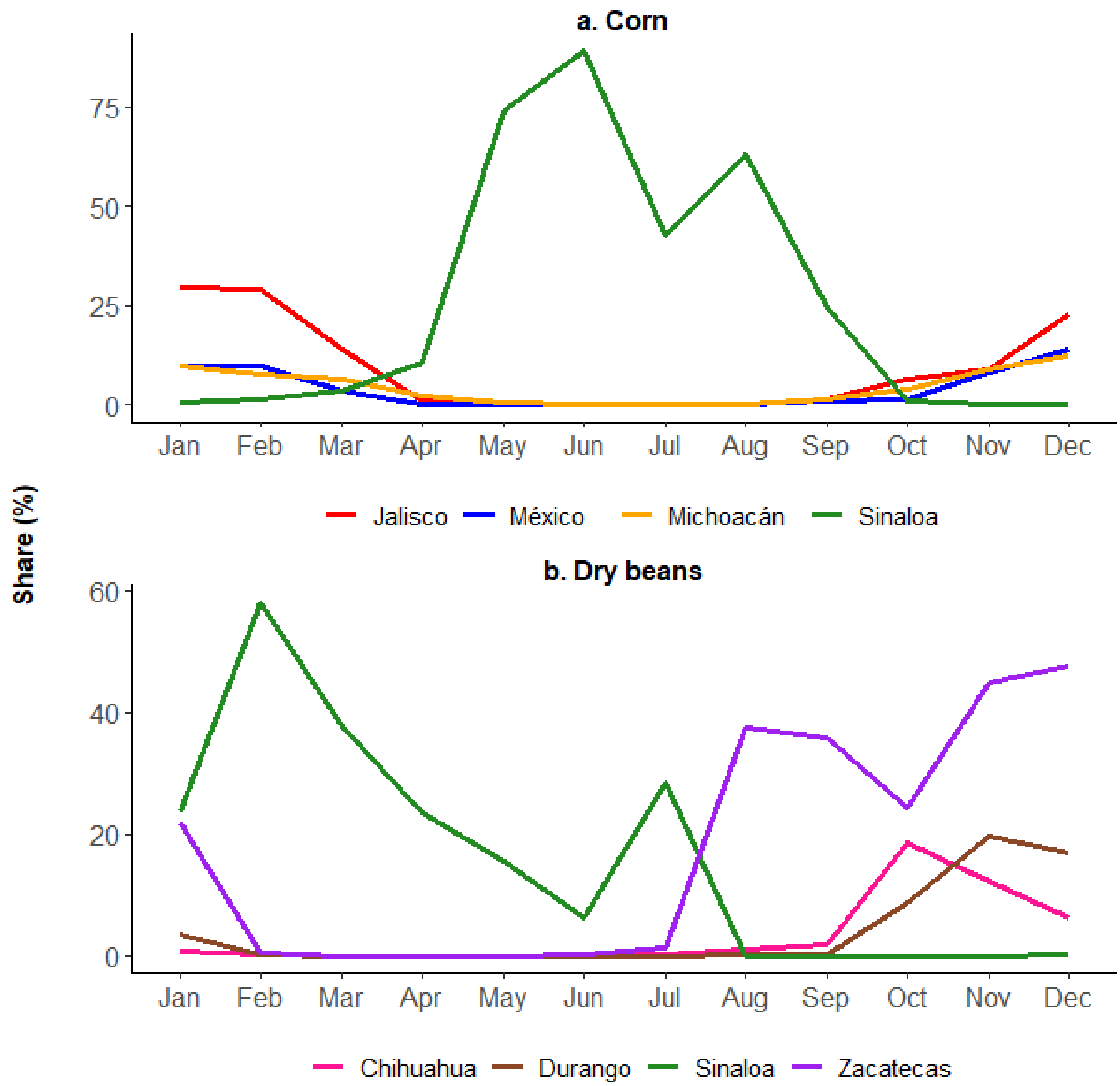
Figure 1 plots the share of the top four producers of each crop in historical monthly production for the period 2004-2020 (SIAP, 2021b).[5] Sinaloa, a state located in northern Mexico, is a major producer of both white corn and dry beans. Its production is mostly irrigated, cultivated in the Fall-Winter 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,

[4] 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 (SIAP, 2021a).

[5] Monthly production data for white corn is not available. Because of this, the corn shares presented in Figure 1 were calculated using monthly production data for aggregated corn which includes white and yellow corn (SIAP, 2021b).

Chihuahua and Durango, all located in the north of Mexico, concentrate about 70% of production at the end of the year.

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

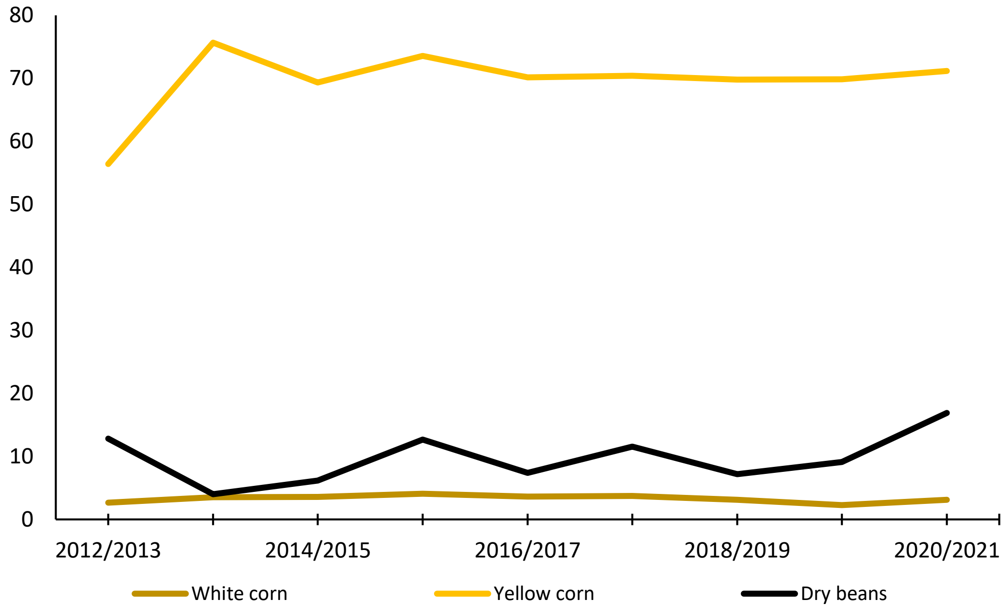


Note: Figure 1 plots the share of the top four producers of each crop in historical monthly production for the period 2004-2020. Monthly production data is available for this period only.
Source: Own elaboration using monthly production data from SIAP (2021b).

The dynamic evolution of the supply of these crops creates a location and time setting in which weather shocks in certain states and months may heavily impact price formation. The sensitivity of market prices to weather shocks will vary with time depending on which producing areas are affected over the course of the year. Market prices are more likely to respond to weather shocks if they hit an important producing area in a particular month. The overall effect of weather shocks on market prices will depend on whether the domestic market is highly dependent on the production of the affected area. For example, in early February of 2011, the state of Sinaloa, a major corn producer, experienced a cold snap with temperatures as low as -8ºC in some locations. This happened right after corn was sown at the beginning of the Fall-Winter season. As a result of these frosts, about 90% of Sinaloa's corn was damaged (USDA, 2011a) which led to subsequent upward pressures in the domestic price of this grain. Between early 2011 and September of the same year, corn prices had increased 75% which also translated into a 12.1% increase in the price of *tortillas* (USDA, 2011b).

The sensitivity of white corn and dry beans prices to extreme weather events also depends on the ability of the domestic market to substitute production deficits with imports. As Figure 2 shows, imports of white corn and dry beans have typically represented a small percentage of the domestic supply. The average for the period 2012-2021 is 3% for white corn and 10% for dry beans. In Mexico, white corn is mostly devoted to human consumption as opposed to yellow corn which is mainly used for livestock feed and the processed food industry. About 70% of the domestic supply of yellow corn comes from imports (see Figure 2). However, yellow corn is a close but not a perfect substitute of white corn for human consumption purposes. In Mexico, traditions and consumer preferences have favored the use of white corn in cooking and the elaboration of *tortillas* (Nuñez and Sempere, 2016). In the event of a weather shock affecting white corn production in Mexico, imports of yellow corn would not necessarily mitigate the upward pressures in the domestic price of white corn. Additional imports of white corn are necessary to alleviate such pressures. 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.

Figure 2. Share of imports in domestic supply (%)



Note: Figure 2 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.
Source: Own elaboration using data from SADER-SIAP (2019, 2020, 2021, 2022a, 2022b).

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:

$$lnP_{it} = \sum_{l=0}^{L} \varphi_s T_{t-l}^{-} + \sum_{l=0}^{L} \gamma_s T_{t-l}^{+} + \sum_{l=0}^{L} \alpha_s Pr_{t-l}^{-} + \sum_{l=0}^{L} \vartheta_s Pr_{t-l}^{+} + \mu_i + \tau_t + \epsilon_{it} \qquad (1),$$

where, lnP_{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. 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 s.d. below its normal; T^{+} which identifies months in which average monthly temperature is 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. An advantage of defining weather shocks in terms of standard deviations is the historical variability of climate in the producing areas. A similar approach is adopted by Skoufias and Vinha (2012 and 2013) when analyzing weather variability in Mexico and its consequences on rural welfare. 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.

In our model, we limit the effect of weather shocks on crop prices to the duration of their phenological cycle which is 6 months for white corn and 4 months for dry beans, on average (Ruiz et al., 2013). As a result, L=5 when the model is applied to white corn prices and L=3 when the model is applied to dry beans prices. 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 separate 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. Dry beans prices at the city level are generated using monthly CPI series obtained from INEGI, the institution in charge of measuring and releasing inflation data in Mexico. To measure inflation, INEGI quotes the price of 299 different items across retail markets in 55 large cities to generate CPI series for each (INEGI, 2018). The current base period of the CPI series provided by INEGI is July 2018. 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:

$$P_{it} = \frac{CPI_{it}}{CPI_{i,July2018}} * Price_{i,July2018} \qquad (2),$$

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.

White corn prices are obtained from SNIIM, which reports the price of a large number of agricultural products quoted at 44 wholesale markets located throughout the country. Prices are collected on weekly basis. White corn prices are available for 39 wholesale markets distributed across 30 Mexican states. Our main variable is constructed by calculating a 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 of as the ones used to make *pozole* and popcorn (INEGI, 2018).[6] 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. The inclusion of other types of corn may bias our estimate of the effect of weather shocks on prices, particularly because other varieties tend to be more expensive than regular white corn.

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.[7] Figure A1 (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.

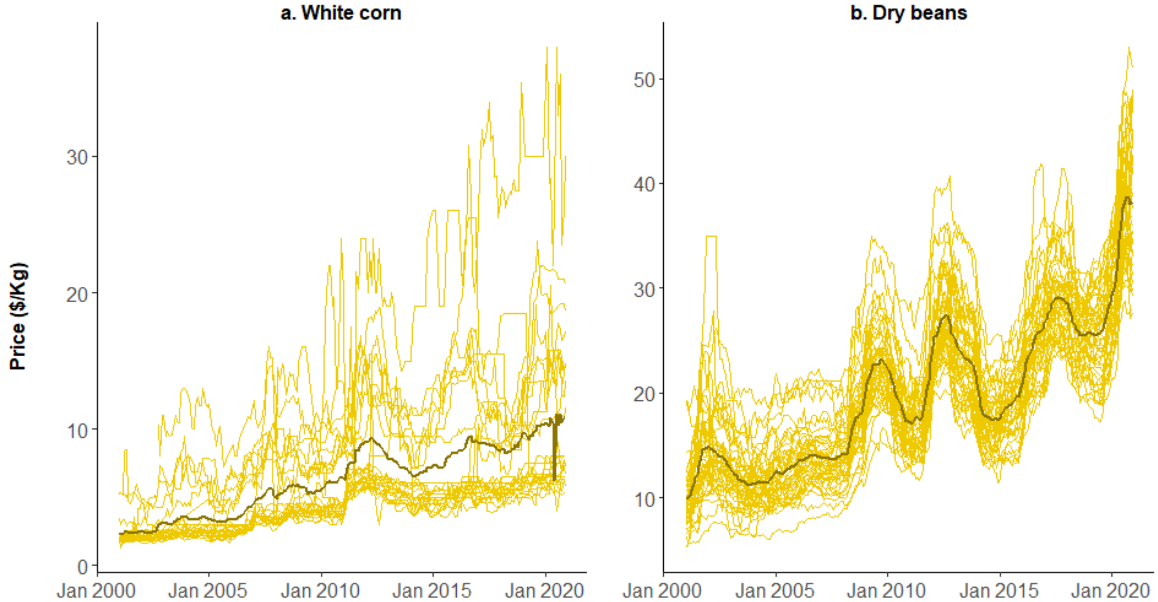
Figure 3 shows the evolution of white corn and dry beans prices during the sample period. The dark brown lines refer to the national average while the light brown lines represent the price series for each of the markets (white corn) and cities (dry beans) in the sample. The price of both crops increased 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 bean prices ranged from 20 to 55 pesos per kilogram. For both, our white corn and dry beans price series, we performed several unit-root tests suited for panel data. The details and results of these tests are presented in Table A1 (in the appendix) and, in general, they reject the null hypothesis that our panels contain unit roots favoring the alternative

[6] 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*.

[7] 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. The chunks of time for which price data is missing are intermittent. Given this level of missing data, we chose to rely on the wholesale markets with more complete price series. In our dry beans sample, we exclude 9 cities because CPI information is not available before July 2018. These cities are Atlacomulco, Cancún, Coatzacoalcos, Esperanza, Izúcar de Matamoros, Pachuca, Saltillo, Tuxtla Gutiérrez and Zacatecas. We also exclude the city of Tlaxcala due to the lack of the commercialization data necessary to identify its supplier states.

hypothesis that panels are stationary. Therefore, we rule out the possibility of spurious results in the estimation of the fixed effects models stated in equation (1). Table A2 (in the appendix) presents summary statistics of our price data at the national and regional levels.[8]

Figure 3. Evolution of white corn and dry beans prices ($/Kg), 2001-2020



Note: The dark brown lines refer to the national average while the light brown lines represent the price series for each of the markets (white corn) and cities (dry beans) in the sample.
Source: Own elaboration with price information from INEGI (2021) and SNIIM (2021).

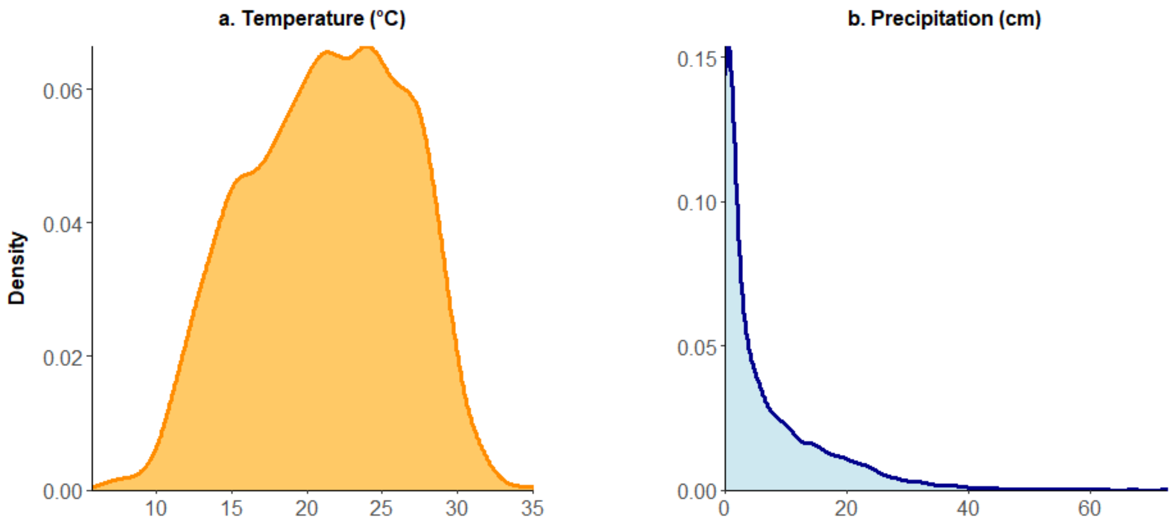
5.2 Weather data

Monthly weather data come from DAYMET (Thornton et al., 2020), a gridded dataset distributed by the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC). Gridded estimates of maximum and minimum temperature as well as accumulated precipitation are available at a 1 km x 1 km spatial resolution for North America. 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 a land use

[8] The regional distribution of the 32 states of Mexico can be seen in Figure A2 (in the appendix) and adheres to regionalization adopted in the Regional Economic Report of Banco de México (Banco de México, 2023). This regionalization groups states based on geography, socioeconomic factors, production patterns and the synchronization of their business cycles.

map generated by the Mexican Ministry of Agriculture (SIAP, 2021c). Figure 4 plots the distribution of monthly average temperature (panel a) and precipitation (panel b) for our sample period. Monthly average temperature ranges from 5.7ºC to 35.0ºC with a mean of 21.3ºC and a large mass of observations concentrated around the 22-28ºC interval. Monthly precipitation varies from 0cm to 73cm with a large proportion of observations concentrated near zero due to the absence of precipitation in some months for some states.[9]

Figure 4. Monthly Average Temperature and Precipitation Distributions, 2001-2020



Source: Own elaboration based on Thornton et al. (2020) and SIAP (2021c).

Figure 5 presents the weather anomalies observed in the sample calculated as deviations from the 40-year climate normal.[10] The information is organized by region. Dark lines identify the regional average deviation whereas light gray lines identify the average deviation for every state located in the region. Climate normals at the regional and state levels were calculated as the average of monthly weather between 1980 and 2019 (40 years). As seen in Figure 5, most of the temperature deviations lie within a 2.5ºC band (panel a). Larger deviations are observed in the sample, particularly in the last decade of the sample period and in the North and Center-north regions. In general, temperature deviations display an upward trend which

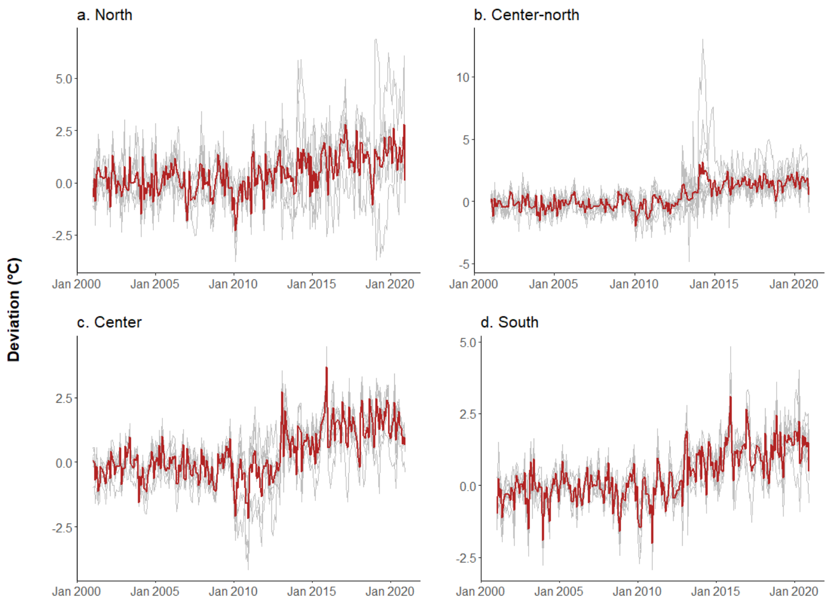
[9] The monthly temperature and precipitation series generated by state and region can be seen in Figure A3.

[10] 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. 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.

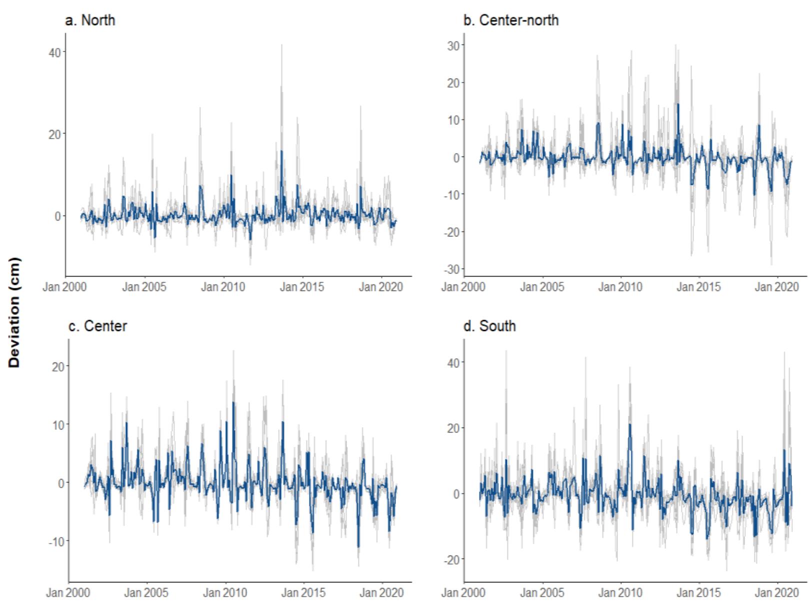
accelerated around 2010. Precipitation deviations (panel b) vary substantially across regions, but episodes of precipitation deficits have also become more frequent in the last decade, especially in the Center-north, Center and South regions.

Figure 5. Temperature and precipitation deviations from the climate normal, 2001-2020

a) Temperature



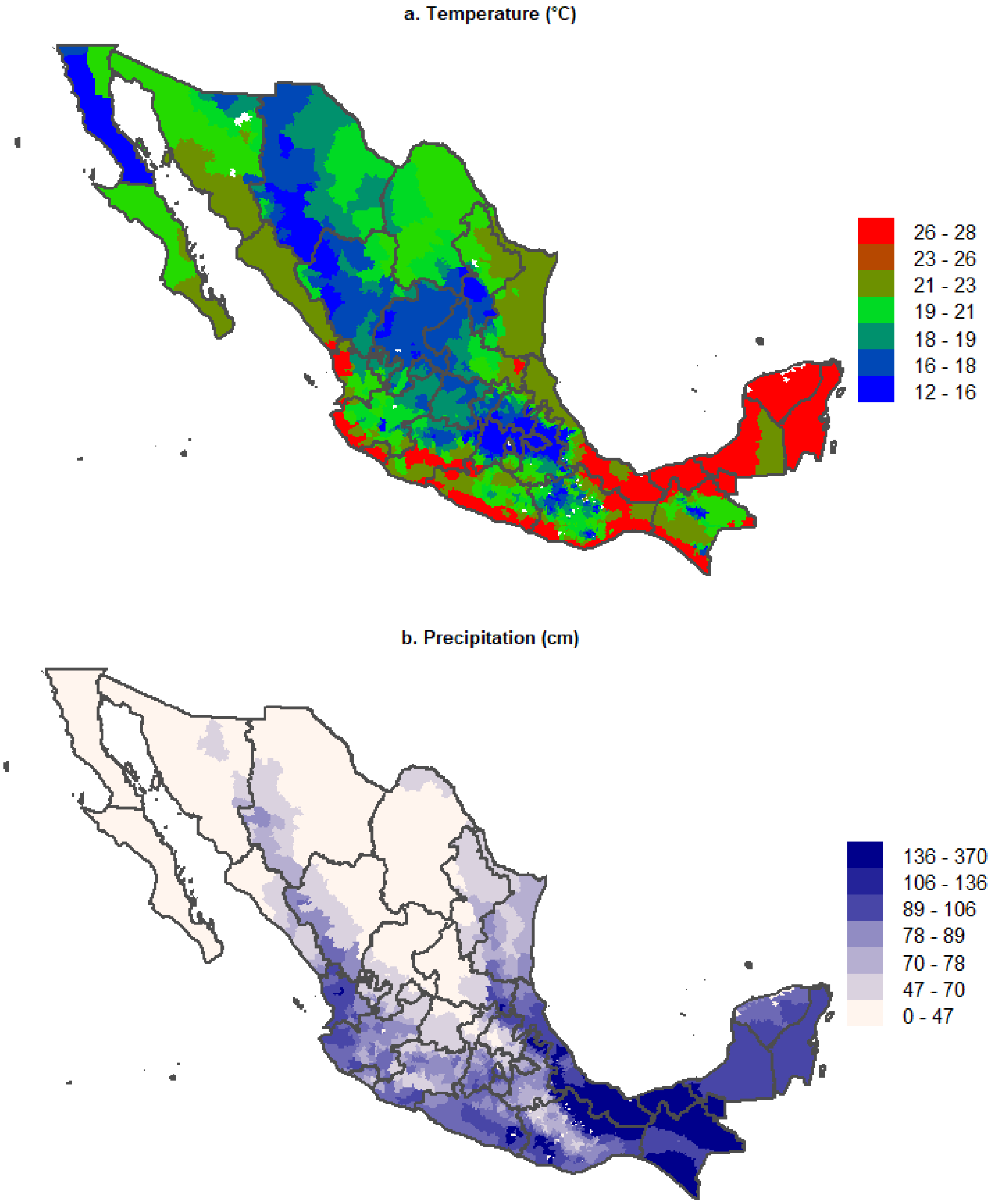
b) Precipitation



Note: Dark lines identify the regional average deviation whereas light gray lines identify the average deviation for every state located in the region.
Source: Own elaboration based on Thornton et al. (2020) and SIAP (2021c).

Lastly, Figure 6 illustrates the large cross-sectional variation in municipal weather contained in the sample. Annual average temperatures (panel a) range between 12ºC and 28ºC. The warmest temperatures are found in coastal areas while the coolest temperatures concentrate in elevated plain areas. Precipitation (panel b) is concentrated in the south of Mexico. Most of the upper part of the country receives less than 70cm of accumulated rain in a typical year.

Figure 6. Average annual temperature and cumulative precipitation at the municipal level, 2001-2020



Source: Own elaboration based on Thornton et al. (2020) and 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. Thus, the commercialization links that exist between markets/cities and the producing areas determine the sensitivity of their prices to weather shocks experienced locally or elsewhere.

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 monthly commercialization data for white corn and dry beans for the period 2004-2020 (SNIIM, 2021). The 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 in every month. We discard possible intermediary states using production data (SIAP, 2021b). Specifically, states whose average yearly production of the crop over the period 2004-2020 is less than 1000 tons are excluded from the list of potential suppliers. 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:

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

where N is the total number of suppliers of state m, d_{mn} is the distance (in kilometers) between state m and its nth supplier and $shprod_{nj}^{k}$ is the share of the nth state supplier in the historic production (2004-2020) of crop k (white corn, dry beans) in calendar month j at the national level.[11,12] 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.[13] 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 have to 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).

[11] 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.

[12] 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 (SIAP, 2021b) does not distinguish auto-consumption, so, we are unable to exclude if 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 (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.

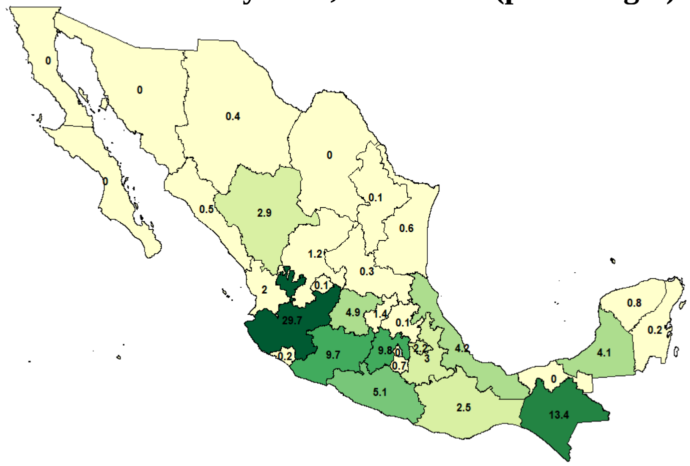
[13] The inverse of the square root of the distance has been used as weighting factor in other empirical work to generate weather variables for a location of interest using nearby locations (Jessoe et al., 2018).

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 into account local production, the relevance index also reflects "internal" sources of weather variation. So, whenever local production is large, weather variation in our T and Pr 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.

Figure 7 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 of the 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 the supply and the weather of the most relevant producing states for each market at different points of the production cycle.

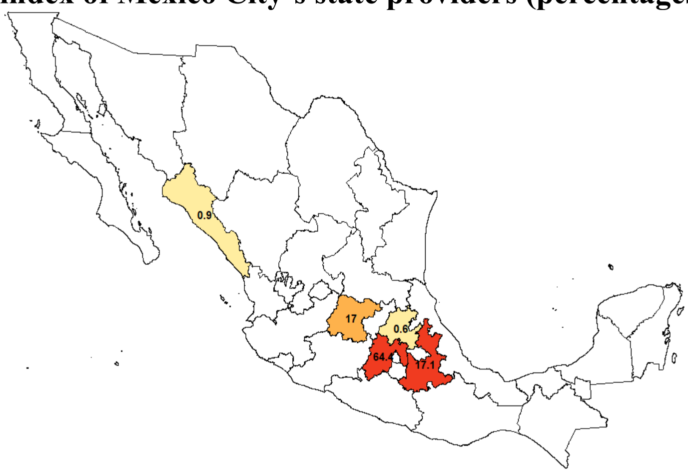
Figure 7. Relevance index example: white corn sold in Mexico City in January

a) **Historic production shares by state, 2004-2020 (percentages)**



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

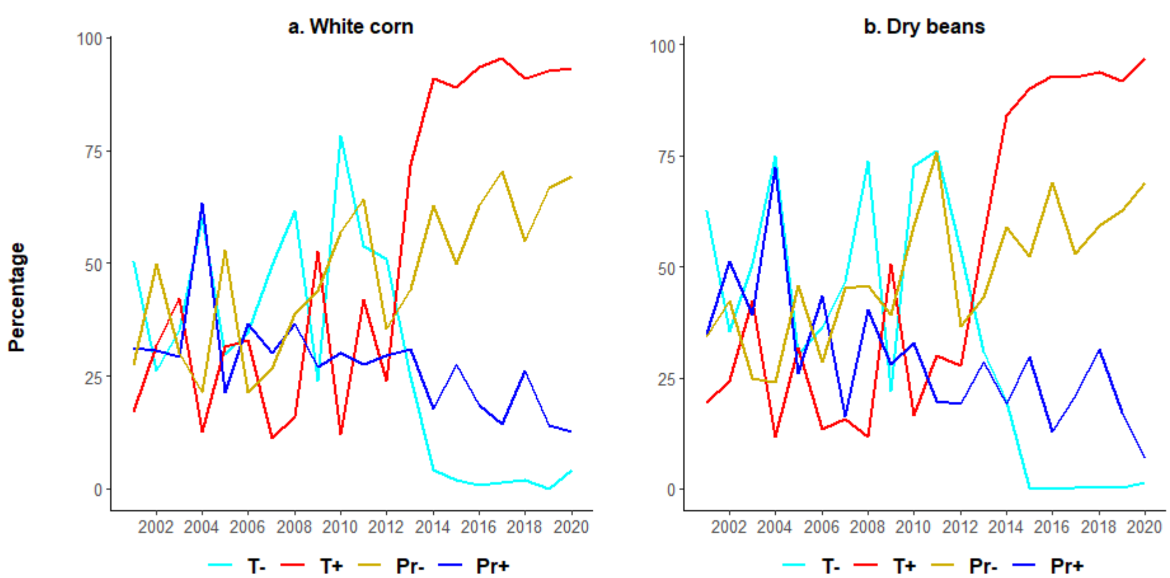
c) **Relevance index of Mexico City's state providers (percentages)**



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

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. For reference, a 1.0 s.d. of the monthly temperature and precipitation normals is, on average, roughly equal to 1°C and 3.7cm, respectively. Figure 8 plots the evolution of the frequency of weather shocks observed in the sample measured as the annual percentage of observations for which these variables take the value of 1. 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 temperature shocks decreased. This result is in line with the temperature and precipitation deviations trends shown in Figure 5 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 s.d. and 2.0 s.d. Also, Table A2 (in the appendix) offers detailed summary statistics of the weather variables used in our price regressions at the national and regional levels.

Figure 8. Percentage of sample observations with weather shocks larger than 0.5 s.d.



Source: Own elaboration based on Thornton et al. (2020), SIAP (2021b and 2021c), and 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 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 and A6 and Table A2). These findings are consistent with recent 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 bean 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 A2).

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

	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}	0.0055	0.0046	0.0232	0.0067	-0.0164	-0.0115
	(0.0077)	(0.0104)	(0.0411)	(0.0059)	(0.0102)	(0.0159)
T^-_{t-1}	0.0135*	0.0192*	0.0204	0.0063	-0.0075	-0.0152
	(0.0067)	(0.0095)	(0.0356)	(0.0049)	(0.0083)	(0.0171)
T^-_{t-2}	0.0144**	0.0216*	0.0186	0.0083	-0.0099	-0.0174
	(0.0067)	(0.0123)	(0.0291)	(0.0060)	(0.0086)	(0.0181)
T^-_{t-3}	0.0153**	0.0173*	0.0185	0.0074	-0.0095	-0.0129
	(0.0067)	(0.0100)	(0.0254)	(0.0063)	(0.0097)	(0.0220)
T^-_{t-4}	0.0121*	0.0164*	0.0171			
	(0.0064)	(0.0090)	(0.0291)			
T^-_{t-5}	0.0155*	0.0196*	0.0143			
	(0.0076)	(0.0101)	(0.0328)			
T^+_{t-0}	0.0176*	0.0245	0.0265	0.0157**	0.0082	0.0053
	(0.0098)	(0.0173)	(0.0193)	(0.0065)	(0.0057)	(0.0103)
T^+_{t-1}	0.0224**	0.0222	0.0398	0.0103*	0.0052	0.0041
	(0.0087)	(0.0154)	(0.0302)	(0.0058)	(0.0057)	(0.0103)
T^+_{t-2}	0.0259**	0.0261*	0.0495	0.0087	0.0024	0.0006
	(0.0101)	(0.0129)	(0.0310)	(0.0055)	(0.0056)	(0.0113)
T^+_{t-3}	0.0218*	0.0216	0.0423	0.0070	0.0008	-0.0037
	(0.0112)	(0.0143)	(0.0299)	(0.0060)	(0.0064)	(0.0125)
T^+_{t-4}	0.0220*	0.0226	0.0550			
	(0.0107)	(0.0165)	(0.0356)			
T^+_{t-5}	0.0223*	0.0316	0.0512			
	(0.0125)	(0.0195)	(0.0393)			
P^-_{t-0}	0.0137**	0.0539*	0.0495	0.0074	0.0161**	0.0743*
	(0.0061)	(0.0267)	(0.0566)	(0.0063)	(0.0078)	(0.0395)
P^-_{t-1}	0.0148**	0.0356	0.0414	0.0111*	0.0171***	0.0704*
	(0.0064)	(0.0209)	(0.0458)	(0.0062)	(0.0063)	(0.0419)
P^-_{t-2}	0.0171**	0.0308	0.0383	0.0117*	0.0161**	0.0663
	(0.0073)	(0.0191)	(0.0514)	(0.0062)	(0.0065)	(0.0395)
P^-_{t-3}	0.0093	0.0288	-0.0227	0.0148**	0.0200**	0.0806**
	(0.0060)	(0.0173)	(0.0268)	(0.0067)	(0.0081)	(0.0357)
P^-_{t-4}	0.0091	0.0291*	0.0061			
	(0.0058)	(0.0147)	(0.0256)			
P^-_{t-5}	0.0117*	0.0335*	-0.0567			
	(0.0061)	(0.0190)	(0.0386)			
P^+_{t-0}	-0.0177**	-0.0037	0.0041	-0.0013	0.0037	0.0038
	(0.0082)	(0.0067)	(0.0099)	(0.0053)	(0.0079)	(0.0114)
P^+_{t-1}	-0.0175*	-0.0018	0.0025	-0.0040	0.0002	-0.0027
	(0.0098)	(0.0078)	(0.0082)	(0.0054)	(0.0080)	(0.0110)
P^+_{t-2}	-0.0163	-0.0026	0.0018	0.0002	0.0035	0.0050
	(0.0105)	(0.0087)	(0.0093)	(0.0053)	(0.0080)	(0.0106)
P^+_{t-3}	-0.0144	-0.0033	0.0048	0.0021	0.0036	0.0119
	(0.0086)	(0.0094)	(0.0091)	(0.0059)	(0.0093)	(0.0112)
P^+_{t-4}	-0.0118	-0.0064	0.0122			
	(0.0076)	(0.0073)	(0.0115)			
P^+_{t-5}	-0.0139**	-0.0099	0.0138			
	(0.0067)	(0.0065)	(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), SNIIM (2021), SIAP (2021b and 2021c), and Thornton et al. (2020).

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 A4 (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. Table A4 shows that our main findings are robust to this change in the weighting procedure albeit with slight differences in the statistical significance for some of the parameter estimates.

Finally, Table A5 (in the appendix) shows the results obtained when we allow for spatial correlation in the error term in our estimation for dry beans prices.[14] This correlation may arise because of unobserved factors affecting prices in one city that could also affect the price of cities nearby at the same time. One of such factors could be the degree of market integration at the state or regional, which is not directly accounted for in the model and that could create a co-movement of prices among cities close to each other. For this robustness test, we estimated a Spatial Error Model assuming that the correlation among errors is limited to the 2, 6 and 10 closest neighbor cities. Table A6 confirms that our main results are robust, in general, to spatial error correlation albeit with some changes in the magnitude and statistical significance of the parameter estimates and regardless of the number of neighbors considered.

Table 2 shows the accumulated effect of temperature and precipitation shocks over the growing period for the different scenarios analyzed. It 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

[14] This robustness test is performed only for dry beans because it requires balanced panel data.

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 no 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 (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) which, if sufficiently large, could create upward pressures in market prices. The next section explores this channel.

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

	White corn (6 months)			Dry beans (4 months)		
	(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.
Accumulated T^-	0.0764**	0.0986*	0.1120	0.0287	-0.0433	-0.0570
	(0.0376)	(0.0564)	(0.1820)	(0.0220)	(0.0353)	(0.0694)
Accumulated T^+	0.1321**	0.1486	0.2644	0.0417*	0.0166	0.0063
	(0.0604)	(0.0917)	(0.1819)	(0.0226)	(0.0220)	(0.0429)
Accumulated P^-	0.0756**	0.2118*	0.0559	0.0451*	0.0693**	0.2916*
	(0.0343)	(0.1145)	(0.1936)	(0.0249)	(0.0279)	(0.1536)
Accumulated P^+	-0.0916*	-0.0277	0.0392	-0.0031	0.0110	0.0180
	(0.0488)	(0.0427)	(0.0498)	(0.0211)	(0.0323)	(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), SNIIM (2021), SIAP (2021b and 2021c), and Thornton et al. (2020).

7. The effect of weather shocks on white corn and dry beans yields

In this section we explore the productivity mechanism through which weather shocks might impact the price of white corn and dry beans. Previous findings document detrimental effects of high temperatures on white corn yields (Schlenker and Roberts, 2009; Burke and Emerick, 2016), but no previous evidence exists for the case of dry beans. Here, we evaluate if extreme weather shocks also explain productivity changes in white corn and dry beans production in Mexico. If yields decrease because of weather shocks, this could be a factor explaining the price increases found in the previous section. We estimate the functional relationship between weather and yields with a fixed effects model that relies on yield and weather data at the municipality level. We model crop yields as a quadratic function of temperature and precipitation. For each crop (white corn or dry beans) and mode of production (rainfed or irrigated), we estimate the following equation:

$$lnY_{ist} = \beta_1 T_{ist} + \beta_2 T_{ist}^2 + \beta_3 Pr_{ist} + \beta_4 Pr_{ist}^2 + \omega_i + \rho_s + \sigma_t + f_r(t) + \epsilon_{ist} \qquad (4),$$

where lnY_{ist} represents the logarithm of the yield of each crop (in tons per hectare) in municipality i, season s *(s=Spring-Summer, Fall-Winter)* and year t. T and Pr stand for average seasonal temperature and accumulated seasonal precipitation. The estimation includes municipality fixed effects (ω_i), which control for time invariant unobserved factors determining crop yields at the municipality level such as the soil suitability for white corn or dry bean production. Season (ρ_s) and year (σ_t) fixed effects absorb time varying unobserved factors affecting crop yields common to all municipalities within the same season or year. Lastly, $f_r(t)$ refers to a region-specific quadratic time trend included in the model to control for time-varying unobserved determinants of crop productivity at the regional level such as technological progress. We include this trend in a quadratic fashion to account for the fact that yield growth may slow down over time due to decreasing returns to scale. In this estimation, standard errors are clustered at the municipality and state-year levels.

Yield data at the municipality level is obtained from SIAP (SIAP, 2021a) for the period 2003-2020 and includes total harvested area (in hectares) and total production (in tons). Yield (in tons per hectare) at the municipality level is calculated as total production divided by total harvested area. A great advantage of this data set is that it separates rainfed and irrigated production which allows us to test the sensitivity of both forms of production to weather shocks. Figures A7 and A8 plot the sample variation of white corn and dry beans yields temporally and over space, respectively.

Table 3 presents the parameter estimates of equation (4). Columns 1 to 2 show results for white corn, while columns 3 to 4 display results for dry beans. There are two main results. First, there is concave "inverted-U" shaped relationship between temperature and the yield of the crops analyzed. In the case of white corn, the parameter estimates of the temperature variables are statistically significant for both, rainfed and irrigated production. The estimated optimal temperatures are 20.3ºC and 22.9ºC, respectively. In the case of dry beans, none of the parameters are estimated with precision; however, the implied optimal temperatures (15.9ºC for rainfed and 23.5ºC for irrigated) achieve statistical significance.[15] The range of estimated optimal temperatures roughly corresponds with the optimal temperature range

[15] The estimated optimal value of temperature is obtained from solving the following first order condition:

$$\hat{\beta}_1 + 2\hat{\beta}_2 T_{ist} = 0$$

where $\hat{\beta}_1$ and $\hat{\beta}_2$ are the temperature parameter estimates of equation (2) reported in each column of Table 3. Standard errors (in parenthesis) are calculated using the delta method. The optimal value for precipitation is obtained analogously.

reported by SAGARPA-FAO (2012). On average, rainfed production of white corn and dry beans occurs in municipalities whose average temperature is above the estimated optimal temperature. The opposite is true for irrigated production. Second, precipitation impacts white corn and dry bean yields when production takes place under rainfed conditions. The parameter estimates of the precipitation variables are statistically significant in columns 1 and 3. The estimated relationship is also concave. The implied optimal precipitation is 221.1cm and 212.8cm for white corn and dry beans, respectively. These values are well above the average precipitation observed in municipalities where rainfed production occurs (around 70cm). In contrast, precipitation does not impact crop yields when irrigation is used (see columns 2 and 4).

Table 3. Panel estimates of the functional relationship between weather and crop yields

	White corn		Dry beans	
	Rainfed	Irrigated	Rainfed	Irrigated
	(1)	(2)	(3)	(4)
T	0.0557*	0.1377***	0.0835	0.0563
	(0.0305)	(0.0280)	(0.0673)	(0.0449)
T^2	-0.0014**	-0.0030***	-0.0026	-0.0012
	(0.0007)	(0.0006)	(0.0017)	(0.0009)
P	0.0031***	0.0008	0.0059***	-0.0012
	(0.0005)	(0.0008)	(0.0013)	(0.0011)
P^2	-0.000007***	-0.000000	-0.000014***	0.000010
	(0.000002)	(0.000005)	(0.000004)	(0.000007)
Optimal weather				
T*	20.3025***	22.9227***	15.9376***	23.5165***
	(2.8574)	(0.9924)	(4.2396)	(4.2085)
P*	221.0614***	-1173.5141	212.7732***	59.7530**
	(25.6640)	(18027.8983)	(30.6634)	(28.7982)
Average weather				
$\bar{T}$ (ºC)	22.3	21.1	21.4	20.8
$\bar{P}$ (cm)	70.2	41.3	67.1	37.8
Controls				
Season FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quadratic regional time trend	Yes	Yes	Yes	Yes
R^2	0.8262	0.8989	0.6287	0.6540
N	47,412	30,213	31,132	17,510

Note: Regressions are weighted by the 2003-2020 average planted area (has) at the municipality level. Standard errors (in parenthesis) clustered at the municipality and state-year level. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own elaboration based on data from SIAP (2021a and 2021c) and Thornton et al. (2020).

We use the parameter estimates of Table 3 to estimate the percentage change in crop yields associated to temperature and precipitation deviations of 0.5 s.d., 1.5 s.d. and 2.0 s.d. below and above their seasonal averages. Specifically, the percentage change in the yield of each crop after a weather shock is calculated using the following formula:

$$\Delta lnYield = \hat{\varphi} * \left(\bar{\bar{W}} - \bar{W}\right) + \hat{\gamma} * \left(\bar{\bar{W}}^2 - \bar{W}^2\right) \qquad (5),$$

where $\bar{W}$ is average weather (temperature or precipitation) and $\bar{\bar{W}} = \bar{W} \pm X\ s.d._{\bar{W}}$ with X={0.5, 1.5, 2.0}. $\bar{W}$ is calculated using the whole sample, that is, pooling all municipalities and year-months.

Table 4 summarizes the results of this simulation. Panel a) shows that irrigated white corn yields are sensitive to negative temperature shocks (column 2). In particular, a 0.5 s.d. decrease in average temperature decreases irrigated white corn yields by 3.0%. As the magnitude of the negative temperature shocks increases, the decline in white corn yields also becomes larger. Panel b) shows that positive temperature shocks decrease white corn and dry beans yields when produced under rainfed conditions (see columns 1 and 3). They also have a detrimental effect on irrigated white corn. The precision of the estimates varies depending on the magnitude of the shock but these results are consistent with the price increases displayed in Table 1 and suggests that a factor explaining the impact of temperature shocks on market prices is the yield reductions they cause in crop production.

Panels c) and d) of Table 4 confirm that rainfed production is highly sensitive to precipitation shocks. For rainfed white corn, yield decreases associated to negative precipitation shocks during the growing season range between 4.8% and 22.8%, depending on the severity of the shock (panel c, column 1). These numbers range between 8.7% and 41.7% in the case of rainfed dry beans production (panel c, column 3). The sign and size of these estimates are in line with the large price effects of dry conditions reported in Table 1. On the other hand, excess precipitation is beneficial for crop yields. Rainfed white corn yields increases associated to positive precipitation shocks range between 4.1% and 12.8% (panel d, column 1). The estimated effects for rainfed dry beans yields are even larger (panel d, column 3).

Interestingly, some of the estimated effects for irrigated white corn are statistically significant (see column 2 in panels c and d) which could be explained by the role that precipitation has at determining the amount of water available for irrigation.

Table 4. Impact of weather shocks on white corn and dry beans yields

	White corn		Dry beans	
	Rainfed	Irrigated	Rainfed	Irrigated
	(1)	(2)	(3)	(4)
a) Temperature decreases				
$\bar{T}$-0.5 s.d.	0.0056	-0.0296**	0.0411	-0.0137
	(0.0156)	(0.0127)	(0.0328)	(0.0198)
$\bar{T}$-1.5 s.d.	-0.0174	-0.1473***	0.0765	-0.0601
	(0.0507)	(0.0453)	(0.0980)	(0.0686)
$\bar{T}$-2.0 s.d.	-0.0460	-0.2355***	0.0707	-0.0927
	(0.0728)	(0.0660)	(0.1348)	(0.0985)
b) Temperature increases				
$\bar{T}$+0.5 s.d.	-0.0171	0.0100	-0.0568	0.0074
	(0.0163)	(0.0111)	(0.0357)	(0.0175)
$\bar{T}$+1.5 s.d.	-0.0855	-0.0286	-0.2172*	0.0032
	(0.0564)	(0.0322)	(0.1227)	(0.0492)
$\bar{T}$+2.0 s.d.	-0.1368*	-0.0773*	-0.3208*	-0.0084
	(0.0821)	(0.0441)	(0.1763)	(0.0656)
c) Precipitation decreases				
$\bar{P}$-0.5 s.d.	-0.0476***	-0.0130	-0.0872***	0.0091
	(0.0076)	(0.0090)	(0.0183)	(0.0121)
$\bar{P}$-1.5 s.d.	-0.1617***	-0.0383	-0.2956***	0.0417
	(0.0264)	(0.0337)	(0.0637)	(0.0440)
$\bar{P}$-2.0 s.d.	-0.2281***	-0.0508	-0.4169***	0.0651
	(0.0378)	(0.0496)	(0.0910)	(0.0642)
d) Precipitation increases				
$\bar{P}$+0.5 s.d.	0.0414***	0.0131*	0.0758***	-0.0043
	(0.0065)	(0.0070)	(0.0157)	(0.0100)
$\bar{P}$+1.5 s.d.	0.1054***	0.0399**	0.1933***	0.0016
	(0.0168)	(0.0166)	(0.0404)	(0.0260)
$\bar{P}$+2.0 s.d.	0.1280***	0.0536***	0.2350***	0.0117
	(0.0211)	(0.0205)	(0.0503)	(0.0336)
N	47412	30213	31132	17510

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 SIAP (2021a and 2021c) and Thornton et al. (2020).

Overall, results in Tables 3 and 4 reveal one of the mechanisms through which weather affects the prices of these two crops. First, weather determines crop yields and the availability of the crop in the market. Frosts, heat waves and droughts decrease yields and reduce supply. Markets form expectations about the immediate and lagged effects that these weather shocks might have on crop availability leading to upward pressures in prices.

8. 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 by the two main state suppliers of each market/city. For our yield estimation, we rely on 18 years of seasonal panel data at the municipality level to estimate the functional relationship between weather and yields and to simulate the impact of weather shocks.

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, the monthly price of these crops increases between 1% and 2% if monthly temperature (precipitation) in at least one of the two main state suppliers of a market/city is at least 0.5 s.d. 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.

We also find that one of the mechanisms through which weather shocks affect the price of these crops is the detrimental effect they have on yields. Rainfed production of white corn and dry beans is highly sensitive to negative precipitation shocks with reductions as large as

23% and 42%, respectively, when precipitation is 2.0 s.d. below its mean. Both white corn and dry beans yields are sensitive to temperature shocks. In particular, white corn irrigated yields are highly sensitive to colder-than-normal temperatures with yield decreases as large as 24% when temperature is 2.0 s.d. below its mean. Both white corn and dry beans yields appear to respond to positive temperature shocks only when they are large. Thus, adverse weather shocks cause yield reductions which creates supply imbalances that ultimately lead to upward pressures in the market price of white corn and dry beans. 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 programing 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. In the case of white corn and dry beans, our yield estimates could complement these policies with a precise figure of the expected reduction in the supply of these crops. 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 and 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 our estimated effects closer to zero.

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 and is 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 while insufficient in several states located in the center and south regions (García Salazar et al., 2020). Thus, another avenue for policy making could be 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. The detrimental effect that weather shocks have on the productivity of these crops could also have important consequences for the welfare of those producers who devote their production to auto-consumption. Besides threatening the stability of white corn and dry beans as a source of income, weather shocks might also threaten their stability as a source of food. In our data, the frequency of heat waves and dry spells has increased over time which could be associated to the long-term trends in temperature and precipitation caused by climate change. Thus, in the future, yield reductions and upward pressures on prices associated to 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.

9. References

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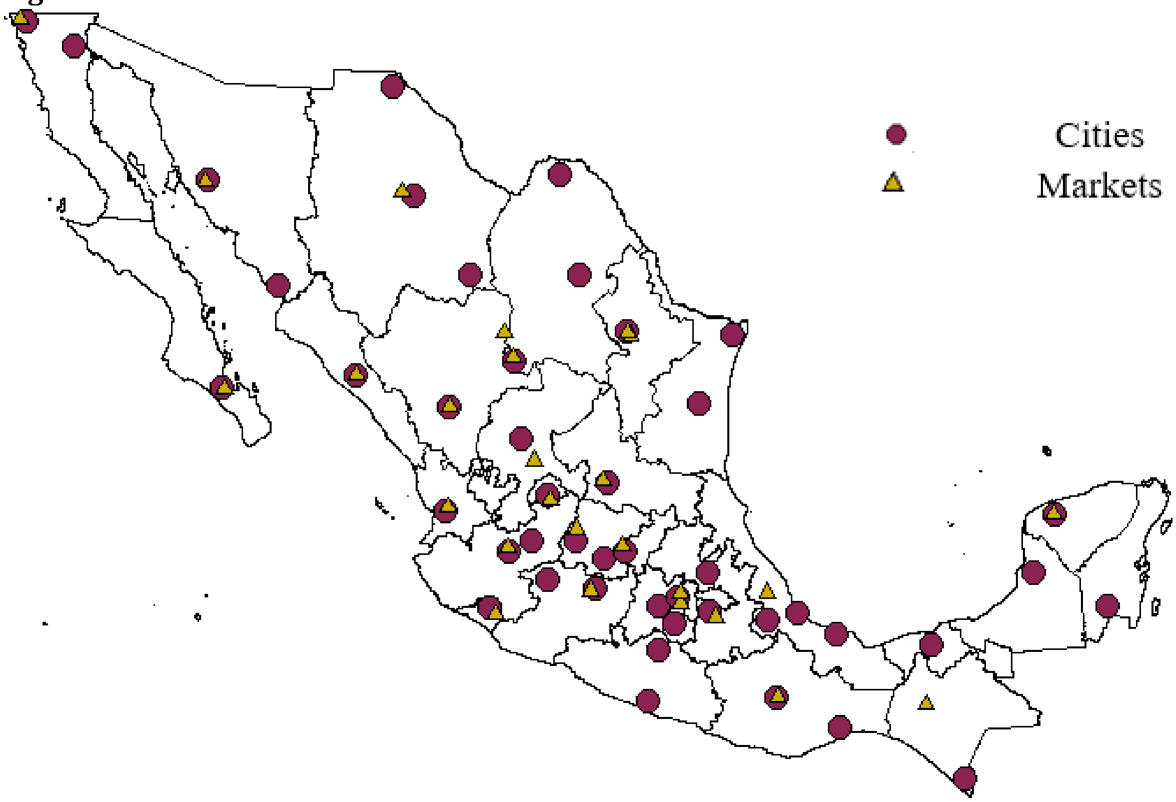
10. Appendix

Figure A1. Location of markets and cities



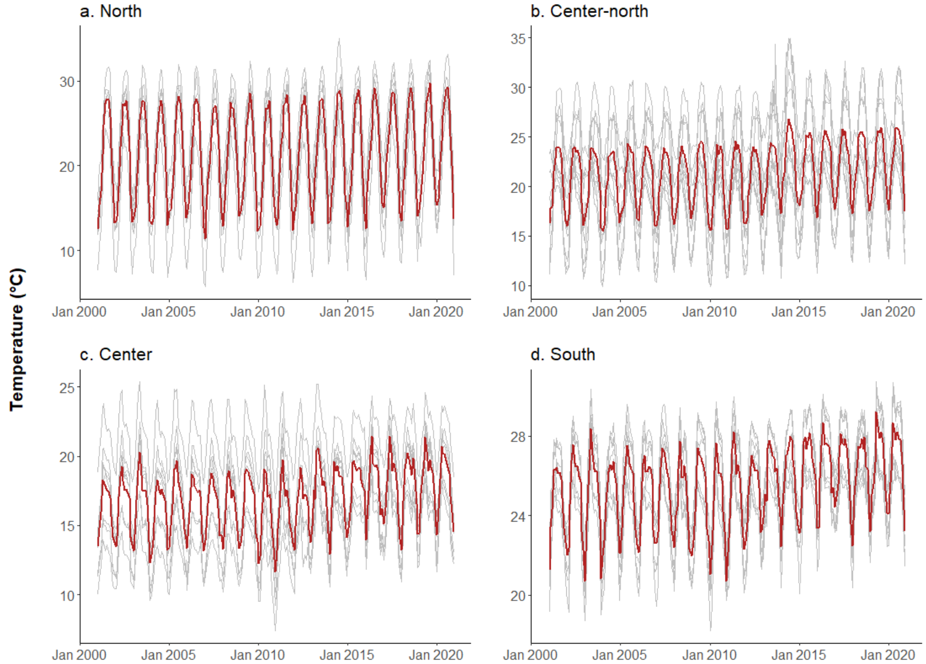
Note: The map shows the location of the 26 markets (white corn) and 45 cities (dry beans) contained in the sample.
Source: Own elaboration based on data from INEGI and SNIIM (2021).

Figure A2. Regions of Mexico

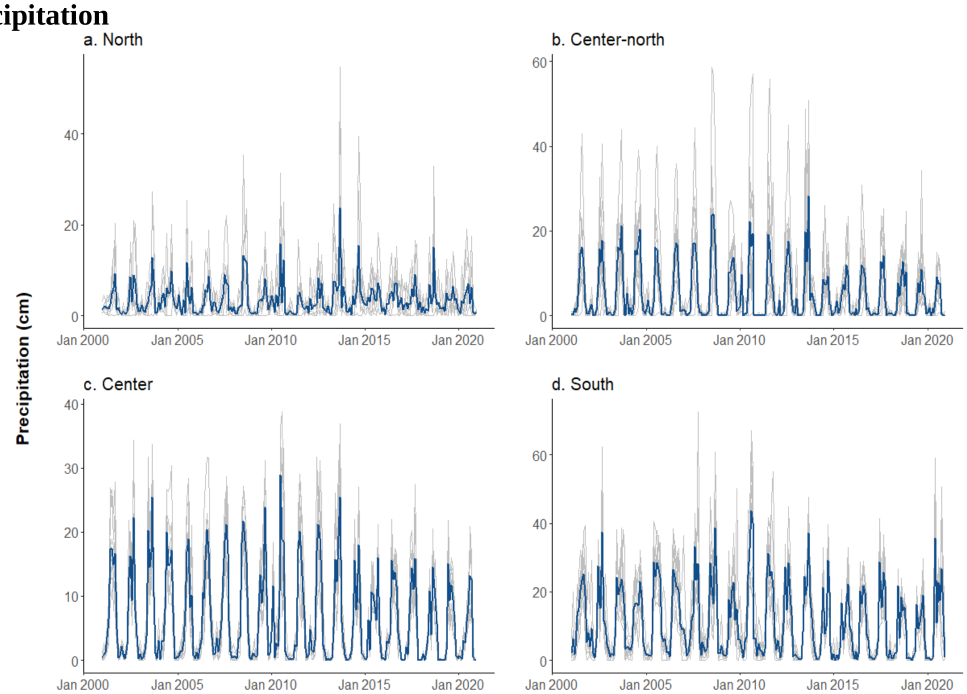
Note: State numbering is as follows: 1=Aguascalientes, 2=Baja California, 3=Baja California Sur, 4=Campeche, 5=Coahuila, 6=Colima, 7=Chiapas, 8=Chihuahua, 9=Ciudad de México, 10=Durango, 11=Guanajuato, 12=Guerrero, 13=Hidalgo, 14=Jalisco, 15=México, 16=Michoacán, 17=Morelos, 18=Nayarit, 19=Nuevo León, 20=Oaxaca, 21=Puebla, 22=Querétaro, 23=Quintana Roo, 24=San Luis Potosí, 25=Sinaloa, 26=Sonora, 27=Tabasco, 28=Tamaulipas, 29=Tlaxcala, 30=Veracruz, 31=Yucatán, 32=Zacatecas.
Source: Own elaboration.

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

a) Temperature



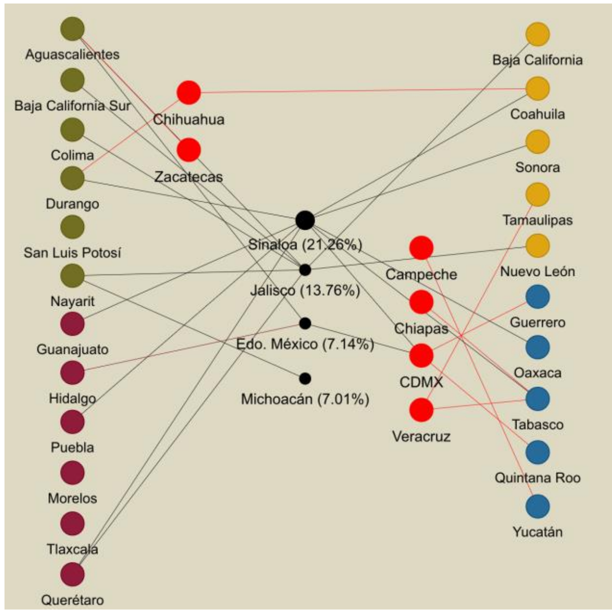
b) Precipitation



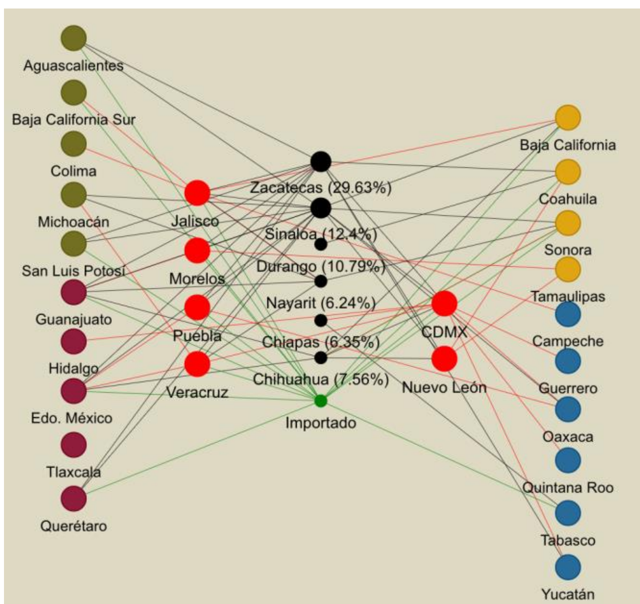
Note: Dark lines identify the regional average whereas light gray lines identify the average for every state located in the region.
Source: Own elaboration based on Thornton et al. (2020) and SIAP (2021c).

Figure A4. Commercialization patterns among Mexican states, continued

a) White corn

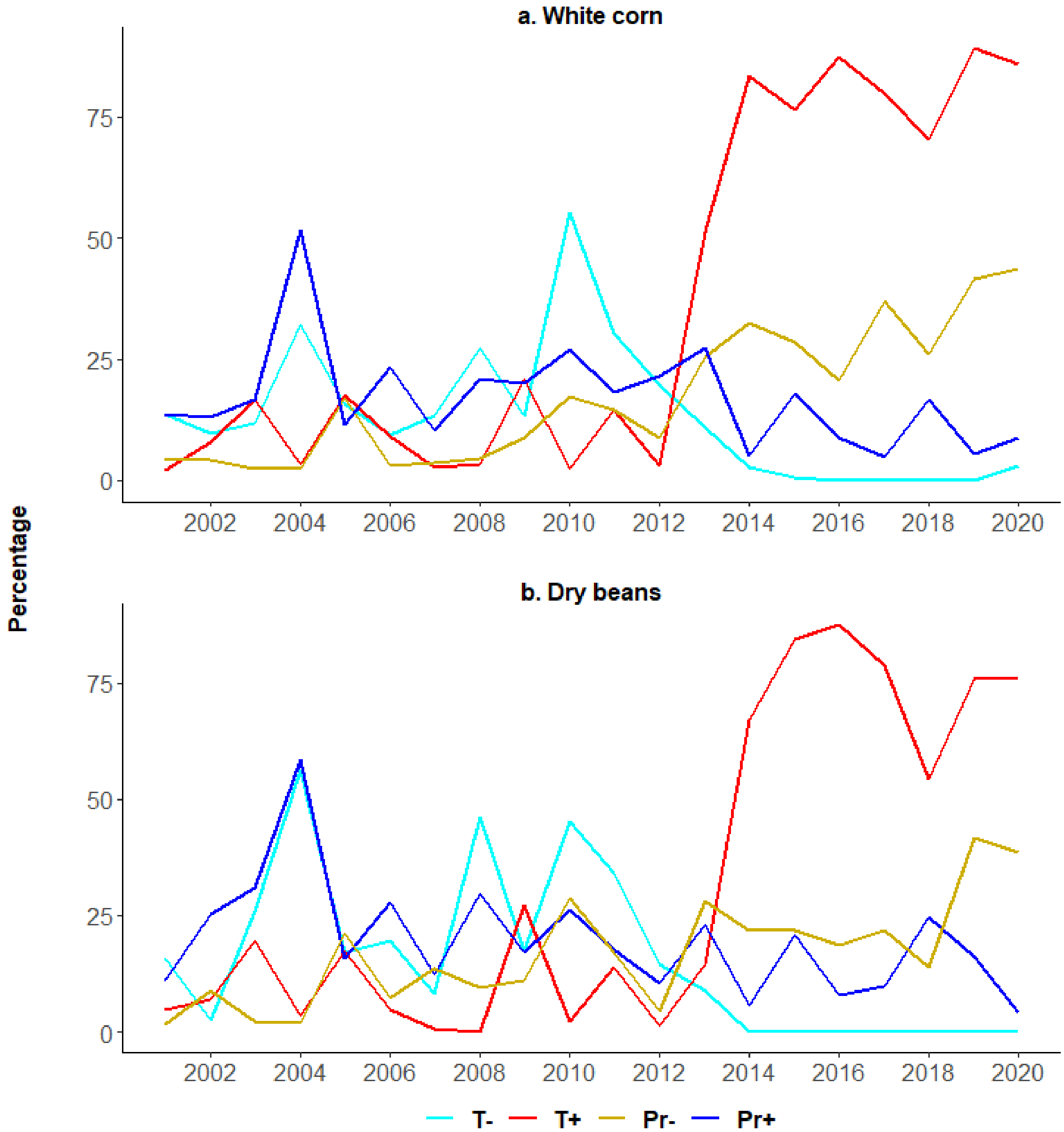


b) Dry beans



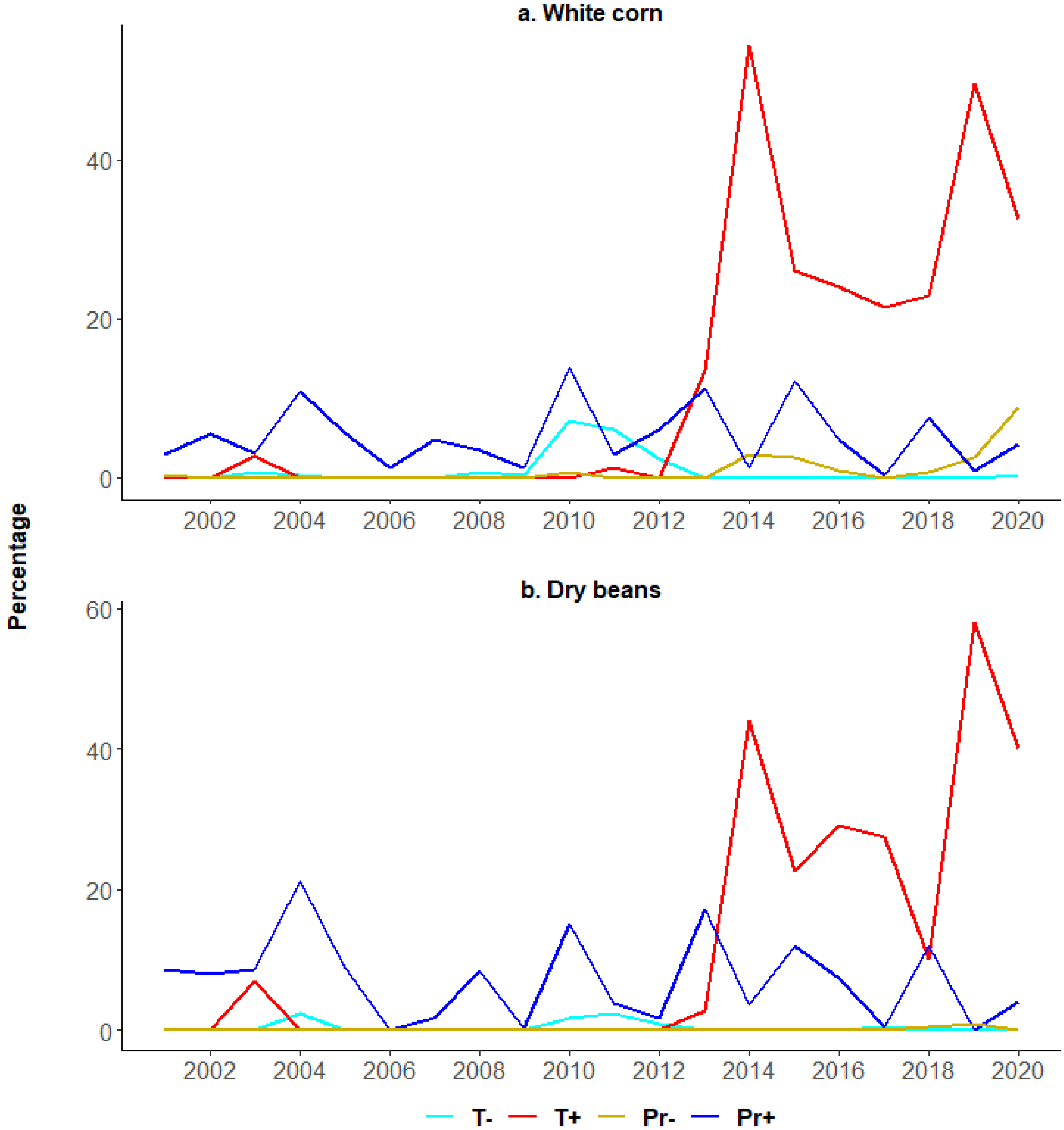
Note: The figure shows the commercialization patterns of white corn and dry beans among Mexican states. Black dots identify producing states that concentrate at least 60% of historic production during the period 2004-2020. The size of each black dot is proportional to the share of each producing state in total historic production (in parhentesis). Red dots represent intermediary states. Lines connecting states indicate that a commercialization link exists between them.
Source: Own elaboration based on data from SIAP (2021b) and SNIIM (2021).

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



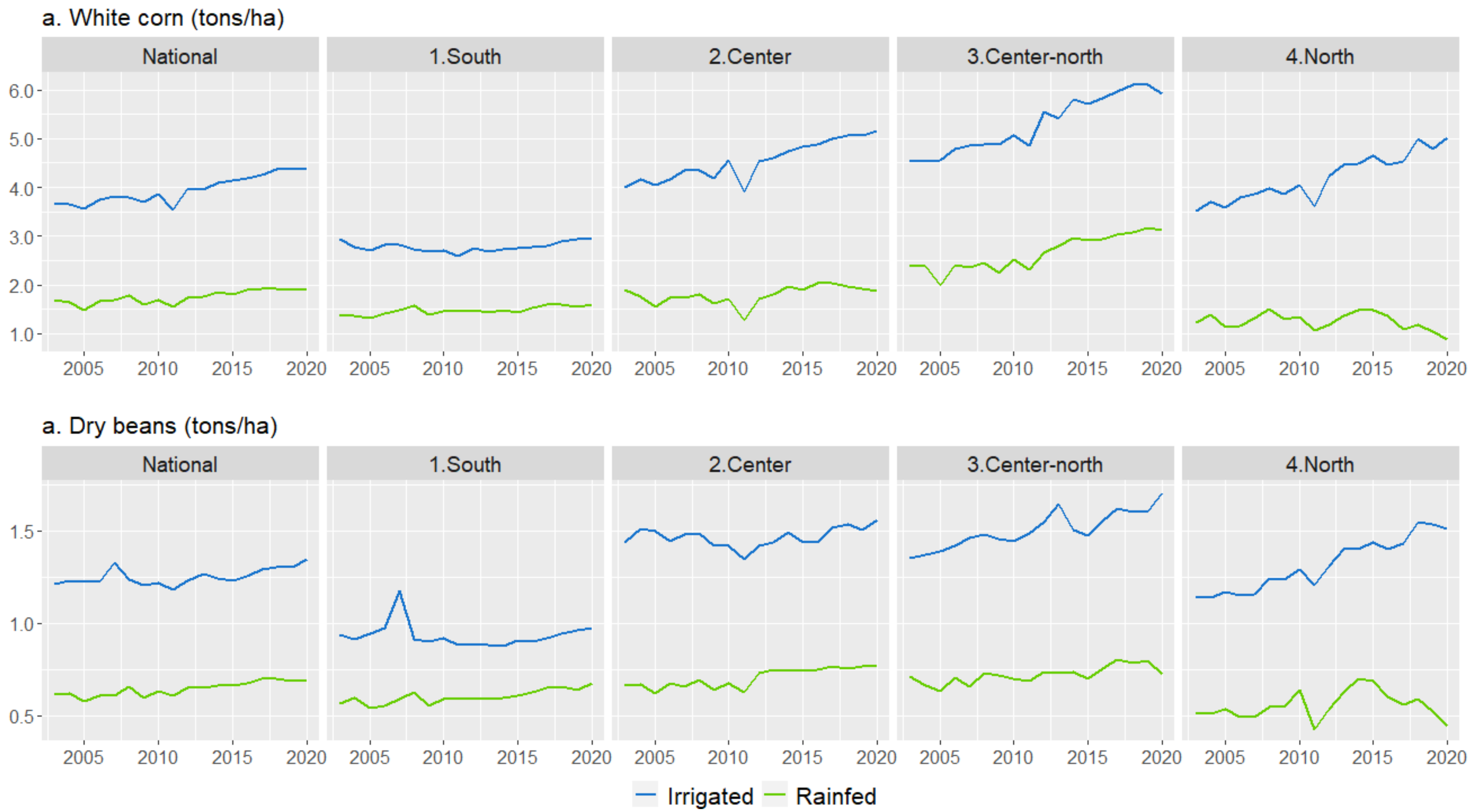
Source: Own elaboration based on Thornton et al. (2020), SIAP (2021b and 2021c), and SNIIM (2021).

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 SNIIM (2021).

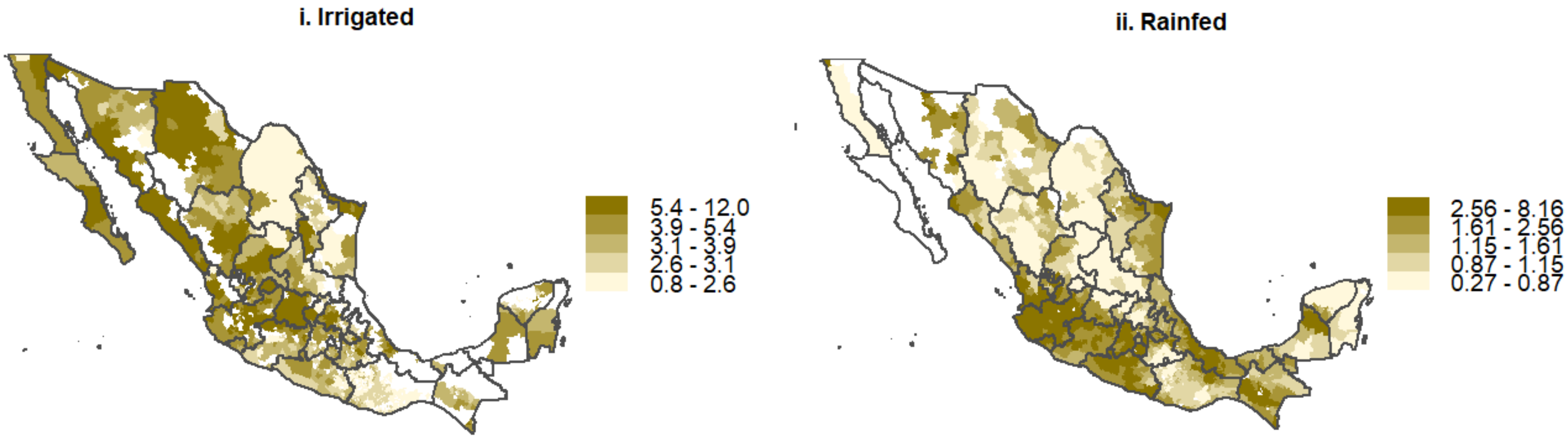
Figure A7. National and regional trends of white corn and dry beans yields



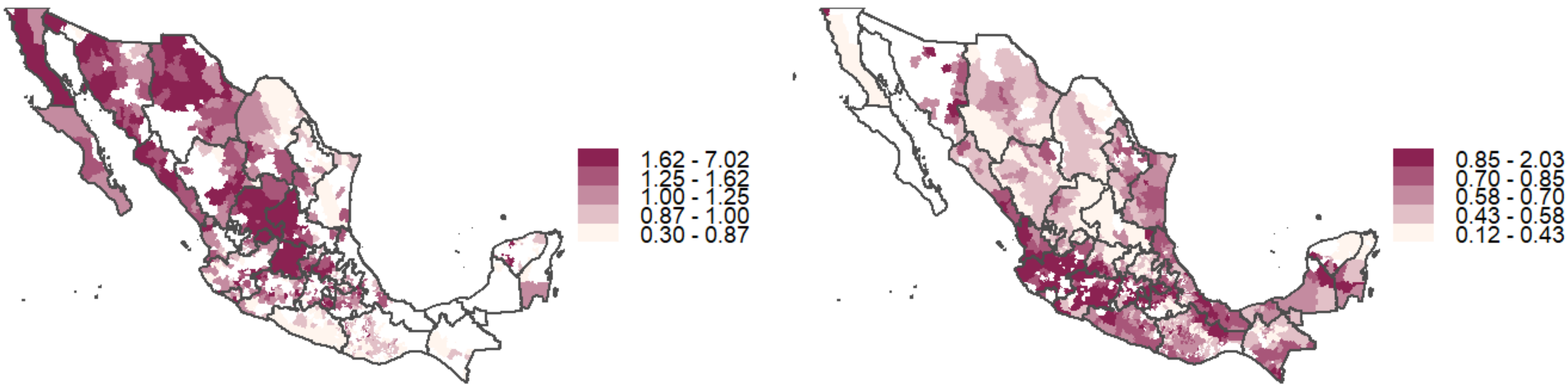
Note: The regional distribution of the 32 states of Mexico can be seen in Figure A2 (in the appendix).
Source: Own elaboration using production data from SIAP (2021a).

Figure A8. Average crop yields at the municipality level (tons/ha), 2003-2020

a) White corn



b) Dry beans



Note: Maps show the average yield of white corn (panel a) and dry beans (panel b) under rainfed and irrigated conditions for the period 2003-2020. Between 2003 and 2020, irrigated and rainfed white corn yields are observed in 1,563 and 2,355 municipalities, respectively. Irrigated and rainfed dry bean yields are observed in 1,168 and 1,986 municipalities, respectively.

Source: Own elaboration using production data from SIAP (2021a).

Table A1. Unit root tests of the white corn and dry beans price series

Test Name	Null Hypothesis	Alternative Hypothesis	Statistic	Value	p-value	Panels
a) White corn						
Levin–Lin–Chu	Panels contain unit roots	Panels are stationary	Adjusted t*	-4.2613	0.0000	6
Harris-Tzavalis	Panels contain unit roots	Panels are stationary	rho Z	-8.8130	0.0000	6
Breitung	Panels contain unit roots	Panels are stationary	lambda	-3.5670	0.0000	6
Im–Pesaran–Shin	All panels contain unit roots	Some panels are stationary	Z-t-tilde-bar	-12.1084	0.0000	24
Hadri LM test	All panels are stationary	Some panels contain unit roots	z	96.7153	0.0000	6
Fisher-type, based on augmented Dickey–Fuller tests	All panels contain unit roots	At least one panel is stationary	Inverse chi-squared P	223.6439	0.0000	24
			Inverse normal Z	-9.1286	0.0000	
			Inverse logit t L*	-11.5915	0.0000	
			Modified inv. chi-squared Pm	17.9266	0.0000	
Fisher-type, based on Phillips–Perron tests			Inverse chi-squared P	234.1553	0.0000	24
			Inverse normal Z	-9.4475	0.0000	
			Inverse logit t L*	-12.2117	0.0000	
			Modified inv. chi-squared Pm	18.9994	0.0000	
c) Dry beans						
Levin–Lin–Chu			Adjusted t*	-6.2103	0.0000	45
Harris-Tzavalis	Panels contain unit roots	Panels are stationary	rho Z	-12.6715	0.0000	45
Breitung			lambda	-5.5589	0.0000	45
Im–Pesaran–Shin	All panels contain unit roots	Some panels are stationary	Z-t-tilde-bar	-11.7551	0.0000	45
Hadri LM test	All panels are stationary	Some panels contain unit roots	z	202.0166	0.0000	45
Fisher-type, based on augmented Dickey–Fuller tests	All panels contain unit roots	At least one panel is stationary	Inverse chi-squared P	266.2190	0.0000	45
			Inverse normal Z	-9.7269	0.0000	
			Inverse logit t L*	-10.2736	0.0000	
			Modified inv. chi-squared Pm	13.1346	0.0000	
Fisher-type, based on Phillips–Perron tests			Inverse chi-squared P	238.6856	0.0000	45
			Inverse normal Z	-8.5200	0.0000	
			Inverse logit t L*	-8.9787	0.0000	
			Modified inv. chi-squared Pm	11.0824	0.0000	

Note: All the test presented in this table are performed using the *xtunitroot* routine of Stata. In all of them, a time trend is included and cross-sectional means are removed to mitigate the effects of cross-sectional correlation. For the Fisher type tests, we assume that the data is generated by an AR(1) process and so, one lag of the dependent variable is included. The Levin–Lin–Chu, Harris-Tzavalis, Breitung and Hadri LM tests require strongly balanced panel data. Because of this, in the case of white corn, they were performed using only the subset of 6 cities for which this condition was met. The Im–Pesaran–Shin does not require strongly balanced panel data but there can be no gaps in each individual time series. For the Fisher-type tests strongly balanced data is not required and the individual series can have gaps.

Table A2. Summary statistics of the variables used in the price regressions (mean values)

	(1) National	(2) 1. South	(3) 2. Center	(4) 3. Center North	(5) 4. North
a) White corn					
Price ($/kg)	6.301	5.7414	5.148	6.7806	6.8043
T^{-}					
0.5 s.d.	0.2974	0.2768	0.3042	0.3052	0.2912
1.0 s.d.	0.1356	0.1253	0.1381	0.1405	0.1315
2.0 s.d.	0.0092	0.0211	0.0127	0.0055	0.0045
T^{+}					
0.5 s.d.	0.5229	0.5337	0.5161	0.5184	0.5297
1.0 s.d.	0.3646	0.3642	0.3619	0.3679	0.3611
2.0 s.d.	0.1246	0.1442	0.1356	0.1145	0.1204
Pr^{-}					
0.5 s.d.	0.4753	0.5674	0.4949	0.4062	0.523
1.0 s.d.	0.1731	0.3358	0.1822	0.1303	0.1308
2.0 s.d.	0.0093	0.0105	0.0068	0.0118	0.0059
Pr^{+}					
0.5 s.d.	0.2782	0.3284	0.3034	0.2542	0.2660
1.0 s.d.	0.1717	0.1926	0.1831	0.1583	0.1724
2.0 s.d.	0.0528	0.0516	0.0475	0.0537	0.0565
Observations	6,009	950	1,180	2,533	1,346
b) Dry beans					
Price ($/kg)	19.72	19.3641	19.7161	19.9664	19.8233
T^{-}					
0.5 s.d.	0.3442	0.3507	0.3458	0.3385	0.3423
1.0 s.d.	0.1564	0.166	0.1563	0.1510	0.1526
2.0 s.d.	0.0036	0.0073	0.0031	0.0028	0.0013
T^{+}					
0.5 s.d.	0.4971	0.5149	0.4948	0.4781	0.4997
1.0 s.d.	0.3199	0.3299	0.312	0.3170	0.3183
2.0 s.d.	0.1205	0.1319	0.1193	0.1139	0.1167
Pr^{-}					
0.5 s.d.	0.4844	0.5274	0.4599	0.4344	0.5061
1.0 s.d.	0.1667	0.2340	0.1526	0.1253	0.1513
2.0 s.d.	0.0007	0.0014	0.0000	0.0014	0.0000
Pr^{+}					
0.5 s.d.	0.2949	0.3299	0.2932	0.2566	0.2990
1.0 s.d.	0.1973	0.2139	0.1969	0.1729	0.2048
2.0 s.d.	0.0710	0.0712	0.0714	0.0740	0.0679
Observations	10,800	2,880	1,920	2,880	3,120

Source: Own elaboration based on data from INEGI (2021), 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	0.0299	0.0513			
	(0.0121)	(0.0183)	(0.0395)			
P^-_{t-0}	0.0160**	0.0576**	0.0525	0.0075	0.0176**	0.0802*
	(0.0066)	(0.0252)	(0.0543)	(0.0066)	(0.0084)	(0.0399)
P^-_{t-1}	0.0171**	0.0405*	0.0449	0.0113*	0.0182**	0.0742*
	(0.0068)	(0.0209)	(0.0464)	(0.0065)	(0.0069)	(0.0427)
P^-_{t-2}	0.0176**	0.0338	0.0382	0.0117*	0.0166**	0.0648
	(0.0083)	(0.0199)	(0.0505)	(0.0064)	(0.0070)	(0.0399)
P^-_{t-3}	0.0093	0.0310	-0.0237	0.0149**	0.0203**	0.0773**
	(0.0067)	(0.0183)	(0.0269)	(0.0068)	(0.0084)	(0.0359)
P^-_{t-4}	0.0076	0.0276*	0.0067			
	(0.0063)	(0.0158)	(0.0255)			
P^-_{t-5}	0.0112*	0.0323	-0.0595			
	(0.0063)	(0.0204)	(0.0387)			
P^+_{t-0}	-0.0161*	-0.0033	0.0054	-0.0004	0.0046	0.0039
	(0.0079)	(0.0072)	(0.0097)	(0.0054)	(0.0080)	(0.0115)
P^+_{t-1}	-0.0161	-0.0003	0.0036	-0.0034	0.0012	-0.0025
	(0.0098)	(0.0081)	(0.0085)	(0.0055)	(0.0082)	(0.0112)
P^+_{t-2}	-0.0159	-0.0020	0.0027	0.0013	0.0046	0.0045
	(0.0101)	(0.0086)	(0.0097)	(0.0055)	(0.0083)	(0.0105)
P^+_{t-3}	-0.0145*	-0.0024	0.0037	0.0026	0.0039	0.0115
	(0.0081)	(0.0094)	(0.0091)	(0.0061)	(0.0096)	(0.0111)
P^+_{t-4}	-0.0123*	-0.0062	0.0103			
	(0.0071)	(0.0070)	(0.0113)			
P^+_{t-5}	-0.0144**	-0.0107	0.0133			
	(0.0065)	(0.0063)	(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), SNIIM (2021), SIAP (2021b and 2021c), and Thornton et al. (2020).

Table A4. 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	0.0010	0.0059	-0.0031	-0.0211*	-0.0039
	(0.0067)	(0.0101)	(0.0305)	(0.0052)	(0.0105)	(0.0149)
T^{-}_{t-1}	0.0101	0.0172*	0.0055	-0.0032	-0.0168**	-0.0055
	(0.0061)	(0.0097)	(0.0250)	(0.0046)	(0.0082)	(0.0147)
T^{-}_{t-2}	0.0103*	0.0145	0.0083	-0.0014	-0.0203**	-0.0108
	(0.0054)	(0.0131)	(0.0231)	(0.0053)	(0.0096)	(0.0150)
T^{-}_{t-3}	0.0150**	0.0121	0.0060	-0.0018	-0.0201*	-0.0074
	(0.0061)	(0.0112)	(0.0185)	(0.0059)	(0.0100)	(0.0191)
T^{-}_{t-4}	0.0097	0.0165*	0.0065			
	(0.0058)	(0.0096)	(0.0231)			
T^{-}_{t-5}	0.0146*	0.0209*	-0.0014			
	(0.0073)	(0.0111)	(0.0240)			
T^{+}_{t-0}	0.0174	0.0207	0.0322	0.0149*	0.0140**	0.0182**
	(0.0122)	(0.0185)	(0.0193)	(0.0084)	(0.0069)	(0.0081)
T^{+}_{t-1}	0.0199*	0.0164	0.0501	0.0109	0.0118*	0.0138
	(0.0102)	(0.0147)	(0.0328)	(0.0076)	(0.0066)	(0.0083)
T^{+}_{t-2}	0.0206*	0.0209*	0.0578*	0.0098	0.0076	0.0120
	(0.0113)	(0.0122)	(0.0338)	(0.0075)	(0.0070)	(0.0088)
T^{+}_{t-3}	0.0212	0.0219	0.0552	0.0058	0.0052	0.0097
	(0.0125)	(0.0147)	(0.0338)	(0.0078)	(0.0083)	(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), SNIIM (2021), SIAP (2021b and 2021c), and Thornton et al. (2020).

Table A5. Spatial panel estimates of the effect of weather shocks on the price of white corn and dry beans using a spatial error model

	0.5 s.d.			1.0 s.d.			2.0 s.d.		
	(1) 2 neighbors	(2) 6 neighbors	(3) 10 neighbors	(4) 2 neighbors	(5) 6 neighbors	(6) 10 neighbors	(7) 2 neighbors	(8) 6 neighbors	(9) 10 neighbors
T^-_{t-0}	0.0108*	0.0089	0.0089	-0.0136	-0.0144*	-0.0140*	-0.0091	-0.0163	-0.0204
	(0.0065)	(0.0064)	(0.0063)	(0.0084)	(0.0083)	(0.0082)	(0.0207)	(0.0202)	(0.0196)
T^-_{t-1}	0.0095	0.0079	0.0072	-0.0068	-0.0073	-0.0072	-0.0180	-0.0237	-0.0270
	(0.0064)	(0.0064)	(0.0063)	(0.0084)	(0.0083)	(0.0081)	(0.0207)	(0.0202)	(0.0197)
T^-_{t-2}	0.0119*	0.0089	0.0091	-0.0104	-0.0105	-0.0106	-0.0212	-0.0216	-0.0238
	(0.0064)	(0.0063)	(0.0062)	(0.0084)	(0.0083)	(0.0081)	(0.0206)	(0.0201)	(0.0196)
T^-_{t-3}	0.0113*	0.0085	0.0082	-0.0085	-0.0085	-0.0083	-0.0170	-0.0210	-0.0238
	(0.0063)	(0.0063)	(0.0062)	(0.0083)	(0.0082)	(0.0080)	(0.0206)	(0.0201)	(0.0195)
T^+_{t-0}	0.0137**	0.0120**	0.0119**	0.0080	0.0088	0.0093	0.0016	0.0023	0.0021
	(0.0056)	(0.0056)	(0.0054)	(0.0060)	(0.0060)	(0.0059)	(0.0085)	(0.0084)	(0.0082)
T^+_{t-1}	0.0075	0.0066	0.0064	0.0052	0.0063	0.0072	0.0008	0.0014	0.0013
	(0.0056)	(0.0056)	(0.0054)	(0.0061)	(0.0060)	(0.0059)	(0.0086)	(0.0084)	(0.0082)
T^+_{t-2}	0.0070	0.0068	0.0063	0.0036	0.0048	0.0055	-0.0013	0.0001	0.0009
	(0.0056)	(0.0055)	(0.0054)	(0.0061)	(0.0060)	(0.0059)	(0.0088)	(0.0087)	(0.0085)
T^+_{t-3}	0.0055	0.0057	0.0056	0.0026	0.0038	0.0054	-0.0063	-0.0046	-0.0038
	(0.0056)	(0.0055)	(0.0054)	(0.0060)	(0.0060)	(0.0059)	(0.0091)	(0.0089)	(0.0088)
P^-_{t-0}	0.0020	0.0023	0.0030	0.0101*	0.0094*	0.0105*	0.0782*	0.0823*	0.0745*
	(0.0045)	(0.0044)	(0.0044)	(0.0055)	(0.0055)	(0.0054)	(0.0435)	(0.0432)	(0.0421)
P^-_{t-1}	0.0067	0.0059	0.0063	0.0112**	0.0106*	0.0110**	0.0735*	0.0791*	0.0702*
	(0.0044)	(0.0044)	(0.0044)	(0.0056)	(0.0056)	(0.0055)	(0.0435)	(0.0432)	(0.0422)
P^-_{t-2}	0.0078*	0.0068	0.0073*	0.0095*	0.0095*	0.0100*	0.0721*	0.0775*	0.0693
	(0.0044)	(0.0044)	(0.0044)	(0.0056)	(0.0056)	(0.0055)	(0.0435)	(0.0433)	(0.0422)
P^-_{t-3}	0.0110**	0.0102**	0.0107**	0.0127**	0.0131**	0.0137**	0.0857**	0.0862**	0.0769*
	(0.0044)	(0.0044)	(0.0043)	(0.0056)	(0.0056)	(0.0055)	(0.0434)	(0.0431)	(0.0421)
P^+_{t-0}	-0.0025	-0.0024	-0.0028	0.0091	0.0090	0.0089	0.0078	0.0109	0.0110
	(0.0050)	(0.0049)	(0.0049)	(0.0056)	(0.0055)	(0.0054)	(0.0097)	(0.0097)	(0.0096)
P^+_{t-1}	-0.0048	-0.0045	-0.0048	0.0045	0.0050	0.0048	0.0018	0.0043	0.0045
	(0.0050)	(0.0049)	(0.0049)	(0.0056)	(0.0055)	(0.0054)	(0.0097)	(0.0097)	(0.0096)
P^+_{t-2}	-0.0004	-0.0001	-0.0004	0.0072	0.0074	0.0073	0.0107	0.0120	0.0116
	(0.0049)	(0.0049)	(0.0048)	(0.0055)	(0.0055)	(0.0054)	(0.0097)	(0.0097)	(0.0096)
P^+_{t-3}	-0.0002	-0.0002	-0.0002	0.0055	0.0057	0.0058	0.0130	0.0134	0.0134
	(0.0049)	(0.0049)	(0.0048)	(0.0055)	(0.0054)	(0.0053)	(0.0094)	(0.0093)	(0.0092)
λ	0.2164***	0.3025***	0.4530***	0.2158***	0.3042***	0.4553***	0.2198***	0.3104***	0.4577***
	(0.0092)	(0.0136)	(0.0155)	(0.0092)	(0.0135)	(0.0155)	(0.0092)	(0.0134)	(0.0154)
R^2	0.0703	0.1166	0.1193	0.1794	0.1925	0.2037	0.0122	0.0036	0.0021
N	10,800	10,800	10,800	10,800	10,800	10,800	10,800	10,800	10,800

Note: Results shown in this table were obtained from the estimation of a spatial error model limiting the correlation among errors to the 2 (columns 1, 4 and 7), 6 (columns 2, 5 and 8) and 10 (columns 3, 6 and 9) nearest neighbors. The Moran´s I test for spatial autocorrelation rejects the null hypothesis of spatial independence in 78% of the time periods contained in the analysis (240 consecutive months) when only the 2 nearest neighbors are considered. This percentage drops to 38% and 15% for the 6 and 10 nearest neighbors. Regressions are weighted by the share of each city on the national CPI and include city and year-month fixed effects. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

Table A6. Summary statistics of the variables used in the yield regressions (mean values)

	(1) National	(2) 1. South	(3) 2. Center	(4) 3. Center North	(5) 4. North
White corn					
a. Rainfed					
Yield(tons/ha)	1.7642	1.4957	1.8011	2.6518	1.2611
Temperature (ºC)	22.3282	23.5367	19.2959	22.3873	23.7815
Precipitation (cm)	70.1651	79.2645	67.3554	56.5518	39.7361
Observations	47,412	24,938	11,346	8,538	2,590
b. Irrigated					
Yield(tons/ha)	3.9618	2.7863	4.5404	5.2812	4.1451
Temperature (ºC)	21.0971	21.7663	18.6511	21.6964	24.1965
Precipitation (cm)	41.2661	40.3809	49.5957	37.7623	28.1374
Observations	30,213	12,198	8,494	6,758	2,763
Dry beans					
a. Rainfed					
Yield(tons/ha)	0.6489	0.6094	0.7052	0.7207	0.558
Temperature (ºC)	21.3452	22.1858	18.8746	21.612	23.5735
Precipitation (cm)	67.064	76.727	65.5922	48.8921	39.7631
Observations	31,132	16,268	7,780	5,220	1,864
b. Irrigated					
Yield(tons/ha)	1.2551	0.9356	1.4666	1.5009	1.3015
Temperature (ºC)	20.8069	21.4682	18.6759	20.7636	24.6839
Precipitation (cm)	37.7969	36.9209	50.2363	27.9281	27.0106
Observations	17,510	6,697	5,117	3,981	1,715

Source: Own elaboration based on data from SIAP (2021a and 2021c) and Thornton et al. (2020).