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Temperature shocks and their effect on the price of agricultural products: panel data evidence from vegetables in Mexico*

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Abstract: In this paper, we estimate the effect of temperature shocks on the price of nine vegetables with a high contribution to Mexico's non core inflation. We utilize monthly panel data of the price index of each vegetable at the city level which we combine with high resolution weather data of the producing states. For every city, we construct a relevant temperature measure by weighting the different temperatures of its supplier states using historic production shares and distance. Our findings elicit a convex U-shaped relationship between temperature and vegetable prices and a high sensitivity of the latter to contemporaneous and lagged temperature shocks that occur within their growing period. Our findings also suggest that temperature shocks may have a detrimental effect on vegetable yields which may be an important driver of the impact on prices.
Keywords: Food Inflation, Weather Shocks, Vegetable Prices, Local Markets
JEL Classification: E31, Q15, Q54

Resumen: En este artículo estimamos el efecto de choques de temperatura en el precio de nueve hortalizas con una elevada contribución a la inflación no subyacente en México. Utilizamos datos en panel mensuales del INPC de cada hortaliza a nivel de ciudad y datos de alta resolución del clima en los estados productores. Para cada ciudad, se generó una temperatura relevante ponderando las temperaturas de sus estados proveedores utilizando su producción histórica y distancia a la ciudad. Los resultados revelan una relación funcional convexa y en forma de U entre la temperatura y el precio de las hortalizas y una elevada sensibilidad de los precios a choques de temperatura contemporáneos o rezagados que ocurren durante su periodo de crecimiento. Los resultados también sugieren que los choques de temperatura pueden tener un efecto negativo en el rendimiento de las hortalizas mismo que sería un factor determinante del impacto de la temperatura en los precios.
Palabras Clave: Inflación en Alimentos, Choques de Clima, Precio de Hortalizas, Mercados Locales

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1. Introduction

The measurement of inflation considers two main aggregates, core and non-core inflation. The latter is typically considered a transitory influence on inflation and includes volatile items of the Consumer Price Index (CPI), such as energy and some food items. Usually, these short-run changes in inflation are formed from unexpected shocks that raise prices but are not likely to lead to a permanent increase in inflation (Wynne M. A., 2008). In Mexico, recent episodes of high inflation can be explained by temporary increases in non-core inflation. In particular, inflation in the *Fruits and Vegetables* component of non-core inflation has been the most volatile and explains about a third of the total non-core inflation observed between 2012 and 2020 (see Figure A1 in the Appendix).

Fruits and vegetables inflation may be caused by different supply and demand factors. On the demand side, the domestic price of vegetables could be highly sensitive to demand shocks from domestic and international markets (Banco de México, 2021). On the supply side, the price of vegetables could be responsive to the seasonality of their production cycle and unexpected weather shocks (frosts, heat waves, floods, droughts) that might affect their productivity. Depending on their magnitude, weather-driven productivity changes could decrease or increase the availability of vegetables in the market and modify their market price. The effect of weather shocks could be magnified if production is geographically concentrated in certain regions and if the local domestic market heavily depends on the production of the affected region. For example, towards the end of 2017, in the north of Mexico, a region of particular importance in vegetable production, was hit with extremely low temperatures. As a result, the supply of tomato, squash, tomatillo (green tomato) and onions in the overall Mexican market was reduced, which caused annual inflation in *Fruits and Vegetables* to increase from 14.9% in November 2017 to 20.7% in January 2018 (Banco de México, 2018).

In this paper, we estimate the functional relationship that exists between temperature and vegetable prices. We use monthly panel data of the price index of nine vegetables that together represent 30.9% of the weight assigned to the *Fruits and Vegetables* component of non-core inflation: squash, onion, chili pepper, tomato, cucumber, tomatillo, lettuce-cabbage and potato.[1] Our price index data varies at the city level and covers the period 2001-2020. We focus on vegetables because their production cycle is short (4 months long on average) which allows us to closely tie short run vegetable price movements with short run temperature shocks. We combine price index data with a unique dataset that contains the commercialization patterns of these vegetables among states. This information allows us to infer the supplier states for each city and construct a relevant temperature measure for each by combining the temperature of its supplier states using production and distance as weighting factors. Thus, our panel estimates capture the production and the commercialization patterns of each vegetable's market. Our estimation strategy relies on a fixed effects model in which present and past realizations of temperature are included as regressors.

Our results reveal a convex U-shaped relationship between temperature and vegetable prices in which very low or very high temperatures are associated with higher vegetable prices. This U-shaped relationship exists for current and past temperatures. Using the estimated functional relationship, we simulate the effect of temperature shocks on vegetable prices. Results from this simulation indicate that vegetable prices are highly sensitive to temperature shocks. For example, a decrease of 2 standard deviations (s.d.) below average temperature would immediately increase the price of squash and onion by 9.6% and 6.0% respectively. Similarly, a 2 s.d. increase above average temperature would immediately increase the price of squash (3.7%), chili pepper (3.3%) and tomatillo (3.3%). Temperature shocks also have lagged effects in the price of all the vegetables analyzed. For example, the price of tomatoes would increase by 5.6%, 2.5% and 9.2% in the first, second and third month after a 2 s.d. increase above average temperature. In general, temperature shocks of at least 2 s.d. raise vegetables prices by a magnitude that is larger than the average monthly change in prices observed during the sample period. Interestingly, the estimated impacts of temperature

[1] For the purposes of this article, by squash we refer to the Mexican variety known as *calabacita* (Mexican squash). Also, by chili pepper we refer to the *serrano* pepper also known as *chile verde* or green pepper. The pair lettuce-cabbage is bundled by INEGI in a single price index because of the similarities among them, including their price variations (INEGI, 2018).

shocks in vegetables prices are larger in markets closer to the main producing areas. Prices in markets surrounding an important producing area affected by a temperature shock could be the most sensitive because such markets are most likely to rely on local production to meet all of their local supply. Prices in markets located farther away might be less sensitive to temperature shocks because in those markets, supply could be fulfilled using a more diversified portfolio of suppliers. Overall, results indicate that temperature shocks are a driving force of upward pressures in vegetable prices and ultimately, inflation.

The convex U-shaped relationship between temperature and vegetable prices that we find is in line with the relationship typically found between temperature and agricultural yields in which very low or very high levels of temperature are associated with lower crop yields (Schlenker and Roberts, 2009; Burke and Emerick, 2016; Moore and Lobell, 2014; Mérrel and Gammans, 2021). This suggest that the productivity damages caused by temperature shocks could be the main mechanism by which they increase vegetable prices. In order to evaluate the hypothesis of productivity affectations, we estimate the link between temperature and vegetable yields using a fixed effects model that relies on vegetable yields and weather data at municipality level. This data varies by season (Spring-Summer, Fall-Winter) and covers the period 2003-2020. Our results reveal a concave inverted U-shaped relationship between temperature and vegetable yields. In general, temperature shocks of at least 2 s.d. above or below average seasonal temperature decrease vegetable productivity. Thus, the supply shortfalls caused by temperature shocks may ultimately lead to increased prices. The sensitivity of vegetable prices to current and past temperature shocks that we find could be due to productivity damages at different stages of the growing period of the vegetable (Ortiz-Bobea and Just, 2013, Ortiz-Bobea et al., 2019) and/or to the updating of supply and price expectations around the timing of the temperature shock (Letta et al., 2021). Our results indicate that vegetable markets adjust prices as a response to temperature shocks and the supply imbalances they create.

The contribution of this paper is threefold. First, this research contributes to the empirical evidence regarding the effect of weather on agricultural prices using panel data (Letta et al., 2021; Banco de México, 2021). Most of the available empirical analysis use time series techniques that rely on variation over time of aggregated measures of prices and weather (Banco de México, 2013; Abril-Salcedo et al., 2020; Ubilava, 2018; Ubilava and Holt, 2013; Ubilava, 2012; Bastiani et al., 2018). Instead, this paper relies on time and spatial variation of weather and prices at more disaggregated levels. Spatially, our price series vary at the 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 the local level affecting local production and prices. Then, it gets transmitted to other markets through commercial exchanges. 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, this research focuses on vegetables, a set of agricultural products that have received little attention in the literature linking weather with agricultural yields and prices. Most of the studies relating weather and yields have centered on grains (namely, corn, wheat, soybean, sorghum and rice) due to their importance in human caloric intake (Schlenker and Roberts, 2009, Burke and Emerick, 2016; Ortiz-Bobea et al., 2019; Welch et al., 2010; Tack et al., 2017). On the other hand, studies relating weather and prices have focused on aggregated food categories (Abril-Salcedo et *al.*, 2020; Banco de México, 2013; Cashin et al., 2017) or, again, on grains (Letta et al., 2021; Banco de México, 2021). This paper contributes to the literature by providing seminal evidence of the causal effect of weather on vegetable yields and prices.

Third, the findings of this paper corroborate 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 et al., 2017). In these settings, the understanding of weather-related risks as an underlying cause of food price increases may facilitate the design of policies seeking to reduce inflation. Besides upward pressures in food prices, weather shocks might also exacerbate inflation in other sectors as agricultural products are often inputs of other processed foods and of restaurant services. With climate change, the frequency and intensity of extreme weather events is expected to increase (Perkins-Kirkpatrick and Lewis, 2020;

Diffenbaugh, 2020), thus, upward pressures on inflation associated to higher agricultural prices could become larger and more frequent in the future.

The organization of this paper is as follows. In section 2 we review the existing literature investigating the effects of weather in food prices. In section 3, we provide some context about the production of vegetables in Mexico. In section 4, we derive a reduced form relationship between temperature and prices. In section 5, we lay out our empirical specification. In section 6, we describe the price and weather data used and the methodology implemented to construct a relevant temperature for each city. In section 7, we present the estimated functional relationship between temperature and weather. In section 8 we use it to simulate the effect of extreme increases in temperature on vegetable prices. In section 9, we deepen our analysis and explore the direct effect of temperature on vegetable yields. We conclude in section 10 by providing some insights on the relevance of these results for policy making.

2. Existing Literature

The role of temperature as a driving factor of agricultural prices has been investigated in previous literature. A first effect comes from the impact that weather shocks may have on agricultural yields. Previous literature has found evidence of a non-linear relationship between temperature and agricultural yields in which yields increase up to a certain temperature threshold, or optimum. Once this threshold is surpassed, yields start to decrease (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016; Moore and Lobell, 2014; Mérrel and Gammans, 2021). It follows that extreme temperatures, say, a frost or a heat wave, could have detrimental effects on agricultural yields reducing the availability of the crop in the market. As a result, extreme temperatures might drive prices up.

The direct effect of weather on agricultural prices has been explored using two main approaches. The first approach relies on time series techniques applied to aggregated measures of prices and weather. Much of the existing literature using time series techniques focus on *El Niño Southern Oscillation* (ENSO), a weather phenomenon that occurs in the tropical area of the Pacific Ocean which modifies weather in several countries and regions around the globe. For example, Ubilava (2018) and Ubilava and Holt (2013) deploy the smooth transition autoregressive framework to study how sea surface temperature anomalies (SST) (deviations from the historical mean) linked to ENSO determine the price dynamics of several agricultural commodities. These studies find a significant effect of SST anomalies on the price of coffee, vegetable oils, oilseeds, fishmeal and salmon. Results vary by commodity but, in general, positive anomalies (*El Niño* episodes) are associated with price increases while negative anomalies (*La Niña* episodes) result in prices decreases. Abril-Salcedo et al. (2020) also apply the smooth transition framework to investigate the influence of SST anomalies on food inflation in Colombia. They find that positive SST anomalies increase the growth rate of food inflation in this country by as much as 7.3% with the effect being observed between the fifth and ninth months following the shock. Bastianini et al. (2018) estimate a structural vector autoregression (VAR) to investigate the effect of SST ENSO anomalies on the production, exports, and international price of Colombian coffee. Their findings suggest that positive SST anomalies decrease coffee prices because higher temperatures stimulate the growth and flowering of coffee trees, which increases production (see also Ubilava, 2012). All of these findings are in line with Cashin et al. (2017) who estimate a Global VAR for 21 countries/regions. Their findings suggest that most countries in their sample experience short-run inflationary pressures following positive ENSO anomalies due, in part, to increased prices of non-fuel commodities, including agricultural raw materials.

The second approach relies on panel data. One of the advantages of this approach is that it utilizes weather and price information that is disaggregated temporally and spatially. The identifying variation in panel data comes from weather anomalies experienced at the local level which could, in turn, affect local prices. This is a more realistic representation of the causal effect that weather may have on price formation, which could be obscured when using aggregated data. Another advantage of the panel approach is the possibility to control for unobserved factors potentially correlated with weather using fixed effects which reduces the threat of omitted variable bias (Dell et al., 2014; Blanc and Schlenker, 2017). In spite of its advantages, the panel approach has been rarely used to investigate the direct effect of weather on prices. Maystadt and Ecker (2014) estimate the effect of weather anomalies on livestock prices and the probability of civil conflict in Somalia using monthly panel data for administrative regions. Their results indicate that larger temperature anomalies are associated a higher likelihood of conflict and that the main mechanism exacerbating civil unrest is the direct effect of weather anomalies on livestock prices. Letta et al. (2021) investigate the effect of weather anomalies on the local price of maize, 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 during the growing season increase the price of these crops, even before any harvest failure is materialized. Similarly, the Bank of Mexico used monthly panel data at the state level to conclude that episodes of low precipitation during the growing period of maize and dry beans increase their prices. The magnitude of the effect increases with the severity of rainfall scarcity (Banco de México, 2021).

This paper contributes to the nascent body of empirical evidence using panel data. Importantly, we propose a methodology to link weather in producing areas with prices in final markets which are often distant from each other.

3. The Context of Vegetable Production in Mexico

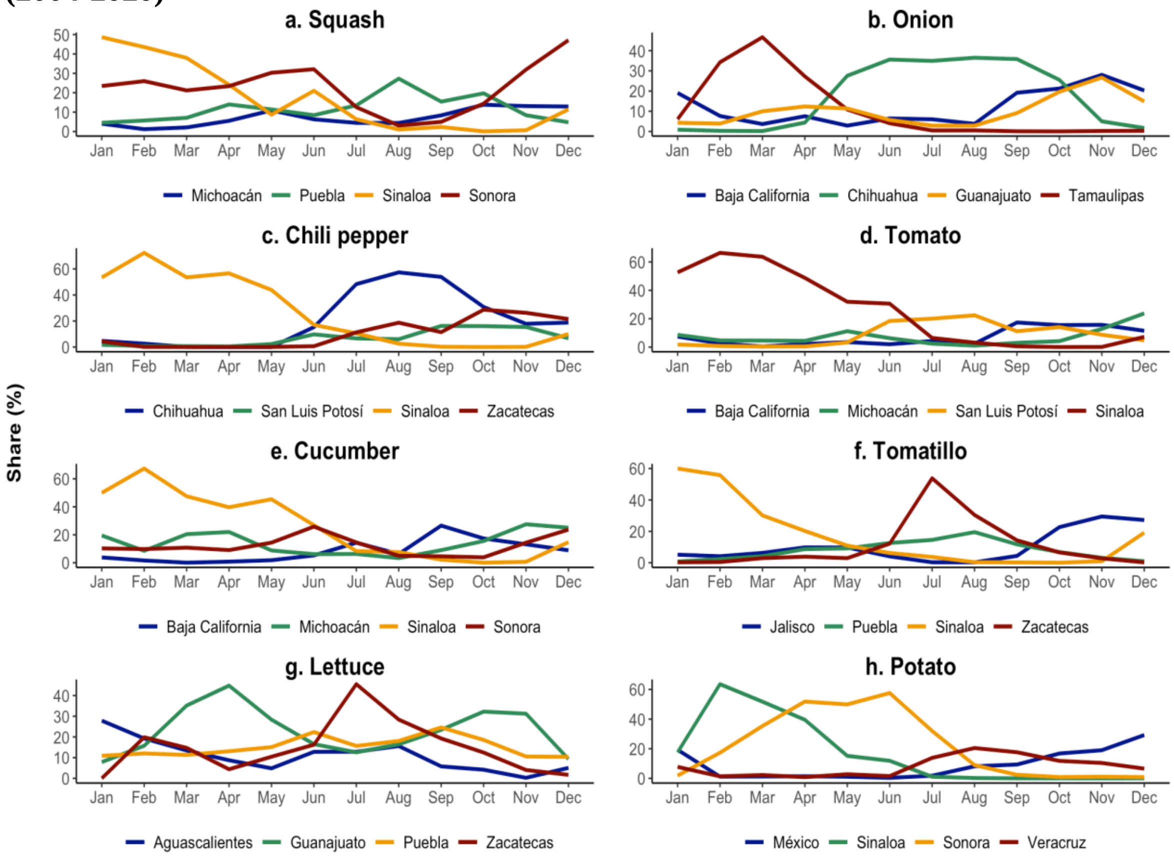
In Mexico, agriculture occurs in two different growing seasons, the Spring-Summer or rainy season which runs from April to September and the Fall-Winter or dry season which runs from October to March. Vegetable production is distributed almost evenly across seasons (52.7% of the value of vegetable production in 2020 was obtained in Spring-Summer) and is almost entirely produced under irrigated conditions (93.6% of the total value of vegetable production in 2020 was produced using irrigation). In the short run, this feature of vegetable production in Mexico makes it more susceptible to temperature shocks and less susceptible to precipitation shocks. In the medium and long run, sustained precipitation shocks might also reduce the amount of water available for irrigation.

Vegetable production is widely dispersed across Mexico; however, some states are particularly important at producing certain vegetables in specific months of the year. Figure 1 plots the share of the top four producers of each vegetable in historical monthly production for the period 2004-2020 (SIAP, 2020a). There are three results to highlight. First, the top four state producers are different for each vegetable, but in most cases, the northern states of Sinaloa, Sonora, Baja California, Chihuahua, Tamaulipas and Zacatecas concentrate a high share of vegetable historic production. This productive configuration makes vegetable supply particularly vulnerable to weather shocks that occur in those states.

Second, for some vegetables and during some months, the overall market heavily depends on the production of a single state. For example, in February, Sinaloa's tomato production is at its peak and concentrates 66.4% of the total production of tomatoes in Mexico. In this month, Sinaloa also concentrates a large proportion of the squash, chili pepper, cucumber, tomatillo and potato production.

Third, the overall vegetable supply evolves with the production cycle of the producing states. This generates different market configurations for each vegetable at different points in time. In some cases, an important state producer is replaced by another important state producer once the production cycle of the former is finished. Such is the case of onion and chili pepper. In other cases, once the production cycle of the top state producer concludes, vegetable supply is spread between several other states. This is the case of tomato and cucumber.

Figure 1. Share of the Top 4 State Producers on Historical Monthly Production (2004-2020)



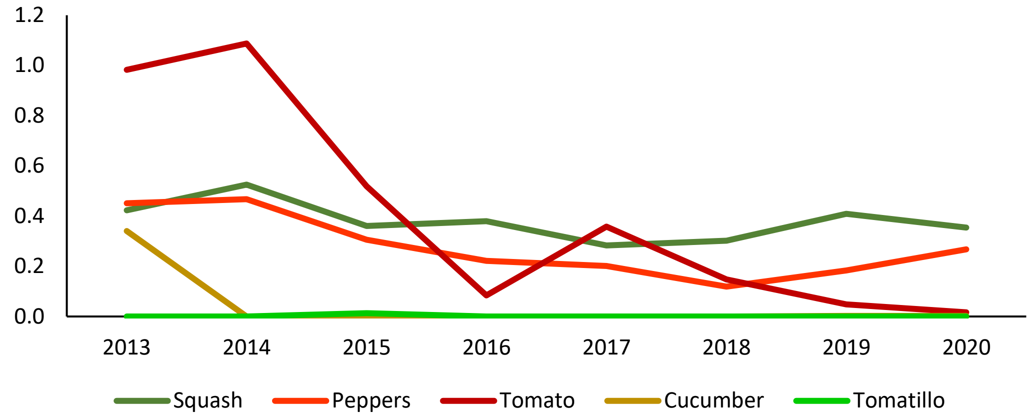
Note: Figure 1 plots the share of the top four producers of each vegetable in historical monthly production for the period 2004-2020. Monthly production data is available for this period only.
Source: Own elaboration using monthly production data from SIAP (2020a).

The changing conditions of the vegetable supply creates a dynamic setting of location and time in which temperature shocks, in certain states and months, matter more to price formation than in others. Consequently, monthly market prices will be responsive to temperature shocks experienced in states where production is highly concentrated in a particular month. This sensitivity varies with time as state producers substitute each other over the course of the year. Their effect on vegetable market prices could be magnified if the affected area is widely connected with markets through commercialization. For example, in February of 2011, the state of Sinaloa, a major vegetable producer, experienced freezing temperatures as low as -8^{o}C. February is when Sinaloa's production of several vegetables is at its peak (see Figure 1) (USDA, 2011). As a result of these frosts, more than 50% of the total area planted with tomato, squash and cucumber and about a third of the area planted with tomatillo and chili pepper were lost (SIAP, 2020a). This event had immediate consequences in their domestic prices. For example, the price of tomatoes sold in Sinaloa increased by 100% with large price increases also observed in other cities (González, 2011). This frost also had an important effect in the price of vegetables in the USA with reports of a 300% increase in tomato prices relative to prices a year before (Notimex, 2011). Mexico is the largest foreign supplier of vegetables to the USA (Davis et al., 2022), which explains the high influence of domestic supply shocks in the market prices of that country.

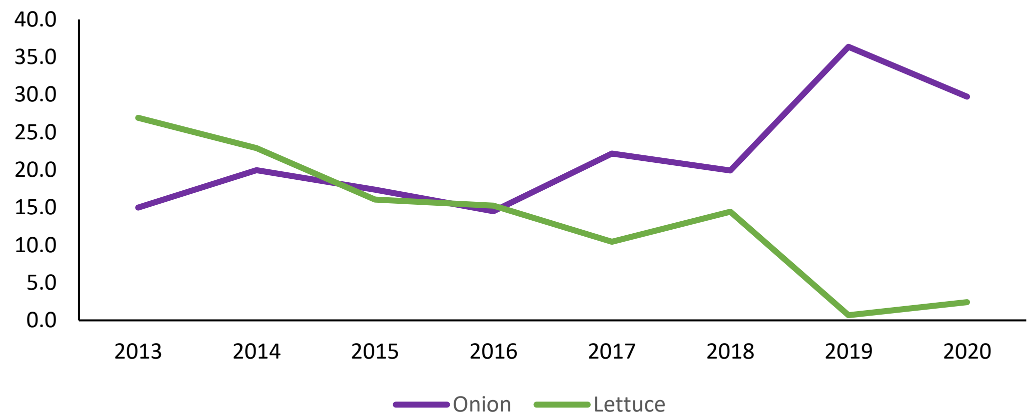
The sensitivity of vegetable prices to extreme weather events also depends on the ability of the market to substitute lost production with imports. Figure 2 shows the imports-to-exports ratio of the vegetables analyzed. Historically, imports of squash, peppers, tomato, cucumber and tomatillo have been low representing less than 1% of exports (panel a). For lettuce (panel b), the imports-to-exports ratio has decreased over time passing from 27.0% in 2013 to less than 3% in 2020. In contrast, the ratio for onions has increased to about 30% in 2020. Finally, while the imports-to-exports ratio for potatoes has decreased (panel c), by 2020, imports were still 30 times larger than exports. Overall, Figure 2 indicates that, for most of the vegetables analyzed, prices are mostly determined domestically with little influence from international prices. Because of this, domestic vegetable prices could be highly sensitive to the negative effects that domestic weather events could have in vegetable production. The price of onions and potatoes could be less affected given the higher reliance of the domestic market on imports. In these cases, international prices would be a major reference for domestic prices.

Figure 2. Imports-to-Exports Ratio for Each Vegetable (percentages)

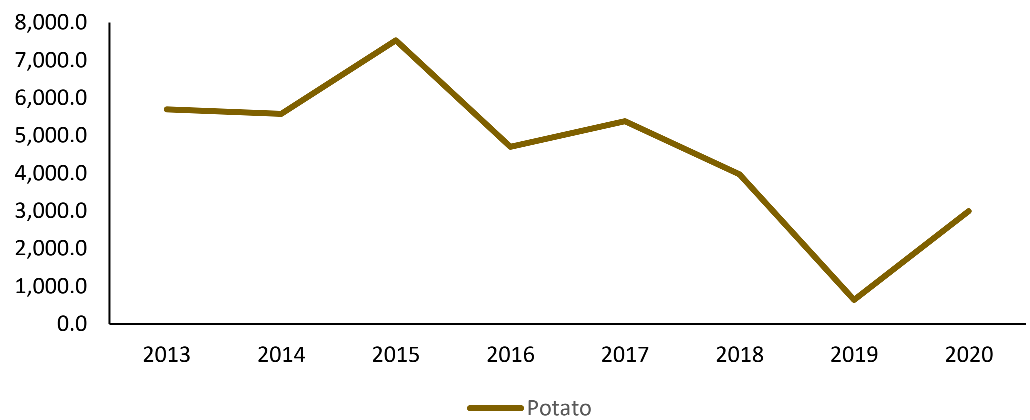
a) Low dependence



b) Moderate dependence



c) High dependence



Source: Own elaboration using data from SIAVI (2022).

Typically, when natural disasters impact agricultural production, imports of food products tend to increase. In some cases, this is facilitated by the elimination of tariffs and quotas for the affected goods (Forbes, 2013; Carbajal, 2022). Between 2003 and 2020, a total of 500 agricultural natural disasters were declared by the Mexican government, all associated with extreme temperature and precipitation events (SEMARNAT, 2022). Farmers located in municipalities covered by these declarations, affected by a natural disaster and without public or private insurance are granted access to governments funds in order to reduce their monetary losses and re-engage in agricultural production. While these funds help stabilize farmers´ income, they might not alleviate the immediate upward pressures in agricultural market prices associated to the possibility of a reduced supply because of the natural disaster.

4. A Reduced Form Relationship Between Temperature and Prices

In this section we present a conceptual framework to rationalize the empirical strategy adopted in the paper. A large body of literature has documented a robust influence of temperature on agricultural yields (Schlenker and Roberts, 2009; Burke and Emerick, 2016). Based on this evidence, we postulate that the main channel by which temperature shocks affect vegetable prices is through their effect on vegetable supply. We assume that the market of each vegetable is in equilibrium and that demand remains constant conditional on controls to generate a reduced form expression of prices as function of temperature using the supply curve.

Let Q_{it} represent the quantity supplied of vegetables in city *i* at time *t*. Also, let T_{it} be a relevant temperature measure for city *i* that somehow weights the temperatures of the N locations that produce vegetables and that supply them to city *i*. The supply of vegetables as function of relevant temperature is given by:

$$Q_{it} = f(T_{it}) \qquad (1)$$

Then, the (inverse) supply function of vegetables can be expressed as:

$$P_{it} = \alpha + \eta f(T_{it}) + \xi_{it} \qquad (2)$$

Equation (2) allows vegetables prices in city *i* to vary as a function of the temperatures observed in its N supplier states. If most of the vegetable supply of city *i* is locally produced, temperature shocks affecting local production will impact local price formation. On the contrary, if most of the vegetable supply of city *i* is imported from elsewhere, then, temperature shocks affecting production on those other areas will determine price formation. In Section 6, we describe the weighting procedure used to construct the relevant temperature measure introduced here.

The estimation of equation (2) yields unbiased parameter estimates of the relationship between temperature and prices as long as the relevant temperature is not correlated with other unknown determinants of vegetable supply and demand.

5. Empirical Strategy

To identify the effects of temperature shocks on vegetable prices, this paper deploys a fixed effects model using price index data at the city level. The estimation controls for unobserved time-invariant factors affecting vegetable prices using city fixed effects. We also control for precipitation in order to account for the possible correlation of local temperature variations with local precipitation variations (Burke et al., 2015). For each vegetable, we estimate the following equation:

$$lnP_{itj} = \delta + \sum_{s=0}^{S} \varphi_s T_{it,j-s} + \sum_{s=0}^{S} \gamma_s T_{it,j-s}^2 + \sum_{s=0}^{S} \alpha_s Pr_{it,j-s} + \sum_{s=0}^{S} \vartheta_s Pr_{it,j-s}^2 + \mu_i + \tau_{tj} + \epsilon_{itj} \quad (3)$$

where lnP_{itj} represents the logarithm of each vegetable's price index in city *i* in year *t* and month *j* which is modeled as a quadratic function of relevant temperature (*T*) and relevant precipitation (*Pr*). These relevant weather measures are constructed by weighting the temperature and precipitation of the different supplier states of the state where city *i* is located. Thus, cities located in the same state are assigned the same relevant weather. In our model, we limit the effect of weather on vegetable prices to the duration of their growing period, 4 months on average (Ruiz et al., 2013). As a result, the model includes up to 3 lags of temperature and precipitation (S=3). By including past realizations of relevant weather, the model allows for the possibility of delayed weather effects on vegetable prices. That is, the possible impact that past weather shocks may have had on vegetable productivity is known by markets at time t and contemporaneous vegetable prices would be adjusted accordingly.

The model includes city fixed effects (μ_i) and month-by-year fixed effects (τ_{tj}). City fixed effects control for all the common time-invariant factors at the city level explaining vegetable prices. Month-by-year fixed effects flexibly control for all the common time-varying factors affecting vegetable prices across markets in each month of the sample. In Mexico, vegetable production is highly seasonal. Because of the varying climatic conditions across the country, there are months when some vegetables are more abundant relative to other months which tends to lower the price. Our month-by-year fixed effects control for the common seasonality between weather and vegetable prices. They also control for any other time-varying factors that have determined vegetable prices over time and that are common to all cities such the evolution of transportation infrastructure, inputs costs and international trade. In our estimation, standard errors are clustered at the city and state-year levels to account for the potential correlation of errors over time in a given city and the potential correlation of errors due to yearly shocks affecting cities located in the same state.

The identifying assumption is that, conditional on μ_i and τ_{tj}, contemporaneous and lagged realizations of relevant weather are not correlated with the rest of unobserved determinants of vegetable prices at the city level (ϵ_{itj}). In other words, weather is expected to be randomly determined. The panel estimation relies on weather anomalies (deviations from the long-term climate) as the main source of identifying variation. Thus, in the very short run these deviations are generally random, unpredictable and unknown to economic agents which gives the fixed effects model strong foundations for causal interpretation (Dell et al., 2014; Blanc and Schlenker, 2017).

6. Data

6.1 Price data

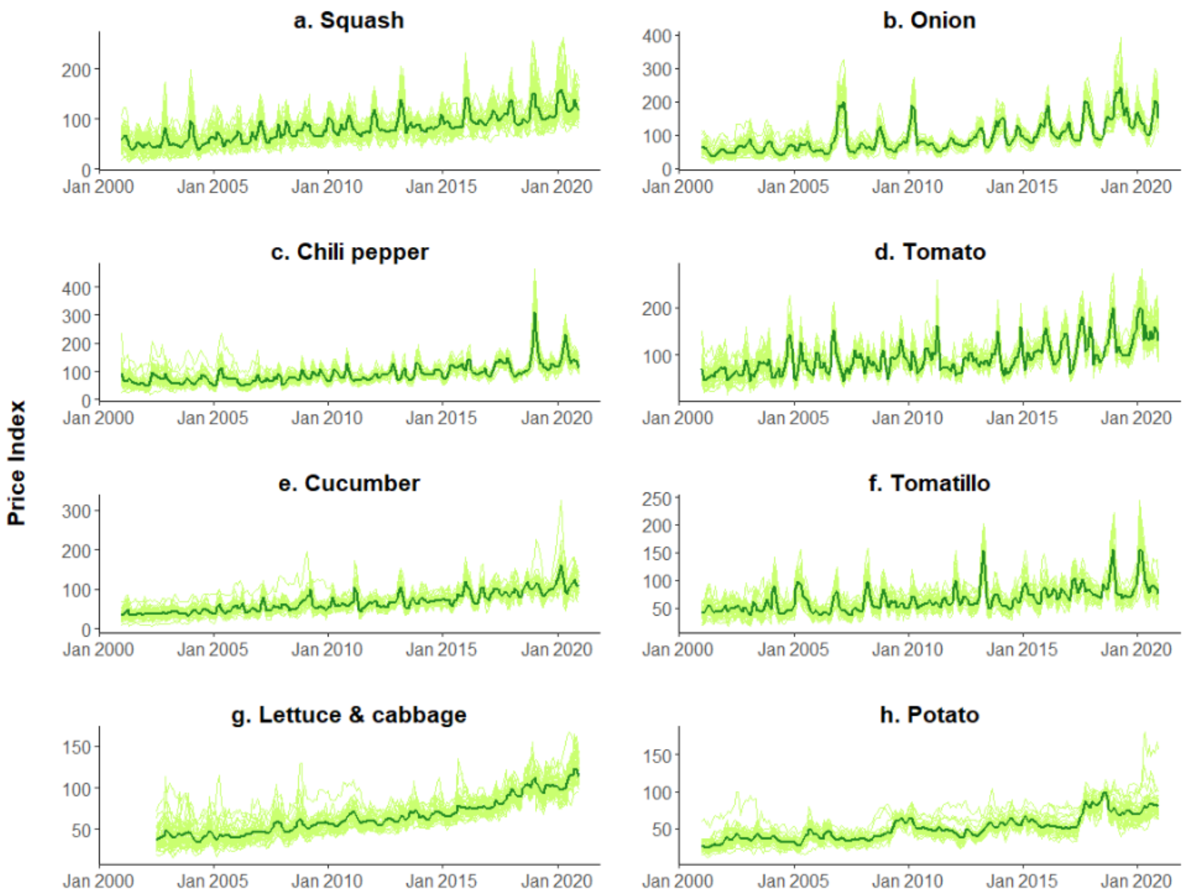
In this paper we model the relationship that exists between temperature and the price of nine vegetables: squash, onion, chili pepper, tomato, cucumber, tomatillo, lettuce, cabbage and potato. Together, these vegetables represent 30.9% of the weight assigned to the *Fruits and Vegetables* component of non-core inflation in Mexico. Time series of the price index for each vegetable are generated by the National Institute of Statistics and Geography (INEGI by its Spanish acronym). INEGI is the federal institution in charge of calculating and publishing the CPI. For this process, INEGI quotes the price of 299 different items in 55 large cities across Mexico. The price index for each of the vegetables analyzed is available at the city level. The pair lettuce-cabbage is bundled by INEGI in a single price index because of the similarities among them, including their price variations (INEGI, 2018). From the 55 cities, we excluded 10 cities from the sample because price index series for these cities were not available before July 2018 or because of the lack of the commercialization information necessary to identify supplier states.[2,3] Our final sample includes 45 cities and covers the period from January 2001 to December 2020. Figure A3 (in the Appendix) displays the location of the 45 cities included in the sample.

Figure 3 shows the evolution of each vegetable's price index during the sample period. Dark green lines refer to the national average while light green lines represent the price index series of each of the 45 cities in the sample. The price of the vegetables analyzed displays a large seasonal component. For example, the price of tomatoes (panel d) tends to increase toward the end of year, when the availability of tomatoes at the national level is low. Then, the price of tomatoes tends to decrease in February-March when the availability of tomatoes is high

[2] On July 2018, INEGI updated its methodology to generate the CPI. As part of this update, INEGI increased the number of cities from 46 to 55 (INEGI, 2018). The cities for which information is not available before July 2018 are Atlacomulco, Cancún, Coatzacoalcos, Esperanza, Izúcar de Matamoros, Pachuca, Saltillo, Tuxtla Gutiérrez y Zacatecas.
[3] The only city excluded due to the lack of commercialization information is Tlaxcala.

and the production of the state of Sinaloa, the largest tomato producer, is at its peak. Figure 3 also shows that vegetables prices vary substantially at the city level.

Figure 3. Evolution of Each Vegetable's Price Index, 2001-2020



Note: Dark green lines refer to the national average while light green lines depict the price series of each of the 45 cities in the sample, July 2018 =100.
Source: Own elaboration based on data from INEGI.

6.2 Weather data

Monthly weather data for the period 1980-2020 was obtained from DAYMET (Thornton et al., 2018), a gridded dataset distributed by the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC) with a spatial resolution of 1 km x 1 km for North America. DAYMET provides monthly averages for minimum and maximum temperature as well as monthly accumulated precipitation. Monthly average temperature results from averaging monthly maximum and minimum temperatures. Weather variables were created for each grid point and aggregated at the state level by averaging grid cell values over agricultural land in each state. To identify agricultural land, we relied on a map generated by the Mexican Ministry of Agriculture (SIAP, 2020b).[4] Thus, our analysis excludes weather data that is not relevant for agricultural purposes.

Figure 4 displays the monthly average temperature series generated for each of the 32 Mexican states (the geographical location of each state can be seen in Figure A2). The orange line highlights the case of Sinaloa, a major vegetable producer, while grey lines depict the temperature series of the other states. Monthly average temperature shows a large interannual and intra-annual variation oscillating between 5.7°C and 35.0°C during the sample period. Temperature also varies largely across space. The state of Sinaloa, for example, is among the hottest states with monthly average temperatures oscillating between 17.0°C and 35.0°C.

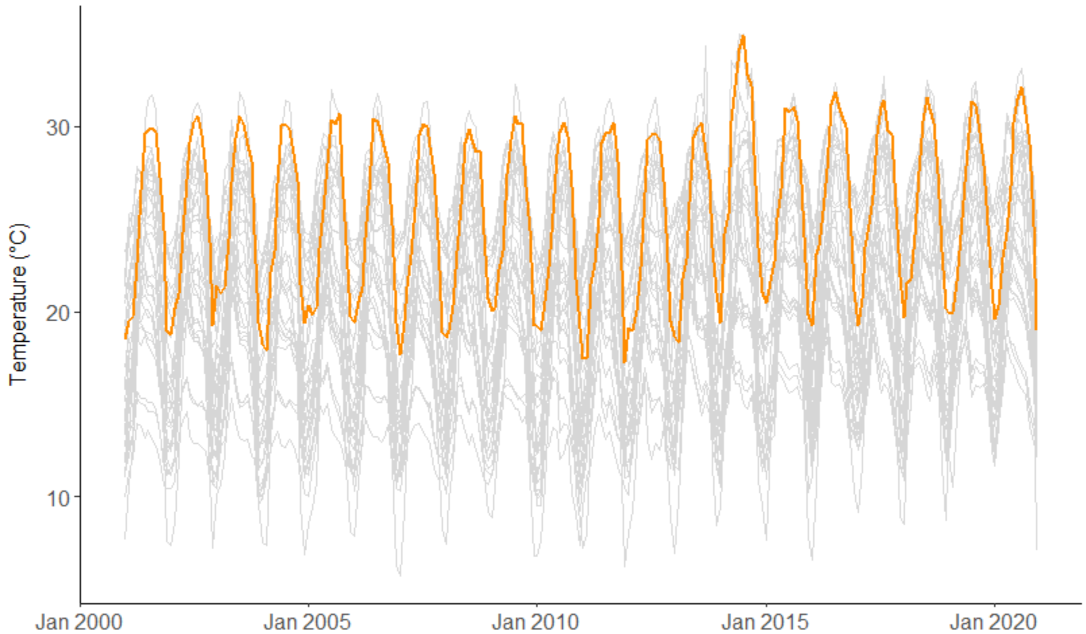
Figure 5 plots the corresponding monthly temperature deviations (anomalies) from the 1991-2020 temperature normal.[5] During the sample period, temperature deviations range from -5.3°C to 12.7°C. Sinaloa displays some of the largest anomalies. In February of 2011, this state experienced some of its lowest temperatures on record because of a cold snap that lasted almost a week. This caused major losses in winter-grown crops including vegetables (USDA, 2011; WMO, 2012). The temperature anomaly for that month was -2.7°C, the lowest for the state of Sinaloa in the sample period. This state also experienced a major heat wave during the first half of 2014 with temperature anomalies as high as 6.5°C in April. In general, deviations from the temperature normal display and upward trend that is more evident in the last ten years of the sample period.[6]

[4] The Mexican Ministry of Agriculture utilizes SPOT5 satellite imagery to estimate agricultural land. The most recent version of this map that is publicly available is representative of the 2010-2011 agricultural year (SIAP, 2020b). We assume that agricultural land over the whole 2001-2020 period remains close to the 2010-2011 agricultural year.

[5] 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. 30-year climate normals are often used in economic literature. In our setting, 30-year normals for temperature and precipitation were obtained by averaging monthly temperature and precipitation from 1991 to 2020.

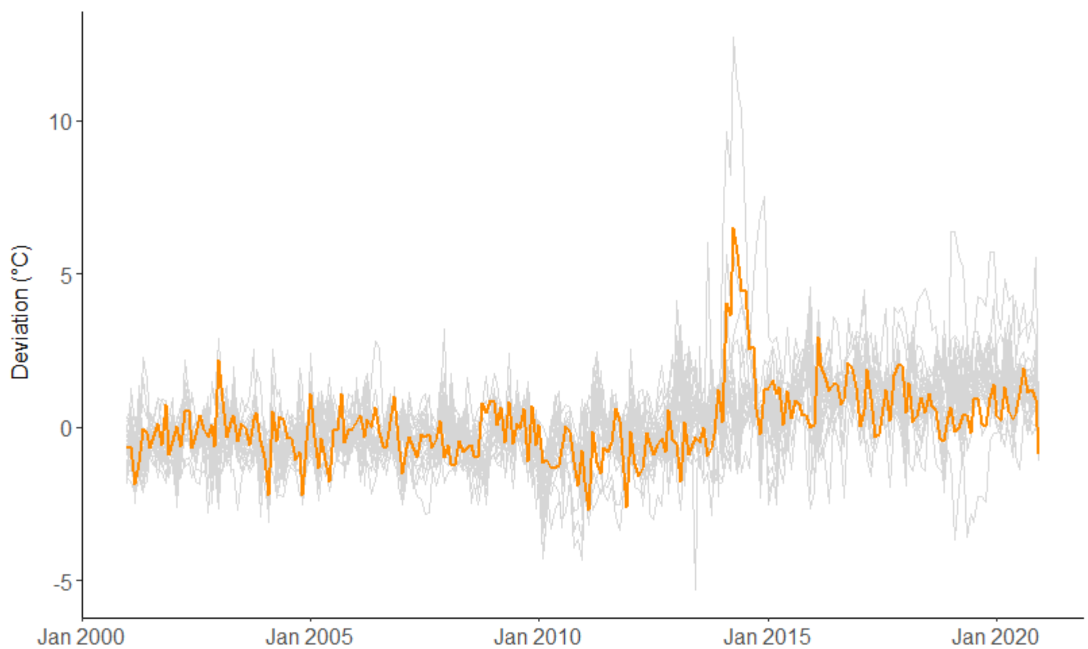
[6] The monthly precipitation series generated can be seen in Figures A4 and A5.

Figure 4. Monthly Temperature Series by State, 2001-2020



Note: Orange lines refer to Sinaloa, a major state producer of vegetables while grey lines depict the temperature series of each of the other 31 Mexican states.
Source: Own elaboration based on data from Thornton et al. (2018) and SIAP (2020b).

Figure 5. Monthly Deviations from the Temperature Normal by State, 2001-2020



Note: Orange lines refer to Sinaloa, a major state producer of vegetables while grey lines depict the temperature series of each of the other 31 Mexican states. Monthly temperature normals calculated as the average for the 1991-2020 period.
Source: Own elaboration based on data from Thornton et al. (2018) and SIAP (2020b).

6.3 Relevant temperature

The vegetables commercialized across the 45 different cities are produced in the same state where the city is located or in other states. If most of the vegetable supply of the city comes from the same state where the city is located, then the temperature shocks associated with price movements at the city level are those experienced in that state. On the other hand, if most of the vegetable supply of a city is produced in other states, then price movements in the city are tied to temperature shocks experienced in those other states. Thus, a city's price sensitivity to temperature changes is determined by the commercialization links that exist between the city and the producing states.

To elicit commercialization patterns among Mexican states, we traced the distribution routes of producing states using monthly commercialization data from the National System of Market Information and Integration (SNIIM by its Spanish acronym), published by the Ministry of Economic Affairs, for the period 2000-2020. While trade volumes are not recorded by SNIIM, the origin (producing) state and the destination (purchasing) state are identified in each operation. For each vegetable and month, we identified a commercialization pattern between a pair of states if vegetables 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 allowed us to identify the supplier states of a vegetable for every state in every month. We discarded possible intermediary states using production data (SIAP, 2020a). Specifically, states whose average yearly production of a vegetable over the period 2004-2020 is less than 1000 tons were excluded from the list of potential supplier states. Diagrams of the commercialization patterns identified for each vegetable for the whole 2000-2020 period can be seen in Figure A6 (in the Appendix).

For every state, we generated a relevant temperature by weighting the temperature of its N supplier states. Specifically, the relevant temperature T for vegetable k sold in a city located in state m in year t and month j results from weighting the temperature of the N supplier states of state m with the following formula:

$$T_{mtj}^{k} = \sum_{n=1}^{N} s_{mnj}^{k} * t_{mntj} \quad (4)$$

where t_{mntj} is the average temperature of the nth state provider of state m in year t and month j and s_{mnj}^{k} is the corresponding weight which is specific for vegetable k and given by:

$$s_{mnj}^{k} = \frac{\frac{1}{\sqrt{d_{mn}}} * shprod_{nj}^{k}}{\sum_{n=1}^{N} \frac{1}{\sqrt{d_{mn}}} * shprod_{nj}^{k}} \quad (5)$$

Here, d_{mn} is the driving distance (in kilometers) between state *m* and its *n*th provider. Distances were calculated using each state's main wholesale market (*central de abasto*)[7] as starting and ending points to closely approximate the real distance traveled by vegetables when exchanged among states. $shprod_{nj}^{k}$ is the share of the *n*th supplier state in the historic production (2004-2020) of vegetable *k* in month *j* at the national level. The production component increases the weight of producing states that have specialized at producing vegetable *k* in 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 cities in state *m* purchase vegetables from states nearby. 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).

We selected historic production to reduce the threat of reverse causality between prices and the shares in production utilized in equation (5). Higher prices for a vegetable might stimulate the production of a state which could result in an increased production share. In fact, production shares over time display certain variability and trends (see Figure A7 in the

[7] A *Central de Abasto* is a wholesale market where food products coming from different producing areas or imported are concentrated to then be sold to specialized local retailers who in turn sell them to final consumers. To generate distances among states, we used the location of 44 *Centrales de Abasto* considered by SNIIM. For states with multiple *Centrales de Abasto*, the starting or ending point was defined as the location of the *Central de Abasto* closest to the state's largest city.

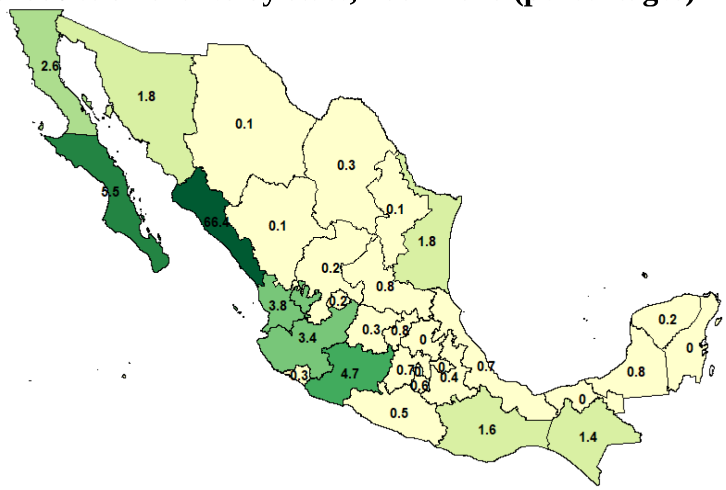
Appendix), thus, historically, prices might have had some effect on the evolution of production shares. By relying on historical production, we minimize the effect of short run changes in prices on short run changes of the shares.

Note that the calculations in equation (4) are made just for the N supplier states of state m which could vary from one month to another. Also, note that while temperature and distances between state providers are not specific for each vegetable, this double-weighting procedure generates a relevant temperature that is vegetable specific because the production component of the weight varies across vegetables. Altogether, the relevant temperature T summarizes in a single variable the commercialization patterns between producing and purchasing states and the production patterns among producing states. The relevant temperature generated was merged to each one of the 45 cities in our sample based on the state in which the city is located. That is, all the cities located in state m were assigned the relevant temperatures generated for state m. Relevant precipitation (Pr) was analogously constructed.

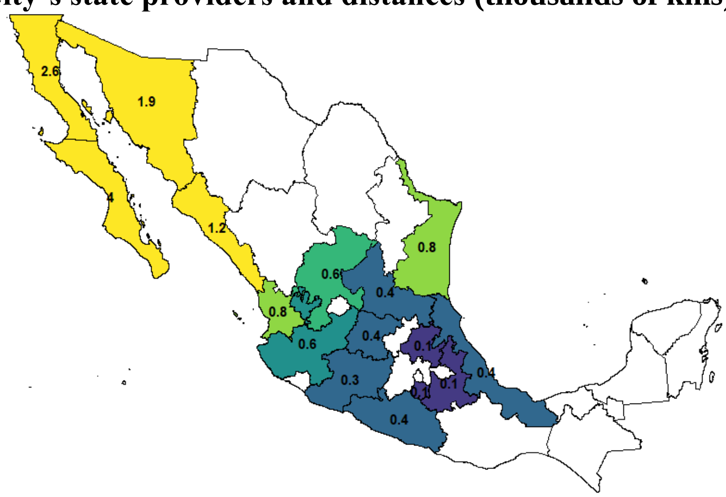
Figure 6 exemplifies this procedure for the case of tomatoes sold in Mexico City during the month of February. Panel A shows the share of every Mexican state in the total historic production of tomatoes during the month of February (2004-2019). The state of Sinaloa accounts for 66.4% of the total historic production because in February tomato production in Sinaloa is at its peak. Panel B shows that between 2004 and 2019, Mexico City bought tomatoes from 16 producing states in February. Among them is Sinaloa which is located 1,236 kms away from Mexico City. Panel C shows the final weight assigned to each producing state after combining panels A and B according to equation (5). The final weight for Sinaloa is 71.4%. In simple words, Sinaloa accounts for 71.4% of the relevant temperature assigned to Mexico City in the month of February. Temperature fluctuations affecting tomato production in Sinaloa in February could have an important influence in Mexico City's tomato prices. The weights shown on panel C vary over time. As the production cycle of tomato evolves over the course of the year, Sinaloa's production is outpaced by other producing states and the weights are reassigned. This dynamic evolution of the weights reflects the changing structure of the tomato market and embed in T the temperature settings of the relevant producing states at different points of the production cycle.

Figure 6. Weighting Example: Tomatoes Sold in Mexico City in February

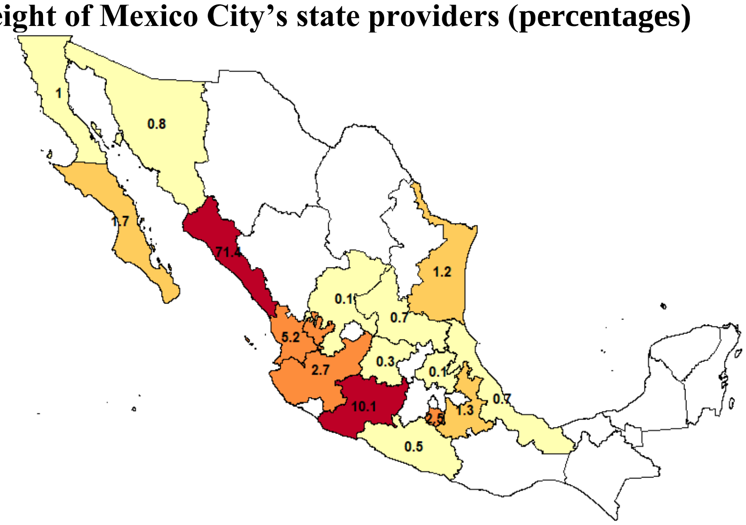
a) Historic production shares by state, 2004-2020 (percentages)



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



c) Final weight of Mexico City's state providers (percentages)



Source: Own elaboration based on data from SNIIM (2020) and SIAP (2020a).

Table 1 presents summary statistics of the relevant temperature and precipitation variables generated. On average, vegetables are produced in temperate settings with mean relevant temperatures oscillating between 18.5ºC and 21.9ºC. Yet, for most of the vegetables analyzed, average monthly temperatures drop below 12ºC and above 34ºC in some months.

Table 1. Summary Statistics of the Working Sample, 2001-2020

	(1) Squash	(2) Onion	(3) Chili pepper	(4) Tomato	(5) Cucumber	(6) Tomatillo	(7) Lettuce & Cabbage	(8) Potato
T (ºC)								
Mean	20.3	19.9	21.3	21.6	21.9	20.7	18.5	21.1
Std. Dev	3.2	3.1	3.8	3.4	3.5	2.6	2.8	4.2
Min	10.1	10.6	6.8	11.0	10.3	11.3	10.1	8.1
Max	34.4	32.4	34.9	34.8	34.9	34.9	30.8	34.8
Pr (mm)								
Mean	57.7	41.5	42.5	43.8	49.9	54.3	60.4	56.5
Std. Dev	70.0	45.2	50.9	55.4	67.3	65.6	68.9	74.8
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max	558.8	411.9	480.0	468.1	554.3	488.8	384.9	553.9
Obs.	**10,800**	**10,800**	**10,560**	**10,800**	**10,720**	**10,800**	**9,900**	**10,800**

Notes: The summary statistics shown in this table are calculated using the whole sample period, that is, statistics are calculated pooling all markets and year-months. The number of observations is lower for some vegetables due to the unavailability of commercialization information for the states of Tlaxcala (all vegetables), Chiapas (chili pepper), Campeche (cucumber) and Hidalgo (lettuce and cabbage). Also, price index information for lettuce and cabbage is not available before July 2002.
Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

7. Results

Parameter estimates of equation (3) are shown in Table 2. Each column shows the results of a separate regression for each vegetable'*s ln(P)* on current and lagged quadratic functions of relevant temperature and precipitation. There are three main results.

First, there is a convex U-shaped relationship between contemporaneous temperatures and the contemporaneous price of most of the vegetables analyzed although the estimated relationship is statistically significant only for the case of squash (at a 1% level), chili pepper and tomato (at a 5% or 10% level). This convex U-shaped relationship between temperature and vegetable prices is consistent with the existence of an optimum temperature, so that temperatures above or below are associated with higher vegetables prices. This result is also consistent with the relationship between temperature and agricultural yields that has been found in related literature in which low and high temperatures are associated with lower yields (Schlenker and Roberts, 2009; Burke and Emerick, 2016; Moore and Lobell, 2014; Mérrel and Gammans, 2021).

Second, there is also a convex U-shaped relationship between lagged temperatures and contemporaneous vegetables prices. This relationship is present in most lags and for most of the vegetables analyzed although the precision of the estimates varies by case. In general, the relationship is estimated with a high precision for squash and tomato (statistically significant at a 1% level for some lags). For the rest of the vegetables, the relationship is estimated with a relatively good precision (at a 5% or 10% level). The varying levels of statistical significance across different lags might indicate that the price of some vegetables is particularly sensitive to temperature at specific points of their growing period. The price of squash and tomato seems particularly sensitive to temperature shocks throughout most of their growing period. In other vegetables this sensitivity is more evident at the beginning (tomatillo), the middle (cucumber) or the end (chili pepper). These results could be explained by the damages caused by temperature shocks to plant health at different stages of development such as the germination, flowering, or ripening periods (Ortiz-Bobea and Just 2013). The biological cycle of each vegetable is different and so is their sensitivity to temperature fluctuations.

Third, precipitation has a limited role at explaining vegetable prices with most of the estimates not being statistically significant. This result is not surprising given the fact that most of vegetable production in Mexico is obtained using irrigation.

Table 2. Panel Estimates of the Relationship Between Weather and Vegetable Prices

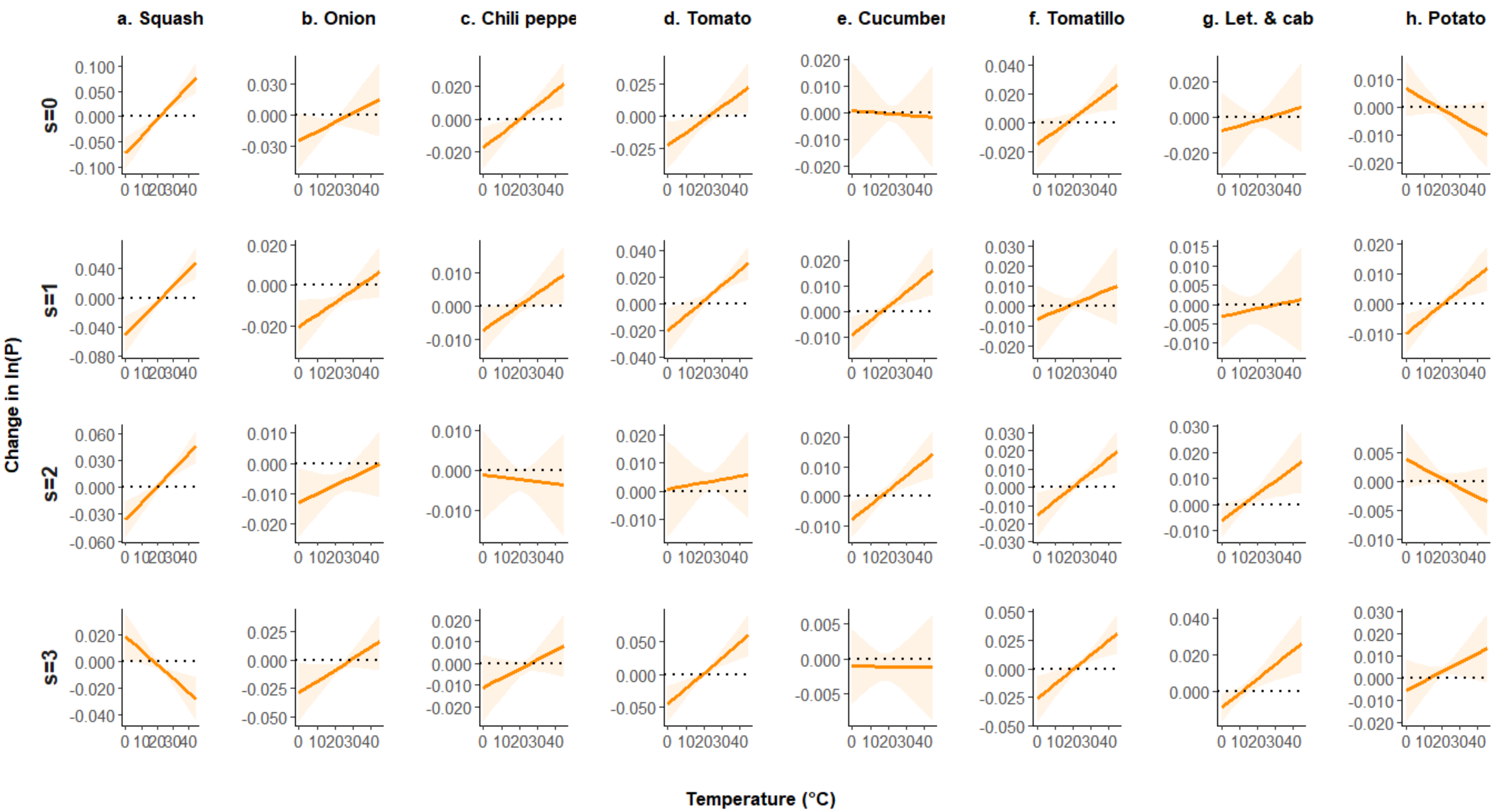
	(1) Squash	(2) Onion	(3) Chili pepper	(4) Tomato	(5) Cucumber	(6) Tomatillo	(7) Lettuce & Cabbage	(8) Potato
T_t	-0.0726***	-0.0248	-0.0175**	-0.0224**	0.0009	-0.0152	-0.0076	0.0065
	(0.0191)	(0.0165)	(0.0078)	(0.0110)	(0.0110)	(0.0104)	(0.0129)	(0.0059)
T_t^2	0.0017***	0.0004	0.0004**	0.0005*	-0.0000	0.0005**	0.0001	-0.0002
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0001)
T_{t-1}	-0.0504***	-0.0205**	-0.0073*	-0.0199*	-0.0088**	-0.0063	-0.0031	-0.0098**
	(0.0153)	(0.0078)	(0.0042)	(0.0103)	(0.0043)	(0.0103)	(0.0050)	(0.0039)
T_{t-1}^2	0.0011***	0.0003*	0.0002*	0.0006***	0.0003**	0.0002	0.0000	0.0002**
	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
T_{t-2}	-0.0359***	-0.0129*	-0.0011	0.0008	-0.0076**	-0.0152**	-0.0061	0.0038
	(0.0119)	(0.0068)	(0.0069)	(0.0102)	(0.0036)	(0.0073)	(0.0039)	(0.0031)
T_{t-2}^2	0.0009***	0.0001	-0.0000	0.0001	0.0002***	0.0004**	0.0003**	-0.0001
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
T_{t-3}	0.0186*	-0.0280*	-0.0111	-0.0446***	-0.0010	-0.0260**	-0.0088*	-0.0056
	(0.0104)	(0.0153)	(0.0093)	(0.0160)	(0.0032)	(0.0119)	(0.0045)	(0.0084)
T_{t-3}^2	-0.0005**	0.0005	0.0002	0.0012***	-0.0000	0.0006**	0.0004**	0.0002
	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Pr_t	0.0036	0.0061***	0.0064***	0.0021	-0.0003	-0.0003	-0.0015	0.0026**
	(0.0023)	(0.0016)	(0.0019)	(0.0016)	(0.0011)	(0.0021)	(0.0013)	(0.0011)
Pr_t^2	-0.0000	-0.0002***	-0.0001**	-0.0000	-0.0000	-0.0000	0.0000	-0.0001***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-1}	0.0057**	0.0037*	-0.0005	0.0010	-0.0014	-0.0011	-0.0000	-0.0013
	(0.0024)	(0.0020)	(0.0015)	(0.0015)	(0.0013)	(0.0014)	(0.0017)	(0.0010)
Pr_{t-1}^2	-0.0001	-0.0001**	0.0000	-0.0001	0.0000	0.0000	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-2}	0.0004	-0.0014	-0.0003	0.0027*	-0.0011	-0.0001	-0.0004	0.0002
	(0.0029)	(0.0026)	(0.0015)	(0.0015)	(0.0013)	(0.0014)	(0.0016)	(0.0010)
Pr_{t-2}^2	0.0001	0.0000	-0.0000	-0.0001	0.0001*	0.0000	-0.0000	-0.0000*
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-3}	-0.0028	-0.0039	0.0020	0.0044**	-0.0004	0.0003	-0.0005	-0.0006
	(0.0028)	(0.0026)	(0.0027)	(0.0019)	(0.0013)	(0.0016)	(0.0015)	(0.0011)
Pr_{t-3}^2	0.0001	0.0001	0.0000	-0.0001	0.0000	-0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.8536	0.9325	0.8872	0.9053	0.8953	0.8678	0.8901	0.9081
N	10800	10800	10560	10800	10720	10800	9900	10800

Note: Regressions are weighted by the share of each city on the national CPI. 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, SNIIM (2020) and Thornton et al. (2018).

Table A1 (in the Appendix), shows that these results are robust to the exclusion of precipitation as a control, which demonstrates that results are not driven by multicollinearity among weather variables. Table A2 (in the Appendix) shows the results obtained when region-by-year-by-month fixed effects are included in the estimation. This identification strategy conditions the identification of the parameters to rely on weather variation over time and across cities within the same region. Results are robust to the inclusion of these fixed effects, but the estimation is less precise because there is less residual variation in prices left to be explained by weather. Table A3 displays the results obtained when we modify the calculation of the production shares used in the weighting procedure to generate relevant weather. Specifically, instead of calculating shares using historical monthly production we use shares calculated using monthly production in 2004, the first year for which monthly data is available. We keep shares constant at 2004 levels to avoid the potential endogeneity that arises by the influence of price movements on the production shares after 2004. Table A3 shows that our main finding, the existence of a convex U-shaped relationship between temperature and vegetable prices, is robust to this change in the weighting procedure albeit some changes in the statistical significance of the estimated parameters for some vegetables. Finally, Table A4 shows the results obtained when we allow for spatial dependence in the error term of a city with its corresponding neighboring cities. Specifically, we estimate a spatial error model assuming that the correlation among errors is limited to the 4 closest cities. With this approach we allow for the possibility of spatial spillovers from weather shocks to prices among neighboring cities. Table A4 confirms that our main results are robust to spatial correlation with minimal differences in the point estimates and their statistical significance.

Figure 7 displays the marginal effects for each vegetable calculated using the parameter estimates of Table 2 and evaluating at different temperature levels. In most cases, the marginal effect is upward slopping with negative values to the left of the optimal temperature and positive values to the right. This means that for average monthly temperatures above the optimal, a 1°C increase translates into higher vegetable prices. The converse is true for average monthly temperatures below the optimal level.

Figure 7. Marginal Effects of Temperature on Vegetable Prices



Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

Several interesting patterns emerge from Figure 7. First, some vegetable prices are sensitive to both colder and hotter than optimal temperatures. Such is the case of squash (lags 0 to 2), chili pepper (lag 0), tomato (lags 1 and 3), cucumber (lags 1 and 2), tomatillo (lags 2 and 3) and potato (lag 1). Lettuce and cabbage seem to be sensitive to only hot temperatures (see lags 2 and 3). Finally, the price of onions seems to be particularly sensitive to cold temperatures (see lags 1 to 3).

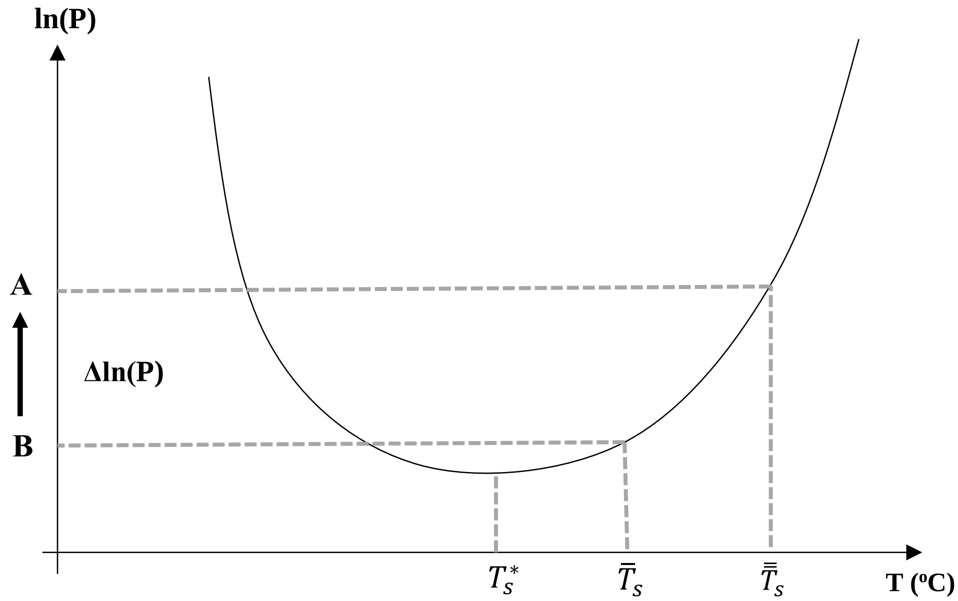
8. Simulating Temperature Shocks

We use the parameter estimates shown in Table 2 to calculate the percentage change in vegetable prices associated with extreme shocks of temperature. Specifically, we simulate a 2 s.d. decrease and increase in monthly average temperatures to recreate a frost and a heat wave. This increase is roughly equal to 6^{o}C above or below observed monthly temperatures (see Table 1). The percentage change in the price of each vegetable after a temperature shock of 2 s.d. in period (lag) *s* is obtained using the following expression:

$$\Delta lnP_s = \widehat{\varphi_s} * \left(\bar{\bar{T}}_s - \bar{T}_s\right) + \widehat{\gamma_s} * \left(\bar{\bar{T}}^2{}_s - \bar{T}^2{}_s\right) \qquad (6)$$

where $\bar{T}_s$ is the average monthly temperature in period (lag) s and $\bar{\bar{T}}_s = \bar{T}_s \pm 2s.d._{T_s}$. $\bar{T}_s$ is calculated by averaging monthly temperatures over the whole sample pooling all markets and year-months. Figure 8 displays a graphic representation of the calculation given by equation (6) for the case of an increase of 2 s.d. The figure also represents the case in which the average temperature $\bar{T}_s$ is larger than the optimal temperature $T^*{}_s$. The percentage change in price after the temperature increase of 2 s.d. is equivalent to the difference between points A and B.

Figure 8. Graphic Representation of a Temperature Shock

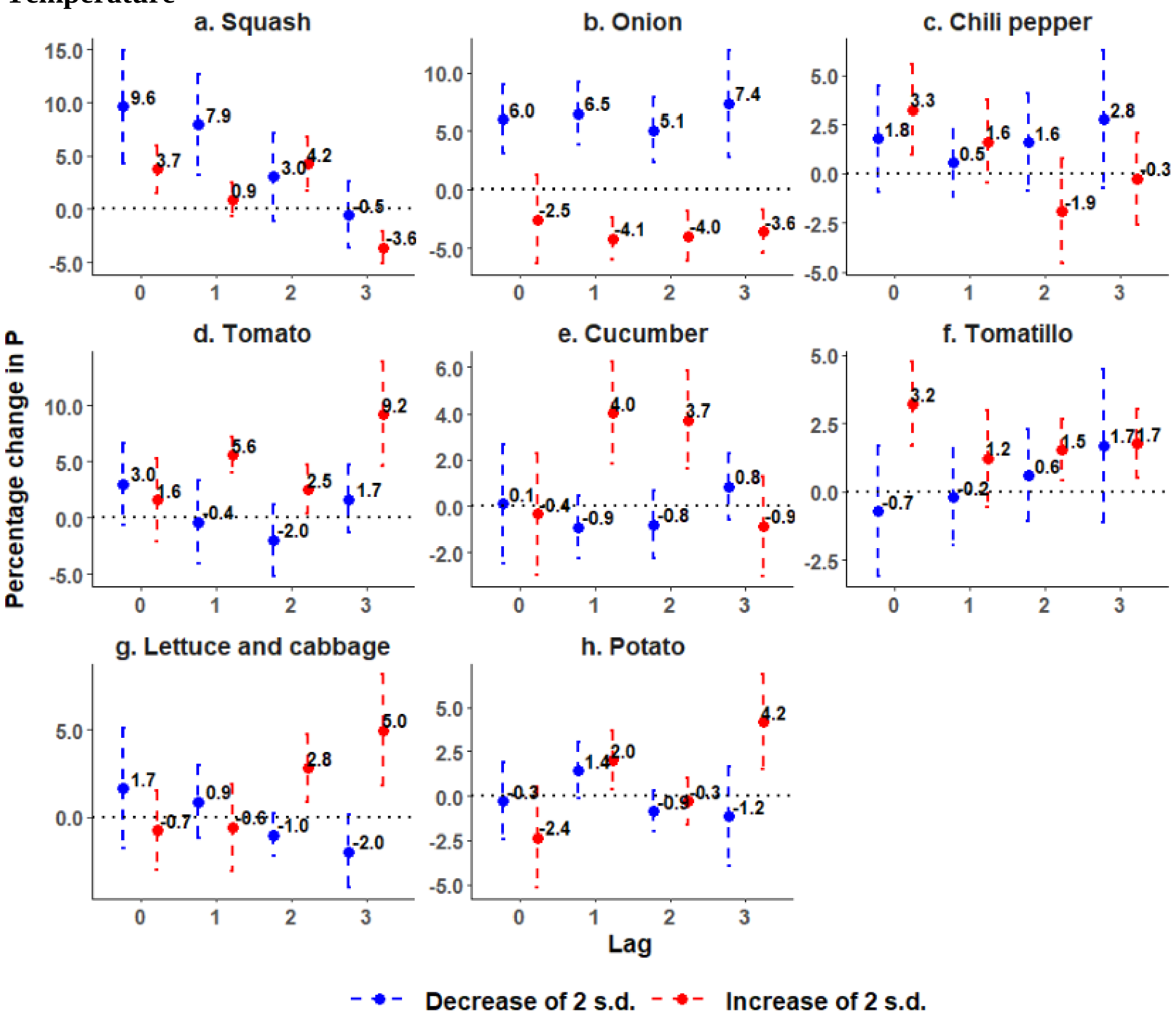


Source: Own elaboration.

Figure 9 summarizes the results. A 2 s.d. decrease in monthly average temperature has a positive and statistically significant effect in the price of squash and onions. In both cases de estimated effects are of considerable magnitude. For example, the price of squash immediately increases 9.6% after the temperature shock and 7.9% one month later. The price of onions is particularly sensitive to low temperatures with estimated effects that are larger than 6.0% in every lag. These findings are in line with previous results that associate extremely cold temperatures with high food inflation in Mexico (Banco de México, 2013). Temperature decreases do not have statistically significant effects in the price of the other six vegetables. A variety of factors could explain this result. First, vegetable imports could increase and mitigate the upward pressure in vegetable prices caused by a frost. Second, for vegetables with a larger imports share, the domestic price could be closely tied to the international price making it less sensitive to domestic weather shocks. This is particularly true for potatoes (see Figure 2). Finally, some vegetables are highly substitutable among each other. Such is the case of tomatoes and tomatillos whose use in Mexican cuisine is almost interchangeable. Also, there is a large number of different chili peppers varieties in

Mexico.[8] In the event of a sizable price increase in one of them, consumers could decide to use another variety.

Figure 9. Percentage Change in Vegetable Prices after a Decrease or Increase of 2 s.d. in Temperature



Note: Bars denote 90% confidence intervals.
Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

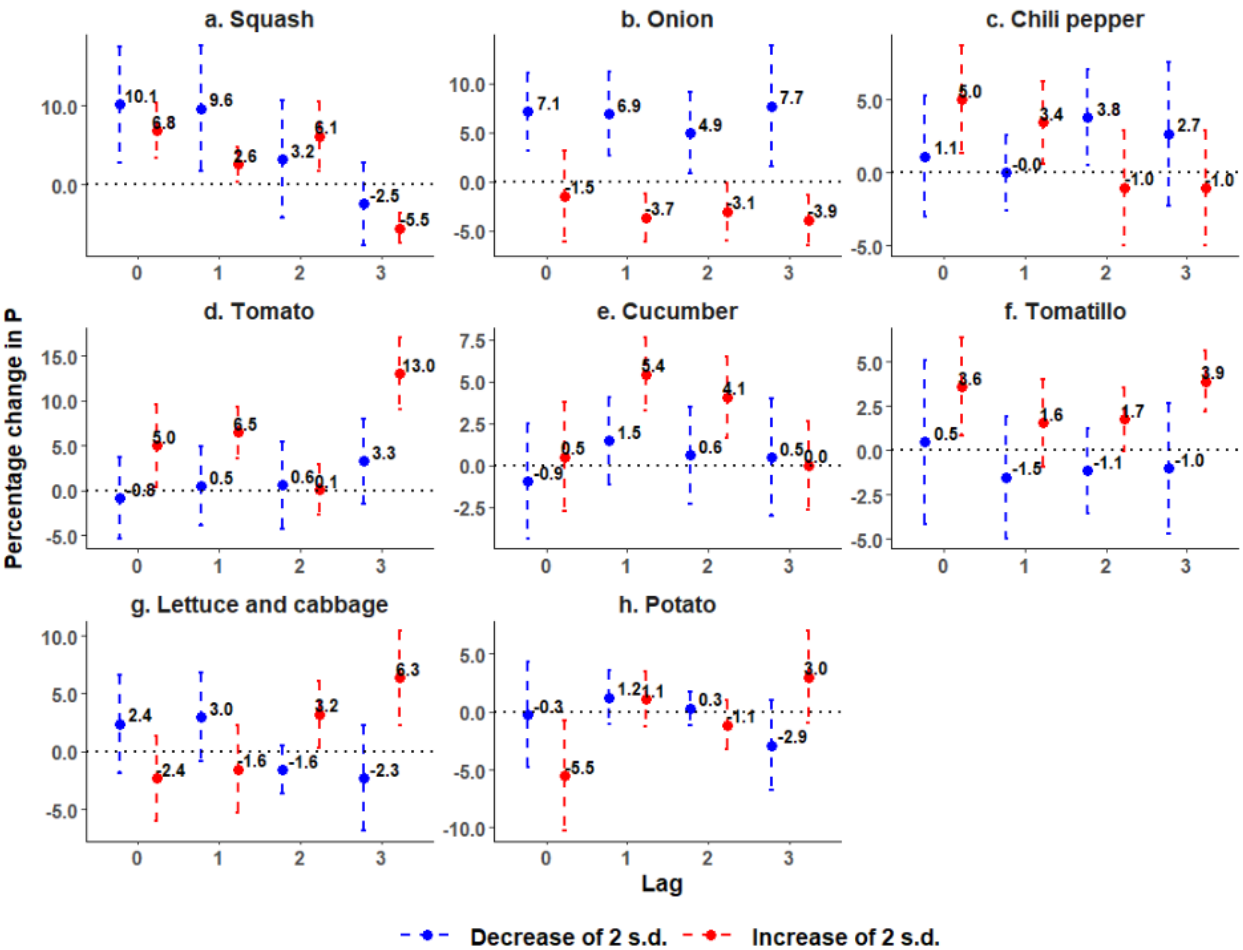
A 2 s.d. increase in average monthly temperatures immediately increases the price of squash (3.7%), chili pepper (3.3%) and tomatillo (3.2%). The temperature shock also has lagged effects on the price of most of the vegetables analyzed. For example, the price of tomato increases by 5.6%, 2.5% y 9.2% in the first, second and third months after the shock. The prices of squash, cucumber, tomatillo, lettuce and cabbage and potato behave similarly. This effect is possibly

[8] https://www.inah.gob.mx/reportajes/597-chiles-y-salsas-en-mexico-un-sabor-a-identidad

explained by damages caused by heat stress in early stages of the crop's development such as the germination or the flowering periods (Ortiz-Bobea and Just 2013) particularly in cool-weather vegetables such as squash, cucumber, lettuce and cabbage.

Figure 10 presents results of this simulation when the estimation is restricted to a sub-sample composed of the main vegetable producers. Specifically, equation (3) is re-estimated using only the 14 states shown in Figure 1 (see parameter estimates in Table A5). By doing this, the estimation only considers prices and relevant weather in cities located in or close to the main producing areas. Such cities are more likely to rely on local production to meet local supply as opposed to more distant cities that could have a more diversified portfolio of vegetable suppliers. In the event of a temperature shock affecting a main producing area, vegetable prices in nearby cities could be more sensitive relative to vegetable prices in more distant cities. Figure 10 suggests that this is the case. In general, the estimated effects of 2 s.d. temperature shocks are larger when the estimation is restricted to the main producing areas. For example, the price of tomato would increase by 13.0% three months after a temperature increase of 2 s.d. above average (panel d). This is 3.8% higher than the effect estimated when using the whole sample (see panel d in Figure 8). The immediate affect is also larger (5.0% vs 3.0%). Overall, these results show that vegetable prices in markets geographically close to main producing areas are the most sensitive to temperature shocks.

Figure 10. Percentage Change in Vegetable Prices after a Decrease or Increase of 2 s.d. in Temperature, Sample Restricted to Main Producers

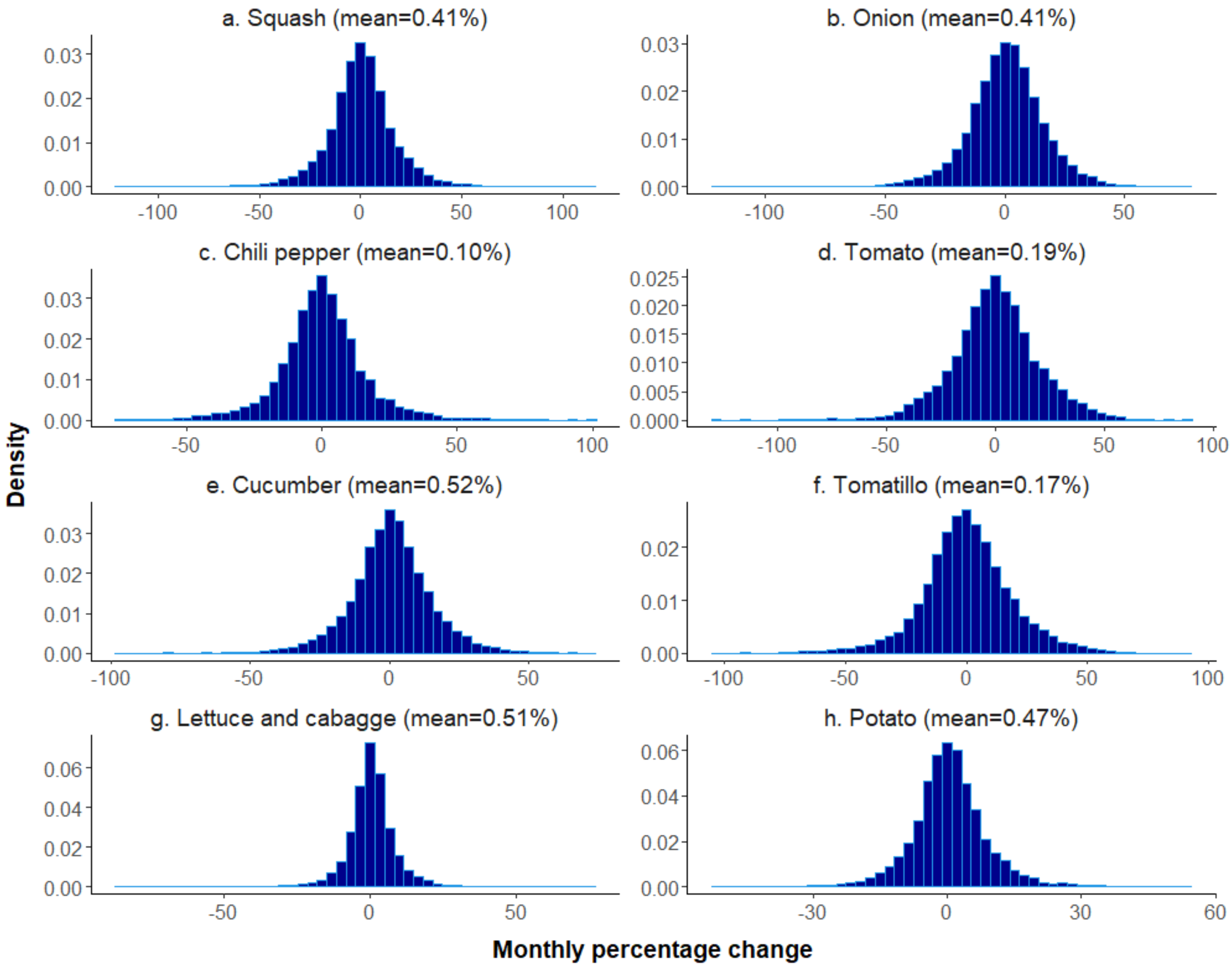


Note: Bars denote 90% confidence intervals.
Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

Observed monthly changes on each vegetable's price index display a large variation with some months experiencing increases or decreases of more than 50% (see Figure 11). Yet, a 2 s.d. temperature shock would induce a change on vegetable prices that is, in general, larger than the mean monthly change of the vegetable's price index. For example, the price of tomatillo would increase 3.2% immediately after a temperature increase of 2 s.d. which is about 19 times the mean monthly change in tomatillo prices observed in the sample period. Some lagged effects are also sizable. The increase in the price of tomato after three months of the temperature increase (9.2%) is about 48 times larger than the observed average monthly change in tomato prices. A 2 s.d. decrease in temperature rises the prices of squash and onions by a magnitude that is also considerable larger than the average increase observed in the sample. Thus, our results show that temperature shocks are one of the factors explaining the observed variation in vegetable prices.

Their effect is large enough to induce larger-than-average price changes. Repeated shocks to temperature might translate into successive increases in vegetables prices which might lead to higher inflation.

Figure 11. Histograms of Monthly Changes in each Vegetable's Price Index during the Sample Period



Note: Histograms based on seasonally adjusted CPI series for each city in the sample.
Source: Own elaboration based on data from INEGI.

9. The Productivity Mechanism

In this section we deepen the analysis of the possible mechanisms leading to price increases after a temperature shock. In particular, we explore the productivity channel by which a temperature shock impacts vegetables prices through its effect on yields. In this section, we offer suggestive evidence of it by exploring the relationship between vegetable yields and temperature. Previous findings have documented a non-linear concave relationship between agricultural yields and temperature (Schlenker and Roberts, 2009; Burke and Emerick, 2016; Moore and Lobell, 2014; Mérrel and Gammans, 2021) but almost all of the existing evidence of this relationship applies to grains. For example, Schlenker and Roberts (2009) find that the corn, wheat and soybean yields in the US decrease sharply once temperature surpasses a 29-32ºC threshold. No previous evidence for the case of vegetables exists. In this section, we investigate whether such concave relationship holds also for the case of vegetables. If it does, then vegetable yield decreases associated to temperature shocks could explain the price increases found in the previous section. To investigate the influence of temperatures on vegetable yields we rely on yield data for each vegetable at the municipality level for the period 2003-2020 (SIAP, 2021). Yield data is separated by agricultural season (Spring-Summer, Fall-Winter) and by mode of production (rainfed and irrigated). We combine yield data with weather data from DAYMET aggregated at the municipality level by averaging grid cell values over agricultural land in each municipality (SIAP, 2020b). Rather than aggregating our weather data to the state level (as in our price analysis), we keep the analysis at the municipality level in order to take advantage of the large yield and weather variation observed in Mexico at the municipality level.[9] For each vegetable, we estimate the following fixed effects model:

$$lnYield_{imst} = \beta_1 T_{imst} + \beta_2 T_{imst}^2 + \beta_3 Pr_{imst} + \beta_4 Pr_{imst}^2 + \omega_i + \sigma_m + \rho_s + \tau_t + \epsilon_{imst} \qquad (7)$$

where $Yield_{mst}$ represents the yield (in tons per hectare) of a vegetable in municipality *i*, mode of production *m (m=Irrigated, Rainfed)*, season *s (s=Spring-Summer, Fall-Winter)* and year *t*. *T* and *Pr* stand for average seasonal temperature and accumulated seasonal precipitation for each municipio, respectively. The estimation includes municipality (ω_i), mode (σ_m), season (ρ_s) and year (τ_t) fixed effects. Seasonal temperature (precipitation) results from averaging (summing up) monthly temperature (precipitation) over the length of each season (April-September for Spring-Summer and October-March for Fall-Winter).

Estimation results for equation (7) are presented in Table 3. Each column presents results for each vegetable with lettuce and cabbage analyzed separately due the availability of yield data for each. Results document a concave inverted-U shaped relationship between temperature and vegetables

[9] A municipality is the lowest level of federal administration in Mexico. As of 2020, there are a total of 2,469 municipalities.

yields in seven out of the nine vegetables analyzed. This relationship is statistically significant in five cases. Such functional relationship implies optimum temperatures than range from 14.6^{o}C in the case of potato to 26.8^{o}C in the case of tomato (see bottom row). Temperatures below and above such optimum are associated to lower vegetable yields. In general, the estimated optimal temperatures fall within the temperature range at which each vegetable is expected to grow optimally (Ruiz et al., 2013). These findings echo the results documented for other crops in related literature and suggest that temperature is also a determinant of vegetable yields. Table 3 also shows that, in general, the relationship between precipitation and vegetable yields is weak, a result consistent with the fact that vegetable production in Mexico takes place mostly under irrigated conditions.

Figure 12 plots the estimated functional relationship for all the vegetables analyzed, except tomatillo and lettuce due to the absence of statistically significant results.[10] Each panel identifies the estimated optimal temperature (thick vertical line) along with the average temperature of the top four producing states (thin vertical lines). The average temperature of each producing state is calculated using as reference the four months in which their share in total production is at their highest (see Figure 1). In general, the average temperature of the main producing states clusters around the estimated optimal temperatures. Thus, positive (heat waves) or negative (frosts) temperature shocks are likely to negatively impact vegetable yields. In the case of onion, cucumber, potato and cabbage, the average temperature of some of the main producing states is larger than the estimated optimal temperature. As a result, the yield and price of these vegetables could be particularly sensitive to heat waves in those areas.

[10] The quadratic function shown in each panel results from evaluating the following expression:

$$lnYield = \widehat{\beta_1}T + \widehat{\beta_2}T^2$$

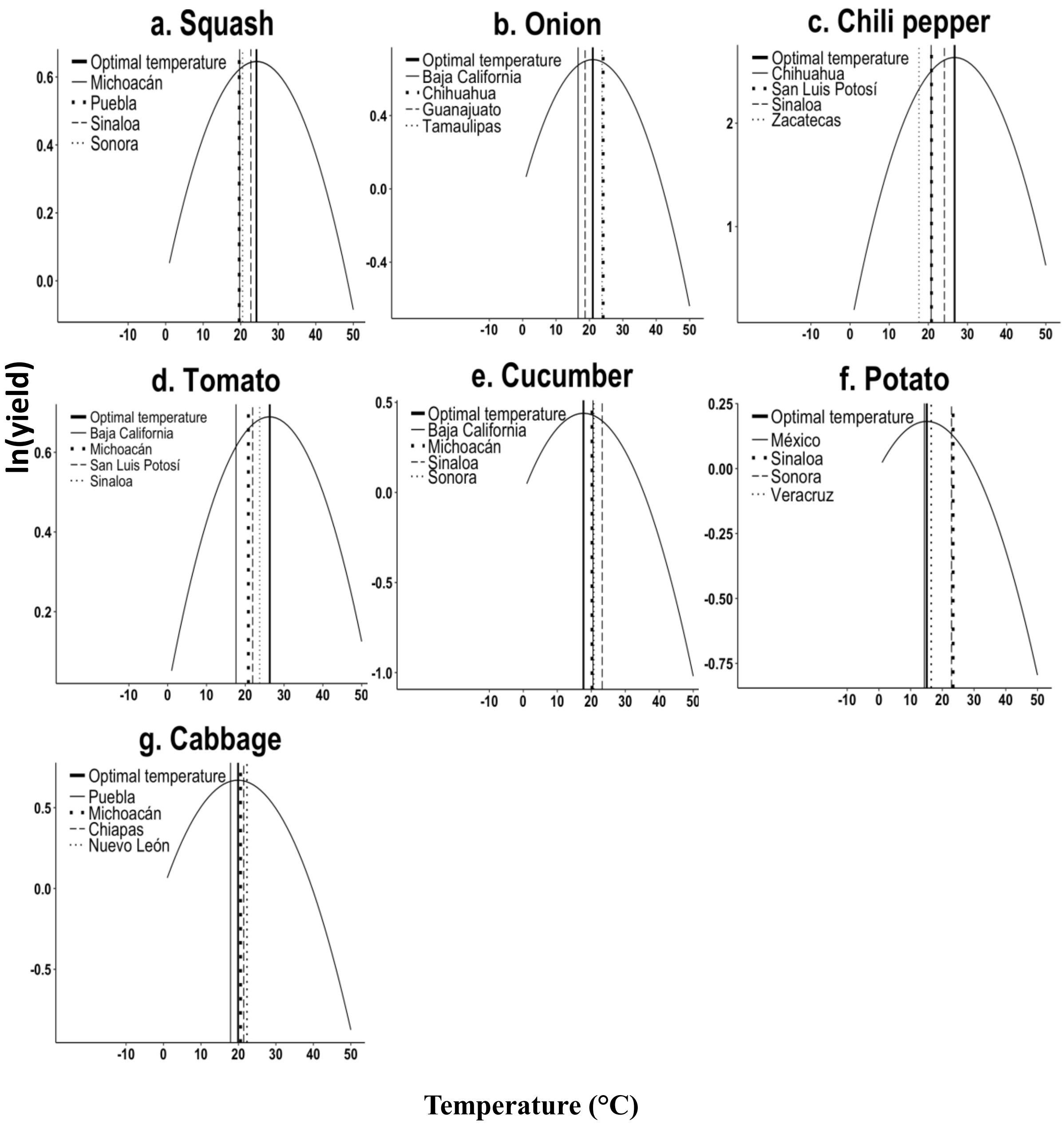
where $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are the paremeter estimates for temperature in equation (7).

Table 3. Panel Estimates of the Effect of Weather on Vegetable Yields

	(1) Squash	(2) Onion	(3) Chili pepper	(4) Tomato	(5) Cucumber	(6) Tomatillo	(7) Lettuce	(8) Cabbage	(9) Potato
T	0.0533**	0.0672***	0.1975***	0.0525**	0.0496	0.0083	-0.0049	0.0675***	0.0241
	(0.0251)	(0.0171)	(0.0680)	(0.0225)	(0.0358)	(0.0333)	(0.0315)	(0.0241)	(0.0302)
T^2	-0.0011**	-0.0016***	-0.0037**	-0.0010*	-0.0014*	0.0002	-0.0001	-0.0017***	-0.0008
	(0.0005)	(0.0004)	(0.0014)	(0.0005)	(0.0008)	(0.0008)	(0.0008)	(0.0005)	(0.0007)
P	0.0019*	-0.0026*	0.0017	0.0026**	-0.0009	-0.0001	-0.0025**	-0.0001	-0.0002
	(0.0011)	(0.0014)	(0.0017)	(0.0011)	(0.0014)	(0.0016)	(0.0012)	(0.0008)	(0.0010)
P^2	-0.0000	0.0000**	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fall-Winter=1	0.0606	-0.0090	0.2194**	0.1075**	-0.0495	0.0121	-0.1508**	0.0180	-0.0731
	(0.0518)	(0.0434)	(0.1049)	(0.0483)	(0.0563)	(0.0669)	(0.0666)	(0.0634)	(0.0591)
Irrigated=1	0.3786***	0.3943***	0.2191***	0.2938***	0.2105***	0.3345***	0.1036*	0.0875***	0.3796***
	(0.0681)	(0.1224)	(0.0461)	(0.0573)	(0.0279)	(0.0434)	(0.0594)	(0.0287)	(0.0814)
Optimum T*	23.67***	20.41***	26.78***	26.82***	17.53***	-17.79	-17.83	20.18***	14.62**
	(2.93)	(1.08)	(2.54)	(4.81)	(4.05)	(133.20)	(212.34)	(2.46)	(7.30)
R^2	0.6830	0.8385	0.8623	0.7383	0.8319	0.6339	0.7055	0.7876	0.8618
N	12795	9156	14741	18396	7943	13394	4635	3934	4213

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 (2021) and Thornton et al. (2018).

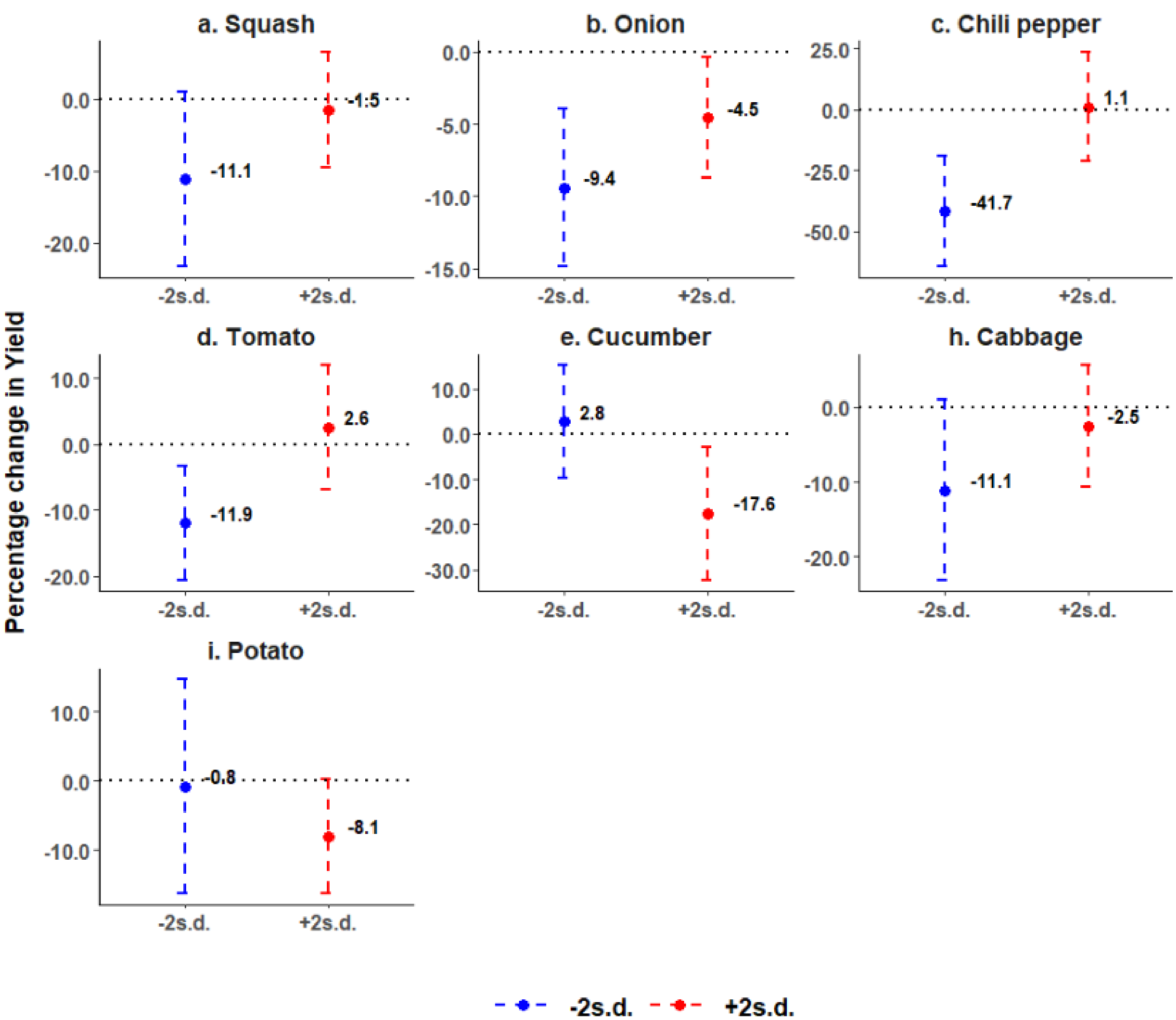
Figure 12. Estimated Functional Relationship Between Temperature and Vegetable Yields



Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

Finally, Figure 13 plots the estimated yield effect of temperature shocks. Using the parameter estimates of Table 3, we calculate the percentage change in vegetable yields associated with a 2 s.d. decrease (increase) below (above) the average seasonal temperature using a procedure similar to the one described in section 7. In general, temperature shocks have a detrimental effect on vegetable yields. In some cases, the effect is sizable. For example, very cold temperatures could decrease chili pepper yields by 41.7%. On the other hand, very hot temperatures could decrease cucumber yields by 17.6%. Overall, results indicate that the productivity channel is one of the mechanisms by which temperature shocks impact vegetable prices.

Figure 13. Percentage Change in Vegetable Yields after a Decrease or Increase of 2 s.d. in Temperature



Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

10. Conclusions

In this paper, we estimate the functional relationship that exists between temperature and vegetables prices using 20 years of monthly panel data at the city level. The estimation accounts for city fixed effects and controls for market seasonality by including month-by-year fixed effects which minimizes the risk of omitted variables bias. Importantly, in our estimation, a relevant temperature for each city is constructed using a double-weighting procedure that considers the historical importance of supplier states in producing each vegetable and their distance to the cities. Our results reveal a non-linear U-shaped relationship between temperature and vegetable prices that exists for current and past temperatures.

Using the parameter estimates of the temperature-price relationship for vegetables we infer the percentage change in monthly prices after a temperature shock of 2 s.d. below and above monthly average temperatures. In some cases, the shock increases prices immediately (squash, onions, chili pepper and tomatillo). In other cases, the shock has lagged effects and prices increase in subsequent periods. This lagged effect is possible due to crop damages at early stages of its growing period (Ortiz-Bobea and Just, 2013) and/or to the updating of price expectations around the timing of the shock (Letta et al, 2021). Price increases due to temperature shocks are not negligible. For example, after a temperature increase of 2 s.d. the price of squash, chili pepper and tomatillo would immediately go up by more than 3%. The price of tomato would increase by more than 9% three months after the shock. Interestingly, the impact of temperature shocks in vegetables prices are larger in cities closer to the main producing areas. In general, price increases explained by temperature shocks are larger than the average monthly increase in each vegetable's price index observed in the sample.

The findings of this article also suggest that temperature shocks may have a detrimental effect on vegetable yields which could be an important driver of the impact on prices. We document a concave relationship between vegetable yields and temperature and evaluate the potential effect of temperature shocks using the estimated relationship. Our results confirm that temperature shocks of at least 2 s.d. decrease the yield of most of the vegetables analyzed. The supply shortfalls caused by the shocks ultimately lead to increased prices. Our results suggest that markets anticipate these damages, form expectations, and adjust vegetable prices accordingly.

Mexican agriculture is frequently exposed to extreme weather with recent examples of frosts, heatwaves, droughts and extreme precipitation. The findings of this paper demonstrate that temperature shocks are among the factors explaining monthly changes in vegetable prices. These results highlight the importance of considering weather events when understanding the sources of inflation for agricultural products. Our results could be used to infer the price effects of heat waves or frosts in the price of vegetables and thus anticipate actions seeking to reduce price volatility. Those actions could include the timely programing of imports to substitute lost production or lower yields and the promotion of policies aimed at reducing the dependency of local markets on few producing areas. The diffusion of technologies seeking to improve the resilience of vegetable crops to high temperatures, such as heat tolerant varieties, could also reduce the sensibility of vegetable prices to temperature shocks. In the context of ongoing climate change, upward pressures on prices associated to temperature shocks could become larger and more frequent (Perkins-Kirkpatrick and Lewis, 2020; Diffenbaugh, 2020), thus, in the future, the effect of temperature shocks on vegetable yields and prices could become larger and more evident and adaptive actions will be necessary to mitigate the adverse effects of climate change on prices.

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12. Appendix

12.1 Tables

Table A1. Estimated Non-Linear Relationship Between Temperature and Vegetable Prices, No Precipitation

	(1) Squash	(2) Onion	(3) Chili pepper	(4) Tomato	(5) Cucumber	(6) Tomatillo	(7) Lettuce & Cabbage	(8) Potato
T_t	-0.0792***	-0.0281	-0.0141*	-0.0169	0.0032	-0.0148	0.0028	0.0065
	(0.0206)	(0.0175)	(0.0072)	(0.0107)	(0.0113)	(0.0106)	(0.0136)	(0.0059)
T_t^2	0.0017***	0.0005	0.0003*	0.0004	-0.0001	0.0005*	-0.0000	-0.0002
	(0.0005)	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0001)
T_{t-1}	-0.0530***	-0.0240***	-0.0092**	-0.0218**	-0.0088**	-0.0065	-0.0029	-0.0108***
	(0.0154)	(0.0069)	(0.0045)	(0.0107)	(0.0043)	(0.0110)	(0.0048)	(0.0039)
T_{t-1}^2	0.0011***	0.0004**	0.0002**	0.0006***	0.0003**	0.0002	0.0001	0.0003***
	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
T_{t-2}	-0.0343***	-0.0135*	-0.0017	-0.0003	-0.0073**	-0.0139*	-0.0076**	0.0024
	(0.0125)	(0.0076)	(0.0065)	(0.0104)	(0.0033)	(0.0075)	(0.0037)	(0.0033)
T_{t-2}^2	0.0008***	0.0002	0.0000	0.0001	0.0002***	0.0004**	0.0003***	-0.0000
	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
T_{t-3}	0.0116	-0.0290**	-0.0129	-0.0529***	-0.0005	-0.0259**	-0.0121***	-0.0058
	(0.0110)	(0.0134)	(0.0090)	(0.0179)	(0.0030)	(0.0114)	(0.0040)	(0.0087)
T_{t-3}^2	-0.0004	0.0005*	0.0002	0.0013***	-0.0000	0.0006**	0.0005***	0.0002
	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.8521	0.9323	0.8866	0.9049	0.8951	0.8678	0.8893	0.9075
N	10800	10800	10560	10800	10720	10800	9900	10800

Note: Regressions are weighted by the share of each city on the national CPI. 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, SNIIM (2020) and Thornton et al. (2018).

Table A2. Panel Estimates of the Relationship Between Weather and Vegetable Prices with Time-Varying Regional Fixed Effects

	(1) Squash	(2) Onion	(3) Chili pepper	(4) Tomato	(5) Cucumber	(6) Tomatillo	(7) Lettuce & Cabbage	(8) Potato
T_t	-0.0592***	-0.0239*	-0.0120	-0.0130	-0.0137	-0.0221**	-0.0208*	0.0072
	(0.0189)	(0.0134)	(0.0097)	(0.0107)	(0.0082)	(0.0101)	(0.0106)	(0.0063)
T_t^2	0.0015***	0.0005	0.0003	0.0003	0.0004**	0.0005**	0.0004	-0.0002
	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
T_{t-1}	-0.0381***	-0.0221***	-0.0149***	-0.0231***	-0.0072*	-0.0154	-0.0016	-0.0049
	(0.0104)	(0.0080)	(0.0052)	(0.0085)	(0.0038)	(0.0110)	(0.0047)	(0.0040)
T_{t-1}^2	0.0009***	0.0004**	0.0004***	0.0006***	0.0002**	0.0003	-0.0000	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
T_{t-2}	-0.0420***	-0.0047	-0.0090	-0.0150	-0.0037	-0.0250***	-0.0044	-0.0008
	(0.0070)	(0.0074)	(0.0069)	(0.0121)	(0.0030)	(0.0079)	(0.0035)	(0.0039)
T_{t-2}^2	0.0010***	-0.0000	0.0002	0.0003	0.0001	0.0006***	0.0002	0.0000
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
T_{t-3}	0.0168	-0.0292**	-0.0043	-0.0547***	0.0013	-0.0290**	-0.0062	-0.0024
	(0.0136)	(0.0123)	(0.0104)	(0.0181)	(0.0031)	(0.0129)	(0.0044)	(0.0095)
T_{t-3}^2	-0.0005*	0.0006**	0.0001	0.0013***	-0.0001	0.0007**	0.0002*	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0001)	(0.0003)	(0.0001)	(0.0002)
Pr_t	0.0024	0.0039*	0.0053**	0.0012	0.0005	-0.0002	-0.0033*	0.0010
	(0.0025)	(0.0021)	(0.0022)	(0.0018)	(0.0013)	(0.0020)	(0.0019)	(0.0012)
Pr_t^2	0.0000	-0.0001*	-0.0001**	-0.0000	-0.0000	-0.0000	0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Pr_{t-1}	0.0027	0.0043**	-0.0006	0.0020	-0.0016	-0.0012	0.0000	0.0011
	(0.0028)	(0.0021)	(0.0016)	(0.0019)	(0.0013)	(0.0016)	(0.0019)	(0.0011)
Pr_{t-1}^2	-0.0000	-0.0001**	-0.0000	-0.0001	0.0000	0.0000	-0.0000	-0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Pr_{t-2}	-0.0001	0.0025	-0.0024	0.0037**	-0.0007	-0.0018	-0.0009	0.0019*
	(0.0031)	(0.0029)	(0.0018)	(0.0016)	(0.0011)	(0.0016)	(0.0018)	(0.0011)
Pr_{t-2}^2	0.0000	-0.0001	0.0001	-0.0001**	0.0000	0.0001*	0.0000	-0.0001***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Pr_{t-3}	0.0009	0.0022	0.0012	0.0040**	-0.0004	0.0010	-0.0018	0.0023*
	(0.0036)	(0.0033)	(0.0027)	(0.0016)	(0.0015)	(0.0014)	(0.0019)	(0.0012)
Pr_{t-3}^2	-0.0000	-0.0001	0.0001	-0.0001**	-0.0000	-0.0000	0.0000	-0.0001***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.8885	0.9396	0.9035	0.9199	0.9132	0.8986	0.9095	0.9204
N	10800	10800	10560	10800	10720	10800	9900	10800

Note: Regressions are weighted by the share of each city on the national CPI. 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, SNIIM (2020) and Thornton et al. (2018).

Table A3. Panel Estimates of the Relationship Between Weather and Vegetable Prices with an Alternative Procedure to Generate Relevant Weather

	(1) Squash	(2) Onion	(3) Chili pepper	(4) Tomato	(5) Cucumber	(6) Tomatillo	(7) Lettuce & Cabbage	(8) Potato
T_t	-0.0641***	-0.0072	-0.0082	-0.0125	-0.0038	-0.0226	-0.0037	-0.0022
	(0.0183)	(0.0126)	(0.0052)	(0.0085)	(0.0111)	(0.0147)	(0.0122)	(0.0060)
T_t^2	0.0015***	0.0001	0.0002	0.0003*	0.0001	0.0006*	0.0001	0.0001
	(0.0004)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0001)
T_{t-1}	-0.0083	-0.0007	-0.0011	-0.0191*	-0.0041	-0.0120***	0.0000	0.0002
	(0.0060)	(0.0044)	(0.0041)	(0.0097)	(0.0028)	(0.0025)	(0.0018)	(0.0017)
T_{t-1}^2	0.0002	-0.0001	-0.0000	0.0005**	0.0001	0.0004***	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
T_{t-2}	-0.0020	-0.0004	0.0051	-0.0197	-0.0047**	-0.0114***	-0.0035***	-0.0019
	(0.0046)	(0.0042)	(0.0073)	(0.0135)	(0.0022)	(0.0034)	(0.0010)	(0.0015)
T_{t-2}^2	0.0001	-0.0001	-0.0002	0.0006*	0.0001**	0.0003***	0.0002***	0.0001**
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
T_{t-3}	0.0023	0.0014	-0.0055	-0.0301	-0.0038**	-0.0054**	-0.0042***	-0.0020
	(0.0028)	(0.0053)	(0.0079)	(0.0187)	(0.0016)	(0.0022)	(0.0014)	(0.0016)
T_{t-3}^2	-0.0001	-0.0002	0.0000	0.0008*	0.0001*	0.0001**	0.0002**	0.0001**
	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Pr_t	0.0037*	0.0066***	0.0028**	0.0051**	-0.0010	0.0006	-0.0013	0.0013
	(0.0019)	(0.0024)	(0.0014)	(0.0023)	(0.0013)	(0.0019)	(0.0012)	(0.0015)
Pr_t^2	-0.0000	-0.0002*	-0.0000	-0.0001	-0.0000	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Pr_{t-1}	0.0042**	0.0049**	-0.0004	0.0006	-0.0024	0.0004	0.0012	-0.0013
	(0.0020)	(0.0019)	(0.0014)	(0.0023)	(0.0015)	(0.0016)	(0.0013)	(0.0014)
Pr_{t-1}^2	-0.0001	-0.0002***	0.0000	-0.0000	0.0000	0.0000	-0.0001*	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-2}	-0.0023	0.0020	0.0016	0.0016	-0.0016	-0.0001	-0.0015	-0.0009
	(0.0020)	(0.0023)	(0.0021)	(0.0025)	(0.0013)	(0.0014)	(0.0012)	(0.0010)
Pr_{t-2}^2	0.0001**	-0.0001	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-3}	-0.0040	-0.0003	0.0034	0.0008	0.0007	0.0006	-0.0039**	-0.0012
	(0.0024)	(0.0019)	(0.0026)	(0.0020)	(0.0014)	(0.0014)	(0.0017)	(0.0009)
Pr_{t-3}^2	0.0001	-0.0000	-0.0000	0.0000	0.0000	-0.0000	0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.8502	0.9316	0.8873	0.9043	0.8955	0.8679	0.8908	0.9092
N	10700	10760	10560	10800	10580	10720	8963	10520

Note: Regressions are weighted by the share of each city on the national CPI. 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, SNIIM (2020) and Thornton et al. (2018).

Table A4. Spatial Panel Estimates of the Relationship Between Weather and Vegetable Prices

	(1) Squash	(2) Onion	(3) Chili pepper	(4) Tomato	(5) Cucumber	(6) Tomatillo	(7) Lettuce & Cabbage	(8) Potato
T_t	-0.0644***	-0.0253	-0.0151**	-0.0189*	-0.0024	-0.0211*	-0.0080	0.0049
	(0.0198)	(0.0164)	(0.0076)	(0.0105)	(0.0087)	(0.0113)	(0.0115)	(0.0060)
T_t^2	0.0015***	0.0005	0.0004**	0.0004*	0.0001	0.0005**	0.0002	-0.0001
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0001)
T_{t-1}	-0.0504***	-0.0209***	-0.0089**	-0.0181*	-0.0184**	-0.0110	-0.0087	-0.0084**
	(0.0159)	(0.0071)	(0.0041)	(0.0098)	(0.0084)	(0.0080)	(0.0072)	(0.0040)
T_{t-1}^2	0.0011***	0.0003**	0.0002**	0.0005***	0.0005**	0.0003	0.0002	0.0002**
	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
T_{t-2}	-0.0434***	-0.0123*	-0.0045	-0.0038	-0.0153**	-0.0170**	-0.0132*	0.0029
	(0.0134)	(0.0064)	(0.0072)	(0.0110)	(0.0065)	(0.0074)	(0.0072)	(0.0030)
T_{t-2}^2	0.0010***	0.0001	0.0001	0.0001	0.0004***	0.0004***	0.0004**	-0.0001
	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
T_{t-3}	0.0217*	-0.0275*	-0.0111	-0.0431**	-0.0139	-0.0224**	-0.0129	-0.0061
	(0.0116)	(0.0148)	(0.0089)	(0.0170)	(0.0091)	(0.0103)	(0.0114)	(0.0087)
T_{t-3}^2	-0.0006**	0.0005	0.0002	0.0011***	0.0003	0.0005**	0.0005*	0.0002
	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Pr_t	0.0035	0.0061***	0.0060***	0.0026*	-0.0004	0.0010	-0.0007	0.0025**
	(0.0025)	(0.0016)	(0.0018)	(0.0016)	(0.0010)	(0.0020)	(0.0013)	(0.0011)
Pr_t^2	-0.0000	-0.0002***	-0.0001***	-0.0001	-0.0000	-0.0000	-0.0000	-0.0001***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-1}	0.0034	0.0037*	-0.0007	0.0016	-0.0019	-0.0005	0.0007	-0.0011
	(0.0030)	(0.0019)	(0.0016)	(0.0016)	(0.0014)	(0.0013)	(0.0016)	(0.0011)
Pr_{t-1}^2	-0.0000	-0.0001**	0.0000	-0.0001	0.0000	0.0000	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-2}	-0.0016	-0.0013	-0.0011	0.0035**	-0.0022	0.0001	0.0001	0.0005
	(0.0035)	(0.0026)	(0.0015)	(0.0016)	(0.0014)	(0.0015)	(0.0016)	(0.0010)
Pr_{t-2}^2	0.0001	0.0000	0.0000	-0.0001**	0.0001***	0.0000	-0.0001	-0.0000**
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pr_{t-3}	-0.0033	-0.0035	0.0007	0.0049***	-0.0012	0.0006	-0.0004	-0.0003
	(0.0035)	(0.0028)	(0.0026)	(0.0018)	(0.0015)	(0.0017)	(0.0016)	(0.0011)
Pr_{t-3}^2	0.0001	0.0000	0.0001	-0.0001**	0.0000	-0.0000	-0.0000	-0.0000*
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	0.7253	0.8951	0.8339	0.8549	0.8358	0.7707	0.8470	0.8304
R^2	10800	10800	10560	10800	10560	10800	9768	10800

Note: Results were obtained from the estimation of a spatial error model limiting the correlation among errors to the 4 closest cities. Regressions are weighted by the share of each city on the national CPI. Standard errors (in parenthesis) clustered at the city level. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

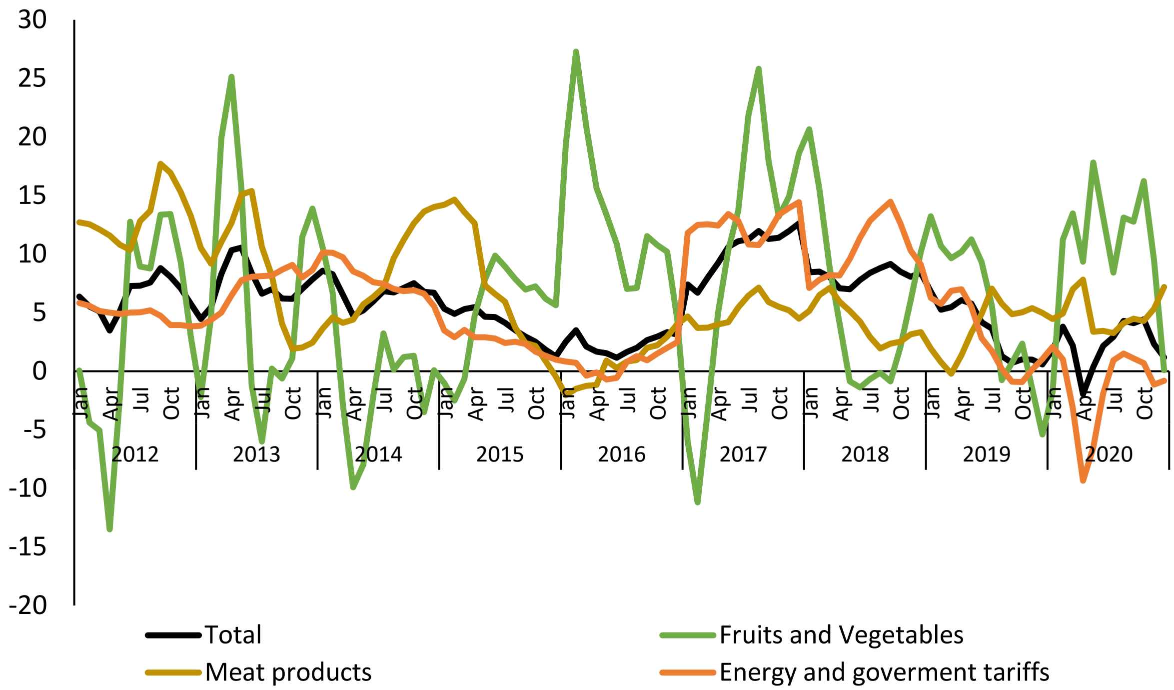
Table A5. Panel Estimates of the Relationship Between Weather and Vegetable Prices, Sample Restricted to the Main Producers

	(1) **Squash**	(2) **Onion**	(3) **Chili pepper**	(4) **Tomato**	(5) **Cucumber**	(6) **Tomatillo**	(7) **Lettuce & Cabbage**	(8) **Potato**
T_t	-0.0730***	-0.0292	-0.0167**	-0.0127	0.0025	-0.0231	-0.0043	0.0125
	(0.0227)	(0.0183)	(0.0074)	(0.0143)	(0.0119)	(0.0146)	(0.0148)	(0.0088)
T_t^2	0.0017***	0.0006	0.0005***	0.0004	-0.0000	0.0006**	0.0000	-0.0004*
	(0.0005)	(0.0005)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0002)
T_{t-1}	-0.0558**	-0.0209*	-0.0086	-0.0238**	-0.0232***	0.0024	-0.0117	-0.0064
	(0.0209)	(0.0109)	(0.0059)	(0.0103)	(0.0081)	(0.0135)	(0.0087)	(0.0052)
T_{t-1}^2	0.0012***	0.0003	0.0003*	0.0006***	0.0006***	0.0000	0.0002	0.0001
	(0.0004)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0001)
T_{t-2}	-0.0367**	-0.0134	-0.0115	-0.0032	-0.0151*	-0.0014	-0.0049	0.0014
	(0.0161)	(0.0083)	(0.0071)	(0.0149)	(0.0074)	(0.0100)	(0.0078)	(0.0037)
T_{t-2}^2	0.0009***	0.0002	0.0002	0.0001	0.0004**	0.0001	0.0002	-0.0001
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
T_{t-3}	0.0310**	-0.0236	-0.0073	-0.0581***	-0.0022	-0.0140	-0.0151	0.0029
	(0.0146)	(0.0187)	(0.0122)	(0.0174)	(0.0094)	(0.0147)	(0.0125)	(0.0103)
T_{t-3}^2	-0.0008**	0.0004	0.0001	0.0015***	0.0000	0.0004	0.0006*	0.0000
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Pr_t	0.0069*	0.0061**	0.0046*	0.0044*	0.0006	0.0024	-0.0046**	0.0022
	(0.0037)	(0.0022)	(0.0025)	(0.0025)	(0.0015)	(0.0027)	(0.0019)	(0.0016)
Pr_t^2	-0.0001	-0.0002*	-0.0001	-0.0001	-0.0001	-0.0000	0.0001*	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Pr_{t-1}	0.0072*	0.0040*	-0.0015	0.0042**	-0.0009	-0.0001	-0.0027	-0.0014
	(0.0038)	(0.0023)	(0.0024)	(0.0020)	(0.0016)	(0.0019)	(0.0028)	(0.0014)
Pr_{t-1}^2	-0.0001	-0.0001	0.0000	-0.0002***	0.0000	-0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Pr_{t-2}	0.0008	0.0012	-0.0007	0.0048**	-0.0007	0.0012	-0.0015	-0.0005
	(0.0040)	(0.0031)	(0.0022)	(0.0019)	(0.0017)	(0.0019)	(0.0025)	(0.0014)
Pr_{t-2}^2	0.0000	-0.0001	0.0000	-0.0001**	0.0000	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Pr_{t-3}	-0.0029	-0.0019	0.0026	0.0050**	-0.0011	-0.0002	-0.0011	0.0001
	(0.0029)	(0.0027)	(0.0032)	(0.0022)	(0.0019)	(0.0023)	(0.0021)	(0.0016)
Pr_{t-3}^2	0.0001	-0.0000	0.0001	-0.0000	0.0001*	0.0000	-0.0000	-0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	0.0125
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.8407	0.9154	0.8558	0.8815	0.8721	0.8406	0.8956	0.8698
N	5280	5280	5280	5280	5280	5280	4884	5280

Note: This table presents results obtained from the estimation of equation (3) restricting the sample to the main vegetable producers defined as the 14 states shown in Figure 1. Regressions are weighted by the share of each city on the national CPI. Standard errors (in parenthesis) clustered at the city level. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own elaboration based on data from INEGI, SNIIM (2020) and Thornton et al. (2018).

12.2 Figures

Figure A1. Non-Core Inflation and its Components, 2012-2020



Source: Own elaboration based on data from INEGI.

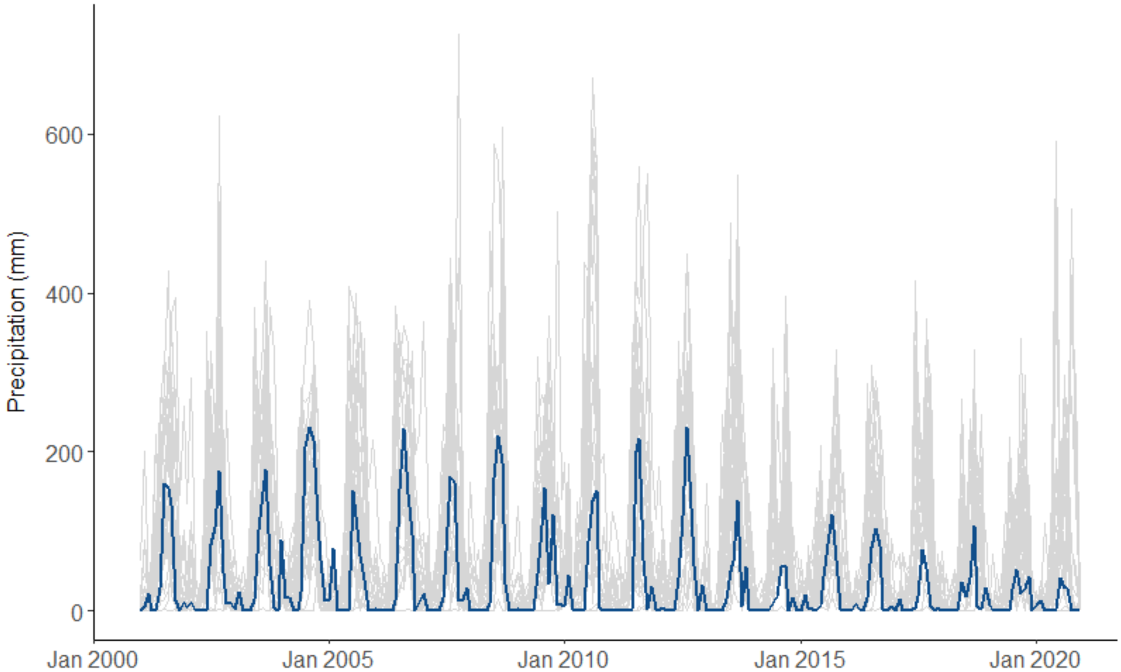
Figure A2. States and Regions of Mexico

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. Location of Cities

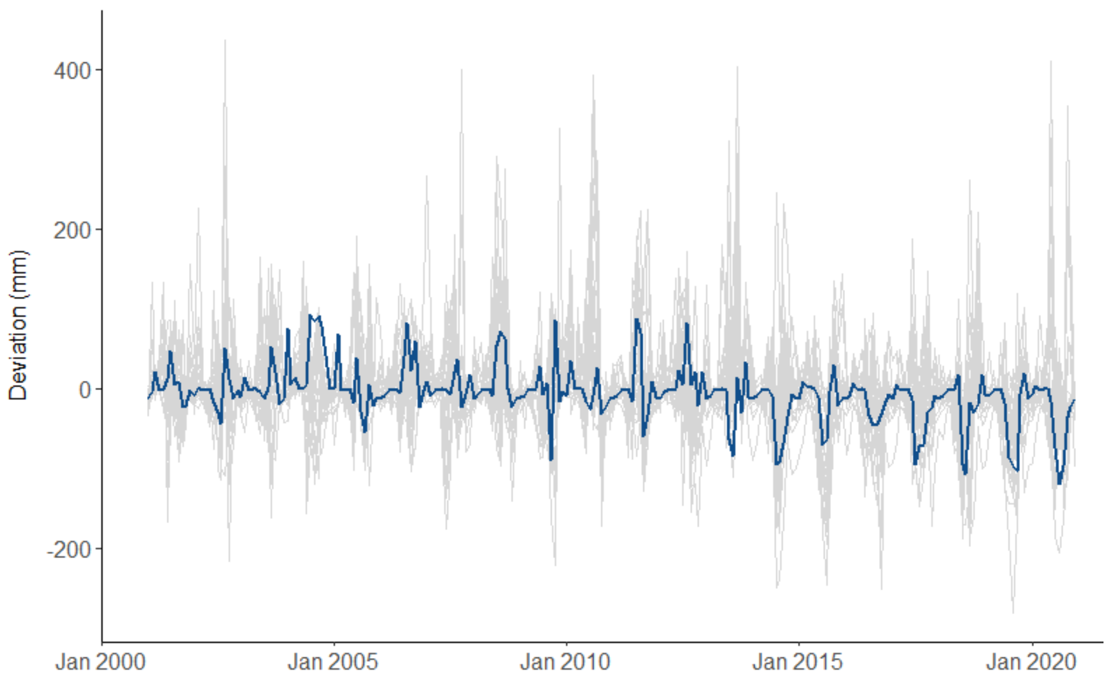
Note: The map shows the location of the 45 cities (red dots) contained in the sample. There is at least one city in every state, except for Tlaxcala. For the city located in this state, data on trading patterns was not available and is thus excluded from the final sample.
Source: Own elaboration based on data from INEGI and SNIIM (2020).

Figure A4. Monthly Precipitation Series by State, 2001-2020



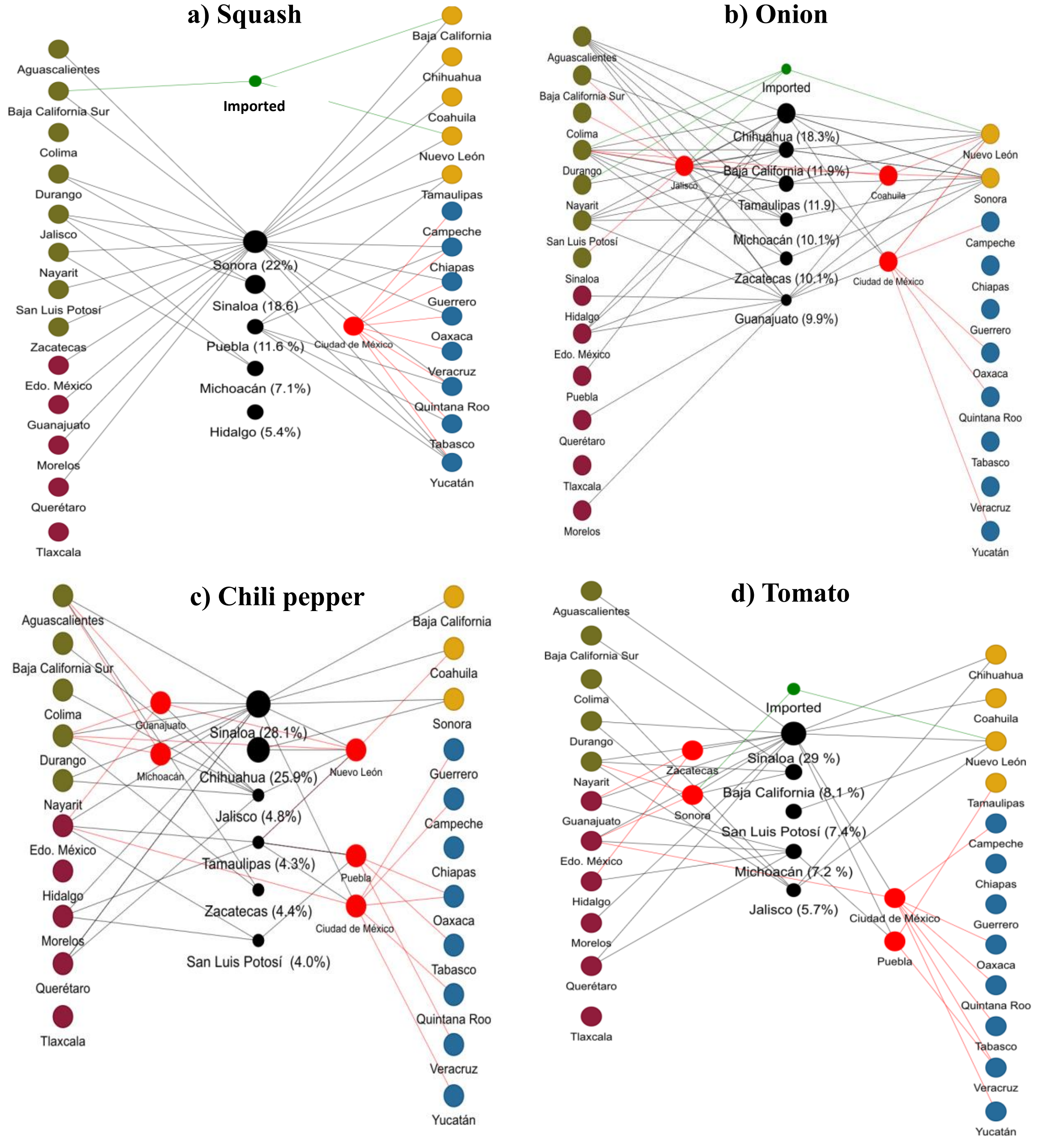
Note: Dark blue lines refer to Sinaloa, a major state producer of vegetables while grey lines depict the precipitation series of each of the other 31 Mexican states.
Source: Own elaboration based on Thornton et al. (2018) and SIAP (2020b).

Figure A5. Monthly Deviations from the Precipitation Normal by State, 2001-2020



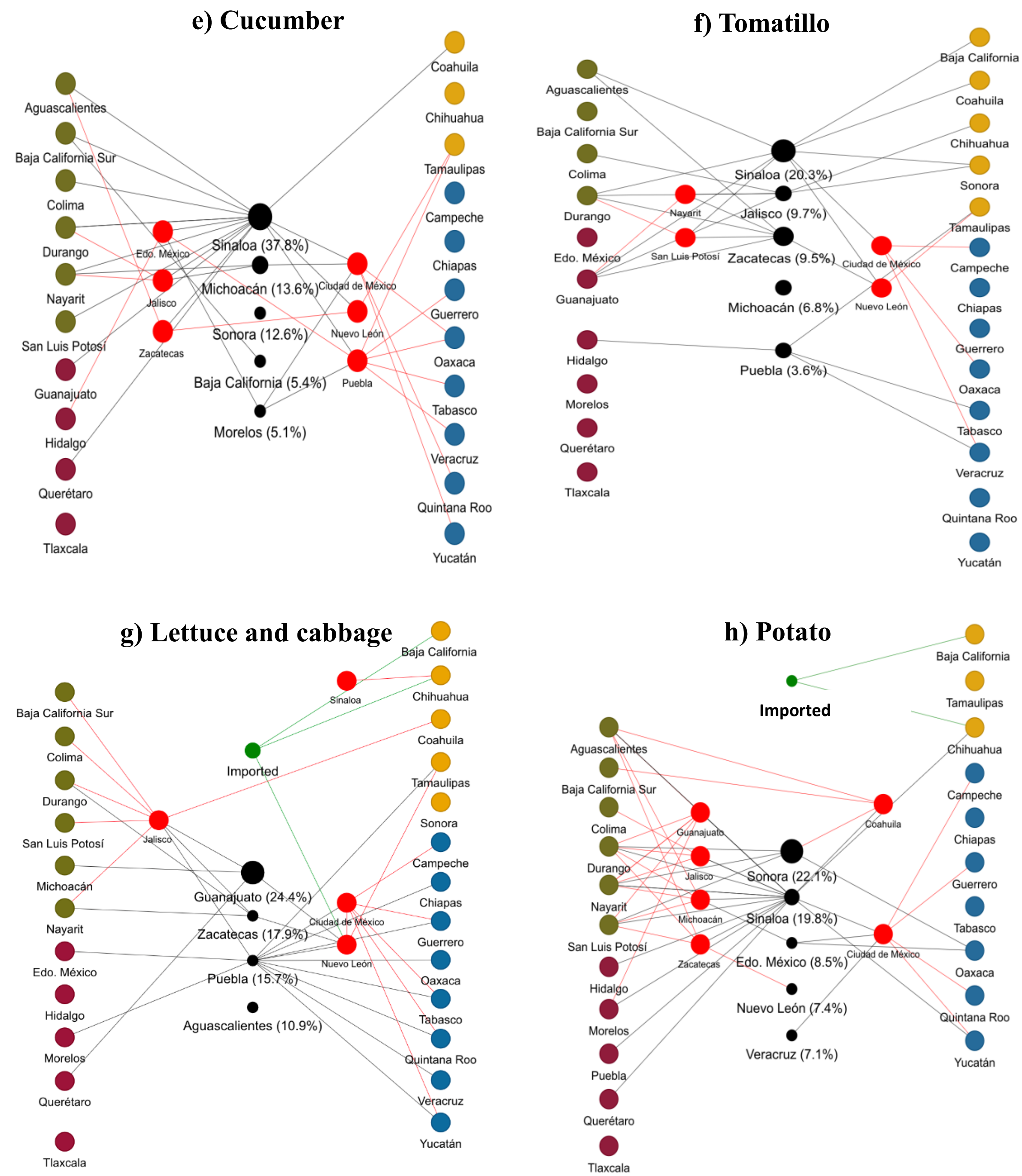
Note: Dark blue lines refer to Sinaloa, a major state producer of vegetables while grey lines depict the precipitation series of each of the other 31 Mexican states. Monthly precipitation normals calculated as the average for the 1991-2020 period.
Source: Own elaboration based on Thornton et al. (2018) and SIAP (2020b).

Figure A6. Vegetable Commercialization Patterns among Mexican States



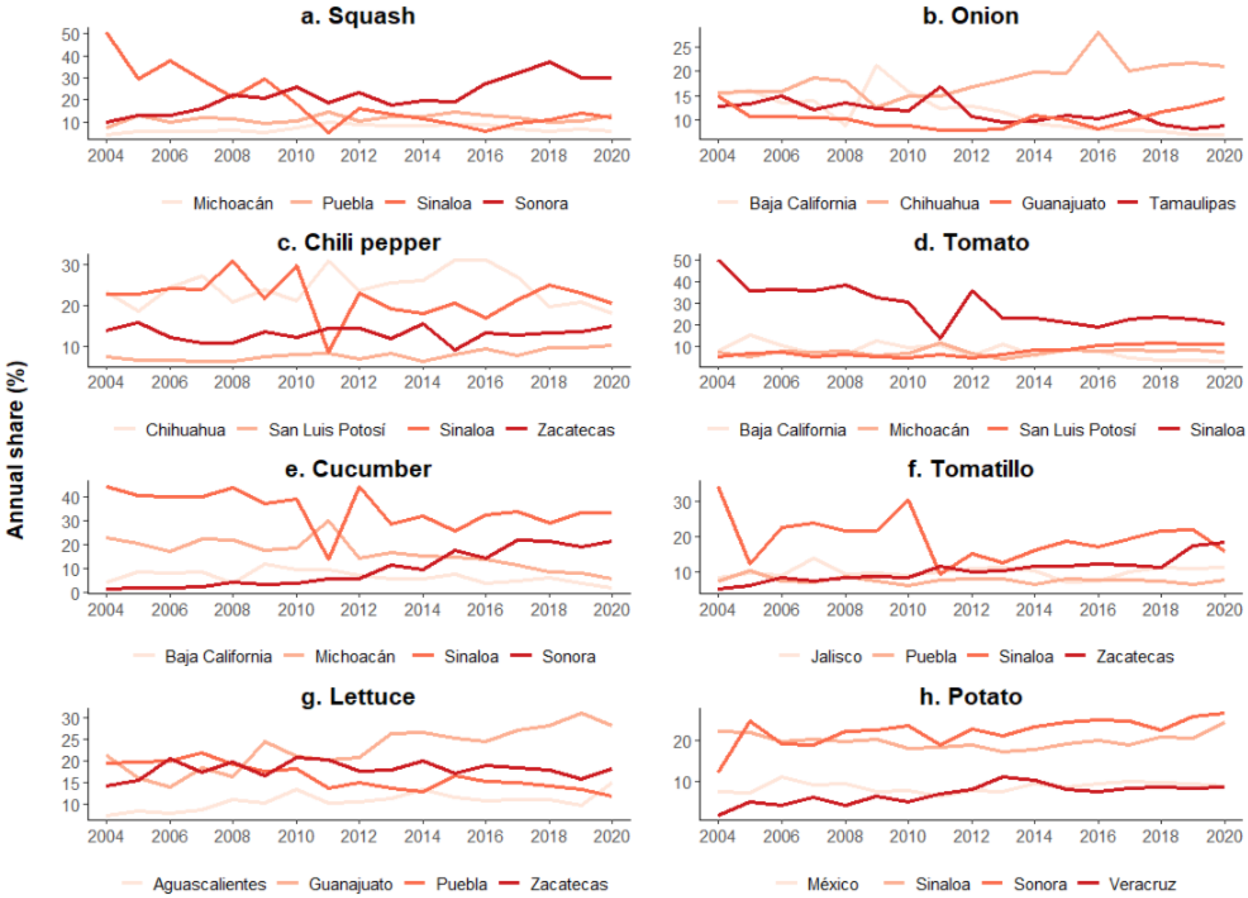
Note: The figure shows the patterns of commecialization among Mexican states for each vegetable. For its construction we first identified state producers using production information for the period 2004-2020. (SIAP, 2020a). Then, using SNIIM data for the period 2000-2020 we identified a pattern of commercialization between a pair of states if vegetables 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). Black dots represent producing states that concentrate at least 60% de the accumulated production during the period 2004-2020. The size of each black dot is proporcional to the participation of each producing state in the total acumulated production (in parhentesis). Red dots represent intermediary states. Lines connecting states indicate that commercialization links exist among them.
Source: Own elaboration based on data from SIAP (2020a) and SNIIM (2020)

Figure A6. Vegetable Commercialization Patterns among Mexican States, continued



Note: The figure shows the patterns of commecialization among Mexican states for each vegetable. For its construction we first identified state producers using production information for the period 2004-2020. (SIAP, 2020a). Then, using SNIIM data for the period 2000-2020 we identified a pattern of commercialization between a pair of states if vegetables 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). Black dots represent producing states that concentrate at least 60% de the accumulated production during the period 2004-2020. The size of each black dot is proporcional to the participation of each producing state in the total acumulated production (in parhentesis). Red dots represent intermediary states. Lines connecting states indicate that commercialization links exist among them.
Source: Own elaboration based on data from SIAP (2020a) and SNIIM (2020)

Figure A7. Share of the Top 4 State Producers on Annual Production (2004-2020)



Note: This figure plots the share of the top four producers of each vegetable in annual production for the period 2004-2020.

Source: Own elaboration using monthly production data from SIAP (2020a).