Extreme Weather and the Diversification of Drug Trafficking Organizations in Mexico

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Abstract

In recent years, Mexican organized criminal groups have diversified their operations beyond the production and transport of illicit drugs into formal agriculture, irrigation, kidnapping, and other markets. At the same time, Mexican agriculture has been susceptible to an increasing frequency of adverse weather shocks. We present a model of cartel operations at the nexus of legal agriculture, illicit agriculture, and migration that demonstrates how weather shocks incentivize cartels to adjust their operations in a way that leads farmers to shift from legal crops to illegal cultivation and out-migration. We test these predictions with a large dataset on Mexican agricultural production, cartel activity, and migration from 2012 to 2019. We find that weather shocks reduce maize production, increase cannabis production, and lead to out-migration. These effects are concentrated in municipalities with a strong presence of agro-cartels. We also find more persistent effects on violence, suggesting that cartels respond to these shocks by consolidating power and diversifying their operations. Further climate change will likely exacerbate these effects.

Keywords: Climate, Agriculture, Organized Crime, Migration
JEL codes: O13, Q54, K42, F22

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1 Introduction

Drug trafficking organizations (DTOs), or organized criminal groups, have become deeply embedded in the fabric of contemporary Mexican politics and life. In the 2024 presidential election, 53% of voters identified public safety as the single most important issue, compared to only 32% naming corruption and 15% citing the economy (Raziel, 2024). By a variety of measures, organized criminal groups have grown substantially in size in recent decades. The estimated membership increased from approximately 115,000 individuals in 2012 to more than 175,000 in 2022 (Prieto-Curiel et al., 2023), while their operational presence now extends to all 32 Mexican states (Emma and Vyas, 2026). Their revenues have also grown considerably, with estimates suggesting that earnings from drug trafficking to the United States rose from \$18–\$29 billion in 2010 to \$37–\$58 billion in 2025 (Aub, 2025). During this period, cartel activities have also expanded in scope. Although their primary revenue source remains the transport and, to some extent, production of illegal drugs, they have increasingly diversified into agricultural extortion and production, synthetic drug trafficking, fuel theft, kidnapping, and irregular migration markets.

At the same time, Mexico is a major agricultural producer and exporter. A relatively large share of its population is employed in the agricultural sector, ranking it first among OECD countries at 11% of its labor force in 2025, compared to an OECD average of 4% (International Labour Organization, 2026). Over the past two decades, Mexican agriculture has become susceptible to increasingly common climatic shocks. Major events such as the 2011–2012 drought, which was the country's most severe in the last 70 years, caused substantial crop losses and exposed the sector's vulnerability to rainfall and temperature extremes (Flores and Branson, 2012). These shocks affect both primary crops, such as maize, which is highly dependent on rainfall and sensitive to heat stress, and secondary high-value crops, such as avocados and vegetables, which are highly sensitive to heat, drought, and extreme rainfall.

In this paper, we find that cartels have responded to these weather-related shocks by entering agriculture and related activities such as water theft and irrigation. One way to buffer against these shocks is through capital investment, especially in irrigation. While many small farmers cannot afford such infrastructure, cartels often can. Farmers have responded to these shocks along two margins, with some acquiescing and working under the auspices of cartels, and others through out-migration. Our findings suggest that as weather shocks intensify in a rapidly changing climate, cartels are likely to strengthen their position in informal agricultural sectors while reducing their role in formal agriculture, potentially harming agricultural productivity. They may also play a larger role in irregular migration markets, an issue with major domestic and foreign policy implications for both Mexico and the United States. Our results imply that the extent to which organized criminal groups become more central to life in Mexico will depend, at least in part, on the country's ability to adapt to climate change.

To illustrate the mechanisms by which weather shocks affect agricultural and migration markets, we present a stylized model of formal and informal agriculture in Mexico with two parties: farmers and cartels. Central to the model is the idea that formal agriculture, largely carried out by capital-constrained small farmers, is more contingent on weather shocks, whereas informal agriculture, largely carried out under the auspices of cartels, is less so because cartels can deploy capital to ensure steady production of illicit drugs. Cartels exploit farmers' capital constraints by both extorting those farmers who wish to operate independently in formal agricultural markets (e.g., corn and avocados) and by extracting surplus from those farmers who opt to work at fixed wages for the cartel in informal agricultural markets, including illicit crops like cannabis. Our model illuminates the circumstances under which weather shocks lead farmers to continue operating independently, work for cartels, or migrate.

We assemble a rich panel dataset of temperature deviations, agricultural production, and cartel activity spanning all Mexican municipalities from 2012 to 2019 and arrive at three robust sets of results consistent with our model predictions. First, weather shocks have sizable negative impacts on agricultural production in terms of both quantity (13% for a one-standard-deviation increase in wet-season temperature) and value (14%) for maize and other crops. These adverse effects, however, are substantially mitigated in areas controlled by cartels that have extended their operations into agriculture. Importantly, we find no comparable mitigation in areas under cartel control that do not engage in agricultural production. Second, there are two clear responses to these temperature deviations on separate margins. Weather shocks are accompanied by increases in violence, as evidenced by a surge in the average homicide rate per 100,000 and an increase in illegal cannabis eradication in areas where agricultural-linked cartels operate. These results are consistent with the notion of cartel consolidation of the agricultural labor market and entry into agricultural production, and are also accompanied by clear migratory responses (20% for a standard deviation increase in the average temperature) as weather shocks lead to increased irregular migration overall and the increased use of smugglers to facilitate migration in areas under cartel control. Third, the persistence of these effects suggests that cartels use them to consolidate their control over new areas. While the effects of weather shocks on maize production, an annual crop, are short-lived, their effects on violence and migration are more durable.

We identify these effects by leveraging the panel structure of our data to isolate plausibly exogenous components of average wet-season temperature deviations. Specifically, we exploit within-municipality variation in temperature relative to historical averages. We also use information on the geographical extent of cartel operations to explore heterogeneity in these effects across municipalities. Finally, we leverage variation in migration routes from the same municipality across different segments of the US-Mexico border to estimate migratory responses to local weather shocks.

To bring these predictions to the data, we combine several sources that allow us to observe the model's three main margins: legal agriculture, illicit agriculture, and migration. Weather shocks are measured using municipality-specific temperature anomalies during the growing season; legal agricultural production comes from administrative crop records; illicit agricultural activity is proxied by cannabis and poppy eradication records; violence is measured using homicide data; and migration outcomes are drawn from survey data on deported Mexican migrants, which allow us to distinguish smuggler-assisted from non-smuggler migration. We also measure cartel presence using municipality-level news-based data and distinguish cartels with strong agricultural linkages from other criminal organizations. This measurement strategy allows us to test not only whether weather shocks affect agriculture and migration, but also whether these effects are concentrated in places where cartels are plausibly positioned to reshape rural economic activity.

Ultimately, we conclude that climate change is likely to sustain migratory pressure and promote a greater cartel presence in the Mexican agricultural industry. This reality must be recognized both by policymakers in the United States who wish to design successful border enforcement, immigration, and trade policies and by policymakers in Mexico who wish to implement domestic security policies aimed at curbing the encroachment of organized crime. However, the increased presence of cartels in agriculture will have an ambiguous impact on the mediation of climate shock-driven migration. If agricultural workers are sufficiently averse to working under cartel auspices, adverse weather will lead to greater migration. If, on the other hand, cartels are more normalized and larger swaths of the Mexican population grow more willing to work under their auspices, then the ensuing influx of capital into agriculture may contribute to a decoupling of adverse weather and migration. In either case, even if this increase in agricultural capital is accompanied by higher agricultural productivity, the surplus is likely to be captured by cartels. More broadly, these findings underscore how the intersection of climate stress and organized criminal activity can reshape rural economies, food production, and migration dynamics in developing countries facing similar challenges.

The remainder of the paper is organized as follows. In Section 2, we provide institutional background for the setting of our analysis, and we discuss three literatures that our work touches on: organized crime, the structure of Mexican agriculture, and the nexus of climate stress, migration, and violence. In Section 3, we present a simple and highly stylized model of cartel-farmer interactions that clarifies how weather shocks operate along three distinct margins, shifting farmers between formal and informal agriculture and migration. In Section 4, we describe our data sources and detail the issues involved in measuring weather shocks, agricultural production, cartel presence and illegal activities, and migration. In Section 5, we describe our empirical strategy and present our results. We conclude in Section 6.

2 Background

Organized crime, parallel governance, and market diversification. Over the past two decades, organized criminal groups in Mexico have evolved from illicit drug-trafficking organizations into diversified economic actors exercising well-defined territorial control. This transformation has been largely shaped by shifts in state policy and enforcement efforts, which led to strategic adaptations by criminal organizations. Empirical research shows, for example, that increased crackdowns in municipalities that elected government-aligned mayors in the late 2000s weakened trafficking groups and triggered violent attempts by rival organizations to seize control of contested territories. These enforcement shocks further diverted drug flows toward alternative routes, producing sharp increases in homicides in municipalities newly exposed to federal intervention (Dell, 2015). Through this sustained process of adaptation and territorial reorganization, cartels have consolidated what scholars describe as "criminal governance" in many Mexican localities, performing state-like functions such as taxation, dispute resolution, and policing (Osorio and Brewer-Osorio, 2025; Uribe et al., 2025).

Beyond territorial control, state repression and inter-cartel competition have driven criminal groups to diversify their portfolios and expand their capacity for violence (Herrera and Martinez-Alvarez, 2022). The War on Drugs, in particular, pushed cartels into regions traversed by existing oil pipelines, transforming small-scale fuel theft into a highly organized criminal enterprise (Battiston et al., 2024). Reflecting this consolidation, Mexico's state oil company reported that illegal pipeline taps rose from 710 in 2010 to nearly 15,000 by 2018 (Woolston, 2025).

A parallel body of work documents cartels' diversification into agriculture. De Haro (2025) shows that the increase in the use of fentanyl in the United States, together with the decreasing demand for Mexican heroin, pushed cartels toward extortion in avocado-producing regions. Strong global demand and rising export prices have further incentivized cartels to take control of agricultural regions, where homicides have risen sharply (Estancona and Tiscornia, 2025).

The combination of territorial governance and economic diversification positions cartels as de facto regulators and capital providers in sectors such as agriculture. By controlling land, inputs, transportation routes, and export channels, they can extort producers, set prices, finance and direct production, and selectively enforce property rights. In areas where cartels dominate, and formal financial and state institutions are weak or absent, Mexican farmers face a constrained choice set. They can try to operate independently and risk extortion and violence, or enter clientelistic arrangements that transfer part of their economic surplus to the cartel in exchange for costly loans or "protection." Cartels thus function simultaneously as rent-seekers and as providers of capital, insurance, and enforcement, though the scope of these roles depends on the underlying characteristics of the sectors into which they expand.

The structure of Mexican agriculture. The structure of Mexico's agricultural sector leaves it vulnerable to both the encroachment of organized crime and exogenous shocks such as climate change. Farms are predominantly small- and medium-scale, and access to formal finance and modern technologies remains limited (World Bank et al., 2015). The 2019 National Agricultural Survey reports that fewer than 10% of producers accessed formal credit and that rainfed agriculture accounted for more than three-fourths of cultivated land (INEGI, 2019). Against this backdrop of weak state presence and limited access to credit and capital, agricultural communities are especially exposed to criminal governance. Cartels can fill institutional gaps by financing production, facilitating access to inputs and transportation routes, enforcing compliance, and establishing clientelist arrangements in which producers transfer part of their economic surplus to the cartel in exchange for protection and market access.

These structural constraints are particularly evident in staple crops such as maize, which dominates the Mexican agricultural sector and accounts for more than half of the total agricultural output (INEGI, 2019). Rising temperatures are projected to generate substantial yield losses, with rainfed maize systems likely to be most affected due to their sensitivity to heat stress;

irrigated fields, on the contrary, are expected to remain relatively stable (Ureta et al., 2020). As a result, poorer states with large indigenous populations, including Chiapas, Oaxaca, and Guerrero, are expected to be disproportionately affected by climate shocks (Estrada et al., 2022). In areas where state capacity is limited, the resulting decline in expected agricultural returns may create conditions favorable to cartel penetration and the expansion of criminal governance in rural communities.

A second feature of Mexico's agricultural sector that contributes to the infiltration of organized crime is the rapid expansion of high-value export crops such as avocados and berries, which generate substantial rents as U.S. demand grows. Mexico's avocado exports to the United States rose from an annual average of 55 million pounds in 2001 to 2.25 billion pounds by 2021, with annual revenues reaching $2.8 billion (Weber and Kramer, 2022; Stevenson, 2022). Over this period, exports were concentrated in Michoacán, the only state authorized to ship avocados to the United States until Jalisco gained access in 2022 (Arciniegas, 2024; Stevenson, 2022). Beyond their profitability, these crops are capital-intensive, requiring upfront investments in irrigation, agrochemicals, and distribution logistics. Where state capacity is weak and formal credit is limited, the combination of high costs and high returns creates openings for cartels to expand into informal capital provision and enforcement. Climate shocks can amplify these incentives by tightening liquidity constraints and eroding producers' outside options, deepening cartel presence in agricultural communities.

Climate, migration, and criminal violence. A large literature examines the link between weather-related events and international migration. This body of work documents substantial heterogeneity across origin and destination countries, baseline income levels, exposure to agriculture, and the possibility of within-country adaptation (Beine and Parsons, 2015; Cattaneo and Peri, 2016; Cattaneo et al., 2019), and identifies two opposing forces. On the one hand, adverse weather shocks reduce agricultural productivity and rural earnings, pushing individuals to seek opportunities abroad (Burzyński et al., 2022; Coniglio and Pesce, 2015). This climate-migration link is particularly evident in countries with established migrant networks and has been documented in both sending countries, such as El Salvador (Ibanez et al., 2025), and destination countries, such as the United States (Mahajan and Yang, 2020).

On the other hand, weather shocks can constrain international mobility by tightening the liquidity, credit, and networks that potential migrants need to finance costly cross-border moves, particularly in poorer countries (Cattaneo and Peri, 2016). Households may redirect available financial and social resources toward immediate recovery rather than longer-distance moves, dampening the migration response. Evidence from Mexico, for instance, shows that agricultural cash-transfer programs and disaster funds can mitigate the impact of weather shocks on migration (Chort and de La Rupelle, 2022). The net migration response, therefore, depends on whether climate stress primarily raises the returns to moving or tightens the constraints on doing so—a distinction that helps explain the cross-country and within-country heterogeneity documented in the global evidence (Beine and Parsons, 2015; Benonnier et al., 2022; Cattaneo and Peri, 2016; Cattaneo et al., 2019).

Despite this heterogeneity, a growing literature suggests that climate change can intensify international migration pressures, particularly where weather events coincide with limited adaptive capacity and large rural agricultural populations (Chort and de La Rupelle, 2022; Ibanez et al., 2025). Mexico occupies a distinctive position in this literature because agricultural exposure, long-standing migration networks, and the presence of organized criminal actors have coexisted for decades. Early work by Feng et al. (2010) emphasizes the agricultural-productivity channel, showing that adverse climate conditions reduce crop yields and are associated with increased migration from Mexico to the United States. More recent evidence documents that extreme weather raises undocumented migration to the United States and reduces return migration (Danza and Lee, 2022; Zhu et al., 2024), and that climate variability shapes labor-market outcomes and migration incentives in rural Mexico, underscoring the link between agricultural exposure and constraints on local adaptation (Jessoe et al., 2018).

Our paper builds on the migration literature to examine a broader set of linked outcomes central to the political economy of rural Mexico. We examine whether temperature-driven weather shocks affect (i) agricultural production, (ii) international migration, and (iii) criminal violence. This framing is motivated by the possibility that climate stress simultaneously reshapes economic returns in agriculture and alters local market power and coercive capacity. In settings where criminal groups can appropriate rents from agricultural value chains or regulate mobility through illicit markets, weather shocks may reduce output, increase emigration pressure, and raise the returns to territorial control, thereby fueling violence. By estimating these responses jointly, we link the climate-migration literature to a broader set of economic and policy adjustments to climate stress, emphasizing how temperature shocks propagate through production, mobility, and violence within the same localities.

3 Model

We present a model of cartel-farmer interactions to examine how climate mediates the links between agricultural production, illicit crop production, and migration. The main insight of our model is that cartel entry into agricultural markets functions as a form of informal insurance for farmers against climate shocks. This insurance role arises from cartels' ability to make certain activities, namely the production of both licit and illicit crops, less susceptible to climate variability through irrigation and other costly capital investments.

The model has two types of players: a single cartel and a large mass of farmers. The cartel operates across two agricultural markets—a competitive formal market for corn (c) and a monopolistic informal market for illicit crops like cannabis (m)—and pursues a corresponding activity in each. In the corn market, it extorts farmers by demanding a share of their crop; in the illicit-crop market, it operates farms directly by commandeering farmer labor and, potentially, farmer land. A continuum of farmers chooses among three activities: producing corn independently, producing illicit crops under the cartel, or migrating. Farmers are differentiated by $\sigma > 0$, the disutility or stigma they bear from producing illicit crops under the cartel, and $\alpha > 0$, their private (net) benefit from migration.

Cartels first set the extortion rate τ on corn, which can be thought of as an *ad valorem* tax on corn production. Farmers then decide whether to grow corn or cultivate illicit crops. A Bernoulli weather shock W is then drawn, where bad weather ($W = 1$) occurs with probability ρ. After observing the weather shock, farmers may switch production or migrate. Let π_c^W denote the (net) value of the corn crop under weather W, and π_m the value of the illicit-crop output. In our model, corn production is conditional on weather with $\pi_c^0 > \pi_c^1$, whereas illicit-crop production is not. This asymmetry reflects the assumption that illicit-crop cultivation occurs under the cartel, which, having access to capital, can irrigate and otherwise mitigate the effects of adverse weather.[1] The cartel demands an endogenous fraction θ of the illicit-crop surplus.

Equilibrium

Farmers choose from three actions, and their decisions are governed by three inequality conditions, each of which corresponds to the margin between any two of those actions. Formally, we can write the farmer's decision rule with a series of mutually exclusive inequalities as follows:

Grow Corn:	$\alpha < (1-\tau)\pi_c^W$	and $(1-\theta)\pi_m - \sigma < (1-\tau)\pi_c^W$
Cultivate Illicit Crops:	$(1-\theta)\pi_m - \sigma > \alpha$	and $(1-\theta)\pi_m - \sigma > (1-\tau)\pi_c^W$
Migrate:	$\alpha > (1-\theta)\pi_m - \sigma$	and $\alpha > (1-\tau)\pi_c^W$

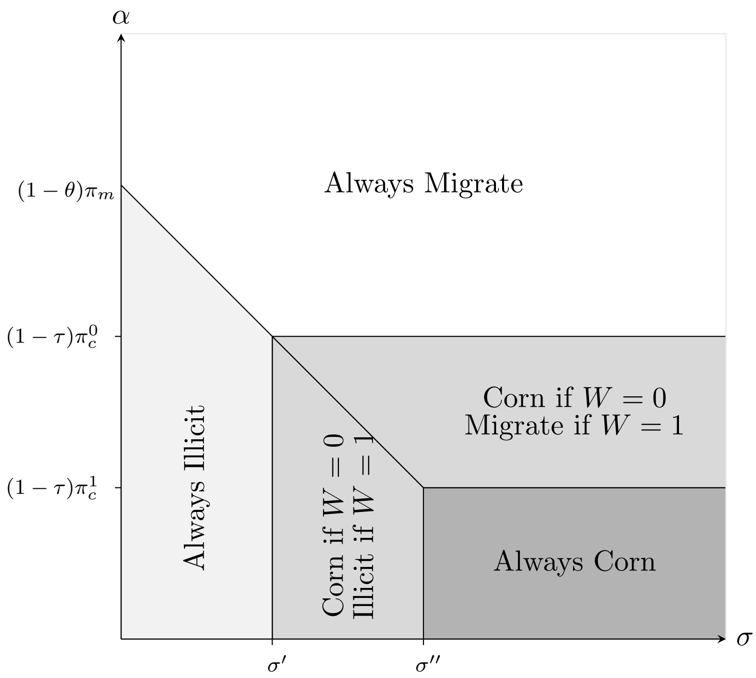
Because the returns to migration and illicit-crop cultivation are independent of this shock, farmers for whom the "Cultivate Illicit Crops" or "Migration" inequalities hold will always make those choices. Meanwhile, farmers for whom the "Grow Corn" inequalities hold include those who always grow corn, and those who switch from corn to illicit-crop cultivation or migration in the face of bad weather.

Depending on the exogenous returns π_m and π_c^W, and the endogenous choices of τ and θ, there are three possible cases to consider. We focus on the most general case, in which $(1-\theta)\pi_m > (1-\tau)\pi_c^0$. That is, a farmer with no distaste for working with the cartel ($\sigma = 0$) and no interest in migrating ($\alpha \leq 0$) would cultivate illicit crops like cannabis for the cartel.[2] Given the farmer's decision rule, it is straightforward to derive the equilibrium actions, which we show graphically in Figure 1.

[1] In reality, illicit-crop cultivation likely retains sensitivity to weather. The logic of our model holds as long as the variance of illicit-crop output is smaller than that of corn.

[2] For completeness, there are two other cases to consider, one in which $(1-\tau)\pi_c^0 > (1-\theta)\pi_m > (1-\tau)\pi_c^1$ (no farmer would cultivate illicit crops in good weather, but some would in bad weather), and one in which $(1-\tau)\pi_c^0 > (1-\tau)\pi_c^1 > (1-\theta)\pi_m$ (no farmer would cultivate illicit crops under any circumstances. These cases can be analyzed using a simpler version of the argument presented here, yielding a few additional insights.

Figure 1: Equilibrium



The various regions in Figure 1 correspond neatly to different empirically relevant groups of farmers. Considering weather shocks as a treatment, the farmers in the medium gray regions can be understood to be compliers, while the farmers in the *Always Migrate*, *Always Illicit*, and *Always Corn* regions can be understood to be either always-takers or never-takers.

Given the farmers' responses, the cartel chooses τ to maximize its profits. The tradeoffs of the cartel are clear. Although a higher τ yields greater returns for the cartel from corn production, it also leads to greater migration, which yields no benefit to the cartel. Formally, the cartel's problem can be written as

$$\max_{\tau,\theta} \rho \left[\int_{\text{Corn, } W\,=\,1} \tau\pi_c^1 + \int_{\text{Illicit, } W\,=\,1} \theta\pi_m \right] + (1-\rho) \left[\int_{\text{Corn, } W\,=\,0} \tau\pi_c^0 + \int_{\text{Illicit, } W\,=\,0} \theta\pi_m \right]$$

Note that the regions of integration are themselves functions of τ.

The most immediate predictions that arise from this model are that adverse weather should result in more migration, more cannabis cultivation and less corn production. These are causal effects. To a first order, the magnitude of these effects is driven by the susceptibility of the crop to weather shocks, and, importantly, is not influenced by the cartel's choices of τ and θ. This is due to the fact that the region of compliers is determined entirely by the difference between π_c^0 and π_c^1.[3]

Over time, the accumulation of weather shocks may lead to an adjustment in prior beliefs

[3] While the size of the region of compliers is not determined by τ, θ and π_m, it is true that the location of the region in $\alpha - \sigma$ space is. Hence, differences in the mass of farmers in this space do provide some scope for second-order effects of τ and θ on the effects of weather shocks.

about the climate risk. We can use our model to analyze how these markets will respond to changes in the parameter ρ. Specifically, we can analyze how the cartel's choices of $\tau^\star$ and $\theta^\star$ will respond to increasing climate risk. Under mild restrictions on the joint distribution of farmer types $f(\alpha, \sigma)$ that ensure the existence of an interior equilibrium, it is straightforward to obtain these comparative statics. We summarize these results in the following Proposition. A more formal statement of the necessary assumptions to ensure an interior equilibrium, along with a full proof of the Proposition, can be found in Appendix 6.

Proposition 1. *Let $(\tau^\star(\rho), \theta^\star(\rho))$ represent an interior equilibrium for the cartel. Suppose that at that equilibrium (1) the returns to increasing τ are lower in bad weather than in good weather, and (2) there are net returns to increasing θ in bad weather. Then*

1. $\frac{d\tau^\star(\rho)}{d\rho} < 0$
2. *The sign of $\frac{d\theta^\star(\rho)}{d\rho}$ is the same as the sign of the marginal difference between the returns to increasing θ in bad weather and in good weather.*

The assumptions of the proposition have intuitive interpretations that correspond to mild restrictions on the distribution of farmer types f. The first assumption effectively compares the fractions of farmers located along the vertical σ' boundary with the fraction of farmers located along the vertical σ'' boundary in Figure 1. Provided that there is not an outsized mass of farmers located along the σ' boundary, this will hold. The second assumption effectively compares the fraction of farmers who cultivate cannabis in bad weather with the fraction of farmers located along the diagonal *Always Migrate-Always Illicit* boundary in Figure 1. Provided that there is not an outsized mass of farmers located along that diagonal boundary, this will hold. In short, these assumptions simply ensure that second-order participation effects do not dominate first-order revenue-generating effects from changes in $\tau^\star$ and $\theta^\star$.

The first conclusion of Proposition 1 states that the cartel will extort corn farmers less in the face of increasing climate risk. The second conclusion of Proposition 1 states that the cartel's response to climate risk in cannabis cultivation is ambiguous and depends on whether bad weather raises or lowers the marginal profitability of increasing the cartel's share of cannabis profits. If worsening weather increases the cartel's ability to extract surplus from inframarginal cannabis farmers, then $\theta^\star$ rises with climate risk. If, instead, worsening weather makes cannabis participation more fragile, then $\theta^\star$ falls with climate risk. This suggests that the availability of migration as an option for farmers plays a key role in determining the ability of cartels to extract surplus in cannabis cultivation. If migration becomes a more appealing option to marginal farmers, then a worsening climate would actually *decrease* θ.

These comparative statics imply the following corollary:

Corollary. *Impacts of Climate Change.*

1. *If climate risk increases the cartel's ability to extract surplus from inframarginal cannabis farmers, then rising climate risk will lead to fewer farmers engaged in cannabis cultivation, fewer farmers engaged in corn production, and more migration.*

2. *If climate risk decreases the cartel's ability to extract surplus from inframarginal cannabis farmers, then rising climate risk will lead to more farmers engaged in cannabis cultivation, less migration, and an ambiguous effect on the number of farmers engaged in corn production.*

The shifts in $\tau^\star$ and $\theta^\star$ implied by the conclusions of Proposition 1 map directly into shifts in the boundaries drawn in Figure 1.

4 Data

The model highlights several key objects of interest: agricultural output, weather shocks, cartel activity, migration, and illegal activities. We gather information on each of these objects from a variety of administrative and secondary sources. The resulting dataset is organized at the municipality-year level for all variables except migration, which is observed at the municipality-border-month level. The data cover the universe of Mexican municipalities over the period 2012–2019. We describe each source in detail below.

Agricultural production. We measure agricultural production outcomes using administrative data from Mexico's Statistical Yearbook of Agricultural Production published by the Secretariat of Agriculture and Social Development (SADER, 2025). The yearbook reports annual production information at the municipality level by crop, agriculture system (irrigated vs. rainfed), and growth cycle (annual vs. perennial). We merge this information with our weather, migration, and cartel data at the municipality-year level using administrative municipality identifiers from the National Institute of Statistics and Geography (INEGI).

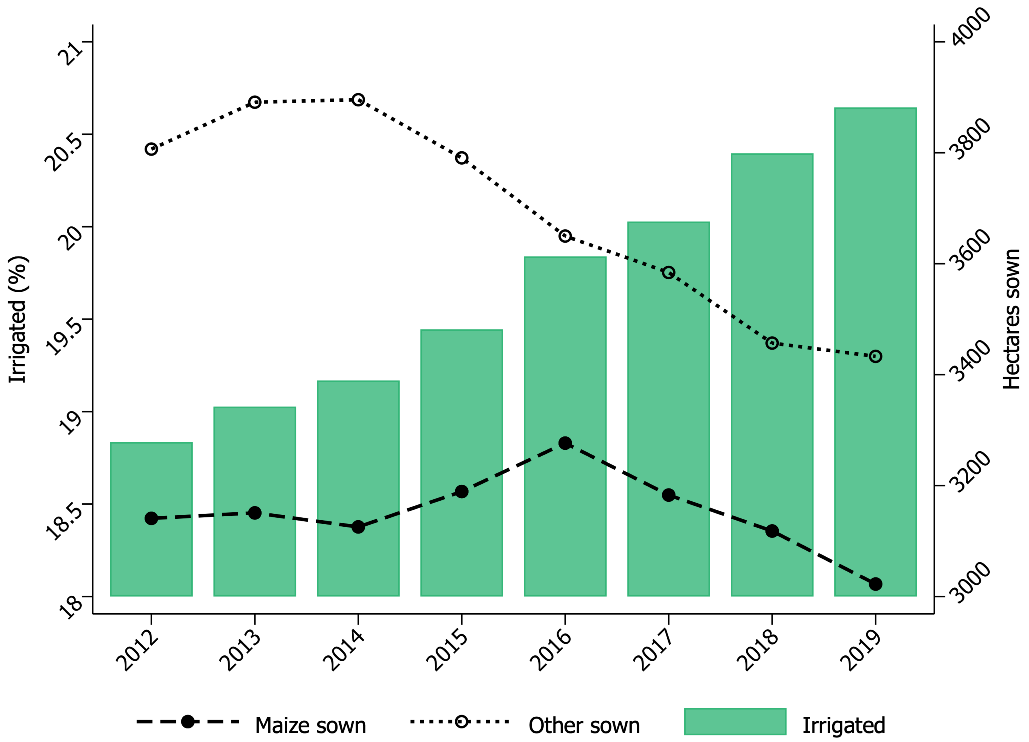
For each municipality m and year y, the records report (i) sown area in hectares, (ii) harvested area in hectares, (iii) physical output in tons, and (iv) production value in thousands of pesos. We construct municipality-year aggregates of total production value, as well as by crop (maize, avocado, and other crops) and farming system (irrigated vs. rainfed). To capture capital deepening as an adaptation margin, we also construct the irrigated share of sown area, defined as irrigated sown hectares divided by total sown hectares.

Figure 2 presents national trends in the sown area and irrigation intensity from 2012 to 2019. The area sown for maize and other crops remained relatively stable through 2016 before falling thereafter. In contrast, the irrigated share increased steadily throughout the sample period. Together, these patterns indicate that the irrigated share has increased even as the total sown area has declined, consistent with capital deepening at the intensive margin.

The main growing season in Mexico, particularly for maize, extends from May through October.[4] Because nearly 70% of Mexican maize production occurs during the spring–summer cycle, and more than two-thirds of this production is rainfed, agricultural output is highly

[4] Existing studies use overlapping but non-identical wet-season windows: March–August (Schlenker and Roberts, 2009), April–September (Danza and Lee, 2022), May–July (Feng et al., 2010), May–August (Zhu et al., 2024), and May–October (Chort and de La Rupelle, 2022; Jessoe et al., 2018).

Figure 2: Trends in Maize vs. Other Sown Area and Irrigated Share



Note: The dashed line reports average hectares sown to maize by year, and the dotted line reports average hectares sown to other crops. Bars report the average irrigated share, in percent. Values are annual averages.

exposed to weather shocks. The remaining production takes place during the fall–winter season, of which 88.4% is irrigated (Gonzalez, 2023).

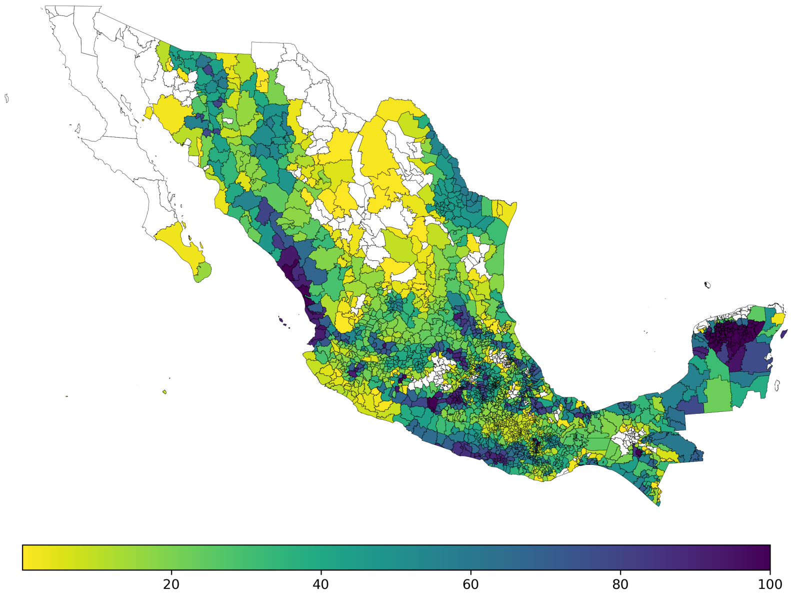
Agricultural suitability measures. To account for heterogeneity in local agricultural potential for the crops of interest, we construct municipality-level agroecological suitability indices for cannabis and maize by overlaying georeferenced soil-profile observations (INEGI, 2013) onto soil map polygons from the FAO Digital Soil Map of the World database (FAO, n.d.) and then aggregating the resulting measures to the municipality level using INEGI municipal boundaries. For each soil mapping unit, we summarize local growing conditions using three key attributes: soil pH, mean temperature, and mean annual precipitation, drawn from nearby INEGI profiles. For the cannabis suitability measure, we interpolate each attribute using inverse-distance weighting from the nearest profile observations, with closer observations receiving greater weight. For maize, we use the same inputs but assign each mapping unit the values from the nearest profile observation.

We then convert each attribute into a unit-free suitability component using ECOCROP absolute and optimal bounds (FAO, 2022),[5] and define overall suitability as the minimum across pH, temperature, and precipitation, consistent with a limiting-factor view of crop growth.

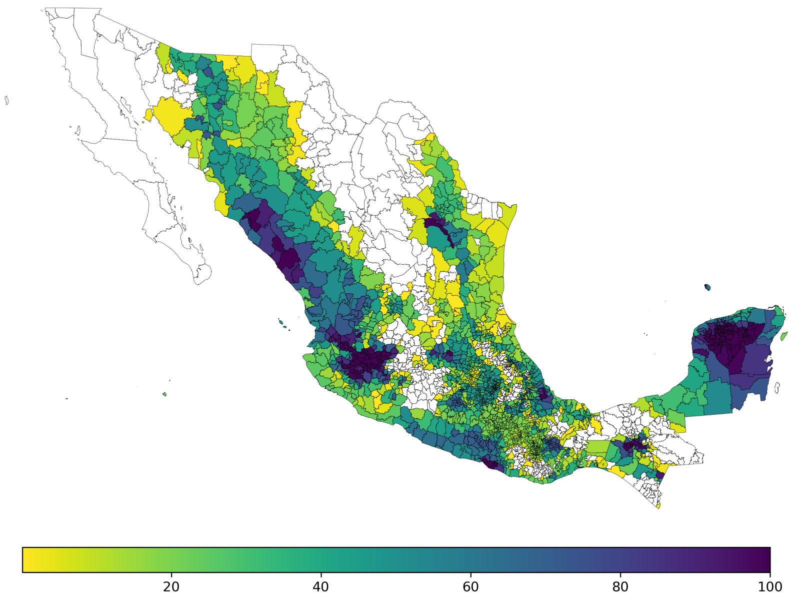
[5] The precise bounds are presented in Table B.1.

Finally, we aggregate mapping-unit suitability to the municipality level by area-weighting the intersections between soil units and municipal polygons, computed in an equal-area projection (measured in hectares).

Figure 3: Crop suitability by municipality



(a) Cannabis suitability



(b) Maize suitability

Note: The sample comprises 2,457 municipalities.

Figure 3 maps the suitability index of cannabis and maize in Mexico at the municipality level. In both cases, suitability is clearly heterogeneous. Higher values cluster along parts of the Pacific corridor and in southern coastal belts, while much of the northern interior and portions of the central plateau display lower suitability. The maps highlight large within-state variation, with high- and low-suitability municipalities often located in close proximity, suggesting that the indices capture granular agroclimatic conditions rather than broad regional differences.

Figure B.4 provides a validation exercise for the agroecological suitability measures used in the analysis. The bars report population-weighted coefficients from municipality-level cross-sectional regressions of standardized outcomes on the corresponding suitability index. The left bar relates cannabis eradication—a proxy for local cannabis cultivation—to cannabis suitability, scaled from 0 to 1. The positive relationship indicates that municipalities with agroclimatic conditions more favorable to cannabis cultivation exhibit higher levels of eradication activity. The two right bars show the analogous exercise for legal agriculture by relating standardized maize and non-maize production outcomes to maize suitability, scaled from 0 to 100. Consistent with a crop-specific comparative-advantage interpretation, maize suitability is more strongly associated with maize production than with non-maize agricultural production. Bars outlined in bold black denote coefficients that are statistically significant at the 5% level.

Temperature deviations. Climate data come from the ERA5 reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2023). We use the standard ERA5 variable `t2m`, defined as air temperature measured at 2 meters above the surface (land, sea, or inland waters).[6] To isolate idiosyncratic temperature variation from persistent geographic and seasonal patterns, we construct municipality- and week-specific temperature deviations relative to historical baselines constructed from the 1998–2007 pre-period.

Let T_{mwy} denote the maximum temperature in municipality m, during calendar week $w \in \{1, \dots, 52\}$, in year y. For each municipality-week pair, we compute a historical mean and standard deviation:

$$\mu_{mw} \equiv \mathbb{E}[T_{mwy} \mid y \in [1998, 2007]] \,, \qquad \sigma_{mw} \equiv \sqrt{\mathbb{V}[T_{mwy} \mid y \in [1998, 2007]]}. \tag{1}$$

These moments define the local climatic baseline against which observed temperatures are evaluated, allowing our analysis to focus on deviations from long-run conditions rather than absolute temperature levels.

We then define standardized weekly temperature deviations as,

$$Z_{mwy} \equiv \frac{T_{mwy} - \mu_{mw}}{\sigma_{mw}}. \tag{2}$$

By construction, Z_{mwy} measures the extent to which realized temperatures deviate from typical

[6] In ERA5, `t2m` is obtained by interpolating between the lowest model level and the Earth's surface while accounting for near-surface atmospheric conditions. The native unit is Kelvin (K), which is converted to degrees Celsius by subtracting 273.15. ERA5 single-level documentation is available through the Copernicus Climate Data Store at https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview.

conditions in municipality m during week w, expressed in standard deviations.

Because our focus is on the relationship between temperature shocks and agricultural production, we use equation (2) to construct a measure of climatic stress that captures cumulative heat exposure during the wet growing season. However, the precise timing of the agriculturally relevant wet season is not uniquely defined in the literature. Existing studies on Mexico and comparable settings typically focus on the broader March–October period, although the exact start and end dates differ across sources (Zhu et al., 2024; Ibanez et al., 2025; Danza and Lee, 2022).

Instead of imposing a single ex ante exposure window, we conduct a grid search over all contiguous weekly intervals within the March–October season and estimate the relationship between temperature shocks and agricultural production for each candidate window. Figure B.1 indicates that the strongest negative association is concentrated in weeks 23–44, which we adopt as our baseline wet-season exposure window.

To capture temperature deviations by growing season, we construct an annual municipality-level temperature deviation measure as the average of the weekly standard deviations between calendar weeks 23 and 44:

$$\text{Temperature Deviation}_{my} \equiv \frac{1}{|\mathcal{W}|} \sum_{w \in \mathcal{W}} Z_{mwy}, \qquad \mathcal{W} = \{23, \dots, 44\}. \tag{3}$$

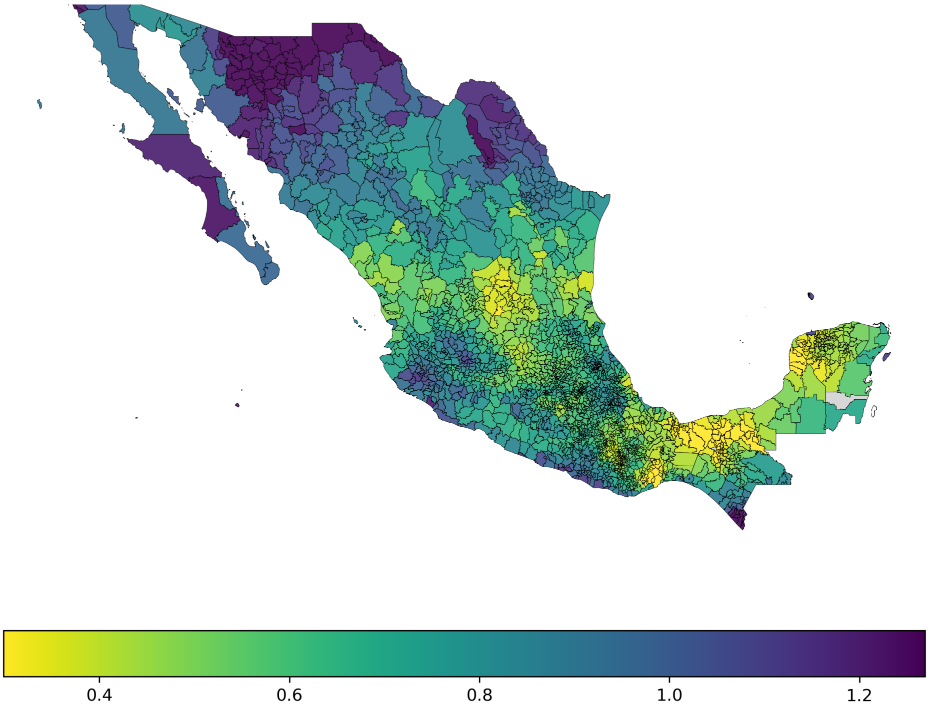
In equation (3), a one-unit increase in Temperature Deviation$_{my}$ corresponds to a one-standard-deviation increase in the average wet-season temperature relative to municipality m's own historical trend for the same period. This approach isolates *unusually* hot growing seasons while accounting for persistent cross-sectional differences in temperature patterns and seasonal cycles (similar to Zhu et al., 2024; Ibanez et al., 2025; Danza and Lee, 2022).

Figure B.3 plots kernel density estimates of the municipality-level wet-season temperature deviation, Temperature Deviation$_{my}$, for each year between 2012 and 2019. Each curve represents the annual cross-sectional distribution of standardized temperature deviations from each municipality's historical mean. The distributions largely overlap and are concentrated between 0.5 and 1.5 standard deviations from the historical baseline, indicating common exposure to wet-season temperatures above the historical baseline during the study period.[7]

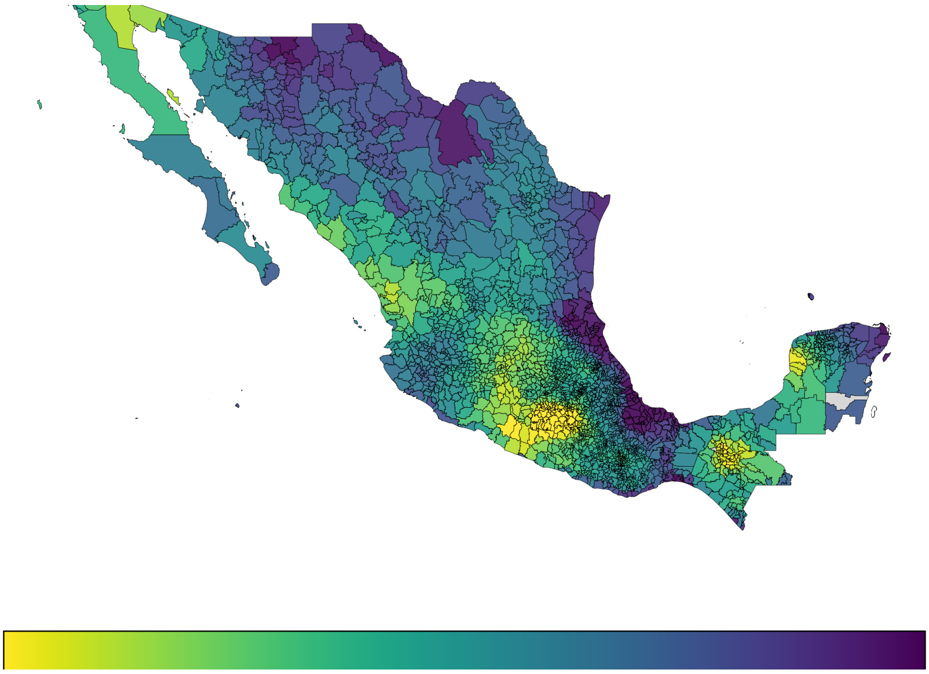
In terms of the geographic variation of the average temperature deviations, Figure 4 maps the spatial distribution of the Temperature Deviation variable in the first (2012) and last (2019) years of the sample. The figures indicate that northern Mexico experienced the largest increases in average temperatures during the wet season relative to the local 1998–2007 trend, while temperatures in the south and southeast remained within half a standard deviation of their long-term trends.

[7] To assess whether extreme realizations of this measure became more pronounced during the sample period, Figure B.2 plots the evolution of selected upper percentiles of the municipality-level distributions.

Figure 4: Municipality temperature deviations relative to the 1998–2007 local trends



(a) Temperature deviations in 2012



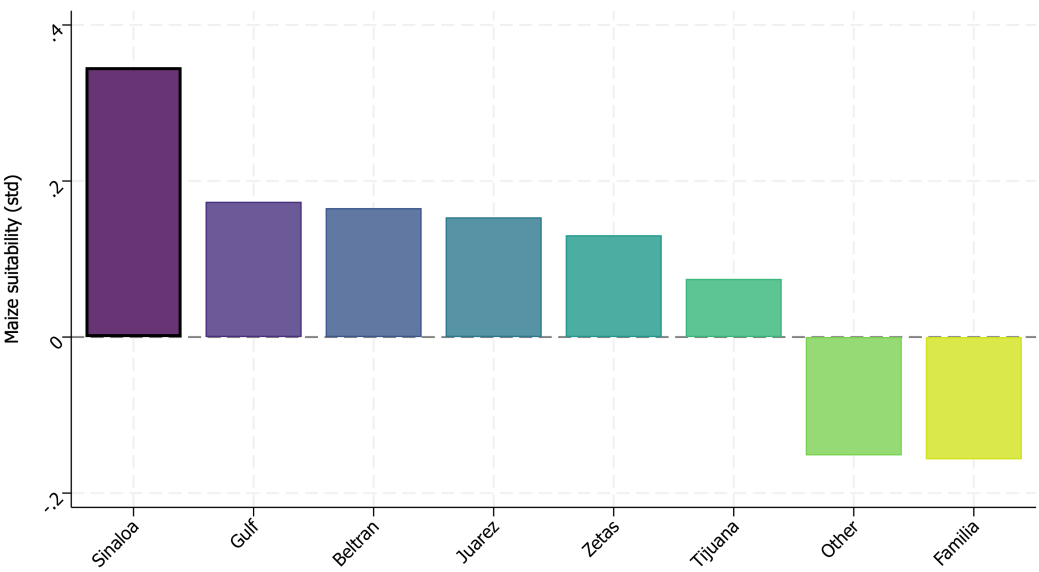
(b) Temperature deviations in 2019

Note: The sample comprises 2,457 municipalities.

Cartel presence. A central object in our empirical analysis is municipalities' exposure to cartels, which may mediate the relationship between temperature shocks and farmers' responses. Measuring organized crime, however, is challenging because administrative and judicial records are often subject to non-classical measurement error, as reporting and enforcement respond endogenously to criminal power and local state capacity (Battiston et al., 2024). To mitigate these concerns, we capture cartel presence using the municipality–year panel assembled by Coscia and Rios (2012), who systematically scrape and code Google News reports on cartel activity to identify cartel presence annually between 1991 and 2010 across all municipalities. Admittedly, a natural concern with news-based proxies is that media coverage is selective. Incidents in remote rural municipalities are less likely to appear in the news than those in urban centers or along major trafficking corridors. However, this selection would lead to the misclassification of cartel-controlled rural municipalities as untreated, biasing the estimated effect of cartel presence toward zero. As such, we interpret our estimates as lower bounds of the true effect.

Because our main sample begins in 2012, we measure cartel presence in the pre-period (2000–2011) to ensure that the indicator is not determined by subsequent weather shocks and outcomes. We define cartel presence using an indicator that equals 1 if any news report links municipality m to a cartel before 2012 and 0 otherwise. We retain the identities of major cartels—Sinaloa, Gulf, Juárez, Tijuana, Zetas, Beltrán-Leyva, La Familia—and a residual 'other' category. Figure B.5 documents the sharp increase in cartel-related news intensity through the

Figure 5: Maize suitability by cartel presence (2000–2011)



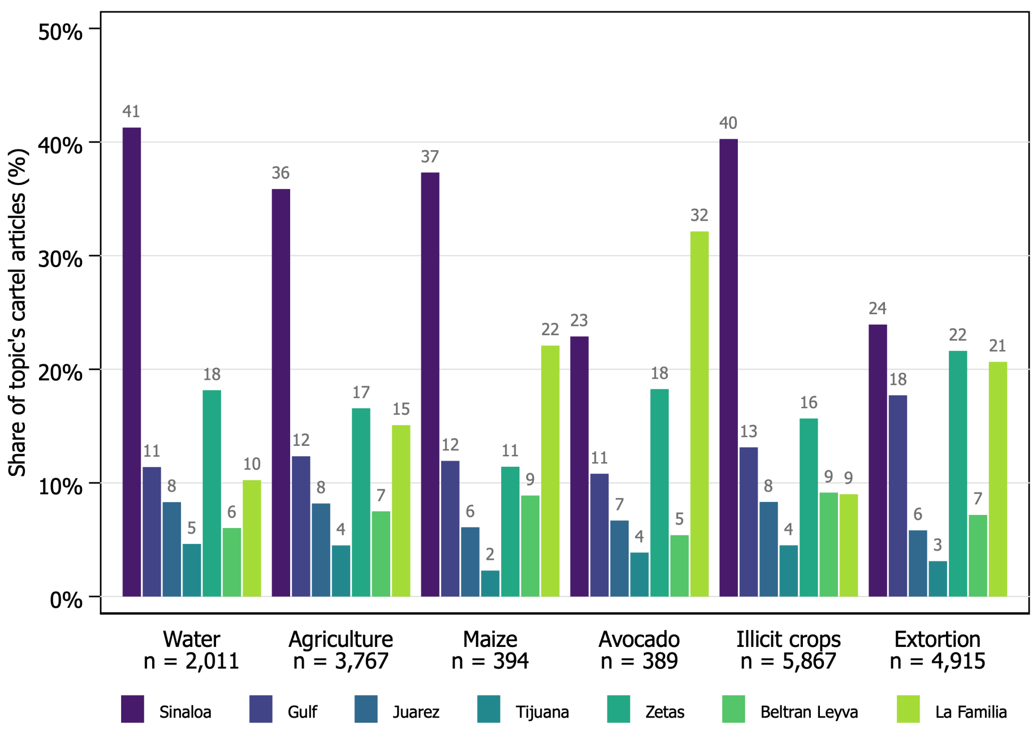
Note: We estimate a cross-sectional regression of standardized maize suitability on cartel-presence indicators. The coefficients report differences in maize suitability, measured in standard deviations, associated with the presence of each cartel, conditional on the presence of other cartels. Maize suitability is measured in hectares and is standardized, and cartel categories are binary indicators. Bars with black outlines denote estimates statistically significant at the 5% level; bars without black outlines are not significant at any conventional level. The sample comprises 2,457 municipalities.

2000s, consistent with widespread cartel expansion and the post-2006 rise in violence following the militarization of counter-narcotic operations (Dell, 2015; Dube et al., 2016).

We exploit heterogeneity in rural linkages by classifying cartels as agricultural-linked if their presence is most strongly associated with maize-growing comparative advantage.[8] Figure 5 shows that municipalities with the presence of the Sinaloa Gulf cartels have the highest average maize suitability, so we treat these organizations as the archetypal agricultural-linked DTOs in the analysis. Figure B.6 shows the baseline spatial distribution of both types of cartels across Mexico. Agriculturally linked and non-agriculturally linked cartels appear in 547 and 216 municipalities, respectively.

Media. The dataset consists of a purpose-built corpus of Mexican newspaper articles mentioning one or more of seven major drug-trafficking organizations. Articles were collected from three complementary sources – publisher sitemaps, the GDELT DOC 2.0 API, and Google News RSS – obtaining 61,720 unique articles published between 2000 and 2025 from 473 news outlets. Coverage is limited before 2009 because online newspaper archives are sparse,

Figure 6: Distribution of cartels across topic-related news coverage



Note: The table reports, for each topic, the share of each of the seven cartels among all articles that name a cartel and mention the topic in the same article. Because an article may name more than one cartel, it enters the count for each cartel it names; consequently the seven shares within a topic sum to 100% by construction. Shares reflect coverage volume — the Sinaloa Cartel appears in about 47% of all cartel articles in the corpus — and coverage is conditional on outlet web availability and sitemap retention.

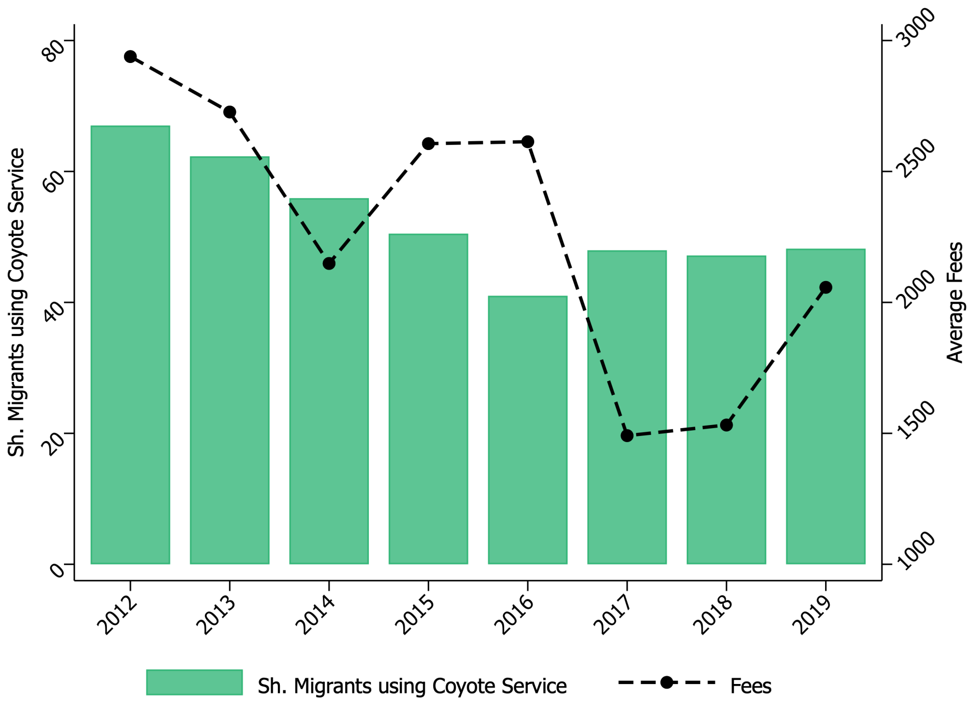
[8] In Panel B of Table B.12, we rule out the possibility that our findings are driven by agricultural suitability.

but becomes substantially more comprehensive in recent years 2015 onward. We identify six topics—water, agriculture, maize, avocado, illicit crops, and extortion/land pressure—using a dictionary of 51 Spanish keywords. An article is classified as linking a cartel to a topic if it mentions both the cartel and at least one keyword from the corresponding topic. Because a single article may mention multiple cartels, it can contribute to more than one organization. Figure 6 shows the share of each cartel among all articles linking a named cartel to a given topic, Mexican press, pooled 2000–2025. For each topic, the bars give the share of the seven cartels among all articles that name a cartel and mention that topic in the same article; bars within a topic sum to 100%. The Sinaloa Cartel accounts for the largest share of articles on water (41%), agriculture (36%), maize (37%), and illicit crops (40%), and remains prominent on extortion (24%) and avocado (23%). Los Zetas are the second most-named organization on extortion, and avocado, while the Gulf Cartel is comparatively more visible on extortion (18%).

Migration. An essential dimension in understanding the relationship between weather shocks, criminal groups, and economic activity is migration as a coping mechanism. To examine this dimension, our analysis relies on data on Mexican migrants deported by US immigration authorities between 2012 and 2019.

The information comes from the returned migrants component of the *Encuesta sobre*

Figure 7: Share of Border Crossers Using a Migrant Smuggler



Note: The bars report the annual share of border crossers who report using a coyote/smuggler (in percent). The dashed line reports the annual average smuggling fee (in 2015 USD; right axis). The sample is restricted to 2012–2019 to avoid pandemic-related disruptions in migration flows. Annual series are constructed by aggregating the underlying micro data within year. The sample comprises 2,457 municipalities.

Migracion en la Frontera Norte de Mexico (EMIF Norte). This component provides a representative sample of individuals who have recently been deported from the United States to Mexico by collecting data at ports of entry along the US–Mexico border. The survey interviews migrants shortly after their return to gather detailed information on their sociodemographic characteristics, municipality of origin, migration histories, use of smugglers, employment and economic conditions in the United States, experiences with US enforcement authorities and detention, as well as their future migration intentions (Moraga, 2011; Amuedo-Dorantes and Pozo, 2014; Feigenberg, 2020).

Figure 7 plots the annual share of border crossers who report using a smuggler, together with the average reported fees paid to smugglers (in 2015 USD), during 2012–2019. The share using a smuggler declines from roughly 65–70% in 2012–2013 to about 40–50% by 2016, and remains stable thereafter. Over the same period, average fees fall sharply after 2016 and only partially recover by 2019. Overall, the figure indicates a decline in the reliance on smugglers during the mid-2010s, coinciding with a pronounced reduction in reported smuggling prices.

Illegal activities and violence. We gather data on illicit activities and violence at the municipality-year level for the 2012–2019 period. Because illicit activities are only partially observable, we triangulate across complementary proxies (illicit crop eradication, drug seizures, and conflict-event classifications) and homicides, which are comparatively difficult to underreport and are more likely to be measured consistently across space and time. Our main proxy for local violence is annual municipality-level homicide data, compiled by INEGI and published with the date and municipality of event occurrence. We aggregate this information to the municipality-year level, defining H_{mt} as the number of homicides in municipality m and year t. To express violence in comparable units, we compute the homicide rate per 100,000 residents of the baseline population to keep the denominators fixed over time.

To benchmark Mexico's cartel violence within a broader taxonomy of organized violence, we complement our data with geo-referenced event records from the Uppsala Conflict Data Program (UCDP). This dataset distinguishes three mutually exclusive categories of organized violence: (i) *state-based armed conflict*, involving at least one state actor; (ii) *non-state armed conflict*, occurring between organized non-state groups; and (iii) *one-sided violence*, in which organized actors deliberately target civilians. These categories are defined using standard operational thresholds (including at least 25 battle-related deaths in a calendar year for conflict classification) and are available at the event level, allowing aggregation to the municipality-year level. This framework is particularly useful for situating cartel violence within established conflict typologies, especially in contexts where dynamics resemble non-state armed conflict and systematic civilian targeting is prevalent.

To proxy for local illicit crop cultivation, we use administrative data from Mexico's Ministry of National Defense (SEDENA) on eradication operations. SEDENA reports, by municipality and year, the number of hectares of marijuana and poppy eradicated. We also use municipality-year data on drugs seized (cocaine and methamphetamine) by the military forces.

5 Results

In this section, we present evidence showing how unusually hot growing seasons affect both legal and illegal agriculture and migration. We pay particular attention to how the presence of cartels mediates these effects. We first document the short-run effects of average wet-season temperature deviations and then assess whether the effects persist beyond the affected growing season.

5.1 Short-Run Effects of Wet-season Temperature Deviations

Our empirical strategy exploits municipality-level variation in unusually hot wet seasons, captured by the wet-season temperature deviation measure, Temperature Deviation$_{my}$, defined in equation (3). For agricultural and violence-related outcomes, we merge outcomes in year y to contemporaneous temperature deviations. For migration outcomes, we align outcomes in year y with temperature deviations during the current and preceding wet season (June–October of year $y-1$), consistent with the timing of agricultural production decisions and subsequent migration responses.

For all specifications, the source of identification is within-municipality fluctuations in wet-season heat exposure relative to municipality-specific historical baselines over 1998-2007. We isolate these fluctuations by controlling for time-invariant municipal characteristics and common shocks across years. Our baseline OLS specification for outcome Y_{my} is given by,

$$Y_{my} = \beta \, \text{Temperature Deviation}_{my} + \alpha_m + \gamma_y + \varepsilon_{my}, \tag{4}$$

where α_m denotes municipality fixed effects and γ_y denotes year fixed effects. Standard errors are clustered at the municipality level, and regressions are weighted by 2010 populations. The coefficient β captures the short-run effect of an unusually hot growing season on the outcomes of interest.

For migration outcomes, we estimate a route-level gravity specification that exploits bilateral flows from origin municipality m to US–Mexico border sector b in month-year t. In gravity models, bilateral flows depend not only on origin–destination frictions, but also on multilateral resistance terms, i.e. the relative attractiveness and accessibility of alternative destinations or routes (Anderson and van Wincoop, 2003; Head and Mayer, 2014). This concern is especially relevant in migration settings, where flows along a given corridor depend not only on origin conditions and bilateral route costs, but also on the attractiveness, accessibility, and enforcement conditions of alternative routes and destinations (Bertoli and Fernández-Huertas Moraga, 2013). We therefore include municipality×border fixed effects, which absorb time-invariant bilateral corridor costs such as distance, migrant networks, and persistent enforcement intensity. We also include border-sector×month-year fixed effects, which serve as destination-time multilateral-resistance terms by flexibly capturing shocks common to all municipalities sending migrants through the same border sector in a given period, including sector-specific enforcement, congestion, and changes in route attractiveness. Identification comes from comparing municipalities with different wet-season temperature deviations within the same border-sector×month-year cell, net of permanent municipality-border corridor differences.

5.1.1 Agricultural Production

Table 1 shows that unusually hot growing seasons reduce agricultural production and increase irrigation. Panel A focuses on various measures of maize production. Columns (1)–(3) indicate that a one-standard deviation in the average wet-season temperatures lowers the average municipality's maize production by 0.0785 tons per 100,000 residents (13% from the sample mean), harvested area by 0.0083 hectares (or 4.2%), and sown area by 0.0043 hectares (2.5%). At the same time, a one-standard-deviation increase in the average wet-season temperature leads to a 0.004 per 100,000 (44%) increase in the number of cultivated hectares lost, highlighting the vulnerability of Mexican agricultural production to climate change. These estimates indicate that heat stress affects both output and the allocation of land into production. The probability that irrigation is present in the municipality-year also rises by a statistically significant 1 percentage point, consistent with greater reliance on irrigation as an adaptation margin.

Panel B shows that the same pattern extends to production values. A one-standard-deviation increase in the average wet-season temperature reduces total agricultural production value by 0.7466 per 100,000 residents (14% of the sample mean), maize value by 0.3268 (or 22%), other-crop value by 0.4198 (11%), and avocado value by 0.1968 (45%), while irrigation again

Table 1: Temperature Shocks and Agricultural Production

Panel A: Quantity	(1) Prod Tons per 100,000	(2) Ha Harvested per 100,000	(3) Ha Sown per 100,000 Maize	(4) Ha Loss per 100,000	(5) Pr. Irrigation
Temperature Shock (t)	-0.0785***	-0.0083***	-0.0043***	0.004***	0.0094*
	(0.0217)	(0.0017)	(0.0014)	(0.0007)	(0.0051)
Obs	19640	19640	19640	19640	19640
Mean Outcome	.609	.16	.169	.009	.501

Panel B: Value	(1)	(2)	(3)	(4)	(5)
		Prod in Value per 100,000			Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-0.7466***	-0.3268***	-0.4198***	-0.1968***	0.0072**
	(0.2119)	(0.0961)	(0.1581)	(0.0545)	(0.003)
Obs	19640	19640	19640	19640	19640
Mean Outcome	5.313	1.473	3.839	.438	.13
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Panel A reports maize-specific physical outcomes: (1) maize production (tons per 100,000 residents), (2) harvested area (hectares per 100,000 residents), (3) sown area (hectares per 100,000 residents), (4) hectares lost per 100,000 residents, defined as sown minus harvested area, and (5) an indicator equal to one if any irrigated area is present in the municipality-year. Panel B reports agricultural production value outcomes per 100,000 residents: (1) total agricultural production value, (2) maize production value, (3) other-crop production value, (4) avocado production value, and (5) the same irrigation indicator. Temperature shock is the wet-season temperature anomaly defined in Section 4. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample includes 19,640 municipality-year observations. * p<0.10, ** p<0.05, *** p<0.01.

rises by 5.5%. Overall, Table 1 shows that temperature shocks have first-order negative effects on agricultural production, while irrigation may provide partial mitigation.[9]

5.1.2 Migration

Table 2 shows that temperature shocks lead to higher out-migration and that this response is concentrated in smuggler-assisted crossings rather than independent migration. A hotter wet season raises migration on both margins. The coefficient on the temperature shock is 0.0076 for migration without a smuggler, 0.0052 for smuggler-assisted migration, and 0.0127 for total migration; all three estimates are positive and statistically precise. At the mean shock, these coefficients imply increases of roughly 25%, 11%, and 16% of the corresponding sample means. The sign pattern is important. It rejects a pure liquidity-constrained response in which agricultural losses simply prevent households from moving at all. Instead, hotter growing seasons appear to raise the payoff to leaving.

The fee result sharpens that interpretation. A one-unit increase in the temperature shock raises smuggling fees by about $1,259 (in 2015 USD); at the mean shock this corresponds to a fee increase of roughly $1,012, or about 24% of the average fee. That pattern is difficult to reconcile with a simple collapse in migrant demand. It is more consistent with a market in which adverse local shocks increase the value of migration and tighten the price of organized intermediation.

To assess the robustness of these findings, we re-estimate migration effects using a variety of specifications that make alternative assumptions on the timing of migration, invoke different sample restrictions, and implement placebo exercises. Table B.5 uses a shorter June–September exposure window; Table B.6 varies the construction of exposure and seasonal alignment; Table B.7 separates contemporaneous from lagged shocks; Table B.8 excludes municipality–border pairs

Table 2: Temperature Shocks and Migration

	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0076***	0.0052***	0.0127***	1258.935***
	(0.0012)	(0.0012)	(0.0018)	(393.9126)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services, (2) migrants per 100,000 residents who used smuggler services, (3) total migrants per 100,000 residents, and (4) smuggler fees (amounts paid to smugglers, in 2015 USD). Temperature shock is constructed over the June–October wet season and aligned to migration outcomes as described in Section 4. Columns (1)–(3) are estimated using 2010 population weights. All specifications include municipality × border fixed effects and border × month-year fixed effects. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<0.10, ** p<0.05, *** p<0.01.

[9] Results are robust to alternative specifications. Table B.2 uses agricultural workers as the denominator, Table B.3 reports outcomes in levels, and Table B.4 adopts an alternative wet-season window (weeks 18–40) commonly used in the literature.

with mechanically zero flows; Table B.9 trims the upper tail of migration outcomes; Table B.10 uses a binary migration measure; and Table B.11 implements a future-shock placebo. Across these exercises, the conclusion is stable: weather shocks increase migration, and the smuggler-related margins remain central to the adjustment.

5.1.3 Agro-Cartel Activity

The model's mechanism should be strongest where cartels are embedded in agricultural markets. If cartels can supply irrigation, organize illicit cultivation, and intermediate migration, then the effect of a heat shock should be amplified precisely in municipalities exposed to agro-cartels, not in places with criminal presence unrelated to agriculture. Table 3 examines that prediction on the production side, examining whether the agricultural effects of weather shocks differ in municipalities that are exposed to agro-cartel activity.

Panel A shows that agro-cartel municipalities respond differently. Outside those municipalities, the direct effect of a heat shock is modest and often imprecise. In agro-cartel municipalities, by contrast, the interaction term is large and negative for total agricultural production value (-0.6901), other-crop value (-0.5790), and avocado value (-0.1136), and positive for the irrigated share (0.0135). Evaluated at the mean shock, the interaction implies an additional decline of about 11% of the mean for total agricultural value, about 13% for other crops, and about 22% for avocados, together with an increase in the irrigated share of roughly 9% of its mean.

This combination is informative. The stronger irrigation response is consistent with the model's idea that cartels can deploy capital in bad states of the world. But the accompanying fall in legal production indicates that this capital does not insure legal agriculture in the aggregate. Instead, the evidence points to selective adaptation alongside a broader reallocation away from legal agricultural activity.

In Panel B, we conduct a placebo exercise in which we define cartel exposed municipalities as only those that linked to cartels without systematic involvement in agricultural markets. The interaction between temperature shock and other-cartel presence is small and statistically insignificant across outcomes. The absence of differential effects contrasts sharply with the strong interaction estimated for agro-cartels and supports the interpretation that the relevant margin is cartel participation in agricultural production rather than cartel presence per se.

Panel C reinforces the same conclusion using outcomes scaled by municipal area. In agro-cartel municipalities, temperature shocks reduce land-normalized production values more strongly and increase irrigation intensity. Although these effects are smaller in percentage terms because the denominators are broader, the qualitative pattern is identical. Taken together, Table 3 indicates that temperature shocks are more damaging in municipalities exposed to agro-cartels, but these same municipalities also display a stronger irrigation response. This combination is consistent with cartel activity reshaping agricultural adjustment to weather stress rather than insulating local production from it.

We also find that the presence of agro-cartels amplify migration and smuggling responses to weather shocks, as shown in Table 4. In agro-cartel municipalities, the interaction term is especially strong for smuggler-assisted migration and for smuggler fees. This pattern is consistent with cartel intermediation in migration routes and with cartel rent extraction when weather shocks weaken local outside options.

Outside agro-cartel municipalities, hotter wet seasons raise total migration but have little effect on smuggler-assisted migration and no detectable effect on fees. In agro-cartel municipalities, the response is much stronger. The interaction term is positive for migration without a smuggler (0.0041), smuggler-assisted migration (0.0070), total migration (0.0112), and fees ($1,888, in 2015 USD). At the mean shock, the interaction implies an additional increase in smuggler-assisted

Table 3: Temperature Shocks on Agricultural Production and Agro-Cartels

Panel A: Baseline	(1)	(2)	(3)	(4)	(5)
		Prod in Value per 100,000			Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-0.259	-0.2484***	-0.0106	-0.1165**	0.0037
	(0.2047)	(0.0698)	(0.1722)	(0.0522)	(0.0032)
Temperature Shock (t) × Agro-Cartels	-0.6901***	-0.111	-0.579***	-0.1136***	0.0135**
	(0.2278)	(0.079)	(0.1995)	(0.0424)	(0.0066)
Obs	19640	19640	19640	19640	19640
Mean Outcome	5.313	1.473	3.839	.438	.13

Panel B: Placebo	(1)	(2)	(3)	(4)	(5)
		Prod in Value per 100,000			Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-0.1625	-0.2321***	0.0695	-0.1071*	0.0038
	(0.2293)	(0.0754)	(0.1964)	(0.0568)	(0.0035)
Temperature Shock (t) × Agro-Cartels	-0.7869***	-0.1274	-0.6595***	-0.1231***	0.0134**
	(0.2471)	(0.0831)	(0.2187)	(0.0474)	(0.0067)
Temperature Shock (t) × Other-Cartels	-0.4423	-0.0749	-0.3675	-0.0434	-0.0009
	(0.3125)	(0.0839)	(0.2786)	(0.0592)	(0.0074)
Obs	19640	19640	19640	19640	19640
Mean Outcome	5.313	1.473	3.839	.438	.13

Panel C: Robustness	(1)	(2)	(3)	(4)	(5)
		Prod in Value per Ha			Irrigation per Ha
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-7.3704	-5.2562	-2.1141	-3.2145	-0.1333***
	(14.0279)	(5.4899)	(11.5707)	(4.879)	(0.0384)
Temperature Shock (t) × Agro-Cartels	-41.1799**	-7.4238	-33.7561**	-13.2447**	0.23***
	(17.4252)	(6.3165)	(15.0177)	(5.637)	(0.0882)
Obs	19640	19640	19640	19640	19640
Mean Outcome	278.888	98.743	180.145	29.388	1.331
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Panel A reports estimates from regressions interacting the temperature shock with an indicator for agro-cartel municipalities. Outcomes are: (1) total agricultural production value per 100,000 residents, (2) maize production value per 100,000 residents, (3) other-crop production value per 100,000 residents, (4) avocado production value per 100,000 residents, and (5) the irrigated share, defined as irrigated sown area relative to total sown area. Panel B reports the analogous specification adding an indicator for other-cartel municipalities, defined as municipalities linked to cartels without systematic involvement in agricultural markets. Panel C reports the agro-cartel interaction specification using land-normalized outcomes: columns (1)–(4) are production values per hectare of municipal area, and column (5) is irrigated area relative to municipal area. Temperature shock is the wet-season temperature anomaly defined in Section 4. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample includes 19,640 municipality-year observations. * p<0.10, ** p<0.05, *** p<0.01.

migration of about 15% of the mean and in smuggling fees of about 36% of the mean.

Table B.12 provides complementary robustness exercises. Panel A adds controls for other-cartel presence to show that the estimated interaction is not a generic artifact of cartel activity. Panel B adds an interaction term between high maize suitability and a measure of agricultural specialization to address concerns that the result is driven by agricultural specialization rather than cartel organization. Panel C disaggregates the agro-cartel indicator into its main components, Sinaloa and Gulf, to assess whether the result is driven by a single organization. Across these exercises, the main conclusion is unchanged: agro-cartels amplify migration responses to temperature shocks and increase the price paid to smugglers.

Table 5 reports the effect of temperature shocks on illegal activities and violence, with a focus on municipalities exposed to agro-cartels. The clearest result concerns marijuana eradication. In Panel A, the interaction between temperature shocks and agro-cartel presence is positive and statistically significant, indicating that unusually hot growing seasons are associated with greater marijuana eradication precisely where criminal organizations are active in agricultural markets. This pattern is consistent with a shift toward illicit agricultural activity when legal agricultural returns deteriorate.

By contrast, the direct effect of temperature shocks outside agro-cartel municipalities is small and statistically indistinguishable from zero. The table also provides little systematic evidence for opium, coca, meth, or homicides in the contemporaneous year. Some coefficients are large in absolute value, but they are estimated imprecisely and do not display a stable sign pattern across specifications. The evidence therefore points to cannabis-related activity as the illicit margin most directly linked to rural production conditions.

Panel B sharpens this interpretation by replacing agro-cartels with other-cartels. The interaction between temperature shocks and other-cartel presence is close to zero and statistically

Table 4: Temperature Shocks on Migration and Agro-Cartels

	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0049***	0.0007	0.0057**	-458.4972
	(0.0013)	(0.0019)	(0.0024)	(683.5928)
Temperature Shock (t) X Agro-Cartels	0.0041**	0.007***	0.0112***	1888.323**
	(0.0019)	(0.0021)	(0.003)	(736.7121)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services, (2) migrants per 100,000 residents who used smuggler services, (3) total migrants per 100,000 residents, and (4) smuggler fees (amounts paid to smugglers, in 2015 USD). Temperature shock is constructed over the June–October wet season and aligned to migration outcomes as described in Section 4. Agro-cartel is a binary indicator equal to one for municipalities linked to cartels active in agricultural markets. Columns (1)–(3) are estimated using 2010 population weights. All specifications include municipality × border fixed effects and border × month-year fixed effects. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Temperature Shocks on Crimes, and Agro-Cartels

Panel A: Baseline	(1) Marijuana Eradicated (sh. ha)	(2) Opium Eradicated (sh. ha)	(3) Coca Kg per 100,000	(4) Meth Kg per 100,000	(5) Homicides Per 100,000
Temperature Shock (t)	-0.0001	-0.0035	-1.2383	-9.2692	-1.4837
	(0.0002)	(0.0034)	(5.3628)	(6.717)	(2.2752)
Temperature Shock (t) × Agro-Cartels	0.0005**	0.0057	-7.0901	-29.6566	-0.6648
	(0.0002)	(0.0035)	(12.0521)	(33.9878)	(2.8688)
Obs	19640	19640	19640	19640	19640
Mean Outcome	.003	.004	1.722	8.787	20.862

Panel B: Placebo	(1) Marijuana Eradicated (sh. ha)	(2) Opium Eradicated (sh. ha)	(3) Coca Kg per 100,000	(4) Meth Kg per 100,000	(5) Homicides Per 100,000
Temperature Shock (t)	-0.0001	0.0001	0.0696	-11.8154	-1.7758
	(0.0002)	(0.0015)	(6.7379)	(8.1961)	(2.2915)
Temperature Shock (t) × Agro-Cartels	0.0005**	0.0021	-8.4032	-27.1002	-0.3715
	(0.0003)	(0.0022)	(12.6502)	(31.7834)	(2.842)
Temperature Shock (t) × Other-Cartels	0.0001	-0.0167	-5.9985	11.6777	1.3397
	(0.0003)	(0.0129)	(7.5678)	(11.8496)	(3.1399)
Obs	19640	19640	19640	19640	19640
Mean Outcome	.003	.004	1.722	8.787	20.862
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: The dependent variables are cannabis eradication, poppy eradication, coca seizures, meth seizures, and homicides. Marijuana and poppy eradication are measured as eradicated hectares relative to total municipal area (ha) per 100; coca and meth are measured in kilograms per 100,000 inhabitants; and homicides are measured per 100,000 inhabitants. Temperature Shock (t) captures contemporaneous abnormal heat exposure. Agro-cartels is an indicator equal to one for municipalities with cartel presence in agricultural markets, while Other-Cartels is an indicator equal to one for municipalities with cartel presence outside agricultural markets. Panel A reports specifications interacting the temperature shock with Agro-Cartels; Panel B reports analogous specifications interacting the temperature shock with Other-Cartels. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample consists of 19,640 municipality-year observations. * p<0.10, ** p<0.05, *** p<0.01.

insignificant for marijuana eradication, whereas the corresponding interaction for agro-cartels remains positive and significant. This difference suggests that the illicit response is not a generic feature of cartel presence, but is instead concentrated in municipalities where criminal organizations are embedded in agricultural markets.

Figure B.8 shows that the temperature-shock × agro-cartel effect is not uniform across space. The interaction is close to zero through most of the distribution of the cannabis-minus-maize suitability measure, but rises sharply in the upper tail, where cannabis suitability substantially exceeds maize suitability. This pattern is consistent with a comparative-advantage mechanism: when a weather shock hits a cartel-linked municipality, the incentive to reallocate activity toward cannabis is largest precisely where the local agro-ecological environment already favors cannabis over maize. Table B.13 addresses a related concern by replacing the agro-cartel indicator with a high-maize-suitability indicator. The resulting estimates show that the main findings are not simply capturing pre-existing agricultural specialization.

Table 6: Temperature Shocks on Agricultural Production

Panel A: Quantity	(1) Prod Tons per 100,000	(2) Ha Harvested per 100,000	(3) Ha Sown per 100,000 Maize	(4) Ha Loss per 100,000	(5) Pr. Irrigation
Temperature Shock (t)	-0.0764***	-0.0084***	-0.0045***	0.0039***	0.0105**
	(0.0228)	(0.0018)	(0.0015)	(0.0007)	(0.0049)
Temperature Shock (t-1)	-0.0119	0.0003	0.0008	0.0005	-0.006
	(0.0181)	(0.0016)	(0.0015)	(0.0007)	(0.0057)
Temperature Shock (t-2)	-0.0165	-0.0003	0.0001	0.0004	-0.0121*
	(0.0242)	(0.0018)	(0.0017)	(0.0006)	(0.0062)
Obs	19640	19640	19640	19640	19640
Mean Outcome	.609	.16	.169	.009	.501

Panel B: Value	(1)	(2) Prod in Value per 100,000	(3)	(4)	(5) Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-0.7076***	-0.3113***	-0.3963***	-0.1787***	0.0071**
	(0.206)	(0.0962)	(0.1527)	(0.052)	(0.0031)
Temperature Shock (t-1)	-0.1954*	-0.0637	-0.1317	-0.0764***	-0.0002
	(0.1096)	(0.0397)	(0.0999)	(0.0231)	(0.0036)
Temperature Shock (t-2)	-0.1502	0.0129	-0.1631	0.0047	-0.0043
	(0.155)	(0.0574)	(0.1381)	(0.0285)	(0.004)
Obs	19640	19640	19640	19640	19640
Mean Outcome	5.313	1.473	3.839	.438	.13
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Mean Temperature Shock (t-1)	.794	.794	.794	.794	.794
Mean Temperature Shock (t-2)	.807	.807	.807	.807	.807
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Panel A reports maize-specific physical outcomes: (1) maize production (tons per 100,000 residents), (2) harvested area (hectares per 100,000 residents), (3) sown area (hectares per 100,000 residents), (4) hectares lost per 100,000 residents, defined as sown minus harvested area, and (5) an indicator equal to one if any irrigated area is present in the municipality-year. Panel B reports agricultural production value outcomes per 100,000 residents: (1) total agricultural production value, (2) maize production value, (3) other-crop production value, (4) avocado production value, and (5) the same irrigation indicator. Temperature shock (t), $(t-1)$, and $(t-2)$ denote contemporaneous and lagged wet-season temperature anomalies. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample includes 19,640 municipality-year observations. * p<0.10, ** p<0.05, *** p<0.01.

5.2 Medium-Run Effects of Weather Shocks

The model is about within-season reallocation after a weather realization. For that reason, its most direct empirical implication is that production and migration effects should be concentrated in the contemporaneous period. We now examine whether the data display broader persistence by adding lagged temperature shocks to the short-run specifications.

5.2.1 Agricultural Production

Table 6 asks whether the contraction in agricultural output persists beyond the affected growing season. The evidence points to limited persistence. In Panel A, the contemporaneous coefficients are the largest in absolute value across maize production, harvested area, and sown area. The one-year lag is smaller and generally imprecise, and the two-year lag is close to zero. This pattern suggests that temperature shocks primarily affect annual agricultural outcomes in the current growing season rather than generating a sustained multi-year contraction.

Table 7: Temperature Shocks on Agricultural Production

Panel A: Baseline	(1)	(2)	(3)	(4)	(5)
		Prod in Value per 100,000			Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-0.2241	-0.2208***	-0.0034	-0.0842*	0.0044
	(0.1955)	(0.0694)	(0.1643)	(0.0501)	(0.0034)
Temperature Shock (t) × Agro-Cartels	-0.6633***	-0.1275	-0.5358***	-0.1318***	0.0118*
	(0.2183)	(0.0793)	(0.1908)	(0.0436)	(0.0065)
Temperature Shock (t-1)	-0.0592	-0.1204**	0.0613	-0.1386***	-0.0036
	(0.1811)	(0.0475)	(0.1683)	(0.0341)	(0.0033)
Temperature Shock (t-1) × Agro-Cartels	-0.2531	0.0776	-0.3308*	0.0826*	0.0098
	(0.2048)	(0.0745)	(0.1911)	(0.0433)	(0.0102)
Obs	19640	19640	19640	19640	19640
Mean Outcome	5.313	1.473	3.839	.438	.13
Panel B: Placebo	(1)	(2)	(3)	(4)	(5)
		Prod in Value per 100,000			Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-0.6976***	-0.3129***	-0.3847**	-0.1819***	0.0079**
	(0.2144)	(0.1021)	(0.1583)	(0.054)	(0.0033)
Temperature Shock (t) × Other-Cartels	0.0826	0.0081	0.0745	0.0436	-0.0043
	(0.2777)	(0.0862)	(0.2416)	(0.051)	(0.0075)
Temperature Shock (t-1)	-0.271**	-0.0692	-0.2018*	-0.0784***	-0.0006
	(0.1274)	(0.0507)	(0.1137)	(0.027)	(0.0041)
Temperature Shock (t-1) × Other-Cartels	0.6311	0.12	0.5111	0.0447	-0.0061
	(0.4218)	(0.094)	(0.4084)	(0.0498)	(0.0091)
Obs	19640	19640	19640	19640	19640
Mean Outcome	5.313	1.473	3.839	.438	.13
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Mean Temperature Shock (t-1)	.794	.794	.794	.794	.794
Mean Temperature Shock (t-2)	.807	.807	.807	.807	.807
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: The dependent variables are: (1) total agricultural production value per 100,000 residents, (2) maize production value per 100,000 residents, (3) other-crop production value per 100,000 residents, (4) avocado production value per 100,000 residents, and (5) the irrigated share, defined as irrigated sown area relative to total sown area. Temperature shock (t) and Temperature shock $(t-1)$ denote contemporaneous and lagged wet-season temperature anomalies. Agro-Cartels is an indicator equal to one for municipalities with cartel presence in agricultural markets. Panel A reports specifications interacting temperature shocks with Agro-Cartels. Panel B reports the corresponding baseline specifications without interaction. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample includes 19,640 municipality-year observations. * p<0.10, ** p<0.05, *** p<0.01.

Panel B shows the same pattern for production values. The contemporaneous temperature shock has large negative effects on total agricultural value, maize value, other-crop value, and avocado production, while the one-year lag is weaker and the two-year lag is mostly negligible. The overall conclusion is that persistence is limited to, at most, one year. This is consistent with the underlying economics of annual agricultural production: unusually hot growing seasons depress current output sharply, but their effects do not cumulate strongly over multiple years. We should expect this for maize, an annual crop.

In Table 7, we explore whether the persistence of weather shocks differs in municipalities exposed to agro-cartels.

The results indicate that the differential effect associated with agro-cartels is concentrated in the contemporaneous year. In Panel A, the interaction between the contemporaneous temperature shock and agro-cartel presence is negative and statistically significant for total agricultural production, maize production value, other-crop production value, and avocado production value. The magnitudes are large. For example, the coefficient of -0.6633 in column (1) is substantial relative to the baseline contemporaneous effect, implying that municipalities exposed to agro-cartels experience significantly larger production losses when a temperature shock occurs. A similar pattern holds for maize value and avocado production.

By contrast, the interaction effects at $t-1$ are smaller and generally imprecise. This indicates that the amplification associated with agro-cartels is primarily contemporaneous rather than persistent. Panel B confirms the broader point that temperature shocks continue to reduce agricultural production across most outcomes, but the additional heterogeneity linked to agro-cartels is largely confined to the current year. The evidence therefore suggests that agro-cartels intensify the immediate production consequences of weather stress but do not generate a strong multi-year persistence in agricultural losses.

5.2.2 Migration

Table 8 examines whether the migration response to temperature shocks persists over time and whether that response is stronger in municipalities exposed to agro-cartels. The results indicate that the main effects are contemporaneous rather than persistent. In column (2), the coefficient on the contemporaneous interaction between the temperature shock and agro-cartel presence is positive and precisely estimated for smuggler-assisted migration, while the corresponding lagged interaction is small and statistically insignificant. A similar pattern appears in column (4), where the contemporaneous interaction is large and positive for smuggler fees, but the lagged interaction is close to zero and imprecisely estimated. Taken together, these estimates indicate that unusually hot growing seasons increase reliance on smugglers and raise the price of smuggling services in agro-cartel municipalities, but that these effects do not persist strongly into the following year.

The estimates for total migration in column (3) reinforce this conclusion. The contemporaneous temperature shock is associated with a statistically significant increase in total migration, and this effect is substantially larger in municipalities linked to agro-cartels. By contrast, the coefficients on the lagged shock and its interaction with agro-cartel presence are small and not statistically distinguishable from zero. Thus, the migration response appears to occur primarily in the immediate aftermath of the shock rather than with delay.

Column (1) shows that migration without smugglers also rises contemporaneously with the shock, and somewhat more so in agro-cartel municipalities. However, the strongest heterogeneous effects are concentrated in smuggler-assisted crossings and smuggling fees, which is more consistent with cartel intermediation than with a broad increase in low-cost independent migration. The contemporaneous interaction implies economically meaningful increases in smuggler-assisted migration and in fees paid to smugglers in agro-cartel municipalities. Overall, the evidence suggests that heat shocks trigger an immediate increase in out-migration, especially through cartel-linked smuggling channels, but provide little evidence of persistence one year later. That timing again fits the model. Migration is an outside option that becomes more attractive as soon as legal agricultural returns fall.

5.2.3 Crimes and Agro-Cartel Activities

Table 9 examines whether the relationship between temperature shocks and criminal outcomes persists over time and whether persistence differs across municipalities exposed to agro-cartels or other-cartels. The evidence does not indicate a broad contemporaneous effect on drug-related criminal activity. In Panel A, the contemporaneous temperature shock is generally small and statistically insignificant across marijuana eradication, poppy eradication, coca seizures, meth seizures, and homicides. The main exception is marijuana eradication: the interaction between the contemporaneous temperature shock and agro-cartel presence is positive and statistically significant, suggesting that unusually hot growing seasons are associated with increased cannabis activity in municipalities linked to agricultural cartels.

The more substantive patterns emerge with a lag. In Panel A, the one-year lag of the temperature shock is negatively associated with coca seizures and positively associated with homicides, with the homicide effect both large and statistically significant. The interaction between the lagged temperature shock and agro-cartel presence is also positive and significant for homicides, indicating that violence rises with delay in municipalities exposed to agro-cartels. This suggests that persistence operates less through immediate changes in seizures or eradication and more through subsequent conflict and violent adjustment. The homicide results suggest that, once those economic margins shift, cartel competition or consolidation may unfold with a delay. Put differently, the economic response is immediate, while the coercive response appears

Table 8: Temperature Shocks on Migration and Agro-Cartels

	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0043***	-0.0001	0.0042*	-366.583
	(0.0014)	(0.0019)	(0.0025)	(703.8642)
Temperature Shock (t) X Agro-Cartels	0.0037*	0.0075***	0.0112***	1852.537**
	(0.0019)	(0.0021)	(0.003)	(759.9203)
Temperature Shock (t-1)	0.0016	0.0026	0.0042	-304.4314
	(0.0014)	(0.0024)	(0.0029)	(622.6694)
Temperature Shock (t-1) X Agro-Cartels	0.003	-0.0013	0.0016	24.779
	(0.0019)	(0.0027)	(0.0035)	(691.3286)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Mean Temperature Shock (t-1)	.799	.799	.799	.799
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services, (2) migrants per 100,000 residents who used smuggler services, (3) total migrants per 100,000 residents, and (4) smuggler fees (amounts paid to smugglers, in 2015 USD). Temperature shock is constructed over the June–October wet season and aligned to migration outcomes as described in Section 4. Temperature shock (t-1) is lagged by one year. Agro-cartel is a binary indicator equal to one for municipalities linked to cartels active in agricultural markets. Columns (1)–(3) are estimated using 2010 population weights. All specifications include municipality × border fixed effects and border × month-year fixed effects. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: Temperature Shocks on Crimes, and Agro-Cartels

Panel A: Baseline	(1) Marijuana Eradicated (sh. ha)	(2) Opium Eradicated (sh. ha)	(3) Coca Kg per 100,000	(4) Meth Kg per 100,000	(5) Homicides Per 100,000
Temperature Shock (t)	-0.0001	-0.0037	4.4782	-3.9096	-3.6208
	(0.0002)	(0.0035)	(7.691)	(6.4933)	(2.3593)
Temperature Shock (t) × Agro-Cartels	0.0004**	0.0056	-10.1995	-34.7772	-1.8168
	(0.0002)	(0.0036)	(12.8772)	(37.9447)	(2.8232)
Temperature Shock (t-1)	-0.0001	0.0002	-24.3352*	-27.1135	4.5875***
	(0.0004)	(0.001)	(14.5685)	(27.5713)	(1.3363)
Temperature Shock (t-1) × Agro-Cartels	0.0004	0.0015	13.851	29.257	11.8984***
	(0.0004)	(0.0013)	(15.1692)	(21.5285)	(3.2984)
Obs	19640	19640	19640	19640	19640
Mean Outcome	.003	.004	1.722	8.787	20.862
Panel B: Placebo	**(1) Marijuana Eradicated (sh. ha)**	**(2) Opium Eradicated (sh. ha)**	**(3) Coca Kg per 100,000**	**(4) Meth Kg per 100,000**	**(5) Homicides Per 100,000**
Temperature Shock (t)	0.0002*	0.0014	-2.9157	-31.1717	-5.195
	(0.0001)	(0.0017)	(7.8716)	(28.4672)	(3.7602)
Temperature Shock (t) × Other-Cartels	-0.0002	-0.0182	-0.5924	32.9754	1.9556
	(0.0003)	(0.013)	(8.8062)	(34.7994)	(3.5767)
Temperature Shock (t-1)	0.0002	0.0011	-14.5268	-4.2097	13.4222***
	(0.0002)	(0.0008)	(14.8965)	(12.6521)	(3.146)
Temperature Shock (t-1) × Other-Cartels	-0.0003	-0.0008	7.4308	-10.7192	-1.8995
	(0.0003)	(0.0022)	(9.4347)	(9.6919)	(3.6043)
Obs	19640	19640	19640	19640	19640
Mean Outcome	.003	.004	1.722	8.787	20.862
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Mean Temperature Shock (t-1)	.794	.794	.794	.794	.794
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services, (2) migrants per 100,000 residents who used smuggler services, (3) total migrants per 100,000 residents, and (4) smuggler fees (amounts paid to smugglers, in 2015 USD). Temperature Shock (t) is the contemporaneous wet-season temperature anomaly, and Temperature Shock ($t-1$) is its one-year lag. Agro-Cartels is an indicator equal to one for municipalities linked to cartels active in agricultural markets. The interaction terms capture whether the migration response to temperature shocks differs in agro-cartel municipalities. Temperature shocks are constructed over the June–October wet season and aligned to migration outcomes as described in Section 4. Columns (1)–(3) are estimated using 2010 population weights. All specifications include municipality × border fixed effects and border × month-year fixed effects. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<0.10, ** p<0.05, *** p<0.01.

slower.

Panel B shows weaker and less systematic heterogeneous effects for other-cartel municipalities. The contemporaneous temperature shock is only weakly associated with marijuana eradication, and the interactions with other-cartel presence are not significant across outcomes. The lagged temperature shock remains positively associated with homicides, but the corresponding interaction is not estimated precisely. Taken together, the results suggest that temperature shocks do not generate a broad immediate increase in criminal production or seizures, but they may contribute to higher homicide rates with a one-year lag, particularly in municipalities where agro-cartels are active.

5.3 Summary of Results

To summarize, the empirical evidence lines up closely with the model's central mechanism. A hotter-than-usual growing season reduces legal agricultural production, raises migration, and increases cannabis-related activity in municipalities where cartels operate in agricultural markets. The heterogeneity is highly specific: it appears for agro-cartels and not for cartels without systematic rural linkages. That pattern is difficult to reconcile with a story based only on violence or weak institutions; it is much more consistent with a mechanism in which cartels exploit adverse weather by shifting production, deploying selective adaptation, and intermediating migration.

The medium-run results add an important qualification. The direct effects on agriculture and migration are mostly contemporaneous, which is what one would expect from a model of seasonal reallocation after a weather shock. The delayed increase in homicides points to an additional dynamic layer—one in which weather shocks first reshape economic margins and then, with some delay, alter territorial competition and coercive capacity. Taken together, the evidence suggests that climate shocks do not simply depress rural incomes. They also reorganize who controls production, mobility, and violence.

6 Conclusion

The likelihood and intensity of weather shocks will almost certainly grow in Mexico in the coming decades. Our theoretical and empirical results suggest that this will present a key opportunity for cartels to expand and diversify their operations in both formal and informal agricultural markets. A worsening climate, together with this cartel response, will combine to exert ever increasing migratory pressure along the US-Mexico border, a situation that is already fraught on both humanitarian and political grounds on both sides of the border.

In favorable weather conditions, cartels face two checks on their rent-seeking ability: if they push too strongly, then farmers will be content to pursue legal agriculture even if subject to mild extortion, and migration always remains a possibility. In poor growing seasons, however, the first check disappears, as legal agriculture no longer remains as attractive an option for capital constrained farmers. Indeed, in areas dominated by agro-cartels, we find robust shifts from formal to informal agriculture and towards migration in the wake of adverse weather shocks.

What is the future of cartels in Mexico in the face of a changing climate? Our findings lead us to speculate on two potential possibilities. In the the first, cartels are nudged to diversify their operations. The organizational demands of operating a firm with broad economies of scope eventually incentivize the cartels to normalize their operations and fold into the formal economy and political process. This should leads to increasing agricultural productivity and decreasing economic out-migration, though this does not come without serious political risk. In the second, cartels overreach in formal and informal agricultural markets. This leads to migratory pressure, which cartels attempt to exploit via entering the market for migration assistance. In the long run, the loss in human capital hampers prospects for growth.

Forward thinking policymakers should note the importance of capital constraints in propagating weather shocks into the agricultural sector and the associated knock-on incentives to cartels. By offering farmers an alternative to drug production or migration by allowing them to adapt to a changing climate through, for instance, irrigation, a third future is possible: one in which cartels limit the scope of their extortion and operations because they can no longer leverage their access to capital. We hope that future work explores these broader impacts of climate change in Mexico.

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Appendix A: Mathematical Results

The Cartel's Problem

We formally restate the cartel's problem as follows. Let (α, σ) be jointly distributed according to a continuously differentiable density $f(\alpha, \sigma)$ with full support on $\alpha > 0$, $\sigma > 0$. Farmers observe the weather shock $W \in \{0, 1\}$ and then choose among corn production, cannabis cultivation, and migration. We can define the net returns to corn and cannabis cultivation respectively as

$$C_w(\tau) \equiv (1 - \tau)\pi_c^w \tag{5}$$

$$M(\theta) \equiv (1 - \theta)\pi_m \tag{6}$$

In state w, the farmer chooses the maximum of $\{C_w,\ M - \sigma,\ \alpha\}$.

To simplify the exposition, we begin by defining a series of algebraic objects that correspond to the regions depicted in Figure 1.The regions of farmer types that choose corn and cannabis in state w can be written as:

$$\mathcal{C}_w = \{(\alpha, \sigma) : \sigma \geq M - C_w,\ \alpha \leq C_w\} \tag{7}$$

$$\mathcal{M}_w = \{(\alpha, \sigma) : \sigma \leq M - C_w,\ \alpha \leq M - \sigma\} \tag{8}$$

which imply the following induced probabilities for corn and cannabis cultivation:

$$P_c(w) \equiv \iint_{\mathcal{C}_w} f(\alpha, \sigma)\, d\alpha\, d\sigma \tag{9}$$

$$P_m(w) \equiv \iint_{\mathcal{M}_w} f(\alpha, \sigma)\, d\alpha\, d\sigma \tag{10}$$

The cartel chooses (τ, θ) to maximize their expected profit, which can be written as

$$\Pi(\tau, \theta; \rho) = (1 - \rho)\left[\tau\pi_c^0 P_c(0) + \theta\pi_m P_m(0)\right] + \rho\left[\tau\pi_c^1 P_c(1) + \theta\pi_m P_m(1)\right]. \tag{11}$$

Because the regions of corn and cannabis cultivation are functions of the choice variables, solving this problem requires repeated applications of Leibnitz' Rule. To facilitate this, we define the following boundary integrals:

$$A(C, M) = \int_{M-C}^{\infty} f(C, \sigma)\, d\sigma \tag{12}$$

$$B(C, M) = \int_0^C f(\alpha, M - C)\, d\alpha \tag{13}$$

These objects correspond to the masses of farmers along the corn–migration boundary (A) and the corn–cannabis boundary (B). Note that $\frac{\partial P_c}{\partial C} = A + B$ and $\frac{\partial P_m}{\partial C} = -B$.

We can now write the first order conditions of the cartel's optimization problem in terms of these intermediate objects:

$$\frac{\partial \Pi}{\partial \tau} = \sum_{w \in \{0,1\}} p_w \, \pi_c^w \left[P_c(w) - \tau \pi_c^w \left(A_w + B_w \right) + \theta \pi_m B_w \right] = 0 \quad (14)$$

$$\frac{\partial \Pi}{\partial \theta} = \sum_w p_w \left[\pi_m P_m(w) - \theta \pi_m^2 \left(\int_0^{M - C_w} f(M - \sigma, \sigma) \, d\sigma + B_w \right) + \tau \pi_c^w \pi_m B_w \right] = 0 \quad (15)$$

where $p_0 = 1 - \rho$, $p_1 = \rho$, $A_w = A(C_w, M)$, and $B_w = B(C_w, M)$.

Define

$$G(\tau, \theta; \rho) = \frac{\partial \Pi(\tau, \theta; \rho)}{\partial \tau} \quad (16)$$

$$H(\tau, \theta; \rho) = \frac{\partial \Pi(\tau, \theta; \rho)}{\partial \theta} \quad (17)$$

Proposition 1 (Formally Restated)**.** *Under the following assumptions:*

A1 $\Pi(\cdot, \cdot; \rho)$ *is twice continuously differentiable and strictly concave in* (τ, θ) *for each* $\rho \in (0, 1)$*, with a unique interior maximum* $(\tau^\star(\rho), \theta^\star(\rho))$

A2 $G(\tau, \theta; 0) > G(\tau, \theta; 1)$ *in a neighborhood of* $(\tau^\star(\rho), \theta^\star(\rho))$*;*

A3 the Jacobian of the first-order conditions for the cartel's maximization problem is diagonally dominant (i.e., $\Pi_{\tau\theta}$ *is sufficiently small relative to* $\Pi_{\tau\tau}$ *and* $\Pi_{\theta\theta}$*.)*

Then:

1. $\dfrac{d\tau^\star(\rho)}{d\rho} < 0$*;*

2. *The signs of* $\frac{d\theta^\star(\rho)}{d\rho}$ *and* $H(\tau^\star, \theta^\star; 1) - H(\tau^\star, \theta^\star; 0)$ *are the same.*

Proof. At the optimum, $G(\tau^\star, \theta^\star; \rho) = 0$ and $H(\tau^\star, \theta^\star; \rho) = 0$. Because Π is C^2 and strictly concave, the Jacobian

$$J(\tau, \theta; \rho) = \begin{pmatrix} G_\tau & G_\theta \\ H_\tau & H_\theta \end{pmatrix} = \begin{pmatrix} \Pi_{\tau\tau} & \Pi_{\tau\theta} \\ \Pi_{\theta\tau} & \Pi_{\theta\theta} \end{pmatrix} \quad (18)$$

is nonsingular and negative definite at the optimum. An application of the implicit function theorem yields

$$\begin{pmatrix} \tau'(\rho) \\ \theta'(\rho) \end{pmatrix} = -\, J^{-1}(\tau^\star, \theta^\star; \rho) \begin{pmatrix} G_\rho(\tau^\star, \theta^\star; \rho) \\ H_\rho(\tau^\star, \theta^\star; \rho) \end{pmatrix}. \quad (19)$$

where

$$G_\rho(\tau, \theta; \rho) = G(\tau, \theta; 1) - G(\tau, \theta; 0) \quad (20)$$

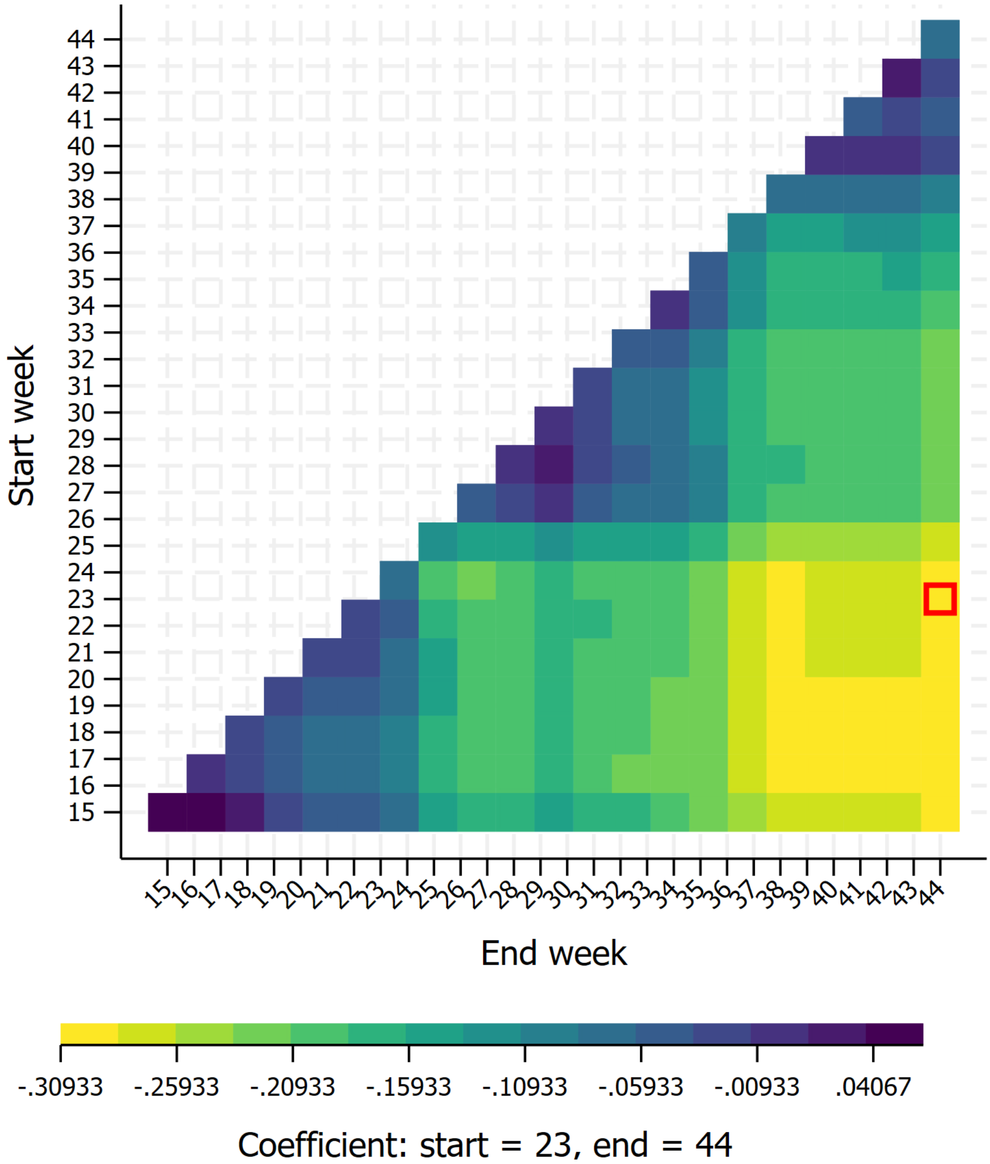
and

$$H_\rho(\tau, \theta; \rho) = H(\tau, \theta; 1) - H(\tau, \theta; 0). \quad (21)$$

The proof of the first claim of the proposition follows from (1) $\Pi_{\theta\theta} < 0$ and $\det J > 0$ (*A1*), (2) $G_\rho(\tau^\star, \theta^\star; \rho) < 0$ (*A2*), and (3) The contribution of the off-diagonal terms in (19) is second order $(A3)$. This implies that the sign of $\tau'(\rho)$ is governed by $-G_\rho/\Pi_{\tau\tau}$, which is negative, and that the sign of $\theta'(\rho)$ is the same as the sign of H_ρ. $\square$

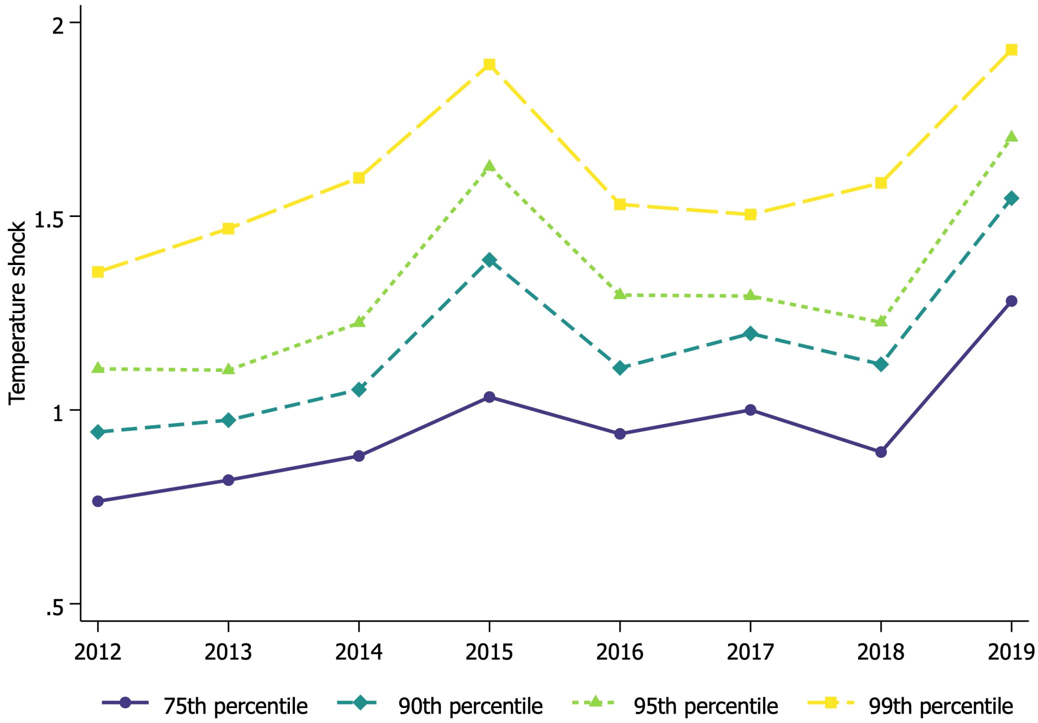
Appendix B: Additional Figures and Tables

Figure B.1: Grid search for the wet-season temperature window



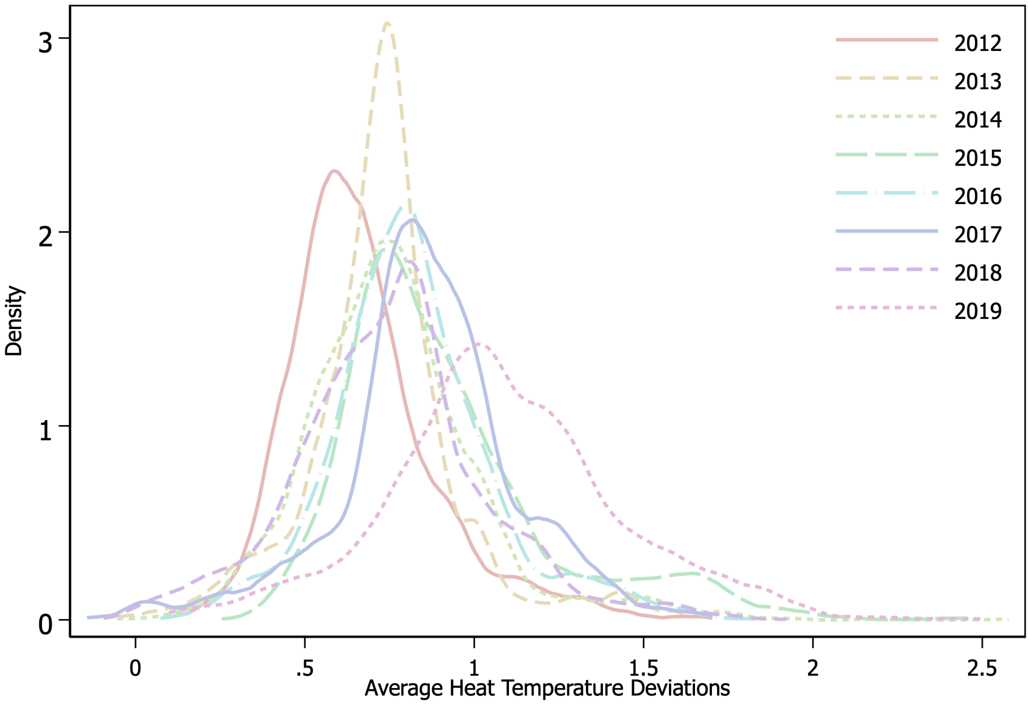
Note: The figure reports the coefficient estimates from a grid search over alternative start and end weeks used to construct the annual temperature shock. For each contiguous window, we average weekly standardized temperature shocks and estimate their association with agricultural production. The horizontal axis reports the ending week of the window, while the vertical axis reports the starting week. The red-bordered cell highlights the baseline window used in the analysis, corresponding to weeks 23–44.

Figure B.2: Upper Percentiles of the *Temperature Shock*



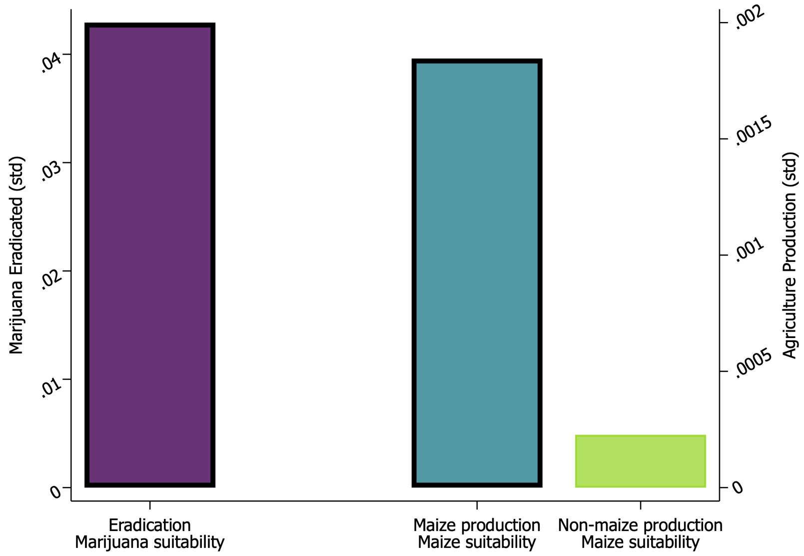
Note: The figure plots selected annual percentiles of the municipality-level wet-season temperature shock, Temperature Shock$_{my}$, over 2012–2019. The shock is defined as the average standardized deviation of weekly 2-meter temperature from its municipality–week historical mean over wet-season weeks 23–44. Percentiles are computed across municipalities within each year. Higher values indicate hotter-than-usual wet seasons relative to each municipality's own historical seasonal distribution.

Figure B.3: Yearly average temperature deviations



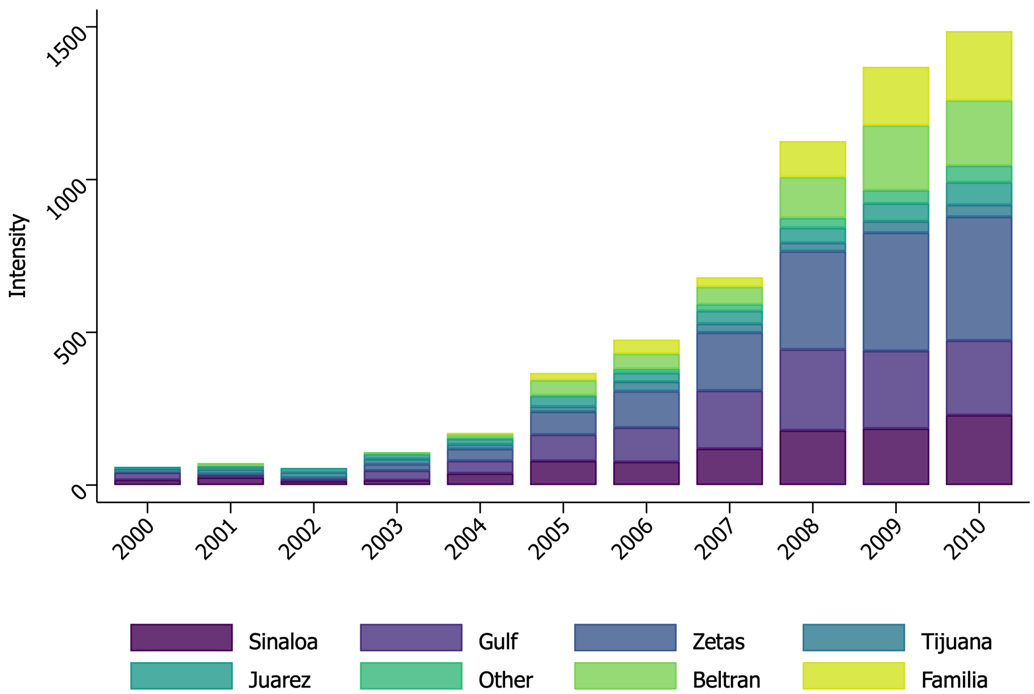
Note: The figure shows the annual distribution of Temperature Deviation$_{my}$, defined as the average standardized deviation of weekly maximum temperatures in municipality m relative to their 1998–2007 historical mean, averaged over wet-season weeks 23–44 (June–October). For the migration analysis, temperature shocks are measured over the wet season immediately preceding the migration outcome year.

Figure B.4: Agroecological suitability and measures of crop production



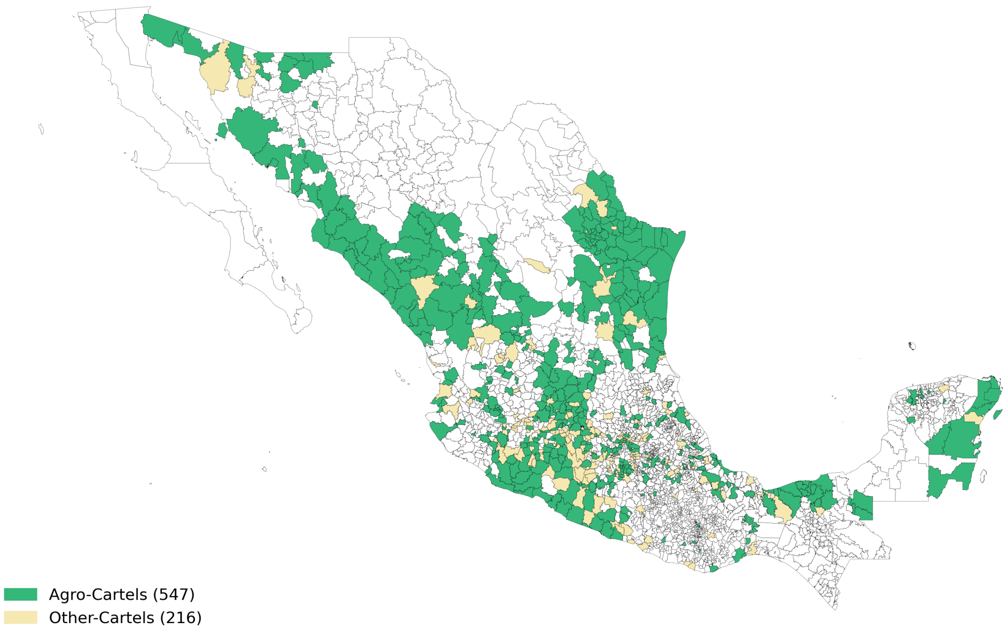
Note: Bars plot population-weighted coefficients from municipality-level regressions of standardized outcomes on the corresponding suitability index. Marijuana eradication is regressed on cannabis suitability, scaled from 0 to 1. Maize and non-maize production outcomes are regressed on maize suitability, scaled from 0 to 100. Positive coefficients indicate that municipalities predicted to be more suitable for a given crop exhibit higher values of the corresponding crop-relevant outcome. Bars with bold black outlines denote coefficients statistically significant at the 5% level. Standard errors are clustered at the municipality level. The sample comprises 2,457 municipalities.

Figure B.5: Trend in cartel-related news over time, by cartel (2000–2010)



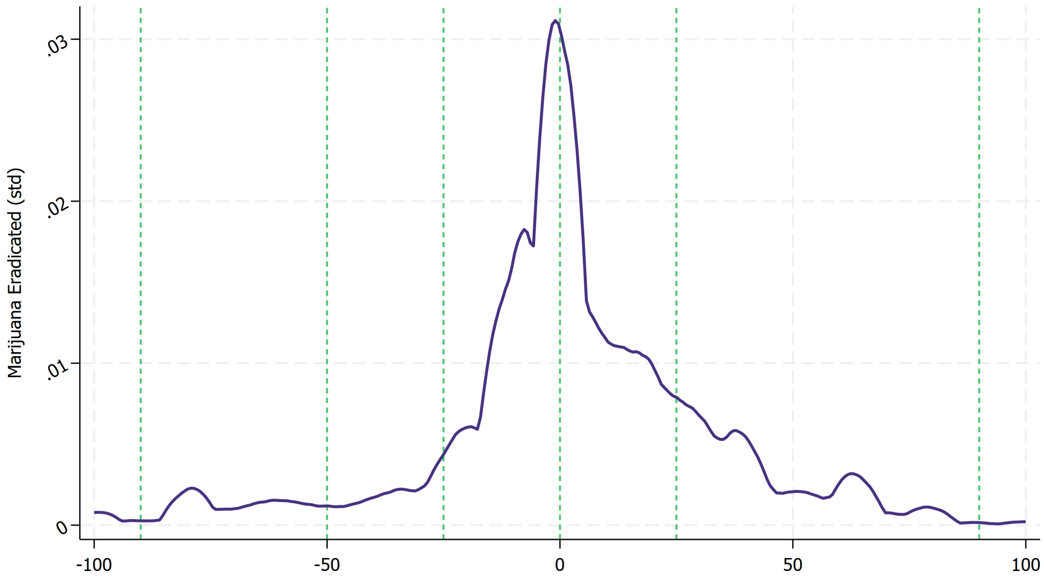
Note: The figure shows the total number of news by cartel each year. The sample includes 2,457 municipalities.

Figure B.6: Agriculturally-linked and Other-Cartels Presence (2000-2011)



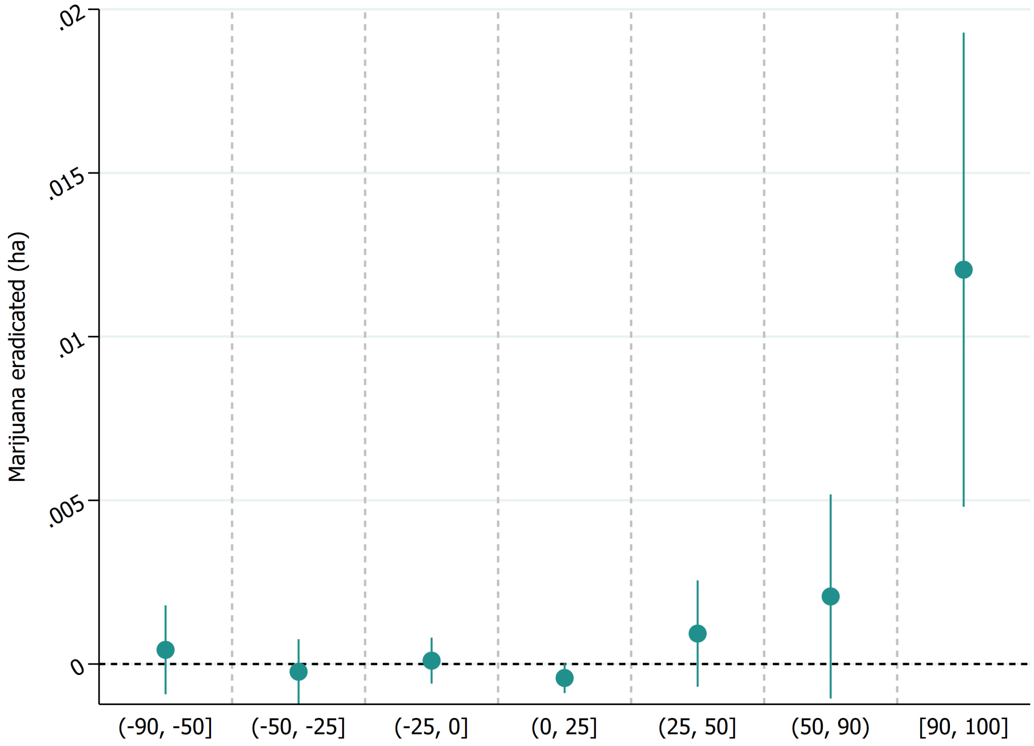
Note: The sample comprises 2,457 municipalities.

Figure B.7: Distribution of the Maize-to-Cannabis measure



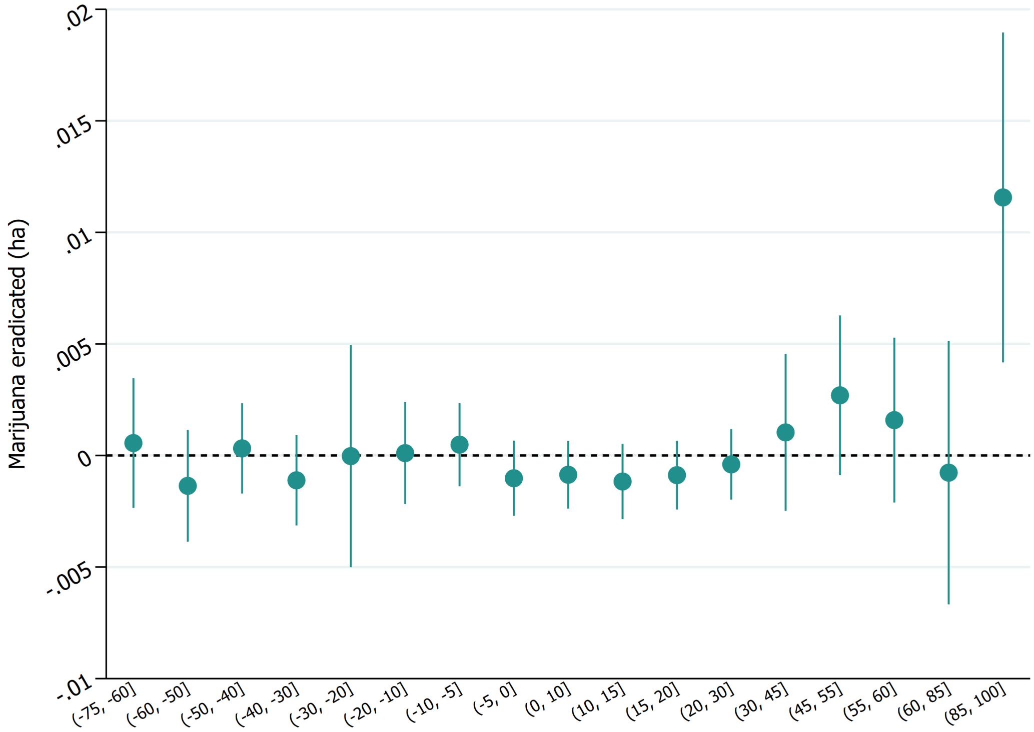
Note: Distribution of the difference between cannabis and maize suitability. Vertical lines display the bins. The sample includes 2,455 municipalities.

Figure B.8: Temperature Shocks, Agro-Cartels, and the Maize-to-Cannabis measure



Note: Outcome is marijuana eradicated, measured in hectares eradicated relative to total municipal area (ha) per 100. Agro-Cartel is a binary indicator equal to 1 if a cartel is present in agricultural markets, 0 otherwise. We plot the interaction between temperature shock$\times$ Agro-Cartel and a categorical bin constructed with the difference between cannabis and maize suitability. The distribution of this variable is shown in Figure B.7 while the bins are: ≤ -90, $(-90, -50]$, $(-50, -25]$, $(-25, 0]$, $(0, 25]$, $(25, 50]$, $(50, 90)$, and $(90, 100]$. The bin ≤ -90 is the baseline. All models include municipality and year fixed effects, and are weighted by 2010 population. Standard errors are clustered at the municipality level. The sample includes 2,455 municipalities.

Figure B.9: Temperature Shocks, Agro-Cartels, and the Maize-to-Cannabis measure - more bins



Note: Outcome is marijuana eradicated, measured in hectares eradicated relative to total municipal area (ha) per 100. Agro-Cartel is a binary indicator equal to 1 if a cartel is present in agricultural markets, 0 otherwise. We plot the interaction between temperature shock× Agro-Cartel and a categorical bin constructed with the difference between cannabis and maize suitability. The distribution of this variable is shown in Figure B.7. The bin ≤ -75 is the baseline. All models include municipality and year fixed effects, and are weighted by 2010 population. Standard errors are clustered at the municipality level. The sample includes 2,455 municipalities.

Table B.1: EcoCrop optimal bounds for crop suitability

Crop	Variable	ℓ_0	ℓ_1	u_1	u_0	Units
Cannabis	Soil pH	4.5	6.0	7.0	8.2	pH units
	Mean temperature	6.0	15.0	28.0	32.0	°C
	Mean precipitation	350	600	1200	4000	mm/year
Maize	Soil pH	4.5	5.0	7.0	8.5	pH units
	Mean temperature	10.0	18.0	33.0	47.0	°C
	Mean precipitation	400	600	1200	1800	mm/year

Note: ℓ_0 and u_0 denote absolute lower/upper bounds (zero suitability). ℓ_1 and u_1 denote the optimal interval (unit suitability). These bounds are drawn from EcoCrop-style at `https://gaez.fao.org/pages/ecocrop-find-plant` for *Cannabis sativa ssp. indica* and *Zea mays*

Table B.2: Robustness I: Temperature Shocks and Agricultural Production

Panel A: Quantity	(1)	(2)	(3)	(4)	(5)
	Prod Tons per 100,000 farmers	Ha Harvested per 100,000 farmers	Ha Sown per 100,000 farmers	Ha Loss per 100,000 farmers	Pr. Irrigation
			Maize		
Temperature Shock (t)	-1.2505***	-0.1329***	-0.0714***	0.0616***	0.0088*
	(0.3387)	(0.0252)	(0.0234)	(0.0102)	(0.005)
Obs	19528	19528	19528	19528	19528
Mean Outcome	7.154	1.52	1.61	.09	.503

Panel B: Value	(1)	(2)	(3)	(4)	(5)
	Prod in Value per 100,000 farmers				Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-11.8644***	-4.9591***	-6.9053***	-3.2618***	0.0073**
	(2.9025)	(1.423)	(2.3699)	(0.8466)	(0.003)
Obs	19528	19528	19528	19528	19528
Mean Outcome	55.074	15.444	39.629	4.154	.13
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Panel A reports maize-specific physical outcomes: (1) maize production (tons per 100,000 farmers), (2) harvested area (hectares per 100,000 farmers), (3) sown area (hectares per 100,000 farmers), (4) hectares lost per 100,000 farmers, defined as sown minus harvested area, and (5) an indicator equal to one if any irrigated area is present in the municipality-year. Panel B reports agricultural production value outcomes per 100,000 farmers: (1) total agricultural production value, (2) maize production value, (3) other-crop production value, (4) avocado production value, and (5) the same irrigation indicator. Temperature shock is the wet-season temperature anomaly defined in Section 4. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample includes 19,640 municipality-year observations. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B.3: Robustness II: Temperature Shocks and Agricultural Production

Panel A: Quantity	(1) Prod Tons	(2) Ha Harvested	(3) Ha Sown Maize	(4) Ha Loss	(5) Pr. Irrigation
Temperature Shock (t)	-26749.28**	-1620.678***	-1115.081***	505.5968***	0.0088*
	(10415.11)	(501.8008)	(432.3891)	(142.9908)	(0.005)
Obs	19528	19528	19528	19528	19528
Mean Outcome	15916.39	3004.77	3146.92	142.15	.5

Panel B: Value	(1) All	(2) Prod in Value Maize	(3) Other	(4) Avocado	(5) Sh. Irrigation Maize
Temperature Shock (t)	-296685.3***	-124209.9**	-172475.4**	-14099.77***	0.0073**
	(107610.7)	(52297.34)	(67022.89)	(4198.387)	(0.003)
Obs	19528	19528	19528	19528	19528
Mean Outcome	142928.8	39778.51	103150.3	12219.77	.13
Mean Temperature Shock (t)	.84	.84	.84	.84	.84
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Panel A reports maize-specific physical outcomes: (1) maize production (tons), (2) harvested area (hectares), (3) sown area (hectares), (4) hectares lost, defined as sown minus harvested area, and (5) an indicator equal to one if any irrigated area is present in the municipality-year. Panel B reports agricultural production value outcomes: (1) total agricultural production value, (2) maize production value, (3) other-crop production value, (4) avocado production value, and (5) the same irrigation indicator. Temperature shock is the wet-season temperature anomaly defined in Section 4. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample includes 19,640 municipality-year observations. * p<0.10, ** p<0.05, *** p<0.01.

Table B.4: Robustness III: Temperature Shocks and Agricultural Production

Panel A: Quantity	(1) Prod Tons per 100,000	(2) Ha Harvested per 100,000	(3) Ha Sown per 100,000 Maize	(4) Ha Loss per 100,000	(5) Pr. Irrigation
Temperature Shock (t)	-0.0612***	-0.0066***	-0.0037**	0.0029***	0.0038
	(0.0217)	(0.0017)	(0.0016)	(0.0006)	(0.0051)
Obs	19640	19640	19640	19640	19640
Mean Outcome	.609	.16	.169	.009	.501

Panel B: Value	(1)	(2)	(3)	(4)	(5)
		Prod in Value per 100,000			Sh. Irrigation
	All	Maize	Other	Avocado	Maize
Temperature Shock (t)	-0.853***	-0.2791***	-0.574***	-0.2159***	0.0078**
	(0.2026)	(0.0899)	(0.1582)	(0.0594)	(0.0031)
Obs	19640	19640	19640	19640	19640
Mean Outcome	5.313	1.473	3.839	.438	.13
Mean Temperature Shock (t)	.861	.861	.861	.861	.861
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Panel A reports maize-specific physical outcomes: (1) maize production (tons per 100,000 residents), (2) harvested area (hectares per 100,000 residents), (3) sown area (hectares per 100,000 residents), (4) hectares lost per 100,000 residents, defined as sown minus harvested area, and (5) an indicator equal to one if any irrigated area is present in the municipality-year. Panel B reports agricultural production value outcomes per 100,000 residents: (1) total agricultural production value, (2) maize production value, (3) other-crop production value, (4) avocado production value, and (5) the same irrigation indicator. Temperature shock is the wet-season temperature anomaly defined over 18-40 weeks. All regressions include municipality and year fixed effects, are weighted by 2010 population, and report standard errors clustered at the municipality level. The sample includes 19,640 municipality-year observations. * p<0.10, ** p<0.05, *** p<0.01.

Table B.5: Robustness I: Temperature Shocks on Migration

	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0059***	0.0055***	0.0114***	1271.623***
	(0.001)	(0.001)	(0.0016)	(435.7595)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct between June and October. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.6: Robustness II: Temperature Shocks on Migration

Panel A: Avg	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t) (*avg)*	0.0056***	0.0038***	0.0094***	934.0478***
	(0.0008)	(0.0008)	(0.0013)	(316.5093)
Panel B: Sum	(1) Migrants Pc w/o Coyote	(2) Migrants Pc w Coyote	(3) Migrants Pc	(4) Fees
Temperature Shock (t) (*sum)*	0.0009***	0.0008***	0.0016***	162.724**
	(0.0002)	(0.0002)	(0.0003)	(64.0351)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t) (avg)	.79	.79	.79	.79
Mean Temperature Shock (t) (sum)	3.228	3.228	3.228	3.228
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct between June and October. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.7: Robustness III: Temperature Shocks on Migration

	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t-1)	0.0036***	0.0002	0.0037	-377.9766
	(0.0013)	(0.0017)	(0.0024)	(527.3314)
Temperature Shock (t)	0.006***	0.0051***	0.0111***	1406.702***
	(0.0011)	(0.0011)	(0.0017)	(380.5019)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Mean Temperature Shock (t-1)	.797	.797	.797	.797
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct between June and October in the current year (t) and the year before (t-1). Agro-cartel is a binary indicator equal to 1 if a cartel is present in agricultural markets, 0 otherwise. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.8: Robustness IV: Temperature Shocks on Migration

	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0127***	0.0092***	0.0219***	1258.935***
	(0.002)	(0.0021)	(0.0033)	(393.9126)
Obs	514752	514752	514752	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct between June and October. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.9: Robustness V: Temperature Shocks on Migration

Panel A: Drop top 5pct	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0075***	0.0054***	0.0129***	1258.642***
	(0.0012)	(0.0011)	(0.0018)	(394.5532)
Obs	2120191	2120191	2120191	7876
Mean Outcome	.024	.038	.062	4207.9
Panel B: Drop top 1pct	**(1) Migrants Pc w/o Coyote**	**(2) Migrants Pc w Coyote**	**(3) Migrants Pc**	**(4) Fees**
Temperature Shock (t)	0.0075***	0.0052***	0.0128***	1258.801***
	(0.0012)	(0.0011)	(0.0018)	(394.0212)
Obs	2120932	2120932	2120932	8152
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Municipality X Border FE	✓	✓	✓	
Border X Month-Year FE	✓	✓	✓	

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct between June and October. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.10: Robustness VI: Temperature Shocks on Migration

Pr.	(1) Migrants w/o Coyote	(2) Migrants w Coyote	(3) Migrants	(4) Fees
Temperature Shock (t)	0.0075***	0.0119***	0.0126***	0.0119***
	(0.0028)	(0.0026)	(0.0029)	(0.0026)
Obs	2121120	2121120	2121120	2121120
Mean Outcome	.004	.005	.009	.005
Mean Temperature Shock (t)	.804	.804	.804	.804
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct between June and October. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.11: Placebo: Temperature Shocks on Migration

	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0083***	0.0052***	0.0135***	1027.859**
	(0.0012)	(0.0012)	(0.0019)	(399.9135)
Future Temperature Shock (t+1)	-0.0006	-0.0002	-0.0007	138.5074
	(0.0005)	(0.0004)	(0.0006)	(154.257)
Obs	2054835	2054835	2054835	8028
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Mean Future Temperature Shock (t+1)	.979	.979	.979	.979
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct using future shocks. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.12: Robustness I: Temperature Shocks on Migration and Cartels

Panel A	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0055***	0.0009	0.0063**	149.2574
	(0.0015)	(0.0022)	(0.0029)	(678.7597)
Temperature Shock (t) X Agro-Cartels	0.0049*	0.0073**	0.0122***	2158.275**
	(0.0025)	(0.0032)	(0.0039)	(871.27)
Temperature Shock (t) X Other-Cartels	-0.0013	-0.0004	-0.0017	-877.9657
	(0.0025)	(0.0035)	(0.0042)	(1001.477)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Panel B	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0031*	-0.0004	0.0027	904.6446
	(0.0018)	(0.0025)	(0.0033)	(669.4637)
Temperature Shock (t) X Agro-Cartels	0.0056**	0.0077**	0.0133***	1951.667**
	(0.0026)	(0.0031)	(0.0038)	(931.4619)
Temperature Shock (t) X Other-Cartels	-0.0007	-0.0001	-0.0008	-1231.93
	(0.0026)	(0.0036)	(0.0043)	(975.7807)
Temperature Shock (t) X Maize (p75)	0.006**	0.0033	0.0093**	-1753.539**
	(0.0026)	(0.0029)	(0.0042)	(691.7527)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Panel C	(1) Migrants per 100,000 w/o Coyote	(2) Migrants per 100,000 w Coyote	(3) Migrants per 100,000	(4) Fees
Temperature Shock (t)	0.0056***	0.001	0.0066**	102.2735
	(0.0015)	(0.0022)	(0.0029)	(697.6747)
Temperature Shock (t) X Sinaloa	0.0042*	0.007**	0.0112***	2498.364***
	(0.0025)	(0.0028)	(0.0037)	(737.7436)
Temperature Shock (t) X Gulf	-0.0028	-0.0003	-0.0031	953.8263
	(0.0032)	(0.0033)	(0.0055)	(839.0089)
Temperature Shock (t) X Other-Cartels	0.0016	0.0004	0.0021	-1872.137*
	(0.0034)	(0.0039)	(0.0057)	(1086.722)
Obs	2121120	2121120	2121120	8225
Mean Outcome	.024	.038	.062	4207.9
Mean Temperature Shock (t)	.804	.804	.804	.804
Municipality X Border FE	✓	✓	✓	✓
Border X Month-Year FE	✓	✓	✓	✓

Note: Outcomes are: (1) migrants per 100,000 residents who did not use smuggler services; (2) migrants per 100,000 residents who did use smuggler services; (3) total migrants per 100,000 residents; and (4) smuggler fees (amounts paid to smugglers in 2015 USD). Temperature shock construct between June and October. Agro-cartel is a binary indicator equal to 1 if a cartel is present in agricultural markets, 0 otherwise. Other-cartel is a binary indicator equal to 1 if a cartel is present but not in agricultural markets, 0 otherwise. Models (1)-(3) are estimated with 2010 population weights. Standard errors are clustered at the municipality level. The sample comprises 2,455 municipalities. * p<.10 ** p<.05 *** p<.01.

Table B.13: Temperature Shocks, Agriculture Specialization, and Crimes

	(1) Marijuana Eradicated (sh. ha)	(2) Opium Eradicated (sh. ha)	(3) Coca Kg per 100,000	(4) Meth Kg per 100,000	(5) Homicides Per 100,000
Temperature Shock	0.00033**	-0.00042	-14.92732	-41.91283	-2.17565
	(0.00013)	(0.00104)	(10.01016)	(34.43277)	(4.09797)
Temperature Shock × Maize (p75)	-0.00027	0.00415	37.28473	50.20411	0.95467
	(0.00033)	(0.00685)	(24.35818)	(34.9344)	(3.56544)
Obs	19640	19640	19640	19640	19640
Mean Temperature Shock (t)	.838	.838	.838	.838	.838
Municipality FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Note: Outcomes are: (1) marijuana eradicated, measured in hectares eradicated relative to total municipal area (ha) per 100; (2) poppy eradicated, measured in hectares eradicated relative to total municipal area (ha) per 100; (3) cocaine seized in kilograms per 100,000 inhabitants; (4) methamphetamine seized, kilograms per 100,000 inhabitants; and (5) Homicides per 100,000 inhabitants. Maize (p75) defines municipalities with high maize suitability. All models include municipality and year fixed effects, and are weighted by 2010 population. Standard errors are clustered at the municipality level. The sample includes 2,455 municipalities. p<.10 ** p<.05 *** p<.01.