Illegal Migration and Weather Shocks: Evidence from Rural Mexico*

Facundo Danza[†] Eungik Lee[‡]

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Abstract

Weather shocks pose many challenges for workers in developing countries. International migration can work as a coping mechanism for this reality. The legal status of migrants is critical to understand the effect of these shocks on workers' well-being. In this paper, we study the effect of weather shocks on legal and illegal migration from rural Mexico to the United States. First, we find that weather shocks in the wet season increase migration. The increase is entirely driven by illegal migrants. Second, we propose a mechanism to explain this result: the effect of weather on agricultural production. We find that weather shocks decrease total harvested land and corn production. Third, we show that young and unwealthy workers are more sensitive to weather shocks. Lastly, we use our estimates to have a first glance at climate change's impact on migration. We find that climate change would increase illegal migration significantly.

Keywords: Illegal Migration, Weather Shocks, Agriculture, Climate Change

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[†]Universidad ORT Uruguay. Email: danza@ort.edu.uy

[‡]Indiana University Bloomington. Email: el43@iu.edu

1 Introduction

In developing countries, workers are highly dependent on the weather for their income and well-being. Hence, weather shocks can dramatically change their career path and life experience (Cattaneo et al., 2019). International migration can work as a coping mechanism for these shocks (Feng et al., 2010; Jessoe et al., 2018; Ibánez et al., 2021). The international community is thus concerned about the influence of climate variability and climate change on migration waves and the legal status of migrants (Gates, 2021).

This concern is prevalent in rural Mexico. Mexican workers have a long tradition of illegal migration to the United States: every year, 3 million agricultural workers try to migrate illegally (Passel & D'Vera Cohn, 2009). Moreover, 20 million agricultural workers are exposed to weather shocks (Dalby, 2013). Dalby (2013) estimates that Mexico is losing 400 square miles of farmland each year due to droughts and irregularities in the rainy season. Hence, the impact of weather shocks on (illegal) migration is of increasing relevance.

In this paper, we investigate how weather affects legal and illegal migration from rural Mexico to the United States. First, we estimate the effect of weather shocks on migration using individual-level data. We define weather shocks as standardized deviations of weather variables.[1] To recover the causal effect of weather shocks on migration, we use a two-way fixed effects model. Second, we propose an underlying mechanism: the effect of weather on agricultural production. Using municipal-level data, we recover the causal effect of weather on agricultural production using the same econometric approach. Lastly, we use our results to project the effect that climate change will have on migration.

Our main data source is the Mexican Migration Project (MMP). The MMP collects information on potential and former migrants in all of Mexico. Importantly, it has detailed information on the legal status of migrants, a key variable in our study. We combine

[1] "Standardized deviation" means the deviation of the weather variable with respect to the historical mean divided by its standard deviation. Our weather variables are precipitation and average, maximum and minimum temperature.

these data with Meteoblue weather data at the community level.[2] This allows us to precisely determine the effect of weather shocks on small and medium-sized communities and the consequential migration decisions of their inhabitants. We add municipal-level data on agricultural production to explain the results through the effect of weather on agricultural activity. Lastly, we use climate projections to study the effect that climate change will have on migration.

Our results can be summarized as follows. First, we find that weather shocks in the wet season have a significant effect on migration from rural Mexico to the United States. The effect is entirely driven by illegal migrants. Furthermore, the effect is substantial: for example, a standard deviation increase in average temperature generates a 22% increase in migration with respect to the baseline.[3] In addition, the effect is more pronounced for young and unwealthy workers. Second, we find that weather shocks have a significant effect on the total harvested land and corn production. The effect is also substantial: for example, an increase in one standard deviation in average temperature decreases the total harvested land by 3.4% and the corn production by 4.4%. Lastly, we use climate projections to understand the effect that climate change will have on illegal migration. Our back-in-the-envelope calculations suggest that, in the scenario in which global temperature increases by 2°C, climate change would increase illegal migration by 66%.

Our paper contributes to understanding the effect of weather shocks on international migration by combining individual-level data on migration with community-level data on weather. Since we have explicit information on the legal status of migrants, we can dive into the effect of weather on legal and illegal migration separately. We also study the heterogeneous effects of weather shocks on migration, we quantify the effect of weather on agricultural production, and we use our causal estimates to project the impacts of climate

[2] MMP defines communities broadly, from "ranchos," which have a population of less than 2,500 people, to middle-size cities, with less than 100,000 people.

[3] On average, 1.52% of our population migrates to the US in a given year. An increase in one standard deviation of average temperature generates a 0.33 percentage point (p.p.) increase in the probability of migration, thus the 22% with respect to the baseline.

change on migration.

Related Literature. Our contribution is threefold. First, we contribute to the discussion on migration as a coping mechanism to weather shocks. The results in this literature are mixed (Cattaneo et al., 2019). On the one hand, weather shocks can prevent migration through liquidity constraints (Cattaneo & Peri, 2016; Bazzi, 2017; Barbosa-Alves & Britos, 2023). On the other hand, weather shocks can foster migration as an insurance policy for income variability and as a response to wage differentials (Hanson & Spilimbergo, 1999; Mueller, Gray, & Kosec, 2014; Jessoe et al., 2018). Our results are in line with the latter.

Second, we contribute to understanding the weather as a driver of international migration. Feng et al. (2010) show that weather-induced reductions in corn production increase migration from Mexico to the United States. Jessoe et al. (2018) find that weather fluctuations affect income and migration, both within Mexico and toward the United States. Ibánez et al. (2021) show that temperature shocks increase migration from El Salvador to the United States. We add further details to this literature on the migration decision, namely the legal status of weather-induced migrants.

The legal status of migrants is particularly relevant for the US-Mexico case. Approximately 11 million Mexican migrants live in the United States illegally (Krogstad, Passel, & Cohn, 5). Reinhold and Thom (2013) shows that Mexican workers try to migrate illegally when they are young and come back to Mexico when they are old. Chort and De La Rupelle (2022) construct state-level flows of illegal immigrants from Mexico to the United States and study the effect of extreme weather events and policies to mitigate their effects. We contribute to this literature using individual-level data on migration and community-level data on weather. This allows us to study the effect of weather on migration in a flexible and precise way. It also allows us to investigate the heterogeneous effects of weather shocks. Moreover, we use data on potential migrants; thus, we can project the effect that climate change will have on migration.

Lastly, we explore a mechanism to explain our results: the effect of weather on agricultural production. In Latin America, weather shocks worsen total production (Dell, Jones, and Olken (2009)). This is particularly prevalent in rural Mexico. Corn, Mexico's main crop in the wet season, is highly dependent on the weather (Schlenker & Roberts, 2009). Skoufias and Vinha (2013) show that a 2°C increase in average temperature generates a 24% decrease in corn production. Skoufias (2007) reports that 65% of Mexican land is rainfed and that agricultural workers do not have a strategy to deal with weather change. Feng et al. (2010) show that drought-induced productivity reductions in corn increase migration from Mexico to the US. We provide further evidence in this regard by quantifying the importance of weather shocks on agricultural production.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 discusses our econometric analysis. Section 4 shows the results. Section 5 provides robustness checks. Section 6 concludes.

2 Data

In this section, we describe our data sources. The main data source is the Mexican Migration Project (MMP), which we commplement with weather data from Meteoblue. We also collect data on agricultural production and climate change projections.

2.1 Main Data Source: Mexican Migration Project

Our main data source is the Mexican Migration Project (MMP). As described in its webpage, "MMP is a unique source of data that enables researchers to track patterns and processes of contemporary Mexican migration to the United States." It interviews potential Mexican migrants from 1982 to 2019. The interviews take place during winter, when seasonal migrants are more likely to return. Although the survey is not created to be representative of all migrants, it represents them closely (Massey & Zenteno, 2000; Massey & Capoferro, 2004; Nawrotzki & DeWaard, 2016).

To be more precise, MMP chooses communities within Mexico and obtains a representative sample of them. Communities are of three types: "ranchos," which have a population of less than 2,500 people; towns, with 2,500 to 10,000 people; mid-sized cities, with 10,000 to 100,000 people; and metropolitan areas, usually a specific neighborhood within a large city.

MMP offers a variety of datasets. We focus on one of them, "LIFE." "LIFE" collects information on the entire history of the head of household in a retrospective fashion: in every survey wave, the head of the household is asked about her location, employment status, and demographic characteristics from her birth until the survey year. The main advantage of these data is that they have explicit information on the legal status of migrants. Moreover, MMP is conducted in many locations (more than 200), which allows us to exploit local variations in weather. Its main disadvantage is that it does not include households whose members are in the US in the survey year; in particular, it does not include households that decided to move to the US once and forever.

We use the surveys from 2000 to 2019 and focus on the period 1990-2019. Since "LIFE" is constructed retrospectively, this means that we have a (unbalanced) panel of 30 years for all heads of households interviewed from 2000 to 2019. We only keep people in their working years, from 18 to 65 years old. To minimize measurement error, we run our main analysis using 10-year backward windows. Lastly, we focus on communities with less than 100,000 people, which are categorized as "ranchos," towns, or mid-sized cities, as described before. These communities are more likely to depend on agricultural production for their economic activity. In summary, we have data on 11,788 individuals from 83 communities for 11-year periods.

Table 1 provides summary statistics of our sample. Our sample is predominantly uneducated men, with an average age of 41 years old. More than half of our sample consists of agricultural workers, and nearly 40% are owners of land or a business. On average, in a given year, 1.52% of our population migrates to the United States, and 73% of them do so illegally. The length of stay in the US varies dramatically, with an average stay of 28 months and a standard deviation of 26 months.

Figure 1 illustrates the geographical location of our sample.[4] As shown on the map, the sample includes communities all over rural Mexico.

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max
Age	41.452	12.167	18	65
Male	0.876	0.330	0	1
Educ. Level (Yr)	6.980	4.348	0	23
Agricultural Worker	0.520	0.500	0	1
Land Owner	0.179	0.384	0	1
Business Owner	0.247	0.431	0	1
Owner	0.374	0.484	0	1
Migrate*	0.015	0.123	0	1
Legally Migrate*	0.004	0.064	0	1
Illegally Migrate*	0.011	0.105	0	1
Length Stayed** (Mh)	28.680	26.500	1	132
Individuals	11,788	11,788	11,788	11,788
Observations	120,297	120,297	120,297	120,297

*Notes: *Migrate refers to an indicative variable equal to one if the worker migrates to the US in a specific period. Since the worker has to be in Mexico to be able to migrate, the total number of observations in that variable is lower, 112,588. **Length of Stayed refers to the number of months migrants stay in the US; thus, it is calculated only for those who did migrate to the US at some point in our data. The number of observations in this case is 6,625.*

2.2 Data: Other Sources

We complement our main data source with numerous others. For weather at the community level, we use Meteoblue data. Meteoblue is a professional weather-forecast company that offers, from 1979 onward, hourly-simulated weather data worldwide. More precisely, it offers a 2km-2km dataset that covers various weather variables, such as precipitation, temperature, and evaporation.[5] Since we study weather shocks, it is vital that we count with precise

[4]For confidentiality reasons, we cannot share the exact location of the communities of this study. We share a (slightly) disturbed location of the municipal centroids in which these communities belong instead.

[5]The company carefully validates its data by comparing historical simulated data with realized historical weather on its website. You can check it out here: https://www.meteoblue.com/en/historyplus.

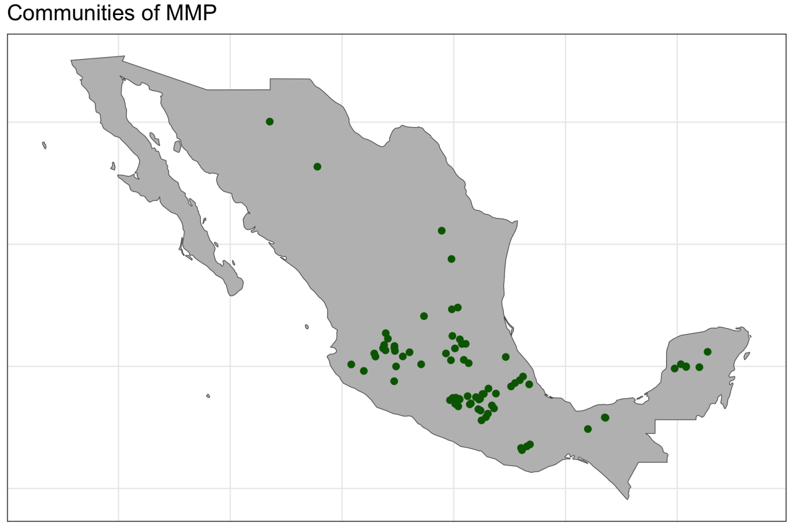

Figure 1: MMP: Communities Location - 2000-2019

Table 2: Summary Statistics - Weather

Variable	Mean	SD	Min	Max	SD within	SD across
Precipitation (mm)	63.48	55.17	4.72	345.15	18.26	49.28
Avg Temperature (°C)	21.34	3.49	14.13	29.56	0.55	3.21
Max Temperature (°C)	26.77	3.51	18.56	34.50	0.83	3.27
Min Temperature (°C)	15.88	3.76	8.76	24.52	0.54	3.33
Communities	88	88	88	88	88	88
Observations	968	968	968	968	968	968

Notes: "SD" refers to the standard deviation of the correspondent variable across communities and time. "SD within" is calculated as the average standard deviation of the correspondent variable of each community across time. "SD across" is calculated as the average standard deviation of each year across communities.

estimations of location-specific weather. Furthermore, MMP surveys mostly small communities; another challenge to our data. Meteoblue data overcome both of these challenges. It provides us with daily data on precipitation, average temperature, maximum temperature, and minimum temperature for each one of the communities in our sample, from 1985 to 2020. Table 2 describes our weather data.

For agricultural production, we use data from the "Servicio de Información Agroalimentaria y Pesquera" (SIAP) at the "Secretaría de Agricultura y Desarrollo Rural" of the Mexican government.[6] We download total harvested land and corn grown for grain in the wet season from 2003 to 2019. We focus on corn because it is by far the main crop in the Mexican wet

[6]You can download the data directly from https://nube.siap.gob.mx/cierreagricola/

season. In our study period, 71% of the harvested land corresponds to corn. Furthermore, corn production is highly dependent on weather, as discussed in Section 1.

On the one hand, agricultural data are open access. On the other hand, they are only available at the municipality level. Thus, we also need weather data at this level. We use another open-access dataset, "Daymet," from the Environmental Sciences Division at Oak Ridge National Laboratory (Thornton et al., 2020). Daymet offers monthly data on total precipitation and maximum and minimum temperature for all of North America at a 1km-1km level from 1980 to 2021. We aggregate this data at the municipality level using municipality maps from the "Humanitarian Data Exchange" (HDX).[7] The process can be entirely replicated in our GitHub Repository.

Lastly, we use climate projections from TerraClimate, which offers worldwide estimates of future climate at the 4km-4km level (Abatzoglou, Dobrowski, Parks, & Hegewisch, 2018). It provides these data for climatic variables and "pseudo-years," which are projected weather realizations. Essentially, the pseudo-years are constructed by simulating weather in a climatic model in which the climate parameters shift as predicted by climate change. We aggregate these data at the municipality level using HDX municipality maps.

3 Empirical Analysis

In this section, we show the relationship between weather shocks and migration.

Figure 2 illustrates our main point. On the x-axis, we plot standardized deviations of the weather variable in the wet season. The standardized deviation is the difference between the realization of the variable and its historical mean divided by its standard deviation. We also call this deviation the "z-score" of the variable. For example, a "1" in the temperature plot means that the temperature was one standard deviation above the historical temperature in the community. On the y-axis, we plot the proportion of migrants in the population; that is, the number of migrants divided by the total number of workers. The dots reflect

[7] You can download the maps directly from https://data.humdata.org/dataset/cod-ab-mex?

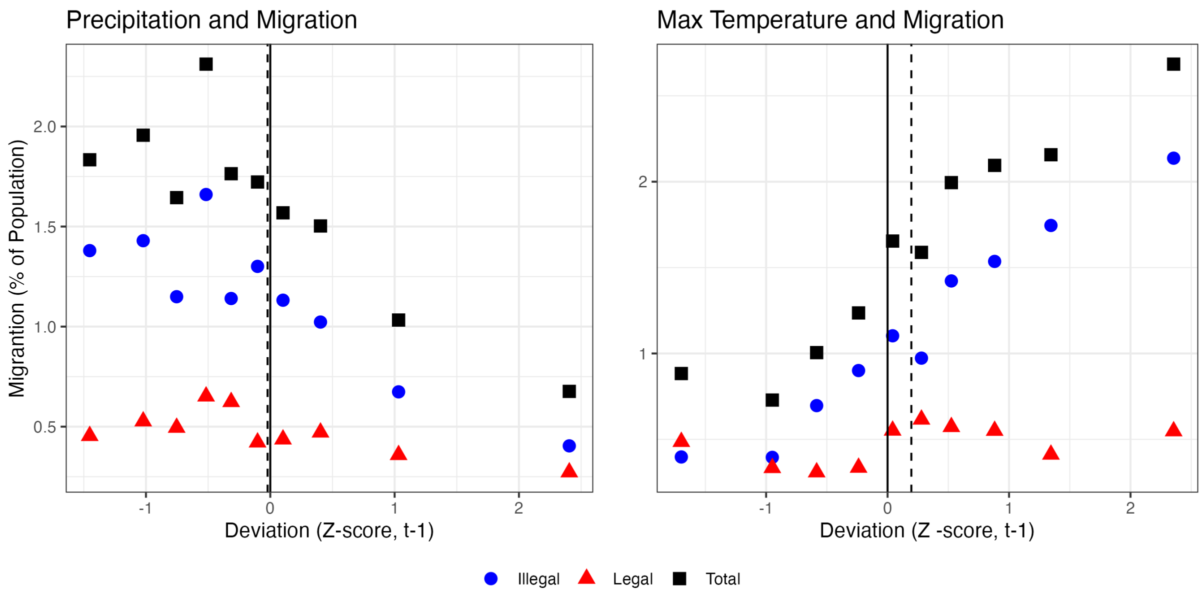

Figure 2: Weather Shocks and Migration

Notes: The dots reflect the proportion of migrants in the population for the standardized deviation of precipitation and maximum-temperature in the wet season. More specifically, each dot groups observations in deciles of the z-score distribution and calculates the proportion of migrants for such deciles. The dotted vertical line reflects the average z-score in our study period. The weather deviation is taken a period before the migration decision. The historical mean is taken over the period 1985-2019.

the proportion of migrants for decile deviations of the weather variable. The relationship between the variables is clear: the higher (lower) the temperature (precipitation), the higher the migration. In addition, the effect is entirely driven by illegal migrants.

We add similar graphs for the average and minimum temperatures in the appendix (Figure A.1). The results are on the same line: the higher the temperature, the higher the migration. The formal econometric specification is discussed in the next section.

3.1 Econometric Specification

In order to identify the effect of weather shocks on migration, we use a two-way fixed-effects model. First, we run each weather variable separately. More specifically, we estimate Equation 1:

$$y_{ijt} = \alpha_i + \gamma_t + \beta_w w_{j,t-1} + \epsilon_{ijt} \tag{1}$$

where y_{ijt} is the variable of interest for a person i from community j at time t, e.g., did he migrate to the US in that specific period;[8] α_i is the person fixed effect; γ_t is the year fixed effect; $w_{j,t-1}$ is the weather "shock," e.g., the z-score of the maximum temperature in the wet season;[9] [10] and ϵ_{ijt} is the error term. We cluster the errors at the community level.

Second, we allow for non-linear effects of weather. We define two specifications, Equation 2 and Equation 3:

$$y_{ijt} = \alpha_i + \gamma_t + \beta_w w_{j,t-1} + \beta_{w_2} w_{j,t-1}^2 + \epsilon_{ijt} \tag{2}$$

$$y_{ijt} = \alpha_i + \gamma_t + \beta_w w_{j,t-1} + \beta_{w_0} \mathbf{I}(w_{j,t-1} > 0) w_{j,t-1} + \epsilon_{ijt} \tag{3}$$

where y_{ijt} is the variable of interest for a person i from community j at time t, e.g., did he migrate to the US in that specific period; α_i is the person fixed effect; γ_t is the year fixed effect; $w_{j,t-1}$ is the weather shock, e.g., the z-score of the maximum temperature in the wet season; $\mathbf{I}(w_{j,t-1} > 0)$ is an indicator function that equals one whenever the z-score is positive; and ϵ_{ijt} is the error term. As before, we cluster the errors at the community level.

Lastly, we include both the average temperature and precipitation in the same specification. More precisely, we estimate Equation 4:

$$y_{ijt} = \alpha_i + \gamma_t + \beta_t t_{j,t-1} + \beta_p p_{j,t-1} + \epsilon_{ijt} \tag{4}$$

where y_{ijt} is the variable of interest for a person i from community j at time t, e.g., did he migrate to the US in that specific period; α_i is the person fixed effect; γ_t is the year fixed effect; $t_{j,t-1}$ is the average temperature shock, the z-score of the temperature in the wet season; $p_{j,t-1}$ is the precipitation shock, the z-score of precipitation in the wet season; and

[8] Due to the very definition of our migration variable, we only consider individuals that are in Mexico at time $t-1$.

[9] The wet season in Mexico goes from April to September, as discussed in Skoufias, Vinha, and Conroy (2011). This choice is thus in line with our proposed mechanism. Moreover, this is in line with Schlenker and Roberts (2009) (albeit with a month difference), who find that precipitation and temperature from March to August profoundly affect US crop production.

[10] The historical mean is calculated for the period 1985-2019.

ϵ_{ijt} is the error term. We cluster the errors at the community level.

4 Results

4.1 First Specification

Table 3 shows our results for the first specification. Weather shocks in the wet season have a significant effect on migration at a 5% level. More precisely, a one standard deviation decrease in precipitation with respect to its historical mean generates a 0.08 percentage points (p.p.) increase in the probability of migrating to the United States. Similarly, a one standard deviation increase in average, maximum, and minimum temperature with respect to their historical mean generates a 0.33, 0.35 and 0.33 p.p. increase in migration, respectively.

The effects are substantial. The average percentage of migrants in a given year is 1.52%. Thus, a decrease in one standard deviation in precipitation implies a 5.26% increase in the probability of migrating with respect to the baseline; and an increase in one standard deviation on average, maximum and minimum temperature implies a 21.71%, 23.02% and 21.71% increase, respectively.

Interestingly, the effect is entirely driven by illegal migrants, as shown in Table 4. A decrease in one standard deviation of precipitation with respect to its historical mean generates a 0.06 p.p. increase in illegal migration; and an increase in one standard deviation in average, maximum, and minimum temperature with respect to their historical mean generates a 0.34, 0.35 and 0.33 p.p. increase, respectively. The estimates for legal migration are not significantly different from zero for any weather variable.

Table 3: Weather Shocks and Migration

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0008**			
	(0.0004)			
Dev Avg Temp (Z-score, t-1)		0.0033***		
		(0.0004)		
Dev Max Temp (Z-score, t-1)			0.0035***	
			(0.0005)	
Dev Min Temp (Z-score, t-1)				0.0033***
				(0.0005)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,588	112,588	112,588	112,588
Adjusted R^2	0.25256	0.25309	0.25302	0.25295

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table 4: Weather Shocks and Migration by Legal Status

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0006*				-0.0003			
	(0.0004)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0034***				-0.0001		
		(0.0004)				(0.0002)		
Dev Max Temp (Z-score, t-1)			0.0035***				−0.00002	
			(0.0004)				(0.0002)	
Dev Min Temp (Z-score, t-1)				0.0033***				−0.00004
				(0.0005)				(0.0002)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	112,587	112,587	112,587	112,587	112,587	112,587	112,587	112,587
Adjusted R^2	0.18086	0.18170	0.18155	0.18146	0.41782	0.41781	0.41781	0.41781

Clustered (commun) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variables equal to one if the agent migrates illegally (legally) to the US in that period. The independent variables are calculated as the z-score in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

4.2 Second Specification: Nonlinear Effects

The results vary slightly if we allow for non-linear effects. We show the results only for illegal migrants, who are the drivers of our results. We add the effect for all migrants and legal migrants in the appendix (Tables A.1 to A.4).

Table 5 shows the results for a quadratic specification. The quadratic term is significant for precipitation and average temperature. These results indicate that large weather fluctuations induce migration waves.

Table 6 shows the results that distinguish between positive and negative shocks. The previous result on precipitation is also apparent in this case: precipitation deviations above the historical mean are drivers of migration. In the case of average temperature, the effect of temperature shocks on migration is more pronounced if the shock is above rather than below the historical mean temperature. More specifically, a one standard deviation above the historical mean generates a 0.41 p.p. increase in migration, larger than the 0.34 p.p. discussed in the previous section. The differential result for positive shocks is not significant for maximum and minimum temperature.

4.3 Third Specification: Temperature and Precipitation

When we estimate a specification with both the average temperature and precipitation, it becomes more apparent that temperature is the variable that explains the results.

Table 7 shows our estimation. As before, the significant relationship between migration and weather shocks concerns illegal migrants. Interestingly, the result is only significant for the temperature variable. In this case, a standard deviation increase in average temperature generates a 0.33 p.p. increase in migration.

Table 5: Weather Shocks and Illegal Migration: Quadratic Specification

Dependent Variable:	Illegal Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0011**			
	(0.0004)			
Dev Precipitation Sq (Z-score, t-1)	0.0005***			
	(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0030***		
		(0.0004)		
Dev Avg Temp Sq (Z-score, t-1)		0.0004*		
		(0.0002)		
Dev Max Temp (Z-score, t-1)			0.0033***	
			(0.0004)	
Dev Max Temp Sq (Z-score, t-1)			0.0002	
			(0.0002)	
Dev Min Temp (Z-score, t-1)				0.0032***
				(0.0006)
Dev Min Temp Sq (Z-score, t-1)				0.0001
				(0.0003)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,587	112,587	112,587	112,587
Adjusted R^2	0.18091	0.18173	0.18155	0.18145

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates illegally to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. "Sq" means the variable squared. The historical mean is taken over the period 1985-2019.

Table 6: Weather Shocks and Illegal Migration: Positive vs Negative Shocks

Dependent Variable:	Illegal Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0023***			
	(0.0008)			
Dev Precipitation > 0 (Z-score, t-1)	0.0029***			
	(0.0010)			
Dev Avg Temp (Z-score, t-1)		0.0015**		
		(0.0008)		
Dev Avg Temp > 0 (Z-score, t-1)		0.0026**		
		(0.0010)		
Dev Max Temp (Z-score, t-1)			0.0024***	
			(0.0006)	
Dev Max Temp > 0 (Z-score, t-1)			0.0016	
			(0.0010)	
Dev Min Temp (Z-score, t-1)				0.0030**
				(0.0013)
Dev Min Temp > 0 (Z-score, t-1)				0.0005
				(0.0017)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,587	112,587	112,587	112,587
Adjusted R^2	0.18092	0.18175	0.18156	0.18145

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates illegally to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. "> 0" means that the variable is an interaction between the weather variable and an indicator variable equal to one whenever the weather variable is greater than 0. The historical mean is taken over the period 1985-2019.

Table 7: Weather Shocks and Migration: Average Temperature and Precipitation

Dependent Variables:	Migrant	Illegal Migrant	Legal Migrant
Model:	(1)	(2)	(3)
Variables			
Dev Prec (Z-score, t-1)	-0.0005	-0.0003	-0.0003
	(0.0004)	(0.0003)	(0.0002)
Dev Avg Temp (Z-score, t-1)	0.0033***	0.0034***	-0.0001
	(0.0004)	(0.0004)	(0.0002)
Fixed-effects			
id	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	112,588	112,587	112,587
Adjusted R^2	0.25310	0.18170	0.41782

Clustered (commun) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

4.4 Mechanism

Ideally, we would observe income. We would then show that weather shocks affect income which in turn affects migration. Since we do not observe income, we study one of its main sources in rural Mexico: agricultural production. As discussed in Section 2, we have agricultural data at the municipality level rather than at the community level.

Following our main specification, we focus on the wet season in Mexico. Since our sample only includes 76 municipalities, we expand our data to all the municipalities within the 17 states that have at least one community in our sample, resulting in 1,960 municipalities.

Figure 3 illustrates our main point. It plots harvested-land deviations with respect to their historical mean against precipitation and maximum-temperature standardized deviations. The dots reflect the average deviations of harvested land for decile deviations of the weather variable. The relationship between the variables is clear: the higher (lower) the temperature (precipitation), the lower the harvested area. We add a similar plot for the minimum temperature in the appendix (Figure A.2).

4.4.1 Econometric Specification

In order to identify the effect of weather shocks on agricultural production, we use a two-way fixed-effects model, too. We estimate three different specifications.

Firstly, we run each weather variable separately; we estimate Equation 5:

$$y_{jt} = \alpha_j + \gamma_t + \beta_w w_{jt} + \epsilon_{jt} \tag{5}$$

where y_{jt} is the variable of interest for municipality j at time t, e.g., logarithm of the total harvested area; α_j, is the municipality fixed effect; γ_t is the year fixed effect; w_{jt} is the weather shock, e.g., the z-score of the maximum temperature in the wet season; and ϵ_{jt} is the error term. We cluster the errors at the municipality level.

Secondly, we propose a non-linear model. We estimate Equation 6:

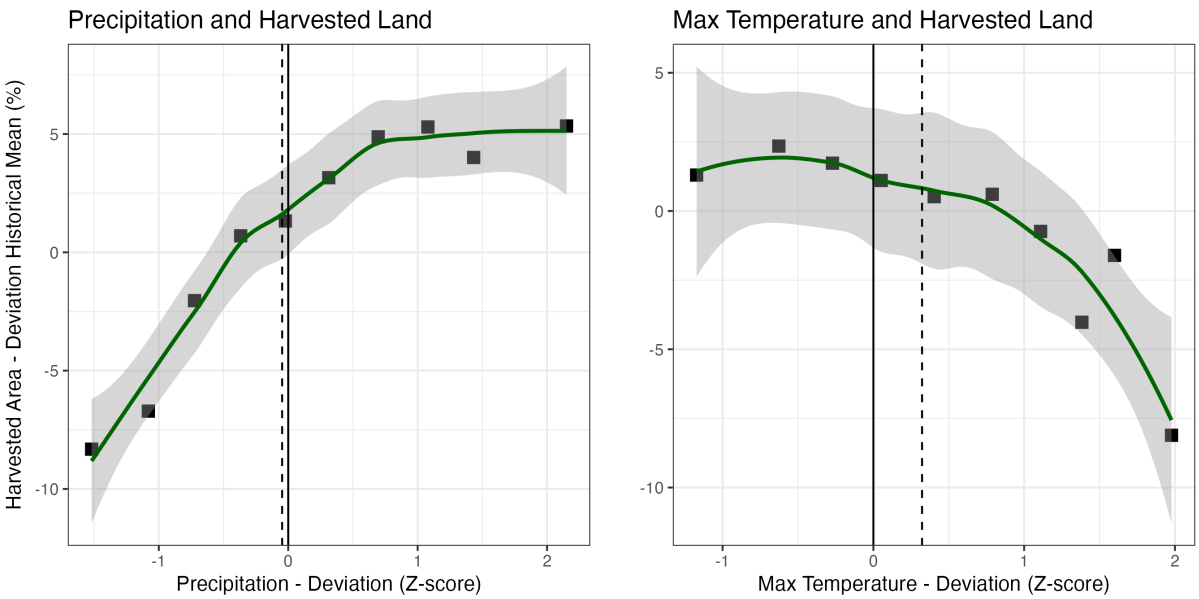

Figure 3: Weather Shocks and Harvested Land

Notes: The dots reflects the harvested-land deviations from its historical mean for precipitation and maximum-temperature z-scores in the wet season. More specifically, each dot groups the observations in deciles of the z-score distribution and calculates the average deviation from the harvested land for such deciles. The historical mean is taken over the period 1985-2019.

$$y_{jt} = \alpha_j + \gamma_t + \beta_w w_{jt} + \beta_{w2} w_{jt}^2 + \epsilon_{jt} \tag{6}$$

where y_{jt} is the variable of interest for municipality j at time t, e.g., logarithm of the total harvested area; α_j, is the municipality fixed effect; γ_t is the year fixed effect; w_{jt} is the weather shock, e.g., the z-score of the maximum temperature in the wet season; w_{jt}^2 is the weather shock squared; and ϵ_{jt} is the error term. As before, we cluster the errors at the municipality level.

Thirdly, we include both average temperature and precipitation in our specification. More precisely, we estimate Equation 7:

$$y_{jt} = \alpha_j + \gamma_t + \beta_t t_{jt} + \beta_p p_{jt} + \epsilon_{jt} \tag{7}$$

where y_{jt} is the variable of interest for municipality j at time t, e.g., logarithm of the total harvested area; α_j, is the municipality fixed effect; γ_t is the year fixed effect; t_{jt} is the average temperature shock, the z-score of the average temperature in the wet season; p_{jt} is the precipitation shock, the z-score of the precipitation in the wet season; and ϵ_{jt} is the error term. We cluster the errors at the municipality level.

4.4.2 Results

The effect of weather on agricultural production is relevant in every specification.

Table 8 displays the results for the first specification. Weather shocks have a significant effect on the total harvested area and corn production at a 1% level. More precisely, a decrease in one standard deviation in precipitation relative to the historical mean increases the total harvested area in 4.45% and the corn production in 4.94%. Similarly, an increase in one standard deviation in average, maximum, and minimum temperature with respect to their historical mean decreases the harvested land area at 3.39%, 2.06%, and 1.31%, respectively, and decreases corn production at 4.44%, 2.16% and 2.18%, respectively.

Table 9 shows the results for the second specification. In most cases, non-linearities are prevalent. Analogously to the migration case, the square coefficient of precipitation is negative, which implies that large precipitation shocks generate a decrease in agricultural production. The quadratic term is also negative for the temperature variables, indicating that the effect of temperature on agricultural production is more prominent with higher temperatures.

Lastly, Table 10 includes both the average temperature and precipitation. The results are in line with the second specification: the results are significant for both precipitation and average temperature.

Table 8: Weather Shocks and Agricultural Production

Dependent Variables:	Log (Harv Area) - Ha				Log (Corn Prod) - Gr, Ton			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipiation (Z-score)	0.0445***				0.0494***			
	(0.0042)				(0.0052)			
Dev Avg Temp (Z-score)		-0.0339***				-0.0444***		
		(0.0050)				(0.0068)		
Dev Max Temp (Z-score)			-0.0206***				-0.0216***	
			(0.0045)				(0.0063)	
Dev Min Temp (Z-score)				-0.0131***				-0.0218***
				(0.0048)				(0.0064)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	32,847	32,847	32,847	32,847	31,998	31,998	31,998	31,998
Adjusted R^2	0.90513	0.90471	0.90459	0.90451	0.89558	0.89530	0.89511	0.89510

Clustered (id) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is the log of the harvested area (tons of corn-for-grain production) in the wet season. The independent variables are calculated as the z-score for the weather variables in the same year and season. The average temperature is calculated as the simple average between maximum and minimum temperature. The historical mean is taken over the period 1985-2019.

Table 9: Weather Shocks and Agricultural Production: Nonlinear Effects

Dependent Variables:	Log (Harv Area) - Ha				Log (Corn Prod) - Gr, Ton			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipiation (Z-score)	0.0488***				0.0527***			
	(0.0046)				(0.0056)			
Dev Precipiation Sq (Z-score)	-0.0084***				-0.0063***			
	(0.0019)				(0.0024)			
Dev Avg Temp (Z-score)		-0.0319***				-0.0431***		
		(0.0050)				(0.0068)		
Dev Avg Temp Sq (Z-score)		-0.0098***				-0.0068**		
		(0.0023)				(0.0032)		
Dev Max Temp (Z-score)			-0.0184***				-0.0212***	
			(0.0045)				(0.0063)	
Dev Max Temp Sq (Z-score)			-0.0051**				-0.0011	
			(0.0023)				(0.0031)	
Dev Min Temp (Z-score)				-0.0146***				-0.0228***
				(0.0049)				(0.0064)
Dev Min Temp Sq (Z-score)				-0.0080***				-0.0053*
				(0.0021)				(0.0030)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	32,847	32,847	32,847	32,847	31,998	31,998	31,998	31,998
Adjusted R^2	0.90519	0.90476	0.90460	0.90456	0.89561	0.89532	0.89511	0.89511

Clustered (id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is the log of the harvested area (tons of corn-for-grain production) in the wet season. The independent variables are calculated as the z-score for the weather variables in the same year and season. "Sq" means the variable squared. The average temperature is calculated as the simple average between maximum and minimum temperature. The historical mean is taken over the period 1985-2019.

Table 10: Weather Shocks and Agricultural Production: Average Temperature and Precipitation

Dependent Variables:	Log (Harv Area) - Ha	Log (Corn Prod) - Gr, Ton
Model:	(1)	(2)
Variables		
Dev Precipiation (Z-score)	0.0412***	0.0449***
	(0.0042)	(0.0053)
Dev Avg Temp (Z-score)	-0.0251***	-0.0351***
	(0.0050)	(0.0069)
Fixed-effects		
id	Yes	Yes
year	Yes	Yes
Fit statistics		
Observations	32,847	31,998
Adjusted R^2	0.90525	0.89575

Clustered (id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) column, is the log of the harvested area (tons of corn-for-grain production) in the wet season. The independent variables are calculated as the z-score for the weather variables in the same year and season. The average temperature is calculated as the simple average between maximum and minimum temperature. The historical mean is taken over the period 1985-2019.

4.5 Heterogeneity

In this section, we investigate the heterogeneous effects of weather shocks. Since we estimate a two-way fixed effect model, we explore heterogeneity by dividing the sample into groups and estimating the model for each group separately. We define three variables that are likely to be relevant in the migration decision: age, wealth, and occupation.

Figure 4 illustrates our motivation for including age. It divides the sample into two groups: "≤ 41," workers younger than 41 years old, and "> 41," workers older than 41 years old. We choose 41 years old to divide the age range into two (almost) symmetric groups. Clearly, the younger group has a higher proportion of (illegal) migrants and is much more sensitive to temperature shocks. This is in line with the literature (e.g., Reinhold and Thom (2013)).

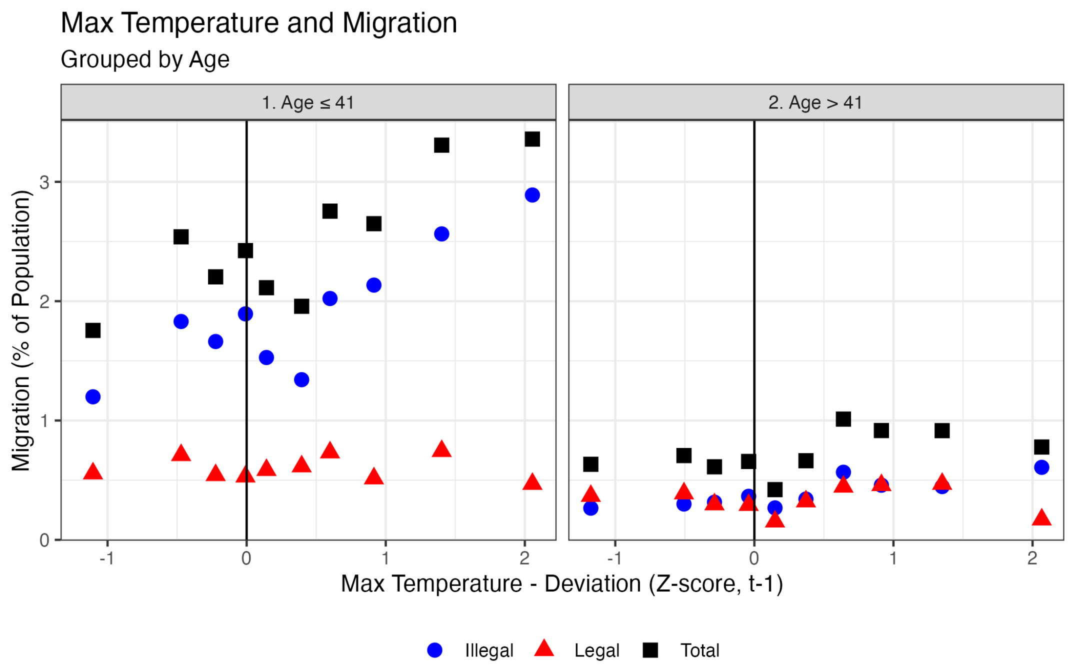

Figure 4: Weather shocks and Migration by Age

Notes: The dots reflect the proportion of Mexican migrants in the population for maximum-temperature z-scores in the wet season. More specifically, each dot groups observations in deciles of the z-score distribution and calculates the proportion of migrants for such deciles. The weather deviation is taken the period before the migration decision. "Age ≤ 41" refers to the workers that were younger 41 years old the year before the migration decision. The historical mean is taken over the period 1985-2019.

Figure 5 shows the results by wealth. Since we do not observe wealth directly, we use ownership of land or a business as a proxy. Thus, we divide the sample into two groups: "non-owners," workers without land or a business, and "owners," workers with land or a business. The effect of wealth on migration are less salient than for age yet clear: non-owners have a higher level of (illegal) migration and the effect of temperature is stronger for such a group.

Lastly, Figure 6 shows the results by occupation. More precisely, we distinguish between two groups: "Ag workers," who were agricultural workers in the year of the weather shock, and "Non-Ag workers," who were not agricultural workers in the year of the weather shock. The effect of occupation on migration appears to be more diffuse than in the previous cases.

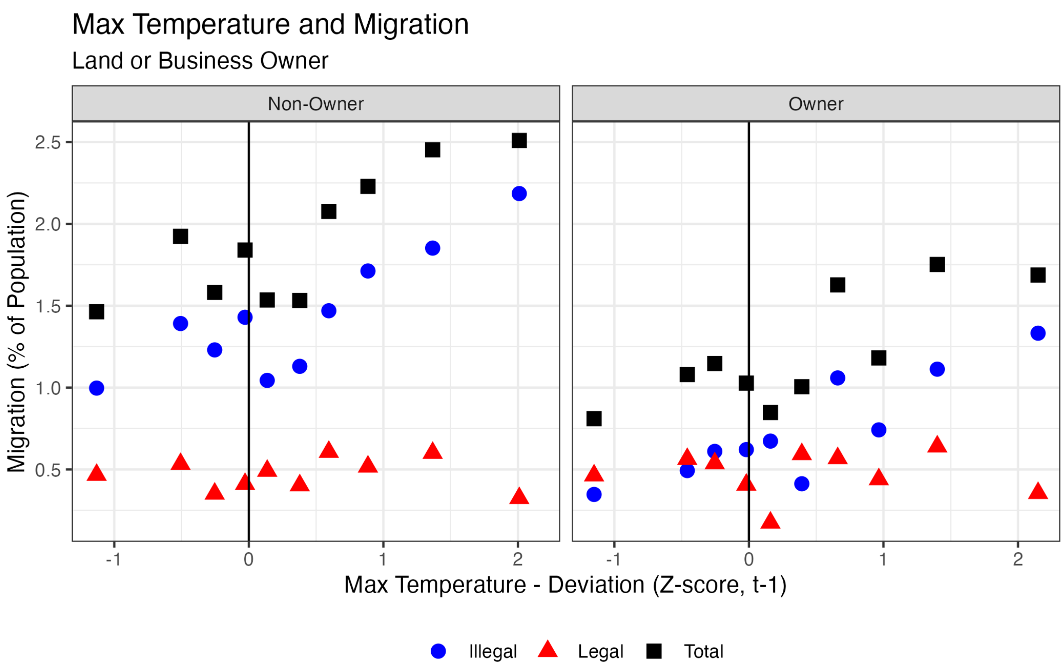

Figure 5: Weather Shocks and Migration by Wealth

Notes: The dots reflect the proportion of Mexican migrants in the population for maximum-temperature z-score in the wet season. More specifically, each dot groups observations in deciles of the z-score distribution and calculates the proportion of migrants for such deciles. The temperature deviation is taken from the period before the migration decision. "Owner" refers to the workers that were owners of land or a business the year before the migration decision. The historical mean is taken over the period 1985-2019.

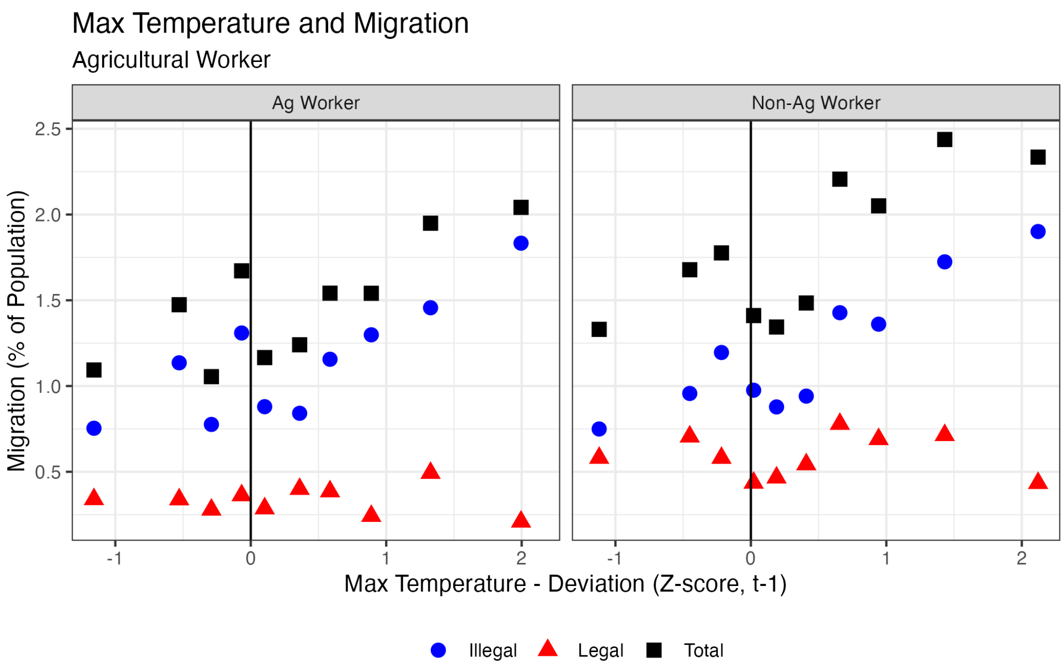

Figure 6: Weather shocks and Migration by Age

Notes: The dots reflect the proportion of Mexican migrants in the population for maximum-temperature z-score in the wet season. More specifically, each dot groups observations in deciles of the z-score distribution and calculates the proportion of migrants for such deciles. The temperature deviation is taken from the period before the migration decision. "Ag Worker" refers to the workers who were agricultural workers the year before the migration decision. The historical mean is taken over the period 1985-2019.

4.5.1 Econometric Specification

As discussed before, we estimate the heterogeneous effect of weather shocks on migration using a two-way fixed-effects model and dividing the sample by groups. More precisely, we estimate, separately for each group, Equation 8:

$$y_{ijt} = \alpha_i + \gamma_t + \beta_w w_{j,t-1} + \epsilon_{ijt} \tag{8}$$

where y_{ijt} is the variable of interest for a person i from community j at time t, e.g., did she migrate to the US in that specific period; α_i is the person fixed effect; γ_t is the year fixed effect; $w_{j,t-1}$ is the weather shock, e.g., the z-score of the maximum temperature in the wet season; and ϵ_{ijt} is the error term. We cluster the errors at the community level.

4.5.2 Results

We show the results only for illegal migration, which is the driver of our results. We add the results for all migration and legal migration in the appendix (Tables A.5 to A.9).

Table 11 shows the results for age. Young workers are much more sensitive to weather shocks. For example, a one standard deviation increase in average temperature with respect to the historical mean generates a 0.57 p.p. increase in illegal migration for young younger than 41 years and a 0.09 p.p. increase in illegal migration for workers older than 41 years.

Table 12 illustrates the results by wealth. Wealthier workers are less sensitive to weather shocks. For example, a one standard deviation increase in average temperature with respect to the historical mean increase illegal migration by 0.38 p.p. for non-owners and by 0.26 p.p. for owners.

Lastly, Table 13 illustrates the results by occupation. The results are slightly more pronounce for agricultural workers. It is worth noticing, however, that our sample is already focused on the rural area of Mexico, which means that all workers likely depend on the agricultural sector, regardless of whether they are working in such a sector.

Table 11: Illegal Migration and Weather Shocks by Age

Dependent Variables:	Illegal Migrant ≤ 41				Illegal Migrant > 41			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0013*				−0.00009			
	(0.0007)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0057***				0.0009***		
		(0.0006)				(0.0003)		
Dev Max Temp (Z-score, t-1)			0.0058***				0.0008***	
			(0.0008)				(0.0003)	
Dev Min Temp (Z-score, t-1)				0.0059***				0.0006**
				(0.0008)				(0.0003)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	57,938	57,938	57,938	57,938	54,649	54,649	54,649	54,649
Adjusted R^2	0.17942	0.18087	0.18057	0.18055	0.25082	0.25097	0.25092	0.25088

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variable equal to one if the agent migrates to the US illegally in that period and younger (older) than 41 years old. The independent variables are calculated as standardized deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table 12: Illegal Migration and Weather Shocks by Wealth

Dependent Variables:	Non-Owner Illegal Migrant				Owner Illegal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0011**				0.0001			
	(0.0005)				(0.0004)			
Dev Avg Temp (Z-score, t-1)		0.0038***				0.0026***		
		(0.0005)				(0.0005)		
Dev Max Temp (Z-score, t-1)			0.0039***				0.0030***	
			(0.0006)				(0.0006)	
Dev Min Temp (Z-score, t-1)				0.0038***				0.0020***
				(0.0006)				(0.0005)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	69,884	69,884	69,884	69,884	42,703	42,703	42,703	42,703
Adjusted R^2	0.21718	0.21799	0.21781	0.21776	0.20259	0.20336	0.20345	0.20294

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the last (first) 4 columns, is an indicator variable equal to one if the agent migrates to the US illegally in that period and is (not) a land or business owner. The independent variables are calculated as standardized deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table 13: Illegal Migration and Weather Shocks by Occupation

Dependent Variables:	Illegal Migrant - Non-Ag				Illegal Migrant - Ag			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0005				-0.0008*			
	(0.0005)				(0.0004)			
Dev Avg Temp (Z-score, t-1)		0.0031***				0.0035***		
		(0.0005)				(0.0005)		
Dev Max Temp (Z-score, t-1)			0.0035***				0.0033***	
			(0.0005)				(0.0006)	
Dev Min Temp (Z-score, t-1)				0.0025***				0.0038***
				(0.0005)				(0.0006)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	59,830	59,830	59,830	59,830	52,061	52,061	52,061	52,061
Adjusted R^2	0.23716	0.23782	0.23783	0.23747	0.19662	0.19747	0.19721	0.19736

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the last (first) 4 columns, is an indicator variable equal to one if the agent migrates to the US illegally in that period and is (not) an agricultural worker. The independent variables are calculated as standard deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

4.6 Extrapolation: Climate Change

Our estimates can help us understand the effect that climate change will have on migration. In this section, we do some back-of-the-envelope calculations to read our results through the lens of climate change.

Climate change will have an effect on both the level and the distribution of climatic variables. To consider both effects, we use data from TerraClimate, which provides data from "pseudo-years." Essentially, these are simulated weather realizations that are generated in a climatic model by changing the climatic variables considering the effect of climate change. Their period of reference is 1990-2015.

We compare the weather in pseudo-years with actual years to understand the climatic shift generated by climate change. We then use our causal estimates to study the effect of climate change on migration.[11]

Figure 7 illustrates the shift in weather that climate change would imply. More precisely, it shows the distribution of the z-scores of maximum temperature with and without climate change. As expected, the distribution is shifted to the right. Furthermore, the variance of the z-score increases.

4.6.1 Results

To project the effect of climate change on migration, we use the estimates in Table 4. The process goes as follows. First, we calculate the deviation that climate change implies in the distribution of the weather variables. We then multiply such deviations by the corresponding coefficient in Table 4.

Table 14 summarizes our results. Naturally, illegal migration would increase: the higher the increase in global temperature, the higher the increase in migration. For the climate model in which the global temperature would increase by 2°C, the change in precipitation

[11] Unfortunately, we can only aggregate weather variables at the municipality rather than the community level. We therefore use the municipality deviations as a proxy of the deviation that climate change would imply at the community level.

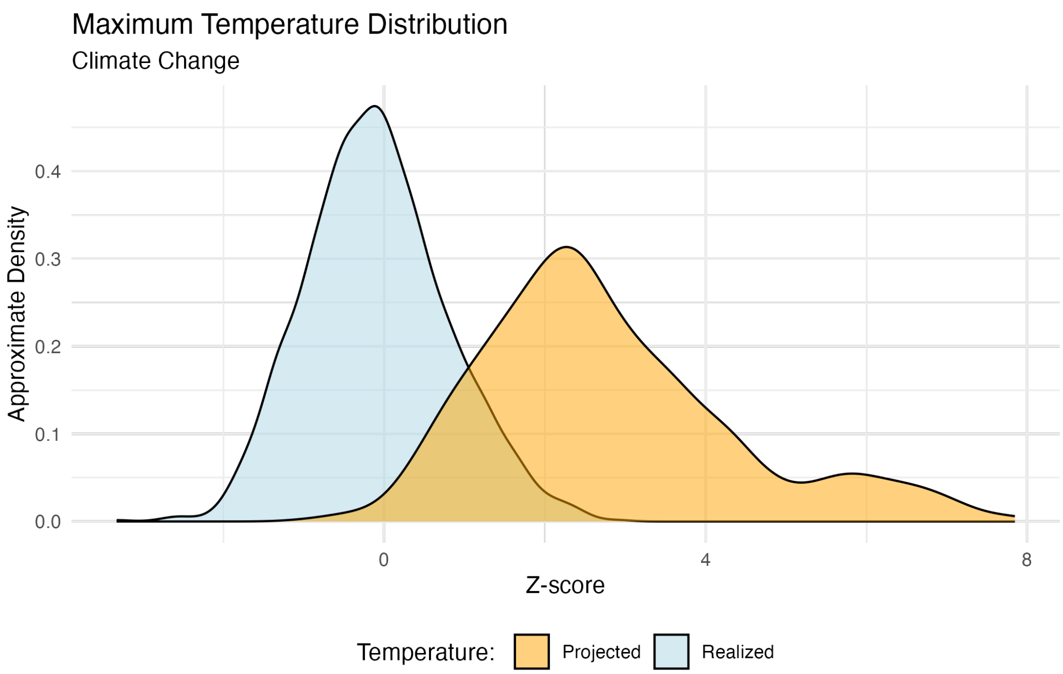

Figure 7: Climate Change: Maximum Temperature distribution for 1900-2015

Notes: This plot reflects the distribution of maximum temperature in the wet season for the municipalities in the (pseudo-)years 1990-2015, for which we have climate change projections. The x-axis is calculated as standardized deviation for the maximum temperature for such a period. The y-axis reflects the approximate density of the variable. The sky-blue density shows the actual distribution of maximum temperature. The orange density displays the projected distribution of maximum temperature for a climate scenario in which global temperatures increase in $2^a C$. *The historical period of reference is 1985-2019.*

would imply, on average, a 0.02 p.p. increase in illegal migration - a 1.18% increase with respect to the baseline. For the climate 4°C model, the change in precipitation would imply a 0.06 p.p. increase in migration - a 5.45% increase with respect to the baseline. The results are much more salient for temperature. For the climate model in which global temperature would increase in 2°C, the effect that climate change will have on maximum and minimum temperature would imply, on average, a 0.73 p.p. and 0.86 p.p. increase in illegal migration, respectively - a 66.36% and 78.18% increase with respect to the baseline. For the climate 4°C model, the change in would more than double.

Table 14: Projected Illegal Migration

	2°C		4°C	
Variable	Deviation	Migration (p.p)	Deviation	Migration (p.p)
Precipitation (Z-score)	-0.25	0.02	-0.71	0.06
	(0.96)	(0.081)	(0.984)	(0.083)
Max Temp (Z-score)	2.47	0.73	5.12	1.56
	(1.809)	(0.627)	(2.3)	(0.796)
Min Temp (Z-score)	2.22	0.86	4.73	1.77
	(1.311)	(0.431)	(1.761)	(0.579)

Notes: The headlines "2°C" and "4°C" refer to an increase in global temperatures for possible climate scenarios. The columns "Deviation" calculate the average expected deviation for each variable for such scenarios in the wet season in the municipalities of our study. The columns "Migration" refer to the average increase in projected illegal migration in p.p. Standard deviations are added in parenthesis. The historical period of reference is 1985-2019.

4.7 Discussion

Climate change supposes a structural change in the workers' problem. Thus, to fully understand its effect on migration, we would need to add a structural model. The previous exercise is, however, informative: the results are likely to be an upper bound to the actual effect of climate change on migration, as workers will likely adapt to the new climate scenario and thus diminish the impact of climate change on yields and migration.

5 Robustness Checks

In this section, we do robustness checks for our main analysis. First, we define temperature shocks differently. Since our proposed mechanism is agricultural production with emphasis on corn, we investigate the effect of "days of excess heat," days with an average temperature above 29°C, following Schlenker and Roberts (2009). Our results are in line with our main specification and can be found in A.11: an increase of one excess heat day increases migration by 0.02 p.p. The increase is entirely driven by illegal migrants.

Second, we crop the data differently. More specifically, we keep 8-year backward windows and 12-year backward windows for information regarding migration of the head of household. The results are virtually unchanged and can be found in Tables A.12, A.13, A.14, and A.15 in the appendix.

Third, we consider a different period for the historical mean. In our main analysis, we used the period 1985-2019; in this robustness check, we use the period 1985-2005. The results are very similar and can be found in Tables A.16 and A.17 in the appendix.

Lastly, we add communities with less than 500,000 people. The results are unchanged and can be found in Tables A.18 and A.19 in the appendix.

6 Conclusion

We study how international migration can work as a coping mechanism for weather shocks. We focus our work in rural Mexico, which has a long tradition of migrants to the United States. Our detailed data allows us to dive into the effect of weather shocks on legal and illegal migration separately. We further propose a mechanism to explain our results: the effect of weather on agricultural production. Lastly, we project the effect that climate change will have on migration.

Our main findings are the following. First, we find that shocks in the wet season increase migration. The increase is entirely driven by illegal migrants. Second, we find that weather shocks decrease the total production of harvested land and corn. Third, we show that young and less wealthy workers are more sensitive to weather shocks. Lastly, we extrapolate our results using climate projection models. We find that climate change would increase illegal migration substantially.

We see some venues in which our work can be expanded. First, the effect of climate change on illegal migration is not fully captured in our results: our approach does not account for adaptation, which will likely be an important factor in the future. Second, it would be interesting to investigate the "delayed" effect of weather shocks. We show that weather shocks generate an immediate increase in illegal migration; they might also generate a delayed increase in legal migration. Lastly, it is important to understand the effect that weather-induced migrants have on local markets.

Overall, our work highlights the relevance of the weather for international migration. Climate change makes this discussion increasingly relevant.

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A Appendix

A.1 Weather shocks and migration

A.1.1 Plots

In this section, we add the plots for weather shocks and migration for average and minimum temperature (Figure A.1).

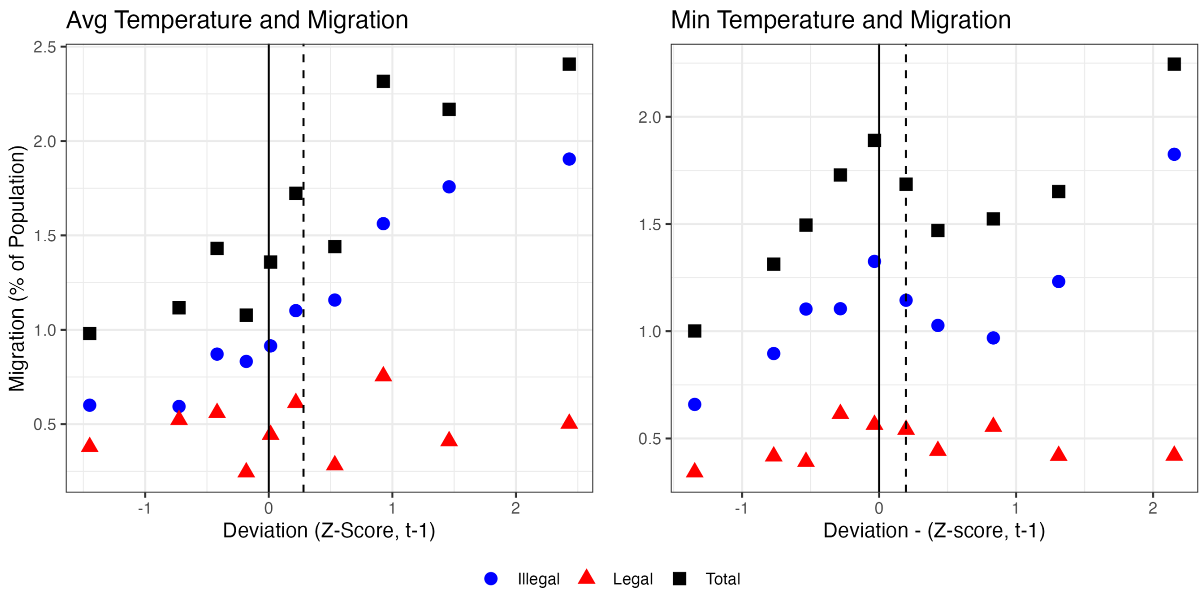

Figure A.1: Temperature Shocks and Migration

Notes: The dots reflect the proportion of migrants in the population for the standardized deviation on average and minimum-temperature deviations in the wet season. More specifically, each dot groups observations in deciles of the z-score distribution and calculates the proportion of migrants for such deciles. The dotted vertical line reflects the average z-score in our period of study. The weather deviation is taken a period before the migration decision. The historical mean is taken over the period 1985-2019.

A.1.2 Weather Shocks and Migration: Nonlinear effects

In this section, we add the non-linear regressions for all migrants, Tables A.1 and A.2, and for legal migrants, Tables A.3 and A.4.

A.1.3 Heterogeneity Results

In this section, we add the results for heterogeneity for all migrants and legal migrants. Tables A.5 and A.8 show the results by age; Tables A.6 and A.9 display the results by wealth; and Tables A.6 and A.9 illustrate the results by occupation.

Table A.1: Weather Shocks and Migration: Quadratic Specification

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0014***			
	(0.0005)			
Dev Precipitation Sq (Z-score, t-1)	0.0006***			
	(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0027***		
		(0.0005)		
Dev Avg Temp Sq (Z-score, t-1)		0.0005**		
		(0.0002)		
Dev Max Temp (Z-score, t-1)			0.0032***	
			(0.0005)	
Dev Max Temp Sq (Z-score, t-1)			0.0002	
			(0.0002)	
Dev Min Temp (Z-score, t-1)				0.0031***
				(0.0007)
Dev Min Temp Sq (Z-score, t-1)				0.0002
				(0.0003)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,588	112,588	112,588	112,588
Adjusted R^2	0.25260	0.25313	0.25302	0.25294

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. "Sq" means the variable squared. The historical mean is taken over the period 1985-2019.

Table A.2: Weather Shocks and Migration: Positive vs Negative Shocks

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0028***			
	(0.0009)			
Dev Precipitation > 0 (Z-score, t-1)	0.0033***			
	(0.0011)			
Dev Avg Temp (Z-score, t-1)		0.0008		
		(0.0009)		
Dev Avg Temp > 0 (Z-score, t-1)		0.0034***		
		(0.0012)		
Dev Max Temp (Z-score, t-1)			0.0021***	
			(0.0007)	
Dev Max Temp > 0 (Z-score, t-1)			0.0020*	
			(0.0011)	
Dev Min Temp (Z-score, t-1)				0.0031**
				(0.0014)
Dev Min Temp > 0 (Z-score, t-1)				0.0003
				(0.0017)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,588	112,588	112,588	112,588
Adjusted R^2	0.25261	0.25315	0.25304	0.25294

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. "> 0" means that the variable is an interaction between the weather variable and an indicator variable equal to one whenever the weahter variable is greater than 0. The historical mean is taken over the period 1985-2019.

Table A.3: Weather Shocks and Legal Migration: Quadratic Specification

Dependent Variable:	Legal Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0003			
	(0.0002)			
Dev Precipitation Sq (Z-score, t-1)	6.5×10^{-5}			
	(9.3×10^{-5})			
Dev Avg Temp (Z-score, t-1)		-0.0003		
		(0.0002)		
Dev Avg Temp Sq (Z-score, t-1)		0.0001		
		(8.94×10^{-5})		
Dev Max Temp (Z-score, t-1)			-6.13×10^{-5}	
			(0.0002)	
Dev Max Temp Sq (Z-score, t-1)			4.53×10^{-5}	
			(7.89×10^{-5})	
Dev Min Temp (Z-score, t-1)				-8.67×10^{-5}
				(0.0003)
Dev Min Temp Sq (Z-score, t-1)				4.8×10^{-5}
				(0.0002)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,587	112,587	112,587	112,587
Adjusted R^2	0.41782	0.41782	0.41781	0.41781

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates legally to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. "Sq" means the variable squared. The historical mean is taken over the period 1985-2019.

Table A.4: Weather Shocks and Legal Migration: Positive vs Negative Shocks

Dependent Variable:	Legal Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0005			
	(0.0004)			
Dev Precipitation > 0 (Z-score, t-1)	0.0004			
	(0.0005)			
Dev Avg Temp (Z-score, t-1)		-0.0007		
		(0.0005)		
Dev Avg Temp > 0 (Z-score, t-1)		0.0008		
		(0.0006)		
Dev Max Temp (Z-score, t-1)			-0.0003	
			(0.0004)	
Dev Max Temp > 0 (Z-score, t-1)			0.0004	
			(0.0005)	
Dev Min Temp (Z-score, t-1)				7.41×10^{-5}
				(0.0005)
Dev Min Temp > 0 (Z-score, t-1)				-0.0002
				(0.0007)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,587	112,587	112,587	112,587
Adjusted R^2	0.41782	0.41782	0.41781	0.41781

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates legally to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. "> 0" means that the variable is an interaction between the weather variable and an indicator variable equal to one whenever the weahter variable is greater than 0. The historical mean is taken over the period 1985-2019.

Table A.5: Migration and Weather Shocks by Age

Dependent Variables:	Migrant $\leq$ 41				Migrant $>$ 41			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0015**				-0.0002			
	(0.0007)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0056***				0.0008**		
		(0.0007)				(0.0003)		
Dev Max Temp (Z-score, t-1)			0.0058***				0.0009**	
			(0.0009)				(0.0004)	
Dev Min Temp (Z-score, t-1)				0.0059***				0.0007**
				(0.0009)				(0.0003)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	57,938	57,938	57,938	57,938	54,650	54,650	54,650	54,650
Adjusted R^2	0.24380	0.24481	0.24464	0.24461	0.34716	0.34723	0.34722	0.34719

Clustered (commun) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variable equal to one if the agent migrates to the US in that period and younger (older) than 41 years old. The independent variables are calculated as standardized deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.6: Migration and Weather Shocks by Wealth

Dependent Variables:	Non-Owner Migrant				Owner Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0014***				-6.98×10^{-5}			
	(0.0005)				(0.0005)			
Dev Avg Temp (Z-score, t-1)		0.0037***				0.0025***		
		(0.0005)				(0.0006)		
Dev Max Temp (Z-score, t-1)			0.0041***				0.0027***	
			(0.0006)				(0.0007)	
Dev Min Temp (Z-score, t-1)				0.0035***				0.0024***
				(0.0006)				(0.0007)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	69,884	69,884	69,884	69,884	42,704	42,704	42,704	42,704
Adjusted R^2	0.27152	0.27207	0.27203	0.27185	0.29952	0.29995	0.29992	0.29982

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the last (first) 4 columns, is an indicator variable equal to one if the agent migrates to the US in that period and is (not) a land or business owner. The independent variables are calculated as standardized deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.7: Migration and Weather Shocks by Occupation

Dependent Variables:		Migrant - Non-Ag				Migrant - Ag		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0007				-0.0010**			
	(0.0005)				(0.0004)			
Dev Avg Temp (Z-score, t-1)		0.0030***				0.0034***		
		(0.0006)				(0.0005)		
Dev Max Temp (Z-score, t-1)			0.0034***				0.0034***	
			(0.0007)				(0.0006)	
Dev Min Temp (Z-score, t-1)				0.0027***				0.0035***
				(0.0006)				(0.0007)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	59,831	59,831	59,831	59,831	52,061	52,061	52,061	52,061
Adjusted R^2	0.31901	0.31942	0.31943	0.31925	0.24135	0.24195	0.24181	0.24182

Clustered (commun) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the last (first) 4 columns, is an indicator variable equal to one if the agent migrates to the US in that period and is (not) an agricultural worker. The independent variables are calculated as standard deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.8: Legal Migration and Weather Shocks by Age

Dependent Variables:	Illegal Migrant ≤ 41				Illegal Migrant > 41			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0003				-0.0001			
	(0.0003)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		-0.0002				1.87×10^{-6}		
		(0.0003)				(0.0002)		
Dev Max Temp (Z-score, t-1)			-4.67×10^{-5}				0.0001	
			(0.0004)				(0.0003)	
Dev Min Temp (Z-score, t-1)				-8.24×10^{-5}				0.0001
				(0.0004)				(0.0002)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	57,938	57,938	57,938	57,938	54,649	54,649	54,649	54,649
Adjusted R^2	0.43746	0.43745	0.43745	0.43745	0.45128	0.45128	0.45128	0.45128

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variable equal to one if the agent migrates to the US legally in that period and younger (older) than 41 years old. The independent variables are calculated as standardized deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.9: Legal Migration and Weather Shocks by Wealth

Dependent Variables:	Non-Owner Legal Migrant				Owner Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0003				-0.0002			
	(0.0002)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		-8.68×10^{-5}				-5.42×10^{-5}		
		(0.0002)				(0.0004)		
Dev Max Temp (Z-score, t-1)			0.0002				-0.0003	
			(0.0003)				(0.0004)	
Dev Min Temp (Z-score, t-1)				-0.0003				0.0004
				(0.0003)				(0.0004)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	69,884	69,884	69,884	69,884	42,703	42,703	42,703	42,703
Adjusted R^2	0.42416	0.42415	0.42416	0.42416	0.44351	0.44350	0.44352	0.44353

Clustered (commun) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the last (first) 4 columns, is an indicator variable equal to one if the agent migrates to the US legally in that period and is (not) a land or business owner. The independent variables are calculated as standardized deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.10: Legal Migration and Weather Shocks by Occupation

Dependent Variables:	Illegal Migrant - Non-Ag				Illegal Migrant - Ag			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0003				-0.0002			
	(0.0002)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		-3.06×10^{-5}				-0.0001		
		(0.0003)				(0.0003)		
Dev Max Temp (Z-score, t-1)			-2.84×10^{-5}				4.99×10^{-5}	
			(0.0004)				(0.0003)	
Dev Min Temp (Z-score, t-1)				0.0002				-0.0003
				(0.0003)				(0.0003)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	59,830	59,830	59,830	59,830	52,061	52,061	52,061	52,061
Adjusted R^2	0.48080	0.48079	0.48079	0.48080	0.36738	0.36737	0.36737	0.36738

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the last (first) 4 columns, is an indicator variable equal to one if the agent migrates to the US legally in that period and is (not) an agricultural worker. The independent variables are calculated as standard deviations in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.11: Temperature Shocks and Migration - Days above 29°C

Dependent Variables:	Migrant	Illegal Migrant	Legal Migrant
Model:	(1)	(2)	(3)
Variables			
Days Above 29°C (#, t-1)	0.0002***	0.0002***	0.000008
	(0.00004)	(0.00003)	(0.00002)
Fixed-effects			
id	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	121,299	121,298	121,298
Adjusted R^2	0.24964	0.18066	0.40719

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable for the first column is an indicator variables equal to one if the agent migrates to the US in that period. The dependent variable for the second (thirst) column is an indicator variables equal to one if the agent migrates illegally (legally) to the US in that period. The independent variable is calculated as total days above 29°C in the wet season a year before the migration decision.

A.1.4 Robustness Checks

In this section, we add the robustness checks discussed in Section 5: Table A.11 shows the results for days-above-29°C specification; Tables A.12 and A.13 show the results using 8-year backward windows; Tables A.14 and A.15 show the results using 12-year backward windows; Tables A.16 and A.17 show the results using 1985-2005 as the historical period; and Tables A.18 and A.19 show the results for communities with less than 500,000 people.

Table A.12: Weather Shocks and Migration - 8 years-window

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0009**			
	(0.0004)			
Dev Avg Temp (Z-score, t-1)		0.0034***		
		(0.0006)		
Dev Max Temp (Z-score, t-1)			0.0037***	
			(0.0006)	
Dev Min Temp (Z-score, t-1)				0.0034***
				(0.0006)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	92,000	92,000	92,000	92,000
Adjusted R^2	0.27418	0.27468	0.27464	0.27457

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.13: Weather Shocks and Migration by Legal Status - 8 years-window

Dependent Variables:		Illegal Migrant				Legal Migrant		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0006				-0.0004*			
	(0.0004)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0035***				-0.0001		
		(0.0005)				(0.0003)		
Dev Max Temp (Z-score, t-1)			0.0036***				6.25×10^{-5}	
			(0.0005)				(0.0003)	
Dev Min Temp (Z-score, t-1)				0.0035***				-6.76×10^{-5}
				(0.0006)				(0.0003)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	92,000	92,000	92,000	92,000	92,000	92,000	92,000	92,000
Adjusted R^2	0.20548	0.20630	0.20616	0.20611	0.42878	0.42876	0.42876	0.42876

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variables equal to one if the agent migrates illegally (legally) to the US in that period. The independent variables are calculated as the z-score in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.14: Weather Shocks and Migration - 12 years-window

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0010**			
	(0.0004)			
Dev Avg Temp (Z-score, t-1)		0.0031***		
		(0.0004)		
Dev Max Temp (Z-score, t-1)			0.0033***	
			(0.0005)	
Dev Min Temp (Z-score, t-1)				0.0031***
				(0.0005)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	131,776	131,776	131,776	131,776
Adjusted R^2	0.23934	0.23981	0.23973	0.23968

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.15: Weather Shocks and Migration by Legal Status - 12 years-window

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0007**				-0.0003*			
	(0.0004)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0032***				-8.02×10^{-5}		
		(0.0004)				(0.0002)		
Dev Max Temp (Z-score, t-1)			0.0032***				1.48×10^{-5}	
			(0.0004)				(0.0002)	
Dev Min Temp (Z-score, t-1)				0.0032***				-2.83×10^{-5}
				(0.0005)				(0.0002)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	131,774	131,774	131,774	131,774	131,774	131,774	131,774	131,774
Adjusted R^2	0.16737	0.16809	0.16794	0.16788	0.41748	0.41747	0.41747	0.41747

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variables equal to one if the agent migrates illegally (legally) to the US in that period. The independent variables are calculated as the z-score in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.16: Weather Shocks and Migration - Historical Mean 1985-2005

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0005**			
	(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0033***		
		(0.0004)		
Dev Max Temp (Z-score, t-1)			0.0033***	
			(0.0005)	
Dev Min Temp (Z-score, t-1)				0.0031***
				(0.0005)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	112,588	112,588	112,588	112,588
Adjusted R^2	0.25256	0.25309	0.25301	0.25293

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2005.

Table A.17: Weather Shocks and Migration by Legal Status - Historical Mean 1985-2005

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0003*				-0.0001			
	(0.0002)				(8.56×10^{-5})			
Dev Avg Temp (Z-score, t-1)		0.0034***				-0.0001		
		(0.0003)				(0.0002)		
Dev Max Temp (Z-score, t-1)			0.0033***				1.4×10^{-5}	
			(0.0004)				(0.0002)	
Dev Min Temp (Z-score, t-1)				0.0032***				-5.89×10^{-5}
				(0.0004)				(0.0002)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	112,587	112,587	112,587	112,587	112,587	112,587	112,587	112,587
Adjusted R^2	0.18086	0.18170	0.18153	0.18144	0.41782	0.41781	0.41781	0.41781

Clustered (commun) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variables equal to one if the agent migrates illegally (legally) to the US in that period. The independent variables are calculated as the z-score in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2005.

Table A.18: Weather Shocks and Migration: Communities with less than 500,000 people

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (Z-score, t-1)	-0.0010**			
	(0.0004)			
Dev Avg Temp (Z-score, t-1)		0.0032***		
		(0.0004)		
Dev Max Temp (Z-score, t-1)			0.0034***	
			(0.0005)	
Dev Min Temp (Z-score, t-1)				0.0030***
				(0.0005)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	121,299	121,299	121,299	121,299
Adjusted R^2	0.24955	0.25005	0.24999	0.24988

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is an indicator variable equal to one if the agent migrates to the US in that period. The independent variables are calculated as the z-score of the weather variable in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

Table A.19: Weather Shocks and Migration by Legal Status: Communities with less than 500,000 people

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (Z-score, t-1)	-0.0007**				-0.0003*			
	(0.0004)				(0.0002)			
Dev Avg Temp (Z-score, t-1)		0.0033***				-9.65×10^{-5}		
		(0.0004)				(0.0002)		
Dev Max Temp (Z-score, t-1)			0.0034***				6.25×10^{-6}	
			(0.0004)				(0.0002)	
Dev Min Temp (Z-score, t-1)				0.0031***				-5.16×10^{-5}
				(0.0004)				(0.0002)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	121,298	121,298	121,298	121,298	121,298	121,298	121,298	121,298
Adjusted R^2	0.18051	0.18130	0.18117	0.18103	0.40721	0.40720	0.40719	0.40719

Clustered (commun) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable, for the first (last) 4 columns, is an indicator variables equal to one if the agent migrates illegally (legally) to the US in that period. The independent variables are calculated as the z-score in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2019.

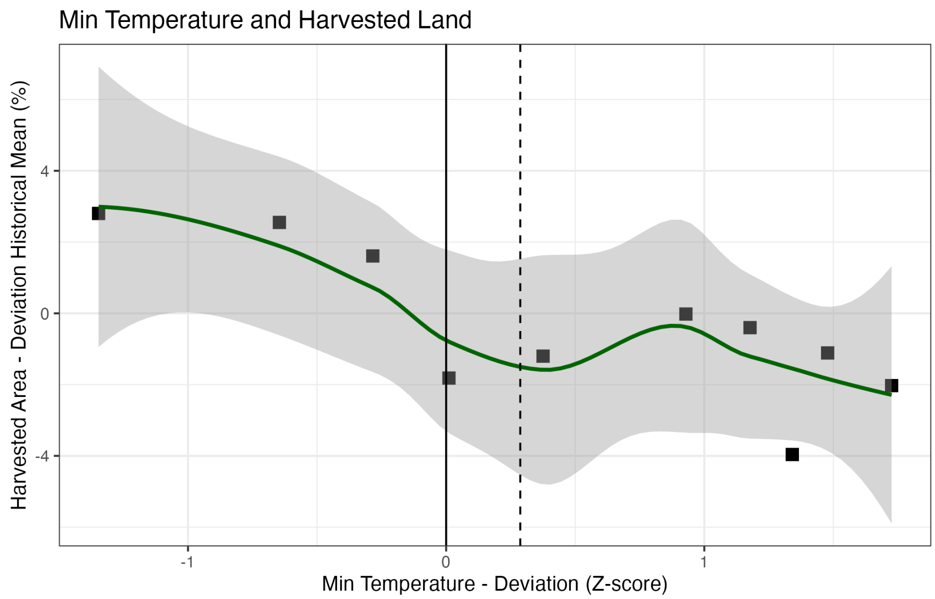

Figure A.2: Minimum Temperature Shocks and Harvested Land

Notes: The dots reflects the harvested-land deviations for its historical mean for minimum-temperature standardized deviations. More specifically, each dot groups the municipalities in deciles of the z-score distribution and calculates the average deviation from the harvested land for such deciles.

A.2 Agricultural Production

In this section, we add the plot for agricultural production and minimum temperature shocks (Figure A.2).