Illegal migration and weather shocks: evidence from rural Mexico*

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Abstract

We study the effect of weather shocks on legal and illegal migration from rural Mexico to the US. First, we find that shocks in the wet season on precipitation and temperature increase migration. The increment is entirely driven by illegal migrants. Second, we propose a mechanism to explain this result: the effect of weather on agri-cultural production. We find that shocks in precipitation and temperature decrease total harvested land and corn production. Third, we show that young and unwealthy workers are more sensitive to weather shocks. Lastly, we use climate projections to have a first glance at the impact that climate change will have on migration. We find that a shift in the size of climate change would double the number of illegal migrants. Since climate change will increase the frequency and intensity of weather shocks, our findings are increasingly relevant.

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

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1 Introduction

Migration has been an important social phenomenon throughout history. Many factors have motivated it, from societal collapse and conflict to the search for better environments and economic conditions. In this paper, we focus on one such factor: weather shocks. In developing countries, weather shocks pose many challenges for agricultural (and non-agricultural) workers. International migration can work as a coping mechanism (Feng, Krueger, & Oppenheimer, 2010; Jessoe, Manning, & Taylor, 2018; Ibánez, Romero, & Velásquez, 2021). The legal status of the weather-induced migrants, however, has been scarcely investigated (Chort & De La Rupelle, 2022). Our work studies this issue.

We focus on rural Mexico, which has a long tradition of illegal migration to the US: every year, 3 million agricultural workers try to migrate illegally.[1] 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.

Our paper can be summarized as follows. First, we estimate the effect of weather shocks on migration using individual-level data from rural Mexico. We define weather shocks as deviations from the historical mean of the weather variables. In order to recover the causal effect of weather shocks on migration, we use a two-way fixed-effects model. We find that shocks in the wet season on precipitation, average temperature, maximum temperature, and minimum temperature have a significant effect on migration. The effect is entirely driven by illegal migrants. Furthermore, the effect is substantial: for example, an increase of 1°C in maximum temperature increases migration by 27% with respect to the baseline.

Second, we propose an underlying mechanism: the effect of weather on agricultural production. Using the same econometrics approach, at the municipality level, we find that shocks on precipitation, maximum temperature, and minimum temperature have a signifi-

[1] PEW Research Centre, 'Mexican Immigrants: How Many Come? How Many Leave?', 2009.

cant effect on total harvested land and corn production.[2]

Lastly, we interpret our results through the lens of climate change. For the climate scenario in which global temperature increases by 2°C, we show that a shift in the size of climate change would double the number of illegal migrants.

We contribute to the understanding of the effect of weather shocks on international migration, combining individual-level data on migration with community-level data on weather.[3] Since we have explicit information on the legal status of migrants, we can delve into the effect of weather on legal and illegal migration separately. We also study the heterogeneous effects of weather shocks and use our causal estimates to have a first glance at the impacts of climate change on migration.

We expand the literature in several ways. First, we zoom into the migration decision, studying the legal status of the weather-induced migrants. Second, we use precise data on weather variables; while most of the literature uses state or municipality-level data, we use community-level data. Lastly, we provide a direct link between weather shocks and migration: the effect of weather on agricultural production. We use data from 1,960 municipalities from 2003 to 2019, also improving the state of the art.

The rest of the paper is organized as follows. Section 2 discusses the literature on the topic. Section 3 describes the data. Section 4 discusses our econometrics analysis and results. Section 5 provides robustness checks. Section 6 concludes.

2 Literature Review

Our paper contributes to three lines of research. First, we contribute to the literature on illegal migration, especially from Mexico to the US. Approximately 11 million Mexican immigrants live in the US illegally (Krogstad, Passel, & Cohn, 5). Hanson and Spilimbergo (1999) show that an increase in US wages relative to Mexican wages is positively correlated

[2] Unfortunately, we do not have data on the average temperature at the municipality level.

[3] "Communities" go from small towns, which have a population of less than 2,500 people, to middle-size cities, with less than 500,000 people.

with illegal migration. Rendon and Cuecuecha (2010) develop a search model which rationalizes this correlation. Reinhold and Thom (2013) discuss the life cycle of illegal migrants: Mexican workers try to migrate illegally when young and come back to Mexico when old. Munshi (2003) investigates the role of networks in local communities in Mexico, which help workers find non-agricultural jobs in the US. He also finds a negative relation between rainfall and migration. We explore the relevance of weather shocks as a "push" factor for illegal migration.

Second, we expand the literature on the effect of weather on agricultural production. In developing countries, weather shocks are a major risk for production. This is particularly prevalent in rural Mexico. Corn, Mexico's main crop, is heavily dependent on weather (Schlenker & Roberts, 2009). For example, 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 rain-fed and that agricultural workers do not have a strategy to deal with weather change. We provide further evidence on this line; our results quantify the importance of weather shocks on agricultural production.

Third, we contribute to the discussion on international migration as a coping mechanism to weather shocks. Workers respond to weather risks in many ways. In developed countries, farmers and firms adopt new technologies (Lee & Ji, 2021) and invest in R&D (Lobell, Schlenker, & Costa-Roberts, 2011). In developing countries, however, such strategies may not be available. Hence, international migration works as an important coping mechanism. Feng et al. (2010) show that drought-induced productivity reductions in corn increase migration from Mexico to the US. Jessoe et al. (2018) find that weather fluctuations affect income and migration, both within Mexico and to the US. Ibánez et al. (2021) show that temperature shocks increase migration from El Salvador to the US. We add to this literature further detail on the migration decision, namely the legal status of the weather-induced migrants.

Lastly, our paper is closely related to Chort and De La Rupelle (2022). They construct state-level flows of illegal migrants from Mexico to the US and study the influence of extreme weather events such as hurricanes. Our research differs from theirs in several ways. First, we use individual-level data on migration and community-level data on weather. Both allow us to study the effect of weather on migration more accurately and directly. It also allows us to delve into the heterogeneous effects of weather shocks. Second, we use data on *potential* migrants, while Chort and De La Rupelle (2022) have data on people who *actually* try to migrate. Lastly, we investigate the role of temperature and precipitation in a broad sense; Chort and De La Rupelle (2022) focus on extreme events only.

3 Data

3.1 Mexican Migration Project

Our main data source is the Mexican Migration Project (MMP). As described in their webpage, "The 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 whole 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 this data is that it has explicit information on the legal status of migrants. Moreover, it 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 1990-2010. Since "LIFE" is constructed in a retrospective fashion, this means that we have an (unbalanced) panel of 21 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-years-backward windows. Lastly, we focus on communities with less than 500,000 people, which are more likely to depend on agricultural production. In summary, we have data on 12,681 individuals from 88 communities for 11-year periods.

Table 1 provides summary statistics of our sample. Figure 1 illustrates the geographical location of our sample.[4]

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max
Age	41.612	12.166	18	65
Male	0.873	0.334	0	1
Educ. Level (Yr)	7.116	4.409	0	23
Agricultural Worker	0.524	0.499	0	1
Land Owner	0.170	0.375	0	1
Business Owner	0.248	0.432	0	1
Owner	0.368	0.482	0	1
Migrate*	0.015	0.120	0	1
Legally Migrate*	0.004	0.063	0	1
Illegally Migrate*	0.011	0.102	0	1
Length Stayed** (Mh)	28.645	26.383	1	132
Individuals	12,681	12,681	12,681	12,681
Observations	129,343	129,343	129,343	129,343

*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, 121,299. **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 6,891.*

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

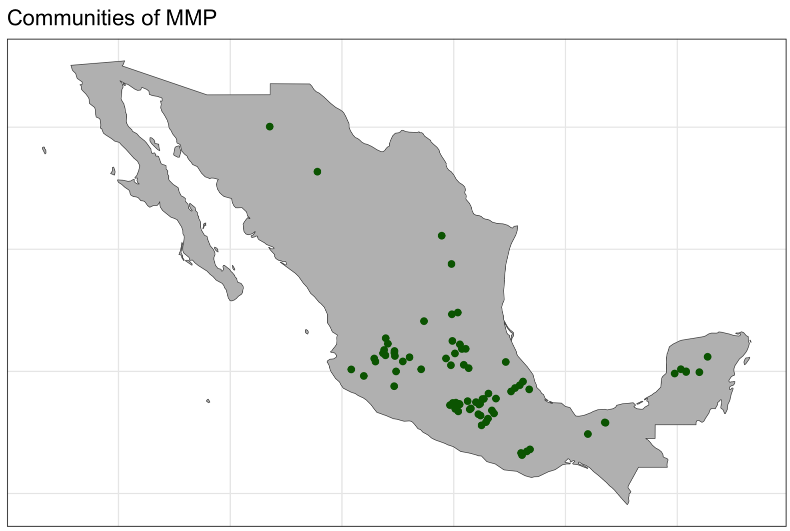

Figure 1: MMP: Communities Location - 2000-2019

3.2 Data: Other Sources

We complement our main data source with numerous others. For weather at the community level, we use data from Meteoblue. Meteoblue is a professional weather-forecast company that offers, from 1979 onward, hourly-simulated weather 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 estimations of location-specific weather. Furthermore, MMP surveys mostly small communities; another challenge to our data. Meteoblue data overcomes both 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" from the Mexican government.[6] We download total harvested land and corn grown for grain in the wet season from 2003 to 2019. Corn is the main crop of Mexico: in our study period, 70.86%

[5]The company 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.

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

Table 2: Summary Statistics - Weather

Variable	Mean	SD	Min	Max	SD within	SD across
Precipitation (cl)	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.

of the total harvested land corresponds to corn. As discussed in Section 2, corn production is highly dependent on weather.

On the one hand, the agricultural data is open-access. On the other hand, it is only available at the municipality level. Thus, we need weather data at such a level as well. 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 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 4km-4km level (Abatzoglou, Dobrowski, Parks, & Hegewisch, 2018). As before, we aggregate this data at the municipality level using municipality maps from the HDX.

4 Empirical Analysis

In this section, we show the relation between weather shocks and migration. Figure 2 illustrates our main point. On the x-axis, we plot deviations for the historical mean of the

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

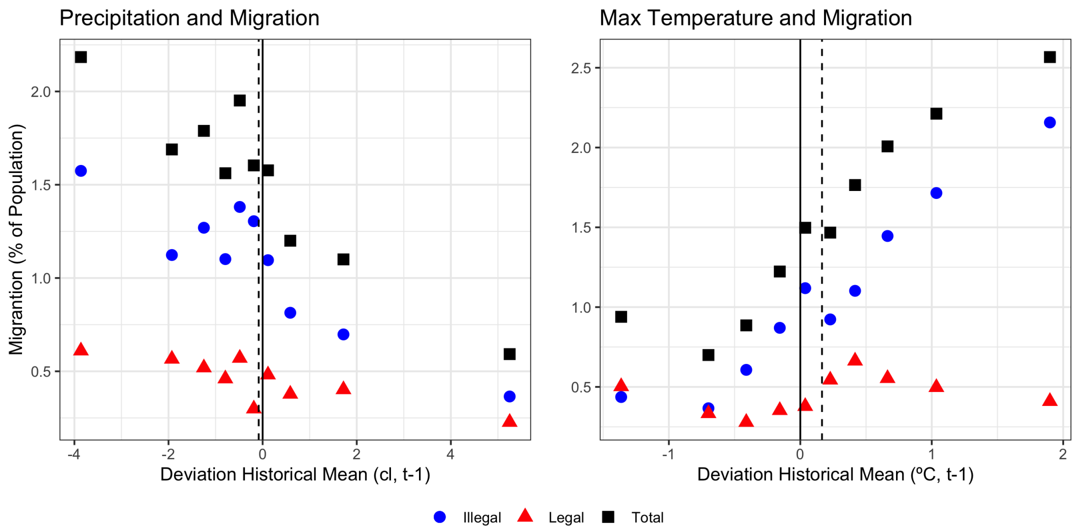

Figure 2: Weather Shocks and Migration

Notes: The dots reflect the proportion of migrants in the population for precipitation and maximum-temperature deviations from the historical mean in the wet season. Specifically, each dot groups observations in deciles of the deviation-from-the-historical-mean distribution and calculates the proportion of migrants for such deciles. The dotted vertical line reflects the average deviation from the historical mean in our period of study. The weather deviation is taken a period before the migration decision. The historical mean is taken over the period 1985-2014.

weather variables; for example, a "1°C" in the temperature plot means a 1°C deviation from the historical maximum-temperature mean. 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 the proportion of migrants for decile deviations of the weather variable. As expected, the higher (lower) the temperature (precipitation), the higher the migration. Moreover, the effect is entirely driven by illegal migrants.

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

4.1 Econometric Specification

In order to identify the effect of weather shocks on migration, we use a two-way fixed-effects model. More precisely, 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 she migrate to the US in that specific period;[8] $w_{j,t-1}$ is the weather "shock," e.g., the deviation of the maximum temperature with respect to its historical mean in the wet season;[9] [10] α_i is the person fixed effect; γ_t is the year fixed effect; and ϵ_{ijt} is the error term. We cluster the errors at the community level.

4.2 Results

Table 3 shows our main results. Weather shocks in the wet season have a significant ef-fect on migration at a 5% level. Specifically, a decrease of 1 centiliter (cl) in precipitation with respect to its historical mean generates a 0.04 percentage-points (p.p) increase in the probability of migrating to the US. Similarly, an increase of 1ºC on average, maximum, and minimum temperature with respect to their historical mean generates a 0.63, 0.41, and 0.44 p.p increase, respectively.

The effects are substantial. The average proportion of migrants in the population on a given year is 1.52%. Thus, a decrease of 1cl on precipitation implies a 2.63% increase in the probability of migrating with respect to such a proportion; and an increase of 1ºC on average, maximum, and minimum temperature implies a 41.16%, 27.08%, and 29.00%increase, respectively.

Interestingly, the effect is entirely driven by illegal migrants, as reflected in Table 4. A decrease of 1cl on precipitation generates a 0.03 p.p increase in illegal migration; and an increase of 1ºC on average, maximum, and minimum temperature generates a 0.66, 0.43, and 0.47 p.p increase, respectively.

[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 are highly correlated with US crop production.

[10] The historical mean is calculated for the period 1985-2014.

Table 3: Weather Shocks and Migration

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0004**			
	(0.0002)			
Dev Avg Temp (°C, t-1)		0.0063***		
		(0.0009)		
Dev Max Temp (°C, t-1)			0.0041***	
			(0.0006)	
Dev Min Temp (°C, t-1)				0.0044***
				(0.0009)
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	0.25006	0.24996	0.24976

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2014.

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 (cl, t-1)	-0.0003*				−0.00009			
	(0.0002)				(0.00006)			
Dev Avg Temp (°C, t-1)		0.0066***				-0.0003		
		(0.0008)				(0.0004)		
Dev Max Temp (°C, t-1)			0.0043***				-0.0001	
			(0.0006)				(0.0003)	
Dev Min Temp (°C, t-1)				0.0047***				-0.0003
				(0.0008)				(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	121,298	121,298	121,298	121,298	121,298	121,298	121,298	121,298
Adjusted R^2	0.18052	0.18135	0.18117	0.18089	0.40720	0.40720	0.40719	0.40720

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2014.

4.3 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 3, we have agricultural data at the municipality rather than 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. Specifically, it plots harvested-land deviations against precipitation and maximum-temperature deviations from their historical means; the dots reflect the average harvested-land-deviations for the decile-deviations in weather. As expected, the higher (lower) the temperature (precipitation), the lower the harvested area. We add a similar plot for minimum temperature in the appendix (Figure A.2).

4.3.1 Econometric Specification

In order to identify the effect of weather shocks on agricultural production, we use a two-way fixed-effects model, too. Specifically, we estimate Equation 2:

$$y_{jt} = \alpha_j + \gamma_t + \beta_w w_{jt} + \epsilon_{jt} \tag{2}$$

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

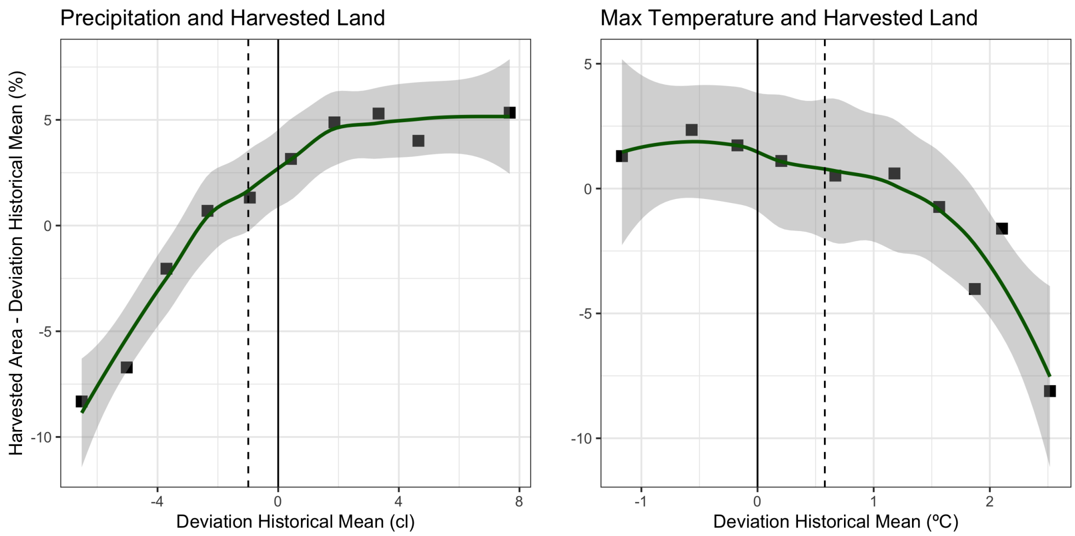

Figure 3: Weather Shocks and Harvested Land

Notes: The dots reflects the harvested-land deviations from its historical mean for precipitation and maximum-temperature deviations from its historical mean in the wet season. Specifically, each dot groups the observations in deciles of the deviation-from-the-historical-mean distribution and calculates the average deviation from the harvested land for such deciles. The historical mean is taken over the period 1985-2014.

4.3.2 Results

Table 5 shows our results. Weather shocks have a significant effect on total harvested area and corn-for-grain production at a 5% level. More precisely, an increase of 1cl on precipitation with respect to the historical mean generates an increase of 0.6% on total harvested area and 0.75% on corn production. Similarly, an increase of 1°C in maximum and minimum temperature with respect to their historical mean generates a decrease of 1.16% and 1.26% on total harvested area, and a decrease in 1.14% and 1.52% on corn production.

Table 5: Weather Shocks and Agricultural Production

Dependent Variables:	Log (Harv Area) - Ha			Log (Corn Prod) - Gr, Ton		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Dev Precipiation (cl)	0.0060***			0.0075***		
	(0.0008)			(0.0011)		
Dev Max Temp (°C)		-0.0116***			-0.0114**	
		(0.0033)			(0.0047)	
Dev Min Temp (°C)			-0.0126***			-0.0152**
			(0.0039)			(0.0062)
Fixed-effects						
id	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	32,847	32,847	32,847	31,998	31,998	31,998
Adjusted R^2	0.90471	0.90454	0.90453	0.89528	0.89507	0.89508

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 deviations from the historical mean on the same year and season. The historical mean is taken over the period 1985-2014.

4.4 Extrapolation

In order to estimate the effect that climate change will have on illegal migration, we would need a structural model.[11] We can, however, do back-of-the-envelope calculations to read our results through the lens of climate change.

More precisely, we can illustrate our results in shifts in the size of climate change. Unfortunately, we can only construct climate projections at the municipality level. Thus, we assume the climate will change uniformly within municipalities. We can then calculate the expected change in precipitation and maximum and minimum temperature for every community and ask: for a shift of the size of climate change, what would be the implied change in illegal migration?

Table 6 summarises our results. As expected, illegal migration would increase: the higher the increase in global temperature, the higher the increase in migration. For the climate model in which global temperature would increase by 2°C, the shift in precipitation would imply a 0.04 p.p increase in illegal migration - a 3.74% increase with respect to the baseline. For the same model, the shift in maximum and minimum temperature would imply a 0.81 and 0.97 p.p increase in illegal migration, respectively - a 75.70% and 90.06% increase with respect to the baseline.

Table 6: Projected Illegal Migration

	2°C		4°C	
Variable	Deviation	Migration (p.p)	Deviation	Migration (p.p)
Precipitation (cl)	-1.11	0.04	-2.38	0.10
	(1.509)	(0.02)	(1.822)	(0.043)
Max Temp (°C)	1.96	0.81	4.45	1.84
	(1.059)	(0.169)	(1.147)	(0.383)
Min Temp (°C)	2.19	0.97	4.30	1.90
	(0.774)	(0.138)	(0.77)	(0.271)

Notes: The headlines "2°C" and "4°C" refer to increase on global temperatures for possible climate scenarios. The columns "Deviation" calculate the expected deviation for each variable for such scenarios in the wet season. The columns "Migration" refer to projected illegal migration for such deviations in p.p. Standard deviations are added in parenthesis. The historical period of reference is 1985-2014.

[11] We are working on a separate paper to address exactly this issue.

4.5 Heterogeneity

In this section, we investigate the heterogeneous effects of weather shocks, specifically the role of wealth and age.

Figure 4 illustrates the results for wealth. It divides the sample into two: "non-owners," workers without land or business, and "owners," workers with land or business. Clearly, non-owners have a higher level of (illegal) migration. Furthermore, the effect of maximum temperature is more steep for this group.

Figure 5 illustrates our results for age. It divides the sample into two: "$\leq$ 41," workers younger than 41 years old, and "$>$ 41," workers older than 41 years old.[12] Clearly, the younger group has a higher proportion of (illegal) migrants. Furthermore, this group is much more sensitive to temperature shocks.

4.5.1 Results

As before, we estimate the effect of weather shocks on migration using a two-way fixed-effects model. This time, however, we divide the sample into the groups defined above. More precisely, we estimate, separately for each group, Equation 3:

$$y_{ijt} = \alpha_i + \gamma_t + \beta_w w_{j,t-1} + \epsilon_{ijt} \tag{3}$$

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

The econometrics results are added in Table 7 and 8. In short, the effect of weather on illegal migration is more pronounced for non-owners and for young workers.

[12] We chose 41 years old just to divide the age range into two (almost) symmetric groups.

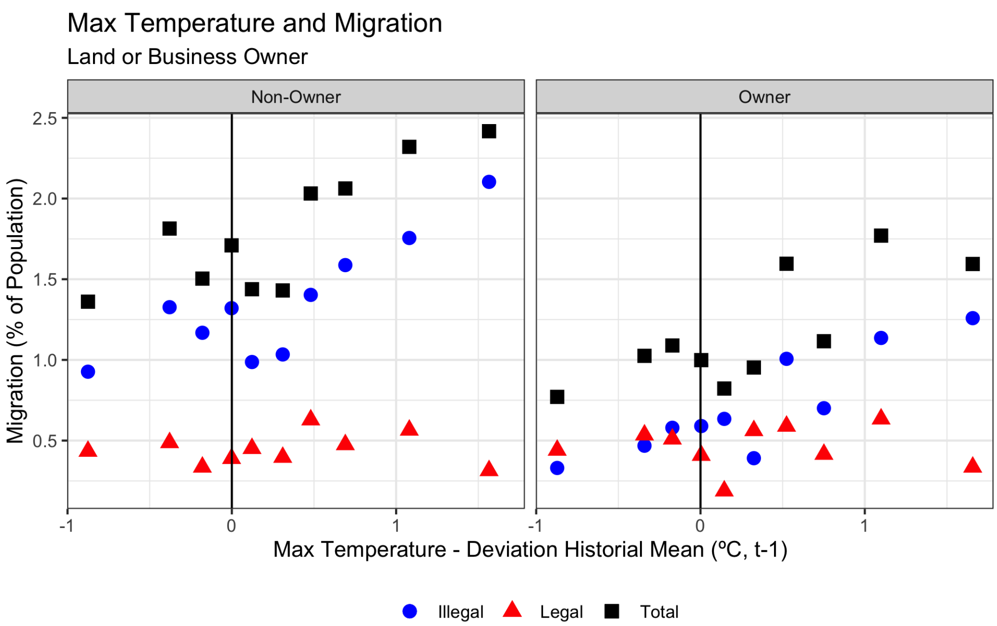

Figure 4: Weather Shocks and Migration by Wealth

Notes: The dots reflect the proportion of Mexican migrants in the population for maximum-temperature deviations from the historical mean in the wet season. Specifically, each dot groups observations in deciles of the deviation-from-the-historical-mean distribution and calculates the proportion of migrants for such deciles. The temperature deviation is taken from the period before the migration decision. The historical mean is taken over the period 1985-2014.

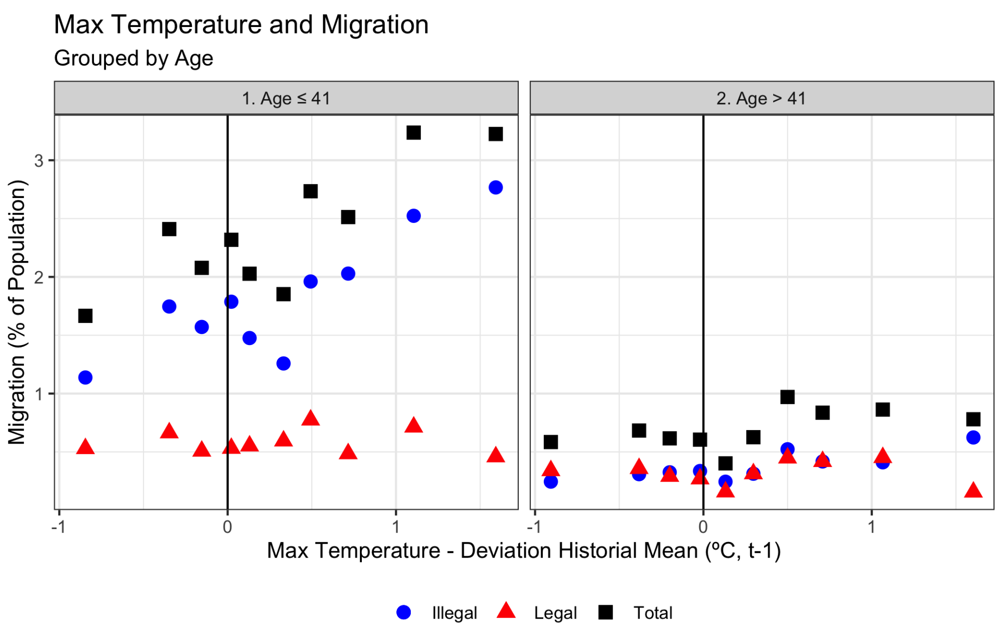

Figure 5: Weather shocks and Migration by Age

Notes: The dots reflects the proportion of Mexican migrants in the population for maximum-temperature deviations from the historical mean in the wet season. Specifically, each dot groups observations in deciles of the deviation-from-the-historical-mean distribution and calculates the proportion of migrants for such deciles. The weather deviation is taken the period before the migration decision. The historical mean is taken over the period 1985-2014.

Table 7: 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 (cl, t-1)	-0.0005**				-0.0001			
	(0.0002)				(0.0002)			
Dev Avg Temp (°C, t-1)		0.0072***				0.0052***		
		(0.0010)				(0.0010)		
Dev Max Temp (°C, t-1)			0.0046***				0.0039***	
			(0.0007)				(0.0007)	
Dev Min Temp (°C, t-1)				0.0053***				0.0029***
				(0.0011)				(0.0009)
Fixed-effects								
id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	76,283	76,283	76,283	76,283	45,015	45,015	45,015	45,015
Adjusted R^2	0.21623	0.21704	0.21682	0.21659	0.20065	0.20147	0.20156	0.20087

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2014.

Table 8: 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 (cl, t-1)	-0.0007**				0.00003			
	(0.0003)				(0.00008)			
Dev Avg Temp (°C, t-1)		0.0113***				0.0014***		
		(0.0013)				(0.0005)		
Dev Max Temp (°C, t-1)			0.0072***				0.0009**	
			(0.0010)				(0.0004)	
Dev Min Temp (°C, t-1)				0.0088***				0.0008
				(0.0014)				(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	61,860	61,860	61,860	61,860	59,438	59,438	59,438	59,438
Adjusted R^2	0.17914	0.18062	0.18023	0.17989	0.25243	0.25255	0.25252	0.25246

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2014.

5 Robustness Checks

In this section, we do robustness checks to 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.1: an increase of one excess heat day increases migration by 0.02 p.p. The increment 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 rather similar and can be found in Tables A.2, A.3, A.4, and A.5 in the appendix.

Third, we consider a different period for the historical mean. In our main analysis, we used the period 1985-2014; in this robustness check, we use the period 1990-2010. The results are also similar and can be found in Tables A.6 and A.7 in the appendix.

Fourth, we keep only the communities with less than 100,000 people. The results are virtually unchanged and can be found in Tables A.8 and A.9 in the appendix.

Lastly, we add forage corn to the corn regression. We only missed significance for the minimum temperature coefficient; the results can be found in Table A.10.

6 Conclusion

We study the effect of weather shocks on migration from rural Mexico to the US. First, we find that shocks in the wet season on precipitation and temperature increase migration. The increment is entirely driven by illegal migrants. Second, we propose an underlying mechanism: the effect of weather on agricultural production. We find that shocks in precipitation and temperature decrease total harvested land and corn production. 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 a shift in the size of climate change would double the number of illegal migrants.

We see some venues in which our work can be expanded. First, the effect that climate change will have on illegal migration remains an open question. For instance, our approach does not account for adaptation, which will likely be substantial. Second, it would be interesting to investigate the "delayed" effect of weather shocks. Specifically, we show that weather shocks generate an immediate increase in illegal migration; it might also generate a delayed increase in legal migration. Lastly, it would be interesting to see the effect that weather-induced migrants have on the local markets.

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

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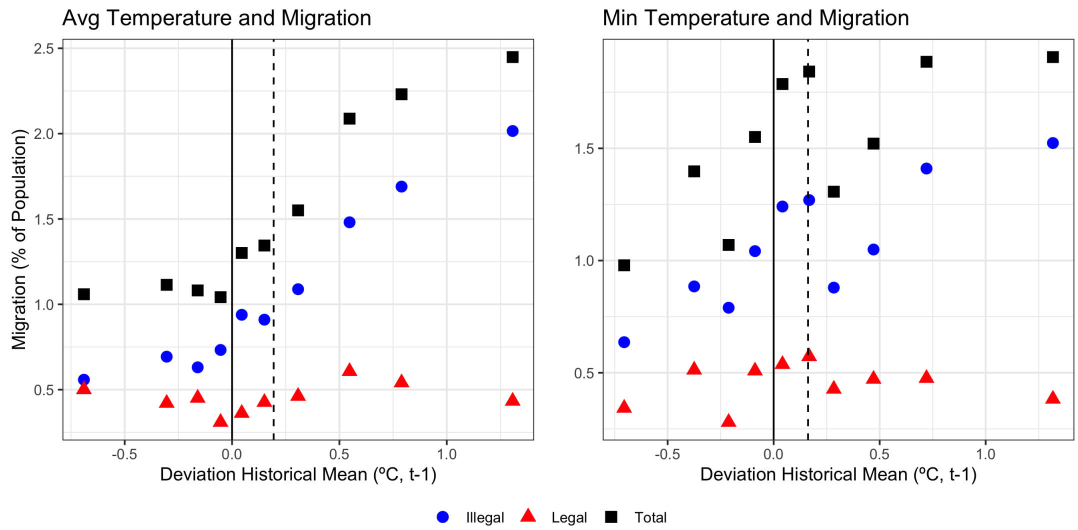

Figure A.1: Temperature Shocks and Migration

Notes: The dots reflects the proportion of Mexican migrants in the population for average-temperature and minimum-temperature deviations from the historical mean in the wet season. Specifically, each dot groups observations in deciles of the deviation-from-the-historical-mean distribution and calculates the proportion of migrants for such deciles. The dotted vertical line reflects the average deviation from the historical mean in our period of study. The weather deviation is taken the period before the migration decision. The historical mean is taken over the period 1985-2014.

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).

A.1.2 Robustness Checks

In this section, we add the robustness checks discussed in Section 5: Table A.1 shows the results for days-above-29°C specification; Tables A.2 and A.3 show the results using 8-years-backward windows; Tables A.4 and A.5 show the results using 12-years-backward windows; Tables A.6 and A.7 show the results using 1990-2010 as the historical period; and Tables A.8 and A.9 show the results for communities with less than 100,000 people.

Table A.1: 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.

Table A.2: Weather Shocks and Migration - 8 years-window

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0005**			
	(0.0002)			
Dev Avg Temp (°C, t-1)		0.0063***		
		(0.0011)		
Dev Max Temp (°C, t-1)			0.0043***	
			(0.0008)	
Dev Min Temp (°C, t-1)				0.0047***
				(0.0010)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	99,101	99,101	99,101	99,101
Adjusted R^2	0.27020	0.27066	0.27057	0.27040

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2014.

Table A.3: 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 (cl, t-1)	-0.0003				-0.0002**			
	(0.0002)				(8.38×10^{-5})			
Dev Avg Temp (°C, t-1)		0.0066***				-0.0003		
		(0.0009)				(0.0005)		
Dev Max Temp (°C, t-1)			0.0043***				-5.6×10^{-5}	
			(0.0007)				(0.0003)	
Dev Min Temp (°C, t-1)				0.0052***				-0.0004
				(0.0010)				(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	99,101	99,101	99,101	99,101	99,101	99,101	99,101	99,101
Adjusted R^2	0.20349	0.20430	0.20410	0.20391	0.41923	0.41920	0.41920	0.41920

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2014.

Table A.4: Weather Shocks and Migration - 12 years-window

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0004**			
	(0.0002)			
Dev Avg Temp (°C, t-1)		0.0060***		
		(0.0008)		
Dev Max Temp (°C, t-1)			0.0040***	
			(0.0006)	
Dev Min Temp (°C, t-1)				0.0044***
				(0.0008)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	143,223	143,223	143,223	143,223
Adjusted R^2	0.23555	0.23602	0.23594	0.23576

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 moves to the US in that period. The independent variables are calculated as deviations from the historical mean in the wet season a year before the moving decision. The historical mean is taken over the period 1985-2014.

Table A.5: 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 (cl, t-1)	-0.0004**				-6.91×10^{-5}			
	(0.0002)				(6.07×10^{-5})			
Dev Avg Temp (°C, t-1)		0.0062***				-0.0002		
		(0.0008)				(0.0003)		
Dev Max Temp (°C, t-1)			0.0040***				-1.42×10^{-5}	
			(0.0006)				(0.0002)	
Dev Min Temp (°C, t-1)				0.0046***				-0.0002
				(0.0008)				(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	143,220	143,220	143,220	143,220	143,220	143,220	143,220	143,220
Adjusted R^2	0.16599	0.16670	0.16655	0.16633	0.40420	0.40420	0.40419	0.40420

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 moves illegally (legally) to the US in that period. The independent variables are calculated as deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1985-2014.

Table A.6: Weather Shocks and Migration - Historical Mean 1990-2010

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0004**			
	(0.0002)			
Dev Avg Temp (°C, t-1)		0.0063***		
		(0.0009)		
Dev Max Temp (°C, t-1)			0.0041***	
			(0.0006)	
Dev Min Temp (°C, t-1)				0.0044***
				(0.0009)
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	0.25006	0.24996	0.24976

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1990-2010.

Table A.7: Weather Shocks and Migration by Legal Status - Historical Mean 1990-2010

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (cl, t-1)	-0.0003*				-9.16×10^{-5}			
	(0.0002)				(6.39×10^{-5})			
Dev Avg Temp (°C, t-1)		0.0066***				-0.0003		
		(0.0008)				(0.0004)		
Dev Max Temp (°C, t-1)			0.0043***				-0.0001	
			(0.0006)				(0.0003)	
Dev Min Temp (°C, t-1)				0.0047***				-0.0003
				(0.0008)				(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	121,298	121,298	121,298	121,298	121,298	121,298	121,298	121,298
Adjusted R^2	0.18052	0.18135	0.18117	0.18089	0.40720	0.40720	0.40719	0.40720

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1990-2010.

Table A.8: Weather Shocks and Migration - Commun less than 100,000 people

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0004**			
	(0.0002)			
Dev Avg Temp (°C, t-1)		0.0064***		
		(0.0009)		
Dev Max Temp (°C, t-1)			0.0042***	
			(0.0007)	
Dev Min Temp (°C, t-1)				0.0049***
				(0.0009)
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	0.25298	0.25282

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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1990-2010.

Table A.9: Weather Shocks and Migration by Legal Status - Commun less than 100,000 people

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (cl, t-1)	-0.0003*				-8.53×10^{-5}			
	(0.0002)				(6.48×10^{-5})			
Dev Avg Temp (°C, t-1)		0.0068***				-0.0004		
		(0.0008)				(0.0004)		
Dev Max Temp (°C, t-1)			0.0044***				-0.0002	
			(0.0006)				(0.0003)	
Dev Min Temp (°C, t-1)				0.0052***				-0.0003
				(0.0009)				(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	112,587	112,587	112,587	112,587	112,587	112,587	112,587	112,587
Adjusted R^2	0.18087	0.18174	0.18153	0.18131	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, 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 deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1990-2010.

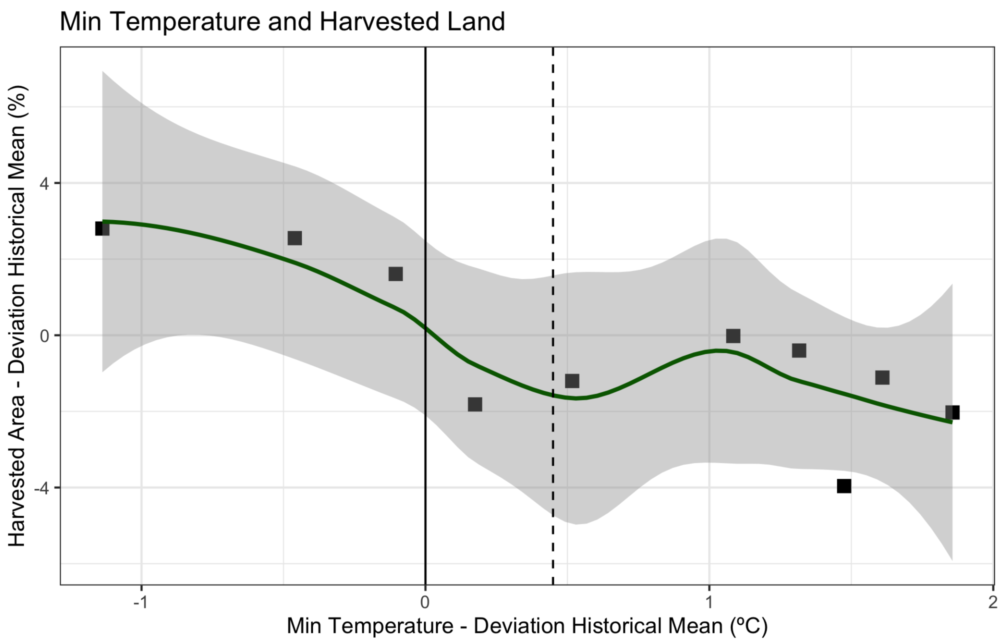

Figure A.2: Minimum Temperature Shocks and Harvested Land

Notes: The dots reflects the harvested-land deviations for its historical mean for minimum-temperature deviations from its historical mean. Specifically, each dot groups the municipalities in deciles of the deviation-from-the-historical-mean 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).

A.2.1 Robustness Checks

In this section, we add the robustness checks discussed in Section 5. Table A.10 shows the results for corn production including forage corn.

Table A.10: Weather Shocks and Corn Production - Add Corn for forage

Dependent Variable:	Log (Corn Prod) - Ton		
Model:	(1)	(2)	(3)
Variables			
Dev Precipiation (cl)	0.0076***		
	(0.0011)		
Dev Max Temp (°C)		-0.0198***	
		(0.0048)	
Dev Min Temp (°C)			-0.0016
			(0.0061)
Fixed-effects			
id	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	32,315	32,315	32,315
Adjusted R^2	0.90550	0.90539	0.90528

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

Notes: The dependent variable is the log of total corn production (for grain plus forage) in tons. The independent variables are calculated as deviations from the historical mean in the wet season a year before the migration decision. The historical mean is taken over the period 1990-2010.