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Illegal Migration and Weather Shocks: Evidence from Rural Mexico

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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 agricultural production. We find that shocks on 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 on the impact that climate change will have on migration. We find that a shift of 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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Migración ilegal y shocks en el clima: evidencia de municipalidades rurales en México

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Este estudio investiga el efecto de shocks en el clima en la migración legal e ilegal desde regiones rurales de México hacia Estados Unidos. En primer lugar, se encuentra que los shocks en precipitaciones en la estación humeda incrementa la migración. Esta migración se encuentra explicada casi en su totalidad por migrantes ilegales. En segundo lugar, se propone un mecanismo para explicar el efecto del clima en la produccion agrícola. Se encuentra que los shocks en precipitaciones y temperaturas disminuyen el área total cosechada y la producción de maiz. En tercer lugar, se muestra que trabajadores jóvenes y de menor riqueza son más sensibles a shocks en el clima. Finalmente, se utilizan proyecciones de clima para obtener una primera estimación del impacto que el cambio climático tendría en migración. Se estima que un cambio del tamaño del cambio climático duplicaría el número de migrantes ilegales. Dado que el cambio climático incrementaría la frecuencia e intensidad de shocks climáticos, los hallazgos de este estudio son cada vez más relevantes.

KEYWORDS

Migración ilegal, shocks climáticos, agricultura, cambio climático

1 | INTRODUCTION

Migration has been an important social phenomenon through history. It has been motivated and influenced by many factors: from societal collapse and conflict to the search for better environments and economic conditions. In this paper, we focus on one of such factors: 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 et al., 2010; Dalby, 2013; Ibánez et al., 2021). The legal status of the weather-induced migrants, however, has been scarcely investigated (Chort and De La Rupelle, 2022). The latter is thus the focus of our work.

We focus on rural Mexico, which has a long tradition of illegal migration; every year, 3 million agricultural workers try to migrate illegally to the US.[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. Thus, the impact of weather shocks on illegal migration is of increasing relevance.

Our research questions are: (i) what is the effect of weather shocks on legal and illegal migration? (ii) which mechanism explains this effect? (iii) what will be the effect of climate change on migration?

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, 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 at a 5% level. The effect is entirely driven by illegal migrants. Furthermore, the effect is substantial; for example, an increase of 1ºC in maximum temperature increase migration in 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 municipality level, we find that shocks on precipitation, maximum temperature, and minimum temperature have a significant effect on total harvested land and corn production at a 5% level.[2]

Lastly, we interpret our results in the lens of climate change. For the climate scenario in which global temperature increases by 2ºC, we show that a shift of 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. We combine 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 in 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 of the impacts of climate change on migration. We expand the literature in several ways. First, we

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

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

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

add further detail in the migration decision, namely the legal status of the weather-induced migrants. Second, we use more 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 in 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 et al., 5). Hanson and Spilimbergo (1999) show that an increase in US wages relative to Mexican wages is positively correlated with illegal migration. Rendon and Cuecuecha (2010) develop a search model which rationalize 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 to find non-agricultural (illegal) jobs in the US. He also finds a negative relation between rainfall and migration. We highlight the importance 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 particular prevalent for rural Mexico. Corn, Mexico’s main crop, is heavily dependent on weather (Schlenker and Roberts, 2009). For example, Skoufias and Vinha (2013) show that a 2ºC increase in average temperature generates a 24% decrease in corn production in Mexico. Skoufias (2007) reports that 65% of its 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 confirm the relevance 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 risk in many ways. In developed countries, farmers and firms adopt new technologies (Lee and Ji, 2021) and invest in R&D (Lobell et al., 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. Dalby (2013) shows a similar pattern for extreme weather events. Ibánez et al. (2021) find 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 with 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 directly and accurately. It also allows us to delve in 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

For migration, we use data from the Mexican Migration Project (MMP). As described in their web-page, “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. Specifically, MMP chooses communities within Mexico and obtains representative samples of those communities. 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. 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 and Zenteno, 2000; Massey and Capoferro, 2004; Nawrotzki and DeWaard, 2016).

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 of the legal status of migrants. Moreover, it is conducted in many locations (more than 200), which allows us to exploit local-wise variations on 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 head 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]

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. This is a 2km-2km dataset that covers numerous weather variables such as precipitation, temperature, and evaporation.[5] Meteoblue provides us daily data on precipitation, average temperature, maximum temperature, and minimum temperature for

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

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

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
Illegaly 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

TABLE 1 Summary Statistics

*Notes: *Migrate refers to a indicative variable equal to one if the worker migrate 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 variables 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 how did migrate to the US at some point in our data. The number of observations in this case is 6,891.*

each one of the communities in our sample from 1985 to 2020. Since we study weather shocks, it is vital that we count with precise estimations of location-specific weather. This poses a challenge for the weather data we use. Furthermore, MMP surveys mostly small communities; another challenge to our data. Meteoblue can respond to both challenges. Table 2 describes our weather data.

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 (ºC)	21.34	3.49	14.13	29.56	0.55	3.21
Max Temperature (ºC)	26.77	3.51	18.56	34.50	0.83	3.27
Min Temperature (ºC)	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

TABLE 2 Summary Statistics - Weather

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.

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% of the total

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

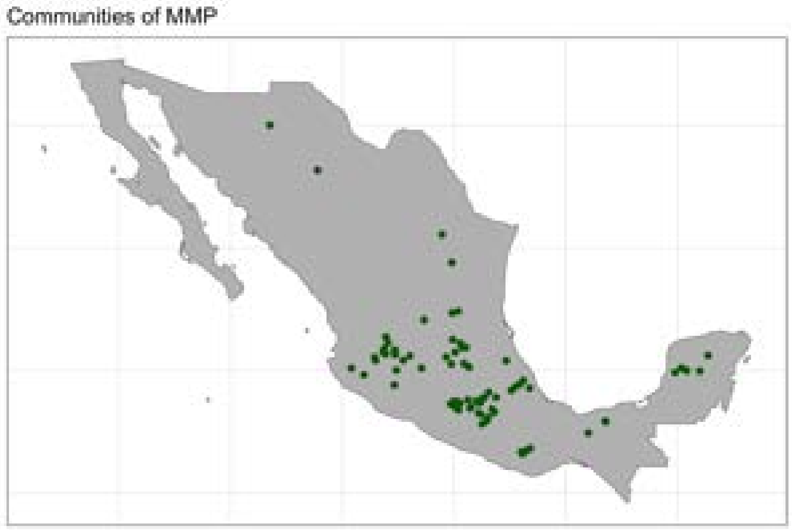

FIGURE 1 MMP: Communities Location - 2000-2019

harvested land corresponds to corn. As discussed in Section 2, corn production is highly dependant on weather.

On the one hand, the agricultural data is open-access. On the other hand, it is only available at municipality level. Thus, we need weather data at such 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, maximum and minimum temperature for all North America at 1km-1km level from 1980 to 2021. We aggregate this data at 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 et al., 2018). As before, we aggregate this data at 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 weather variables; for example, a “1ºC" in the temperature plot means a 1ºC deviation from 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.

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

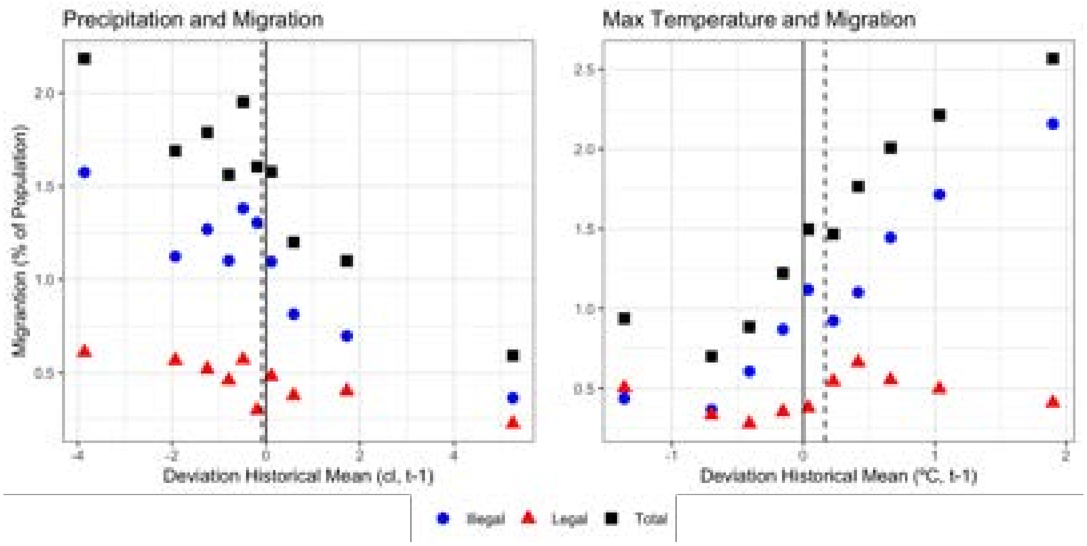

FIGURE 2 Weather Shocks and Migration

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.

4.1 | Econometric Specification

In order to identify the effect of weather shocks on migration, we use a two-way fixed-effects model. Specifically, we run the following regression:

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

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 community level.

4.2 | Results

Table 3 shows our main results. Weather shocks in the wet season have a significant effect on migration at a 5% level. Specifically, a decrease of 1 centiliter (cl) on 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 historically mean generates a 0.63, 0.41, 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 et al. (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 during March to August is highly correlated with US crop production.

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

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

TABLE 3 Weather Shocks and Migration

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.

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.

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 (ºC, t-1)		0.0066***				-0.0003		
		(0.0008)				(0.0004)		
Dev Max Temp (ºC, t-1)			0.0043***				-0.0001	
			(0.0006)				(0.0003)	
Dev Min Temp (ºC, 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*

TABLE 4 Weather Shocks and Migration by Legal Status

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 municipality rather than 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 which have at least one community in our sample. We end up with 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 run the following regression:

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

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 municipality level.

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. Specifically, 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 1ºC 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.

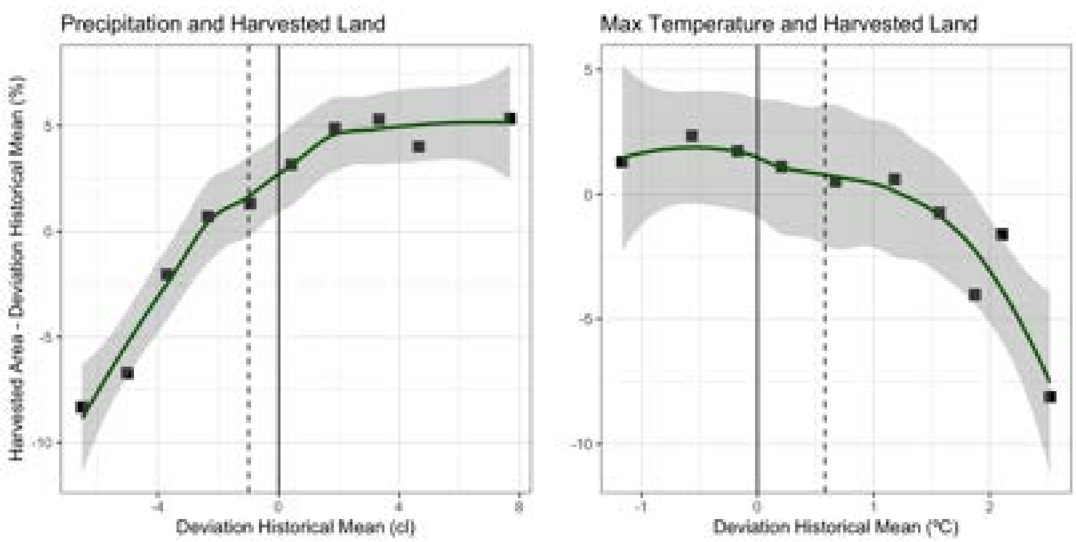

FIGURE 3 Weather Shocks and Harvested Land

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.

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 (ºC)		-0.0116***			-0.0114**	
		(0.0033)			(0.0047)	
Dev Min Temp (ºC)			-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*

TABLE 5 Weather Shocks and Agricultural Production

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 in the lens of climate change.

Specifically, we can illustrate our results in shifts of the size of climate change. Unfortunately, we can only construct climate projections at municipality level. Thus, we assume the climate will change uniformly within municipalities. We can then calculate the expected change in precipitation, 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 summarise 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 in 2ºC, the shift on precipitation would imply a 0.05 p.p increase on illegal migration - a 4.62% increase with respect to the baseline. For the same model, the shift on maximum and minimum temperature would imply a 0.82 and 0.98 p.p increase on illegal migration, respectively - a 75.93% and 90.74% increase with respect to the baseline.

	2ºC		4ºC	
Variable	Deviation	Migration (p.p)	Deviation	Migration (p.p)
Precipitation (cl)	-1.13	0.05	-2.40	0.10
	(1.512)	(0.02)	(1.823)	(0.043)
Max Temp (ºC)	1.98	0.82	4.46	1.84
	(1.06)	(0.17)	(1.151)	(0.384)
Min Temp (ºC)	2.21	0.98	4.32	1.91
	(0.765)	(0.139)	(0.761)	(0.272)

TABLE 6 Projected Illegal Migration

Notes: The headlines "2ºC" and "4ºC" 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.

4.5 | Heterogeneity

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

Figure 4 illustrates the results for wealth. It divides the sample in 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 in two: "$\leqslant$ 41," workers

[11] We are currently working in such a model.

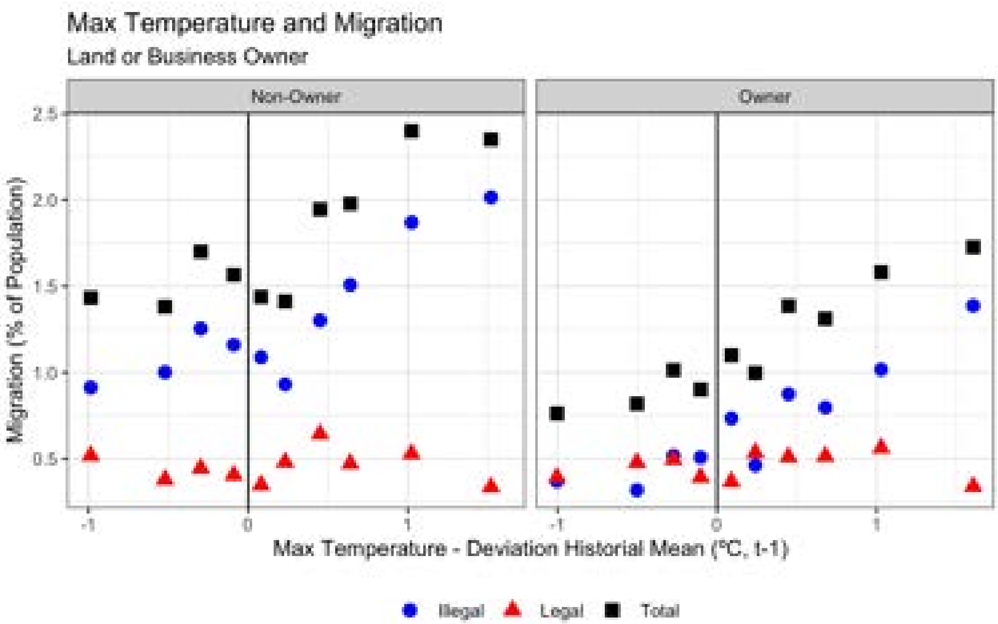

FIGURE 4 Weather Shocks and Migration by Wealth

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 temperature deviation is taken the period before the migration decision. The historical mean is taken over the period 1985-2014.

younger than 41 years old; and "> 41," workers older than 41 years old.[12] Clearly, the younger group has higher the proportion of (illegal) migrants. Furthermore, this group is much more sensitive to temperature shocks.

The formal econometrics analysis is added in Table 7 and 8; the effect of weather on illegal migration is more pronounce for non-owners and for young workers.

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

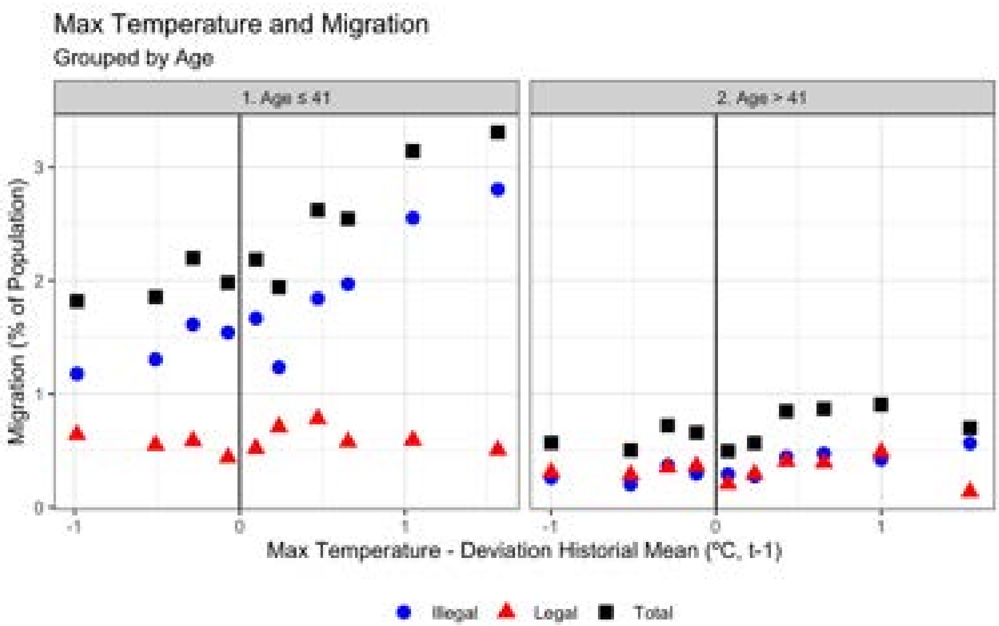

FIGURE 5 Weather shocks and Migration by Age

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.

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**				−0.00009			
	(0.0002)				(0.0002)			
Dev Avg Temp (ºC, t-1)		0.0077***				0.0050***		
		(0.0010)				(0.0011)		
Dev Max Temp (ºC, t-1)			0.0048***				0.0038***	
			(0.0007)				(0.0008)	
Dev Min Temp (ºC, t-1)				0.0060***				0.0028***
				(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	68,735	68,735	68,735	68,735	41,496	41,496	41,496	41,496
Adjusted R^2	0.23283	0.23378	0.23348	0.23331	0.21181	0.21258	0.21264	0.21201

Clustered (commun) standard-errors in parentheses

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

TABLE 7 Illegal Migration and Weather Shocks by Wealth

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.

Dependent Variables:		Illegal Migrant $\leqslant 41$				Illegal Migrant > 41		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (cl, t-1)	-0.0007**				0.00001			
	(0.0003)				(0.00008)			
Dev Avg Temp (ºC, t-1)		0.0118***				0.0013**		
		(0.0013)				(0.0006)		
Dev Max Temp (ºC, t-1)			0.0076***				0.0008**	
			(0.0010)				(0.0004)	
Dev Min Temp (ºC, t-1)				0.0091***				0.0008
				(0.0015)				(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	55,384	55,384	55,384	55,384	54,847	54,847	54,847	54,847
Adjusted R^2	0.19668	0.19831	0.19788	0.19748	0.25788	0.25798	0.25796	0.25791

Clustered (commun) standard-errors in parentheses

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

TABLE 8 Illegal Migration and Weather Shocks by Age

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 propose mechanism is agricultural production with emphasis on corn, we define "days of excess heat" as days with an average temperature above 29ºC following Schlenker and Roberts (2009). Our results are in line with our main specification and can be found in A.1. Specifically, an increase of one excess-heat-day increase migration in 0.02 p.p. The increment is entirely driven by illegal migrants.

Second, we take 8 years-backward windows and 12-years-backward windows. The results are rather similar, and can be found on 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.

Forth, 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 on 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 on 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 of 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 as 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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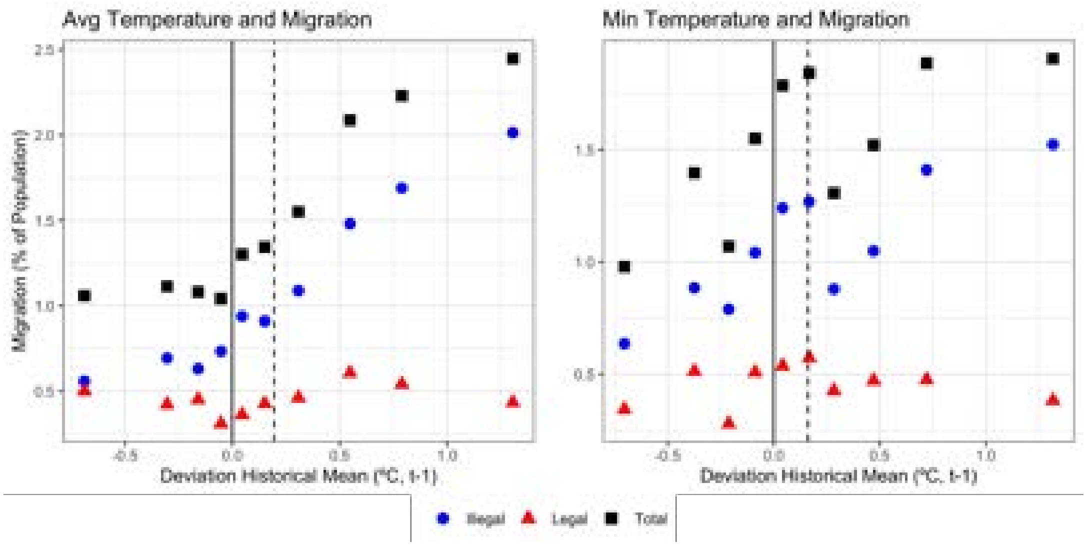

FIGURE A.1 Temperature Shocks and Migration

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-29ºC 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.

Dependent Variables:	Migrant	Illegal Migrant	Legal Migrant
Model:	(1)	(2)	(3)
Variables			
Days Above 29ºC (#, 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*

TABLE A.1 Temperature Shocks and Migration - Days above 29ºC

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 29ºC in the wet season a year before the migration decision.

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0006**			
	(0.0003)			
Dev Avg Temp (ºC, t-1)		0.0061***		
		(0.0012)		
Dev Max Temp (ºC, t-1)			0.0042***	
			(0.0009)	
Dev Min Temp (ºC, t-1)				0.0044***
				(0.0011)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	87,954	87,954	87,954	87,954
Adjusted R^2	0.29270	0.29309	0.29302	0.29282

Clustered (commun) standard-errors in parentheses

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

TABLE A.2 Weather Shocks and Migration - 8 years-window

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.

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (cl, t-1)	-0.0004*				-0.0002**			
	(0.0002)				(0.00009)			
Dev Avg Temp (ºC, t-1)		0.0064***				-0.0003		
		(0.0010)				(0.0005)		
Dev Max Temp (ºC, t-1)			0.0043***				−0.00009	
			(0.0008)				(0.0004)	
Dev Min Temp (ºC, t-1)				0.0047***				-0.0003
				(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	87,954	87,954	87,954	87,954	87,954	87,954	87,954	87,954
Adjusted R^2	0.22634	0.22705	0.22691	0.22665	0.43525	0.43523	0.43522	0.43523

Clustered (commun) standard-errors in parentheses

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

TABLE A.3 Weather Shocks and Migration by Legal Status - 8 years-window

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.

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0004**			
	(0.0002)			
Dev Avg Temp (ºC, t-1)		0.0061***		
		(0.0008)		
Dev Max Temp (ºC, t-1)			0.0041***	
			(0.0006)	
Dev Min Temp (ºC, t-1)				0.0046***
				(0.0009)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	132,334	132,334	132,334	132,334
Adjusted R^2	0.24265	0.24316	0.24306	0.24289

Clustered (commun) standard-errors in parentheses

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

TABLE A.4 Weather Shocks and Migration - 12 years-window

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.

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (cl, t-1)	-0.0003**				−0.00006			
	(0.0002)				(0.00006)			
Dev Avg Temp (ºC, t-1)		0.0064***				-0.0003		
		(0.0008)				(0.0003)		
Dev Max Temp (ºC, t-1)			0.0042***				-0.0001	
			(0.0005)				(0.0002)	
Dev Min Temp (ºC, t-1)				0.0048***				-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	132,332	132,332	132,332	132,332	132,332	132,332	132,332	132,332
Adjusted R^2	0.17331	0.17412	0.17395	0.17369	0.40618	0.40618	0.40618	0.40618

Clustered (commun) standard-errors in parentheses

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

TABLE A.5 Weather Shocks and Migration by Legal Status - 12 years-window

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.

Dependent Variable:	Migrant			
Model:	(1)	(2)	(3)	(4)
Variables				
Dev Precipitation (cl, t-1)	-0.0004**			
	(0.0002)			
Dev Avg Temp (ºC, t-1)		0.0065***		
		(0.0009)		
Dev Max Temp (ºC, t-1)			0.0043***	
			(0.0007)	
Dev Min Temp (ºC, t-1)				0.0045***
				(0.0010)
Fixed-effects				
id	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	110,232	110,232	110,232	110,232
Adjusted R^2	0.26208	0.26263	0.26252	0.26230

Clustered (commun) standard-errors in parentheses

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

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

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.

Dependent Variables:	Illegal Migrant				Legal Migrant			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (cl, t-1)	-0.0003*				-0.0001*			
	(0.0002)				(0.00007)			
Dev Avg Temp (ºC, t-1)		0.0068***				-0.0003		
		(0.0008)				(0.0004)		
Dev Max Temp (ºC, t-1)			0.0044***				-0.0001	
			(0.0006)				(0.0003)	
Dev Min Temp (ºC, t-1)				0.0050***				-0.0005
				(0.0009)				(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	110,231	110,231	110,231	110,231	110,231	110,231	110,231	110,231
Adjusted R^2	0.19421	0.19513	0.19491	0.19463	0.41612	0.41612	0.41611	0.41612

Clustered (commun) standard-errors in parentheses

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

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

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.

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

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

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.

Dependent Variables:		Illegal Migrant				Legal Migrant		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Dev Precipitation (cl, t-1)	-0.0003*				−0.00008			
	(0.0002)				(0.00006)			
Dev Avg Temp (ºC, t-1)		0.0068***				-0.0004		
		(0.0008)				(0.0004)		
Dev Max Temp (ºC, t-1)			0.0044***				-0.0002	
			(0.0006)				(0.0003)	
Dev Min Temp (ºC, 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*

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

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.

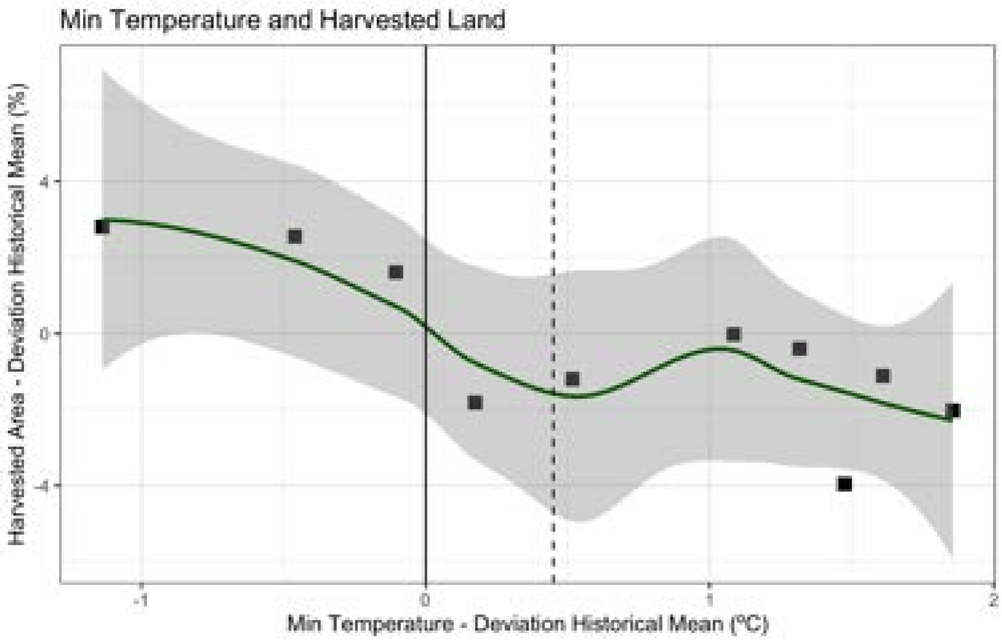

FIGURE A.2 Minimum Temperature Shocks and Harvested Land
Notes: The dots reflects the harvested-land deviations for its historical mean for minimum-temperature deviations from its historical mean. Specifically, each dot groups the municipalities in deciles of the deviation-from-the-historical-mean distribution 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.

Dependent Variable:	Log (Corn Prod) - Ton		
Model:	(1)	(2)	(3)
Variables			
Dev Precipiation (cl)	0.0076***		
	(0.0011)		
Dev Max Temp (ºC)		-0.0198***	
		(0.0048)	
Dev Min Temp (ºC)			-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*

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

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.