Climate Change as a Determinant of Migrant Family Reunification

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Abstract

ABSTRACT: This paper investigates the role of extreme climate as a push factor for family reunification migration. We leverage a novel data set on Mexican agricultural workers in the United States with detailed family separation history and family characteristics. Furthermore, we use a data-driven approach to identify the optimal weather window – one that minimizes prediction error measured in the out of sample root mean squared error compared to the traditional method. We unveil evidence showing that shifts in agricultural productivity induced by changes in extreme climatic conditions during optimal weather windows in Mexican states contributed to the decision of family reunification migration, while more conventional weather windows (e.g., annual averages) fail to provide a consistent assessment.

Keywords: Family reunification; extreme weather; data-driven optimal weather window.

JEL Codes: J61, Q54, Q15.

1 Introduction

Family reunification migration is arguably one of the most direct manifestations of labor migration networks. Latest estimates from the OECD revealed that 43% of permanent migration to OECD countries was a result of family reasons, amounting to annually over 2.5 million migrants (OECD, 2024). Notwithstanding the salience of family reunification migration, a paucity of data on family migration history in nationally representative population surveys had meant that quantitative analyses of the triggers of family reunification migration remain thin. Furthermore, depending on the migration motivation of the principal migrant, the underlying economic, social and/or political contexts that prompt family reunification decisions can differ greatly and thus difficult to generalize.

The salience of the cumulative causation chain guiding family reunification decisions can be examined from several perspectives. First, from a network migration perspective, a longstanding literature featuring theoretical and empirical approaches question whether having a prior migrant in the family facilitates or negates the need for future migration attempts from the same family. These studies juxtapose the (i) information advantages and migration cost savings potentials of networks, and (ii) the family income diversification prospects made possible by the remittance earnings of an established migrant. While the former network effect tends to facilitate future migration attempts, the latter income diversification effect can go in opposite direction and negate the need for additional moves.[1] The main research challenge is the causal identification of the tradeoffs that ensue when the migration of one member of a family spillover to affect the decision-making of the next member, taking into serious account potential unobserved heterogeneity and spurious correlations issues along the way.

Second, and a far less well-understood question is as follows. Conditional on having a family connection in a destination country, what triggers or policy changes

[1] For example, having a family member abroad can provide material and job search support (Chau, 1997; Orrenius and Zavodny, 2005; McKenzie and Rapoport, 2007; Munshi, 2014), and information sharing (Borjas, 1992; Munshi, 2003). DiMaggio and Garip (2012) synthesizes a rich interdisciplinary literature covering networks that reinforce norms of behavior through social approval and / or sanctions (Piore, 1979).

nudge a family to favor reunification in the destination country instead of the origin country.[2] The answer to this question is important for reunification in the destination country not only contributes to a major share of migration worldwide, the relocation of a family marks an arguably more irreversible relocation decision than single-person moves. This is the task we set ourselves in this paper.

To this end, we leverage restricted access data from the National Agricultural Workers Survey (NAWS). The data set is an employment-based random sample survey of crop workers in the United States.[3] In particular, the data set documents the characteristics of Mexican agricultural workers in the US at their employment location, as well as information on family separation history as well as family characteristics. This offers a rare opportunity to study the events or conditions that trigger family reunification decisions. By limiting our scope to Mexican farmworkers who were working in the US agricultural sector at the time of the survey, our goal is to ensure that our analysis sample consists of a relatively homogeneous group of individuals that share similar pull-push factors of migration.

We examine the role of extreme weather conditions as a migrant origin-based trigger of family reunification decisions. In recent years, global climate change has arisen to become an era-defining challenge with far-reaching and unprecedented consequences, and workers in the agricultural sector are notably vulnerable to climate risks (IPCC, 2022). While agricultural households have handled climate-induced risks through various methods such as investment in irrigation (Woznicki et al., 2015), and adopting more resilient crops (Chen and Gong, 2021), physical relocation to a preferable location has been a topic of much research interest (e.g. Cattaneo and Peri (2016); Molina et al. (2022); Zhu et al. (2024)). In this context, family reunification can be seen as a family-level adaptation to climate-induced risks.

The literature on climate change and migration often disagrees on the role of

[2] Basu et al. (2022) examines the role of border enforcement as a policy change that affects family reunification attempts.

[3] The NAWS samples and interviews workers at the site of employment. Multi-stage sampling account for seasonality, regions, county-group level farm labor areas (the sampling unit), county, zip code regions, employer and crop workers. Interviews are allocated proportionate to the amount of farm labor estimated within a given region and cycle. Roster of establishments or farms engaged in Crop Production (NAICS 111) and Support Activities for Crop Production (NAICS 1151) is constructed based primarily on the Quarterly Census of Employment and Wages.

climate on migration. Developments in the literature include results that indicates limited role of climatic variables in the determination of migration (Beine and Parsons, 2015), but we also see evidence that rainfall deficits hinder migration (Robalino et al., 2015; Grace et al., 2018), or evidence that show extreme temperature events accelerating out-migration (Feng et al., 2010; Marchiori et al., 2012), and studies that show high degrees of heterogeneities in responses (Koubi et al., 2016; Riosmena et al., 2018). As migration responses is highly context specific, and since the variables adopted to represent the climatic conditions are not identical across studies, this may be a natural result.

However, another potential reason for such mixed results that remains to be explored may lie in the common factor that we observe in the standard method of introducing climatic variables into the analysis. The overwhelming majority of studies adopt a measure of weather that encompass the entire year, which may be a cause of introducing unwanted measurement errors. In this paper, we adopt a data driven method developed by Li and Ortiz-Bobea (2022) that allows us to hone in on the optimal window of time compared to the traditional method of including the entire year's climatic variables.

Specifically, this method involves discovering and adopting the optimal window of weather – the months of the year in which the climatic variables should be included in the analysis by running a gridsearch process. Since our sample consists of agricultural workers and their partners who are often separated in states with diverse climatic conditions, the crops of that are relevant for each individual, and thus the growing seasons, are likely different. By flexibly allowing and recovering the optimal windows of weather to differ by origin states, we minimize non-classical measurement errors that may have played a role in the mixed conclusions left in the literature, as the direction of the bias is a priori unknown to the researcher (Borjas, 1980; Abay et al., 2019).

We first apply the gridsearch method to the analysis of the role of extreme weather in agricultural productivity for all Mexican states included in our sample. We select the most dominant crops from each of the Mexican states by land area used in the harvest of crops and confirm the importance of selecting the optimal window of weather for each state separately. We find that using the optimal window of weather in analyzing the agricultural productivity model can reduce prediction error measured in the out of sample root mean squared error compared to the traditional method of including the entire year's weather. We then verify the role of climatic conditions during the optimal windows as a driver of migrant family reunification decisions, and contrast these findings with other specifications that adopt more conventional windows in the literature. Specifically, we show that when the climatic conditions of the origin have greater predictive power over the yield of agricultural products in said regions, the same climatic variables are also prediction-improving for family reunification migration.

Our results demonstrate that choosing the optimal window of weather has important implications for interpreting the role of extreme temperature. When climatic conditions are measured during the crop-specific optimal windows, increased exposure to extreme heat in origin states consistently increases the likelihood of family reunification across model specifications. In contrast, when weather is measured over the conventional January to December period, the estimated effects are unstable, showing large positive coefficients in simpler models but diminishing sharply and even turning negative once household-level controls are introduced. This contrast highlights the importance of aligning climatic measures with agriculturally relevant periods. Using optimal windows reduces measurement error and produces more credible estimates that link climate-induced shocks in agricultural productivity to migration decisions.

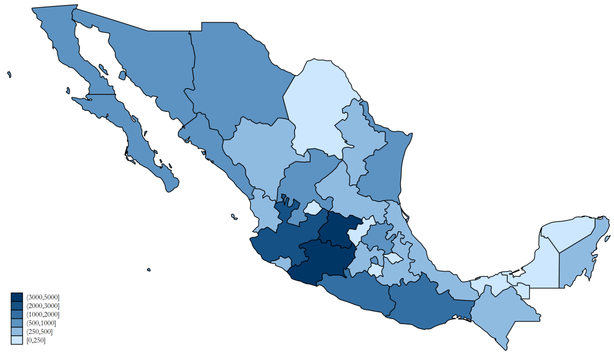
In this paper we contribute to the literature by providing one of the first analysis into the process of international family reunification migration. In particular, while a sizable literature has been developed in the study of human mobility induced by climate change (Molina et al., 2022; Zhu et al., 2024; Mueller et al., 2014; Hunter et al., 2013), a question that remains largely unanswered is the role of climatic shocks in the odds of family reunification cross-border migration. As the literature on migrants' remittances (Giuliano and Ruiz-Arranz, 2009; Rapoport and Docquier, 2006) illustrates, international migration often involves a nontrivial duration of family separation for many migrant families, and it has also been demonstrated that migration of a subset of household members is a method in which families in vulnerable conditions handle risks arising from climatic variations (Dillon et al., 2011). Therefore, understanding the decisions of households to relocate, and reunite is a crucial piece that is not present in the current dialogue.

In addition, this paper contributes to the literature on climate-induced migration by verifying whether agricultural productivity is indeed a channel through which weather can affect migration decisions. Feng et al. (2010) examined crop yields and migration decisions in the Mexico-US context, utilizing census data to show that climatic factors works through the agricultural sector to induce outmigration to the US. Kubik and Maurel (2016) also examines the role of climatic variation on agricultural production, and its implications on internal migration in the context of Tanzania. We develop upon these studies by expanding the crop selection to a variety of crops, and directly observing households rather than relying on state level census data as a proxy for migration. Also, we are able to relax the exclusion restriction imposed by the instrumental variable approach which has been adopted by previous work, which requires that the agricultural productivity alone is the channel through which climatic variation can affect migration decisions.

2 Data and Variables

In the following sections, we provide background information on the data used in our empirical analysis, summarize major trends through descriptive statistics, and explain the logic behind our variable construction. The National Agricultural Workers Survey (NAWS), conducted by the U.S. Department of Labor, provides nationally representative data on farm-related work and the agricultural workforce. This survey is administered annually through face-to-face interviews and collects information on employment status, economic conditions, and demographics of farm and farm-adjacent workers.

Figure 1. Migrants' Origin States



Note. This figure presents the cumulative number of first-movers from each Mexican state over the study period.

For our analysis, we restrict the sample to male workers of Mexican origin who self-report as married. We focus on cases where the first-mover is male, as the overwhelming majority (92%) of instances in our data follow this pattern. This restriction allows us to concentrate on a more homogeneous group of migrants who are likely to share common push and pull factors shaping family migration plans. We further limit the sample to families where the first mover entered the U.S. between 1980 and 2015, to align with our data on agricultural production. These restrictions yield a final sample of 23,858 married male agricultural workers who migrated to the U.S. from Mexico. The majority of agricultural migrants during this period originated from the states of Michoacán, Guanajuato, Jalisco, and Oaxaca, which together account for 53% of all migrants. Figure 1 plots the origins of each migrant family in the dataset.

For these workers, the restricted NAWS sample provides information on the Mexican state of most recent residency prior to U.S. entry and the U.S. state of residence at the time of the survey, which we label as `origin` and `destination`, respectively. A limitation of this approach is that it relies on the assumptions that (a) family members left behind in Mexico have not resided in other Mexican states between the time of entry and the time of the survey, and (b) individuals residing in a given state do not engage in agricultural production in another state. If these assumptions hold, identifying the state of residency provides a distinct advantage, as it allows us to link agricultural production and climatic conditions to specific origin states.

We also observe the year of U.S. entry for spouses, which allows us to measure the number of years the family has been separated across international borders. We define family reunification as having occurred in any year when the spouse previously located in Mexico joins the principal migrant in the United States. Approximately 87% of households in our sample experienced a separation of more than one year, with an unconditional average separation duration of 4.2 years. Summary statistics on migrant families are presented in Table 1. The average age of the first mover at the time of entry into the United States was 21.43 years, and, conditional on eventual family reunification, the average separation lasted 2.78 years. Among the first movers, approximately 19% were involved in agricultural work classified as "shuttled" labor, and 47% reported lacking legal authorization to work in the U.S. Regarding spouses' participation in the U.S. labor market, 11.7% reported no involvement in farm-related work, while 19.2% indicated that they had worked on farms.

To measure climatic variation, we use data from the PRISM Climate Group, which provides 4 km gridded climate data for the study region. This dataset includes daily mean, maximum, and minimum temperatures, along with precipitation data. For our purposes, the data are aggregated at the state-month level. To account for differences in the distribution of agricultural production, climatic variables are weighted by cropland count data. In our main specifications, we construct 5°C temperature bins,[4] which measure the proportion of days where the mean temperature falls within predefined ranges. We also employ average maximum temperature, mean temperature, and minimum temperature as alternative measures, while controlling for average precipitation.

Although alternate definitions of weather are explored, our main results rely on the assumption that annual fluctuations in the distribution of high-and low-temperature days in an origin state are plausibly exogenous. Figure 2 illustrates the spatial distribution of extreme temperature days across Mexican states from 1975 through 2014 in five-year intervals. The maps reveal considerable heterogeneity across regions. Northern states consistently experience a higher frequency of days above 30°C, while the central highland states display relatively fewer. Southern states also show sustained exposure to high-temperature days, although the magnitude varies across decades.

[4] Roughly equivalent to 9°F temperature bins.

Table 1. Summary Statistics: NAWS

	Mean	Std. Dev.	Min	Max
Year of First Move	1989	6.97	1980	2015
First Mover's Age at Migration	21.43	7.76	16	73
Wage from Primary Task	7.9	2.87	2	30
Shuttled Labor	0.19	0.39	0	1
Work Authorization	0.47	0.49	0	1
Number of Children	1.05	1.27	0	10
Spouse in Farm Work	0.2	0.39	0	1

Equally important is the variation over time. Comparing maps across periods, we observe fluctuations in the intensity and spread of extreme temperature days even within the same states. These temporal shifts are not uniform across regions, suggesting that the distribution of hot days is driven by broader climatic cycles rather than local economic or institutional factors. This combination of spatial heterogeneity and intertemporal variability supports the assumption that year-to-year differences in the distribution of extreme temperatures are plausibly exogenous to human activities and therefore provide a credible source of quasi-random variation for our empirical strategy.

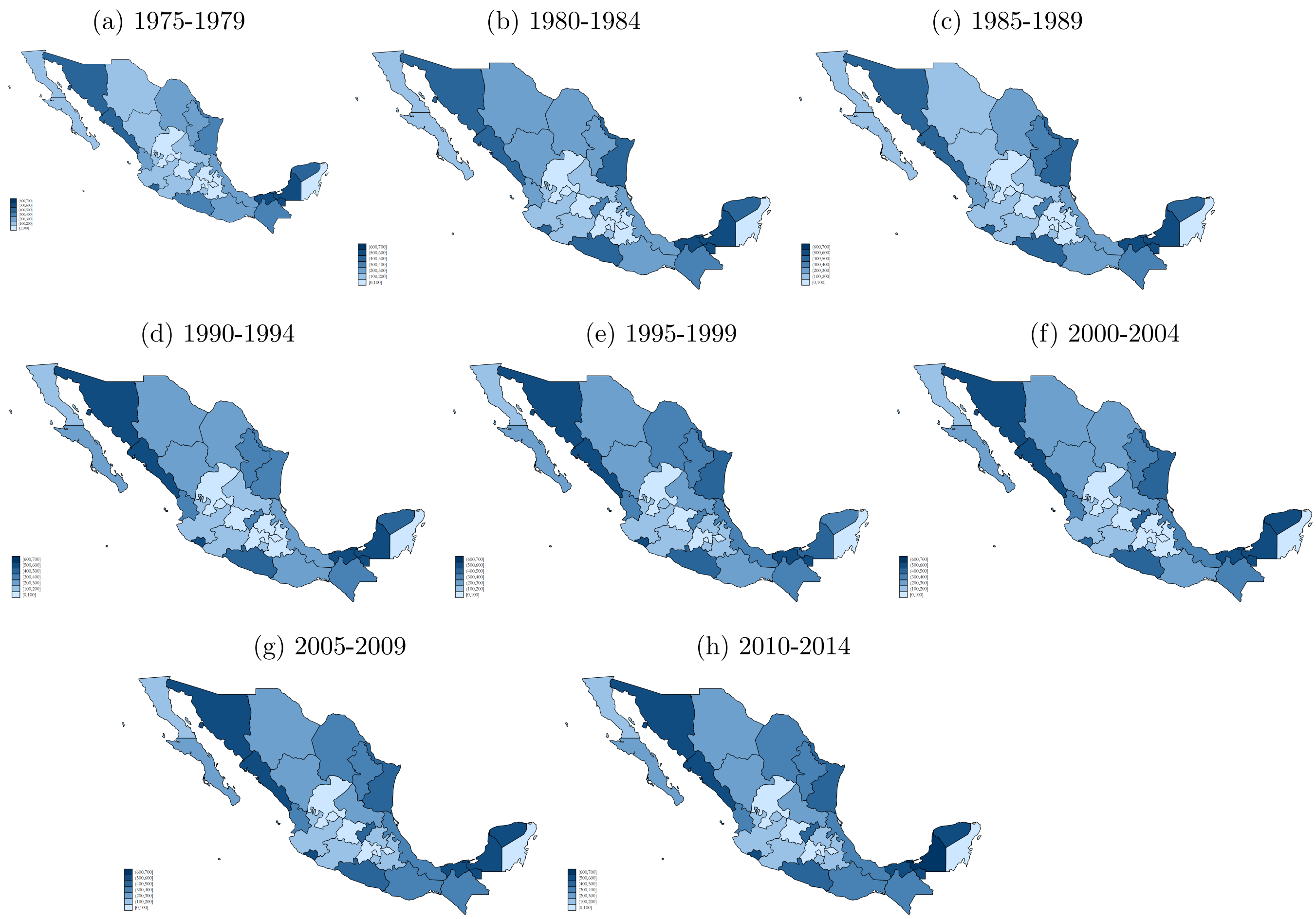
To capture agricultural heterogeneity, we draw data from the Servicio de Información Agroalimentaria y Pesquera (SIAP). The SIAP dataset includes information on crop yield and land area used for 146 distinct crops in Mexico, recorded on a year-state basis. These crops range from field staples such as wheat and soybeans to fruit products such as apples and grapes. Because crops vary substantially across origin states, a central challenge is selecting representative crops for each state. For instance, it would be implausible to assume that crops central to the agricultural sector of Baja California are equally relevant to farmers in Nayarit. To address this, we use SIAP data to construct a crop share measure for each state from 1980 to 2015.

Formally, $\texttt{Share}_{ic}$ represents the proportion of total agricultural land that crop c occupies in state i over the years 1980 to 2015. We select the top five crops occupying the most land in each state and exclude any crop accounting for less than 1% of agricultural land within a state. Table 2 lists the top agricultural products in each state within our sample during the study period, specifically for states where at least

50 first movers originated.

$$\texttt{Share}_{ic} = \frac{\sum_{t=1980}^{2015} \texttt{Area}_{ict}}{\sum_{c \in C_{it}} \sum_{t=1980}^{2015} \texttt{Area}_{ict}} \tag{1}$$

Figure 2. Top Bin Occurrences



Note: This figure shows the number of days exceeding 30°C for each 5-year period by origin states, categorized into intervals of (0,100], (100,200], . . . , (600,700].

Table 2. Top Agricultural Products By Land Share

State	Rank #1	#2	#3	#4	#5
AGU	Corn	Beans	Alfalfa	Guava	Oats
BCN	Wheat	Cotton	Alfalfa	Barley	Sorghum
CHH	Corn	Oats	Beans	Alfalfa	Cotton
CHP	Corn	Coffee	Beans	Grass	Cocoa
CMX	Corn	Oats	Cactus	Beans	Broccoli
COA	Grass	Corn	Sorghum	Cotton	Oats
COL	Grass	Lemon	Coconut	Corn	Sugarcane
DUR	Beans	Corn	Oats	Sorghum	Alfalfa
GRO	Corn	Coconut	Grass	Coffee	Mango
GUA	Corn	Sorghum	Wheat	Beans	Alfalfa
HID	Corn	Barley	Beans	Alfalfa	Coffee
JAL	Corn	Grass	Sorghum	Sugarcane	Wheat
MEX	Corn	Oats	Grass	Barley	Wheat
MIC	Corn	Sorghum	Avocado	Grass	Wheat
MOR	Corn	Sorghum	Sugarcane	Beans	Tomato
NAY	Beans	Corn	Sorghum	Grass	Sugarcane
NLE	Grass	Corn	Sorghum	Wheat	Oranges
OAX	Corn	Grass	Coffee	Sugarcane	Beans
PUE	Corn	Beans	Coffee	Barley	Peanuts
QUE	Corn	Beans	Alfalfa	Sorghum	Barley
SIN	Corn	Sorghum	Beans	Wheat	Soybeans
SLP	Corn	Grass	Beans	Sugarcane	Oranges
SON	Wheat	Corn	Soybeans	Cotton	Safflower
TAM	Sorghum	Corn	Grass	Soybeans	Safflower
VER	Corn	Sugarcane	Grass	Coffee	Oranges
ZAC	Beans	Corn	Oats	Chili	Barley

3 Optimal Windows

Our empirical strategy relies on two models. First, we examine the relationship between agricultural yields in the Mexican states of migrants' origin and the corresponding climate, and we discuss adjustments to the selection of optimal weather windows for each state. The optimal weather window refers to the months of the year during which variations in weather best explain variations in crop yields. Once these windows are identified, we estimate the impact of climatic variation on Mexican agricultural migrants.

Our first model applies the methods of Li and Ortiz-Bobea (2022) to analyze the impact of climatic variables on agricultural productivity in Mexican states. The calendar year is divided into 78 segments, which can be expressed as follows:

$$\mathcal{S} = \{[\texttt{Jan}], \cdots, [\texttt{Dec}], [\texttt{Jan}, \texttt{Feb}], \cdots, [\texttt{Nov}, \texttt{Dec}], [\texttt{Jan}, \texttt{Mar}], \cdots, [\texttt{Jan}, \texttt{Dec}]\} \quad (2)$$

For each of the 78 segments of the year, and for each of the top five crops identified for each origin state, we test the predictive power of including climatic variables, referred to as the "weather-augmented model," compared to a baseline model that excludes climatic variables, which we refer to as the "baseline model."[5] The grid search procedure to identify the optimal segments for each state-crop combination is as follows:

A. Baseline Agricultural Model

For each state i, crop $c \in \mathcal{C}i$, and year t, we estimate crop yield with time as the only independent variable to serve as the baseline model:

$$\texttt{yield}ict = \alpha + \delta \cdot \texttt{t} + \varepsilon_{ict} \quad (3)$$

B. Weather-Augmented Agricultural Model

For each segment of the year $s \in \mathcal{S}$, and for each climatic variable $\texttt{w} \in \mathcal{W}$, we estimate crop yield with time and climate variables as the independent variables, leaving out a randomly chosen year $\bar{\texttt{t}}$:

$$\texttt{yield}ict = \alpha + \delta \cdot \texttt{t} + \sum \texttt{w} \in \mathcal{W}\beta_s \texttt{w}^s it + \varepsilon ict \quad , \quad t \neq \bar{t} \quad (4)$$

C. K-fold Grid Search

[5] One may also explore windows that cross calendar years, such as [($\texttt{Nov,y}$), ($\texttt{Feb,y+1}$)]. However, because agricultural yield data are tabulated at the calendar year level, we excluded such windows from the analysis.

Repeat step B for `N` years and calculate the root mean squared error (RMSE) for each state-crop combination.

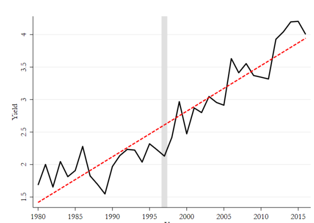
D. Computing Results

Compare the estimation error from the baseline model to the RMSE obtained from step C.

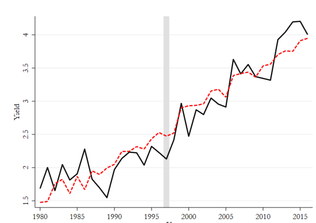
A visualization of this process is provided in Figure 3. In each panel, the solid line represents the annual yield of corn in Michoacán, the dotted line shows the model's estimate of yield, and the shaded region indicates the year $\bar{\mathtt{t}}$ that was excluded in the grid search process. Panel (a) presents the baseline model, which uses a single linear time trend to estimate yield. Panels (b) through (d) depict results from models that incorporate climatic variables in addition to the linear time trend, but apply different weather windows. While the baseline prediction is not a reliable benchmark, the inclusion of climate variables does not guarantee improved predictive accuracy, and the degree of improvement varies depending on the segment selected.

Figure 3. Kfold Visualized: Michoacán

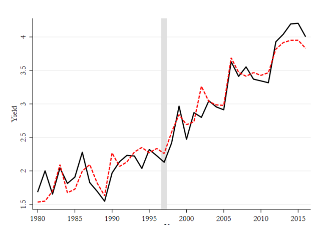
(a) Linear: No Weather Used



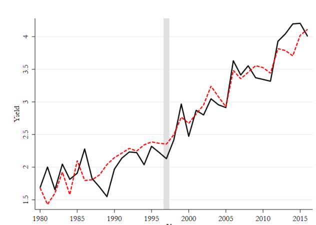
(b) Weather in April



(c) Weather Between Jun. and Jul.



(d) Weather Between Feb. and Sep.



Note. This figure illustrates part of the grid search process used to identify the optimal window. The example shows the origin state with the highest number of first-movers and its most important crop, corn. The solid lines represent actual corn yields, while the red dotted lines indicate various specifications used to predict yield.

The objective of this procedure is to identify the segment of the year during which the inclusion of climatic variables is most beneficial for estimating crop yields. In the main results from this model, negative values indicate an improvement in predictive accuracy. In addition to identifying the RMSE-minimizing weather window, we also examine the effects of detrimental weather on agricultural yields to assess whether our findings align with the existing literature. The coefficients obtained from this model correspond to the top temperature bin, which measures the proportion of the weather window during which temperatures exceeded 30°C.[6] We also consider the coefficient on the monthly maximum temperature within the weather window.

An important question that arises from this procedure is how to select the optimal weather window. Each origin state produces multiple crops, and each crop may have a distinct growing period during which climatic variables improve model precision most effectively. Figure 4 displays the optimal weather windows determined for the origin state of Michoacán and its top five crops. For corn, the critical period is the window $[\texttt{Jun}, \texttt{Aug}]$ as shown in panel (a). For avocados and grass, the optimal windows are $[\texttt{Jul}, \texttt{Aug}]$ and $[\texttt{Feb}, \texttt{Apr}]$, respectively, shown in panels (b) and (c). The final two crops both identify the optimal window as $[\texttt{Jun}, \texttt{Sep}]$.

The most restrictive approach would be to take the intersection of the windows for each state. This ensures that months unimportant to any crop within our sample are excluded from the analysis, thereby reducing the risk of introducing nonclassical measurement error. However, this approach has drawbacks: it may not be feasible for states with diverse agricultural sectors where growing seasons do not overlap, and it risks discarding useful data. For example, in the case of Michoacán, the single largest origin state in terms of the number of migrants, the intersection approach would lead to a null weather window.

A more lenient approach is to take the *union* of the windows, which in the case of Michoacán would be $[\texttt{Feb}, \texttt{Sep}]$. The advantage of this method is that it ensures a window is chosen for all states in the sample. However, for states with a wide range of crops and non-overlapping growing seasons, this approach may result in a window that is overly broad, partly undermining the benefits of the grid search. Given these

[6] Approximately 89.6°F.

trade-offs, we adopt the *union* approach for selecting optimal windows. Once the optimal weather window is determined for each origin state, we then evaluate the impact of extreme climatic conditions as a push factor in the family reunification of Mexican agricultural workers.

4 Climate Driven Migration

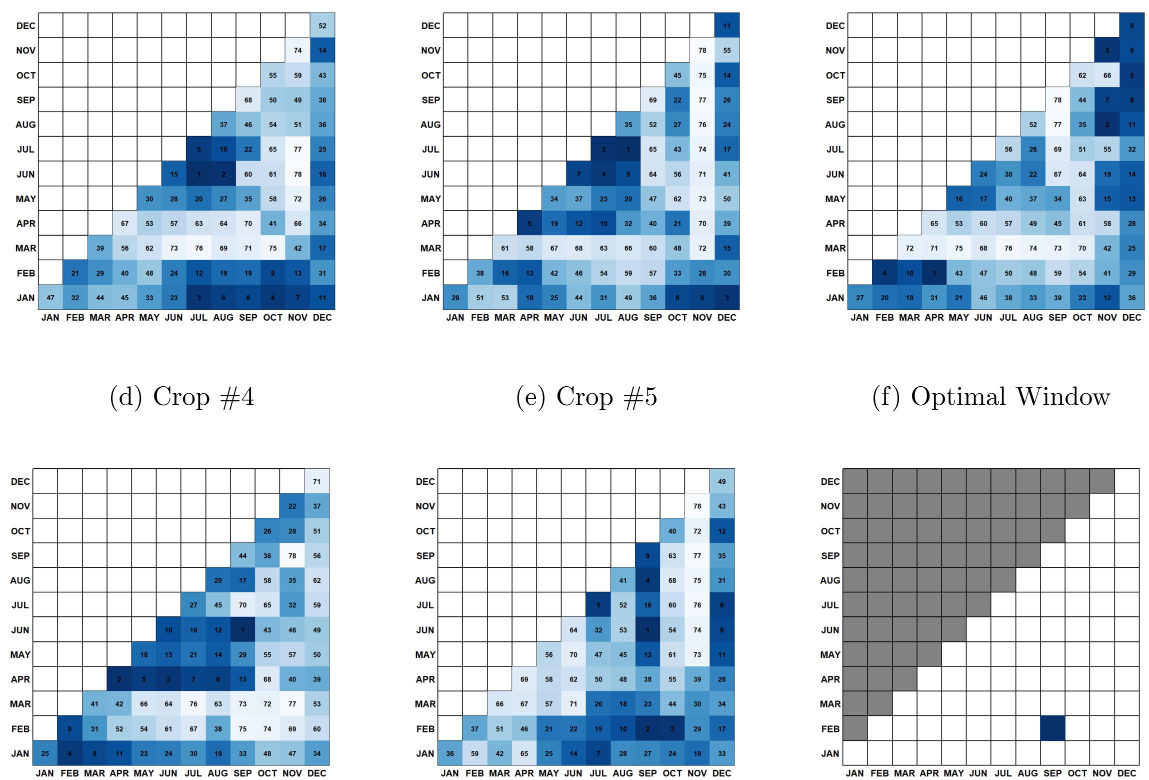
Our main empirical specification is a fixed-effects logit model that relates the probability of migration to exposure to extreme heat. Specifically, we model the log-odds of family reunification for individual i in origin state s at time t as:

$$\log \frac{P(\texttt{Reunited}ist = 1)}{P(\texttt{Reunited}ist = 0)} = \beta W_{ist} + \alpha_s + \delta_t + \gamma X_{ist} + \varepsilon_{ist} \tag{5}$$

Family reunification is defined as the year in which the spouse in Mexico joins the principal migrant in the United States. The set W_{ist} includes climatic variables such as temperature bins, precipitation, and relative humidity. Our primary variable of interest is the share of days above 30°C in the optimal weather window of origin s. The controls X_{ist} include time-varying household characteristics such as the age of the first mover at migration, the calendar year of migration, and the number of children. We also include an event-time variable to capture the number of years since the husband's entry into the United States, which allows us to account for dynamic effects over the separation period. State fixed effects control for time-invariant differences across origins, while year fixed effects capture macro-level shocks.

Table 3 reports estimates from the fixed-effects logit model. All specifications include the full set of climatic variables and fixed effects, but the table reports only the coefficient on the top temperature bin, defined as the share of days in the optimal window exceeding 30°C.

Figure 4. Optimal Window: Michoacán



(a) Crop #1 (b) Crop #2 (c) Crop #3

(d) Crop #4 (e) Crop #5 (f) Optimal Window

Note. This figure depicts the process of determining the optimal window for each origin state, based on the five most important crops for that state. The example highlights Michoacán, the origin state with the greatest number of first-movers.

Table 3. Climate Driven Migration

	(1)	(2)	(3)	(4)	(5)
Extreme Temperature	.71***	.85**	.15***	.05***	.03*
	(.013)	(.02)	(.03)	(.021)	(.017)
Precipitation	1,907***	695***	97	520***	501***
	(62.8)	(99.04)	(143.0)	(123.1)	(102.2)
Years of Separation		.84***	1.35***	1.14***	.81***
		(.002)	(.004)	(.003)	(.002)
Age at Migration			-.053***	-.057***	-.019***
			(.007)	(.005)	(.004)
Number of Migrants				-.0001***	-.0004***
				(.00007)	(.00006)
No. of Children					.97***
					(.028)
Observations	23,858	23,858	23,858	23,858	23,808

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Across specifications, the coefficient on extreme temperature is positive and statistically significant. In column (1), the estimate is 0.71, which corresponds to an increase of about 3.9 percentage points in the probability of reunification. Column (2) shows a slightly stronger effect of 0.85, translating into a 4.5 percentage point increase. As additional household-level controls are added in columns (3) through (5), the magnitude of the effect declines to 0.15, 0.05, and 0.03, which correspond to 0.5, 0.1, and 0.07 percentage point increases in the probability of reunification, respectively. Although attenuated, the effects remain positive and significant, suggesting that extreme heat during the agricultural growing season increases the likelihood of reunification among Mexican agricultural migrants. While the estimated effects may appear small, it is important to note that the measure of extreme temperature is defined as the share of days above 30°C in a given window. For many origin states in the sample, this share varies by 10–30 percentage points year-to-year, implying that the cumulative effect on the probability of reunification can be relatively large.

We next consider alternative constructions of the weather window. Table 4 reports results when climatic variables are measured over the conventional January-December period, as is common in the literature.

Table 4. Climate Driven Migration: Conventional Window

	(1)	(2)	(3)	(4)	(5)
Extreme Temperature	1.62***	.33***	.32***	.29	-.28***
	(.024)	(.03)	(.03)	(.3)	(.055)
Precipitation	138***	-25.6	187.7	30.7	1430
	(9.51)	(208.8)	(211.2)	(212.1)	(303.9)
Years of Separation		.78***	.79***	.8***	-1.37***
		(.002)	(.002)	(.002)	(.003)
Age at Migration			.01***	.008**	-.14***
			(.003)	(.003)	(.007)
Number of Migrants				-.003***	.0001*
				(.00005)	(.00008)
No. of Children					.82***
					(.04)
Observations	23,858	23,858	23,858	23,858	23,808

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results differ considerably from the optimal-window specification. In column (1), the estimated coefficient on extreme temperature is 1.62, much larger than in the main model, but the effect falls sharply in subsequent specifications. By column (5), the coefficient turns negative. This reversal highlights the importance of carefully selecting agriculturally relevant weather windows. Using a full-calendar definition, which does not align with crop-specific growing seasons, risks confounding the relationship between temperature variation and agricultural productivity, thereby obscuring the link to migration outcomes.

Finally, Table 5 contrasts the main specification with alternative definitions of weather. Here, column (1) reports results using annual mean temperature in the optimal window, column (2) uses maximum temperature, and column (3) uses minimum temperature. All three measures yield positive and significant coefficients, though the magnitudes differ at 0.09 for mean temperature, 0.14 for maximum temperature, and 0.02 for minimum temperature. The consistency across measures reinforces the conclusion that higher temperatures in the origin state are associated with a greater likelihood of reunification. Precipitation effects are less consistent across columns, but the coefficients on extreme temperature measures remain robust.

Table 5. Climate Driven Migration: Alternate Measures of Climate

	(1)	(2)	(3)
Temperature	.09***	.14***	.02*
	(.013)	(.015)	(.01)
Precipitation	-212*	-4.68	-339***
	(120)	(123)	(120)
Years of Separation	1.2***	1.2***	1.2***
	(.003)	(.003)	(.003)
Age at Migration	-.09***	-.1***	-.084***
	(.006)	(.006)	(.006)
Number of Migrants	-.0004	-.00006	-.00005
	(.00007)	(00008)	(.00007)
No. of Children	.8***	.78***	.88***
	(.032)	(.035)	(.033)
Observations	23,808	23,808	23,808

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Taken together, these results show that exposure to extreme heat in the agricultural growing season of the origin state increases the probability that migrant families reunify in the United States. The effect is strongest when temperature is defined using crop-specific optimal weather windows, and weaker or unstable when broader or less precise measures are used. This pattern supports the interpretation that climate-driven shocks to agricultural productivity function as push factors in migration decisions, with extreme heat serving as a credible driver of family reunification.

5 Conclusion

In this paper, we examine the role of extreme weather conditions on family reunification migration in the Mexico-US context. We focus on the reunification of agricultural worker families across the Mexican-US border, as a result of extreme climate conditions that are arguably exogenous to the decision-making of the individual families. In order to establish the link between the role of extreme climate on migration through agricultural productivity, we introduced a newly developed data driven methods into the analysis of international migration, by first of all obtain the optimal windows of weather that correspond to the segment of the year which is the most relevant to agricultural migrants. We find that for the vast majority of states in our sample, which consist of agricultural workers and their families, the optimal window does not align with the orthodox method of utilizing the entire year's weather. As the climatic conditions in a month and its consecutive month is expected to be correlated, empirical results based on the entire year may be susceptible to nonclassical measurement errors, which produces biases of undetermined directions. Utilizing the gridsearch method, we find that consistent with the outstanding literature, exposure to heat in critical periods is detrimental to crop yields. Meanwhile the same conditions that are detrimental to crop yields in the migrant sending states are push factors for family reunification migration. Based on these results we conclude that shifts in agricultural productivity induced by changes in the climatic conditions in the origin states contribute to the decision of family reunification migration.

We believe that there are many ways to extend this study. First, this paper followed a common practice in the climate migration literature to include sending country climate conditions as the only route based on which extreme weather conditions can impact migration patterns. Ideally, one would adopt a gravity model of migration that allows for both sending and destination states controls to simultaneously impact international migration. In our context, one would implement a gridsearch method using U.S. agricultural productivity data as well. Park (2023) presents an attempt in this direction. Second, one may adopt alternate measures of agricultural productivity such as profits from the agricultural sector or total factor productivity. Doing so effectively directly assess the relationship between climate and agricultural productivity as opposed to the yield of a collection of individual crops.

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