# Responses to Extreme Temperatures: Labor Markets and Migration Decisions in El Salvador*

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**Abstract**

By 2017, one-quarter of people born in El Salvador were estimated to live in the U.S. We show that extreme temperatures negatively impact agricultural production and increase international migration. Corn producers respond by reducing demand for agricultural workers and substituting them with household labor. Unlike other contexts, there is no evidence of reallocation to the non-agricultural sector. This, combined with a strong history of migration to the U.S., explains the increase in international migration. Our findings underscore how international migration serves as a response to extreme temperatures when local labor markets fail to absorb displaced workers and if financially feasible.

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# 1 Introduction

The frequency and length of heat waves have increased since the middle of the twentieth century, a trend likely to intensify in the coming decades (IPCC, 2021). This has important implications for small farmers since ample evidence shows that extreme temperatures depress crop yield, agricultural productivity, and agricultural income.[1] If these trends persist, the rising costs that climate change imposes on subsistence farmers could hurt hundreds of millions of people and affect global efforts to reduce rural poverty.[2]

The effects of extreme temperatures can be particularly large in regions with rain-fed agriculture and for small agricultural producers in lower- and middle-income countries, who seldom have access to mechanisms that manage risk. Incomplete financial markets to manage risk limit the ability of households to compensate for income losses caused by extreme temperatures and to protect themselves *ex-ante* through insurance. As a consequence, agricultural households respond in the short term to these losses through costly strategies such as asset sales, changes in agricultural practices, an expansion in the use of household labor (including children), participation in subsistence activities, and distress migration (Rosenzweig and Wolpin, 1993; Jayachandran, 2006; Carter and Lybbert, 2012; Hornbeck, 2012; Jessoe et al., 2016; Aragón et al., 2021).

Our paper contributes to the literature by measuring the effects of extreme temperatures on agricultural production and examining the complex ways in which farmers in El Salvador respond to income losses caused by these temperature changes. Specifically, we investigate how farmers adjust their use of production inputs, focusing on changes in labor

[1] The following papers, among others, show the impact of weather shocks on agricultural production: Deschênes and Greenstone (2007), Schlenker and Roberts (2009), Schlenker and Lobell (2010), Feng et al. (2010), Dell et al. (2014), Burke and Emerick (2016), Aragón et al. (2021), Colmer (2021), Ortiz-Bobea et al. (2021), and Albert et al. (2024); and (ii) use other proxies, including rainfall, for weather shocks: Deschênes and Greenstone (2007), Feng et al. (2010), Schlenker and Lobell (2010), Hornbeck (2012), Hornbeck and Naidu (2014), and Ortiz-Bobea et al. (2019).

[2] In 2016, there were 570 million farms in 167 countries: 89 percent were family farms and the great majority were small farms. Forty-nine percent were in lower-income countries (Lowder et al., 2016).

demand that prompt farm workers to reallocate to the non-agricultural sector or migrate abroad.

The setting of El Salvador offers several advantages for this research. First, a large percentage of the population still earns income from agriculture, especially compared to other Latin American countries. Most of the agricultural producers are subsistence farmers who work small land plots, are largely dependent on the rain cycle, and live in contexts with incomplete markets (FAO, 2016; WB, 2024). Second, the country is increasingly vulnerable to extreme weather events, in particular droughts and high temperatures have intensified during recent decades with three extreme droughts in the last 10 years alone. Figure 1 illustrates the trend of increasing temperature levels in El Salvador. Third, the strong presence of criminal organizations on the majority of urban areas in the country imposes a burden on labor markets, presumably reducing the possibility for workers to switch from the agricultural to the non-agricultural sector (Melnikov et al., 2020). Finally, El Salvador has a long history of migration to the United States that began during the civil war in the 1980s and has continued ever since. In 2017, over one-quarter of the country's population was estimated to be living in the United States (Abuelafia et al., 2019). The large migrant network in the United States may significantly reduce migration costs, rendering international migration financially feasible.[3]

Using annual data from a variety of sources, we document that extreme temperatures decrease the production of seasonal crops, which are particularly sensitive to spikes in temperature, especially corn—-El Salvador's main staple crop. We find that one additional week with extreme temperatures during the main growing season reduces corn production by 4.1 percent and corn production per hectare by 6 percent. Agricultural producers adjust in the short run by reducing labor demand for non-household agricultural workers and substituting them for household members. One additional week with extreme temperatures decreases

[3]For a more detailed discussion about the trends of extreme weather in El Salvador and migration from El Salvador to the U.S. see Online Appendix Section A1.

the number of non-household workers by 2.6 percent for corn-producing households. This contraction of labor demand leads to a decrease in the employment share of agricultural workers growing corn. One additional week of extreme temperature decreases this share by 2.7 percent relative to the mean, along with a fall in this sector's average wages. We find no evidence of reallocation to non-agricultural occupations but we do observe a significant increase in the probability of migration to the United States. One additional week of extreme temperature during the main growing season causes migration from corn-based agricultural households to rise by 0.18 percentage points, which is 27.7 percent relative to the mean. Our results are generally robust across a variety of alternative specifications.

Our analysis captures both permanent and temporary migration; however, our data does not allow us to distinguish between these two categories. The results highlight that international migration is likely to play a particularly key role in *ex-post* insurance against climate shocks in places like El Salvador. Two characteristics of El Salvador may explain the strong response through international migration: barriers in labor markets that prevent the full absorption of displaced agricultural workers into the non-agricultural sector, and a long-standing history of migration and established migrant networks in the U.S. Our results highlight the role of the integration of labor markets and access to informal risk-coping mechanisms in explaining the effect of temperature spikes on the decision to migrate internationally (Jayachandran, 2006; Graff Zivin and Neidell, 2014; Jessoe et al., 2016; Colmer, 2021).

We make several contributions to the literature. First, we provide evidence on how extreme temperatures affect agricultural production in a context of incomplete risk markets and barriers in local labor markets, thereby prompting agricultural producers to respond through international migration (Guiteras, 2009; Feng et al., 2010; Auffhammer et al., 2012; Fishman, 2016; Jessoe et al., 2016; Blakeslee and Fishman, 2018; Aragón et al., 2021; Colmer, 2021). We expect different effects of extreme temperatures in countries where farmers can

access financial and insurance markets and non-agricultural sectors may absorb the laid-off agricultural workers.[4] In contexts where labor markets are not fully integrated, the non-agricultural sector cannot absorb new workers and/or migration costs are low, migration might be more prevalent (Massey et al., 1990; Munshi, 2003; Jayachandran, 2006; Hunter et al., 2013; Nawrotzki, 2015; Mahajan and Yang, 2020; Clemens, 2021; Colmer, 2021).

By using microdata to identify the mechanisms behind these relationships, we explore the role of local labor markets and access to migrant networks as push-and-pull factors in migration responses. Most of the previous literature relies on a reduced-form strategy to identify the effects of weather shocks on migration but rarely delve into the mechanisms. Some papers explore agriculture as a mechanism but use aggregate data either at the country, state, or county level (see, e.g., Feng et al., 2010; Hornbeck, 2012; Hornbeck and Naidu, 2014; Cai et al., 2016; and Cattaneo and Peri, 2016). Jayachandran (2006), Aragón et al. (2021), and Colmer (2021), who use microdata for agricultural producers, are among noteworthy exceptions. We reinforce this literature with evidence on the role of labor markets as a transmission mechanism for the negative impact of extreme temperatures on agricultural workers, some of who react by leaving El Salvador. Labor reallocation is an important margin of adjustment for mitigating extreme temperatures, but unlike Colmer (2021) we find no evidence of workers moving to the non-agricultural sector. The economic environment in El Salvador without well-integrated markets and weak urban labor markets, presumably due to the effects of crime (Melnikov et al., 2020), together with low access to formal credit and a strong migrant network that lowers migration costs, explain the effect of extreme temperature on the decision to migrate internationally. This contribution holds substantial importance as it underscores the significance of understanding the local economic conditions in order to identify the potential mechanisms by which weather shocks impact local labor markets and migration choices.

[4]Some examples for developed countries are Deschênes and Greenstone (2007), Schlenker and Roberts (2009), Schlenker and Lobell (2010), Hornbeck (2012), Hornbeck and Naidu (2014), Burke and Emerick (2016), and Ortiz-Bobea et al. (2019).

Second, we show that access to risk-management mechanisms (such as remittances) mitigates the need to contract labor demand and therefore reliance on distress migration. Our results highlight how incomplete markets in developing countries force rural households to rely on migration—in this case, international migration—to counteract declines in income. It is vital to understand the interactions of these elements in order to design policies to prevent distress migration and facilitate intentional migration from regions where agriculture may no longer be feasible. Migration might lead to better short-term *and* long-term outcomes if it is voluntary and not for lack of better-coping mechanisms. Under certain conditions, however, it can prompt persistent negative effects for both migrants and the households they leave behind. Financial and insurance mechanisms should be tailored to the specific needs of small farmers in order to mitigate the negative impacts of extreme weather events and to prevent distress migration.

Third, we provide evidence on the dynamics of exposure to extreme temperatures. We find significant effects of both contemporaneous and lagged cumulative exposure to extreme temperatures on migration responses, consistent with Kleemans (2023). The results suggest there are two potential responses to extreme temperatures: an increase in migration following a bad wage draw caused by extreme temperatures (*ex-post* risk coping strategy) and the accumulation of preceding good wage draws resulting from favorable temperatures (investment strategy).

The rest of the paper proceeds as follows. Section 2 develops the conceptual framework from which we derive testable hypotheses, section 3 describes our data, section 4 explains our empirical strategy, and presents our results. We discuss conclusions in section 5.

## 2 Conceptual Framework

This section develops a conceptual framework to predict the relationship between exposure to extreme temperatures and international migration, drawing on the work of Kleemans

(2023). In this paper, the author develops a dynamic savings model adding location as a state and choice variable, when households face risk and liquidity constraints. Each period, households receive a random wage draw and decide whether to send household members to another location. Within this framework, migration serves as an *ex-post* risk coping strategy in response to unexpected negative shocks to agricultural productivity, or as an investment decision following one or more positive shocks.

Kleemans (2023) predicts an increase in migration following both a bad wage draw (*ex-post* risk coping strategy) and the accumulation of preceding good wage draws (investment strategy). In addition, the model predicts how each migration strategy is related to the length of the migration period – temporary vs. permanent migration – and distance of migration –short- versus long-distance. Given migration costs and liquidity constraints, *ex-post* risk coping migratory responses are expected to be temporary and to nearby rural destinations, while investment moves are expected to occur over longer periods and distances.

Our conceptual framework is an extension of this model. Due to the structure of our dataset, we are unable to test for differential effects based on the geographic distance between origin and destination, or the duration of migration moves. In fact, we only observe international migration as the data does not elicit information on internal migration.

In line with Kleemans (2023), we adopt the framework in which households may employ migration as either an *ex-post* risk coping strategy or an investment strategy. We differentiate between two potential locations: *Home*, where the household is interviewed at time $t$; and *International*, any international location where a household member resides at time $t$. When staying *Home*, household members may continue working on the *agricultural sector*, shift to the *non-agricultural sector* or become *unemployed*.

We introduce two additional dimensions to Kleemans' model to account for the specific context of El Salvador. Firstly, we account for the fact that the large percentage of Salvadorean population living abroad may contribute to reducing migration costs when moving

internationally and ease the liquidity constraint from one or a series of bad wage draws. The *remmittances* variable captures the easing of the liquidity constraint and reduction of migration costs, while the *networks* variable gauges the strength of the migrant's connections at the destination and hence the lower migration costs to the U.S. Secondly, we examine the role of *local labor markets* as a buffer to bad wage draws. Households may shift from the agricultural to the non-agricultural sector to compensate for the reduction in income after a bad wage draw.

We present below testable predictions for household's behavior as predicted by the model under different wage draws. A bad wage draw at time $t$ will either push households to shift to the non-agricultural sector or to migrate abroad.

*Prediction 1A: A bad wage draw at time t will increase international migration* if the expected wages at the destination, minus the migration costs, are higher than the expected wages in the non-agricultural sector or the bad wage draw.

*Prediction 1B: A bad wage draw at time t will push households to shift from the agricultural to the non-agricultural sector* if the expected wages in the non-agricultural sectors are higher than the bad wage draw minus the reallocation costs.

A persistent positive wage draw in preceding periods (positive income shock) would allow the household to accumulate wealth, thereby covering the migration costs to an international destination where the expected wage draws are higher than at the origin.

*Prediction 2: Cumulative positive wage draws in preceding periods will increase international migration.*

International migration often involves more risk and higher economic expenses than relocating domestically within a country. When local labor markets can successfully absorb workers from an affected sector, reliance on international migration as a risk coping mechanism may be less likely. Nonetheless, if expected wages in the non-agricultural sector are

not sufficiently large, because of weak labor markets (i.e. low wages and/or high unemployment rates), or barriers to reallocate across sectors, reliance on international migration may increase.

*Prediction 3: Barriers in local labor markets at origin increase international migration.*

The existence of migrant networks have an ambiguous effect on the decision to migrate in response to a negative economic shock. On one hand, a robust network in an international destination can reduce the costs associated with migration, facilitating the process. On the other hand, a well-established network may also increase access to remittances, which can alleviate liquidity constraints. This in turn could diminish the necessity to rely on distress migration.

*Prediction 4: Networks at destination have an ambiguous effect on the decision to migrate in response to a negative economic shock.*

Empirically, we will estimate a model to test the effect of both contemporaneous and repeated exposure to extreme temperatures on the decision to migrate internationally, while also examining heterogeneous effects based on access to non-agricultural labor markets and migration networks.

# 3 Data

Our empirical analysis draws on several data sources to study the effects of extreme temperatures on agricultural production, labor markets, and migration. Figure A2 in the Online Appendix provides an overview of our three main data sources, the fieldwork calendar, and key outcomes. Detailed descriptions of these sources are available in Appendix A2.

Data on agricultural production come from the Multiple Purpose National Agricultural Survey (ENAMP), a survey representative at the provincial level for corn producers,

conducted by the Ministry of Agriculture from 2013 to 2018. Our sample includes 19,325 agricultural producers during our period of study. This cross-sectional survey provides detailed information on crop yields, land size, agricultural inputs, and self-reported prices.

Our analysis focuses on corn production, for several reasons. First, corn is the main staple crop in El Salvador (see Figure A3), which is produced by 83 to 90 percent of the surveyed sample and serves as a primary source of caloric intake (Nawrotzki, 2015; WB, 2018). Second, it is a short-cycle crop for which temperature impacts can be traced back in the same period. Third, other papers have found a significant association between temperature shocks and corn production.[5]

Corn production in El Salvador has three growing seasons: *primera* (June-July), *postrera* (August-September), and *apante* (November-December). Our estimates measure the effect of extreme temperature during *primera* as it is the main growing season as illustrated in Figure A4.

Labor and migration outcomes are measured using the Multiple Purpose Household Survey (EHPM), a yearly nationally representative cross-sectional survey from El Salvador's official statistics agency, covering 207,249 households from 2009 to 2018. This survey includes data on household members' sociodemographic characteristics, employment, income, and migration status. Labor outcomes for the working-age population (10-65 years) include employment, hourly wages, weekly hours worked, and monthly wages. Our primary outcome variable, likelihood of migration, is a dummy equal to 1 when at least one household member migrated abroad in the surveyed year. We multiply the dummy by 100 to ease the interpretation of the coefficients.

Temperature data come from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature, a data grid of one km resolution that features eight-

[5] Deschênes and Greenstone (2007), Schlenker and Roberts (2009), Schlenker and Lobell (2010), Feng et al. (2010), Roberts and Schlenker (2011), Ortiz-Bobea et al. (2019), and Burke and Emerick (2016).

day temperature averages for 2000–2018. We aggregate the grid to the municipal level with a weighted mean using the area covered. Our primary measure of extreme temperatures is the number of weeks during the main growing season in which the temperature was 2 SD above its historic mean during that same week.[6] To create our measure of extreme temperature we follow the following steps: first, we estimate historical means and standard deviations for temperature for the main growing period between 2000 and 2003; second, we standardize the temperature for each municipality by comparing it to these historic means and standard deviations; and, third we define extreme temperature as being 2 SD above the mean (McKee et al., 1993). Our variable of interest is the number of weeks with extreme temperatures during the main growing season (8 weeks from June to July).[7]

Temperature is our main variable of interest because it is a stronger predictor of crop yields than rainfall (Lobell and Burke, 2008; Burke and Emerick, 2016; Ortiz-Bobea et al., 2019; Ortiz-Bobea et al., 2021; Colmer, 2021). Extreme temperatures are more difficult to manage than low rainfall because the latter is storable and can be replaced by groundwater resources (Colmer, 2021); average temperature has increased over the years while rainfall is more erratic (Ortiz-Bobea et al., 2021); and rainfall is more likely to have greater measurement error than temperature (Burke and Emerick, 2016). In fact, recent studies find that temperature has a stronger effect on staple crops than precipitation does (Schlenker and Lobell, 2010; Nawrotzki, 2015; Carleton and Hsiang, 2016; Jessoe et al., 2016; Aragón et al., 2021).

Figure 2 displays the spatial and temporal distribution of our extreme temperature measure. Two main observations can be made. First, extreme temperatures vary widely across municipalities. In 2015, for example, some southeastern municipalities experienced five weeks of extreme temperatures, whereas some northwestern municipalities experienced

[6]For easier interpretation we will refer to a week to the eight-day period.

[7]Section A2.3 provides a detailed description of the extreme temperature definition. In section 4.6 we test our results using alternative definitions and thresholds to define extreme temperatures.

zero weeks. Second, there is also prolonged exposure to extreme temperatures in specific municipalities. This repeated exposure to extreme temperatures, alongside the theoretical rationale for distinguishing in our model between contemporaneous and lagged exposure, underscores the necessity of treating these measures separately. A potential concern is the correlation level between the two measures, which could introduce multicollinearity into the model, thereby limiting the potential of identifying the separate effects. However, the correlation coefficient of 0.216 between the measures is modest. We discuss the interpretation of the contemporaneous and lagged effects further in section 4.

We control for numerous baseline and time-variant characteristics at the municipality level. In section A2.4 in the Appendix we explain in detail each variable serving as a control in the different models (Table A1 shows the controls used for each specification). Tables A2 and A3 present descriptive statistics for the variables employed in our study. Almost 0.8 percent of households had at least one member who migrated abroad the year before the survey. The percentage of employed individuals among working age population was 51 percent. On average, these individuals worked 41 hours a week and had an hourly wage of 2.3 dollars.[8] Twenty four percent of employed individuals worked in the agricultural sector and 14 percent worked in the agricultural sector producing corn.

# 4 Empirical Strategy and Results

## 4.1 Agricultural Production

We start by estimating the effect of extreme temperatures on agricultural production. Our empirical model exploits both temporal and spatial variations in extreme temperature during corn-growing seasons between 2009 and 2018 in El Salvador.

To estimate the effect of extreme temperatures on agricultural production, we use data

[8]The sample to calculate the hourly wage is lower compared to the sample used to calculate the weekly hours worked since we exclude individuals who reported an hourly wage of zero.

from the ENAMP available between 2013 and 2018. Specifically, we estimate the effect of extreme temperature on agricultural outcomes for corn and other seasonal crops:

$$log(y_{ijt}) = \alpha + \delta_1 T_{jt} + \delta_2 \sum_{k=t-4}^{k=t-1} T_{jk} + X'_{ijt}\gamma + \\ \beta Z_{jt} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{ijt} \tag{1}$$

Where $T_{jt}$ represents the number of weeks of extreme temperature during the main growing season of year $t$ and municipality $j$, and $\sum_{k=t-4}^{k=t-1} T_{jk}$ is the total number of weeks with extreme temperatures during the main growing season of the previous four years. Including the latter term follows the conceptual framework from section 2 and facilitates comparing the models that estimate the impact on agricultural production, labor markets, and migration, ensuring consistency. Additionally, it ensures that $\hat{\delta}_1$ does not capture the effects of extreme temperature from previous seasons.

Recall that the agricultural survey collects information during the last quarter of the year. Therefore, a household interviewed during the survey year $t$ reports its production for the last growing and harvest season in year $t$. In our model, $y_{ijt}$ represents the agricultural outcome for producer $i$ in municipality $j$ in year $t$ during the agricultural growing season.

Our main specification controls for time-variant household characteristics ($X'_{ijt}$) such as household head's education, number of household members, and access to irrigation for corn. We also include a vector with time-variant controls at the municipality level ($Z'_{jt-1}$). Given that temperature might be highly correlated with other climatic variables, we follow previous literature (Jessoe et al., 2016; Auffhammer, 2018; Ortiz-Bobea et al., 2019; Colmer, 2021) and include in this vector measures of extreme rainfall and droughts, defined as the number of months with rainfall levels 2 SD below or above its historic mean (2003-2006)

during the main growing season.[9]

Finally, we include interactions between socioeconomic variables measured at baseline (2005 and 2007) and linear time trends ($W'_{j2005}$) that control for any pre-trend at the municipality level that could bias the results.[10] Our model's validity relies on the assumption that, conditional on the previous controls, there were no unobserved time-varying differences within municipalities correlated with extreme temperature. All the models are estimated using double-clustered standard errors by municipality and year. It is meaningful to note that, since we measure the effect of extreme temperature rather than the effect of climate change, our results should be interpreted as short-term effects rather than long-term adjustments by agricultural producers.

Table 1 reports the results of estimating equation (1) with the full set of controls. The dependent variables are: the logarithm of corn production (panel A), the logarithm of corn yield per hectare calculated with the total land plot size (panel B) and with total land cultivated in corn (panel C), the logarithm of the Total Factor Productivity (TFP) (panel D), and labor productivity (panel E). Column 1 shows the effect of the contemporaneous measure of extreme temperature without controlling for extreme temperature in previous years, and column 2 adds those controls. Both the magnitude of the coefficients and their significance do not change across specifications, which is consistent with the fact that our identification strategy captures within-season, short-term temperature effects.

The results show consistently negative effects of extreme temperature on all outcomes other than labor productivity. Focusing on column 2, we find that one week with extreme temperature during the main growing season decreases corn production by 4.1 percent (panel A). Yield per hectare falls between six percent (panel B) and 5.1 percent (panel C), and TFP

[9]The results are robust to including these controls. They are also robust to controlling for the level of soil moisture and extreme soil moisture during main growing season (Ortiz-Bobea et al., 2019). Soil moisture information comes from FLDAS dataset (Famine Early Warning Systems Network Land Data Assimilation System) from NASA. It is measured in $m^3/m^3$ units within 0-100 centimeters underground.

[10]See Appendix A2 for a detailed explanation of the variables included in these controls

drops by 4.5 percent (panel D) for each week with extreme temperature during the main growing season. Panel E shows no significant effects on labor productivity, which suggests a drop in demand for agricultural workers. In Table A4, we add controls across columns to test the robustness of the model. Reassuringly, the results are robust to adding the full set of controls. The lagged effects have a negative but not significant impact on agricultural production outcomes, further reassuring that contemporaneous extreme temperatures are the main drivers of economic shocks to agricultural farmers.

Overall, we find robust evidence that extreme temperatures reduce corn production in El Salvador, which may prompt farmers to respond by adjusting the intensive use of inputs such as land and workers. We investigate these responses in the next section.

## 4.2 Input Adjustments

We now examine how agricultural producers adjust their use of production inputs in the short run. Given that we measure responses in the short-term, the margin for adjustment is limited. Two key features influence these adjustments. First, when exposed to extreme temperatures during the growing season, most production inputs are fixed as decisions have already been made. Hence, the margin for adjustment is limited. Second, agricultural producers with restricted or no access to financial markets employ other strategies to offset income losses and smooth consumption. One such strategy is to lay off hired workers and substitute them with household workers, thereby protecting the agricultural producer's household income. Consequently, the negative impact of extreme temperatures may transmit to labor markets, affecting workers in both agricultural and non-agricultural sectors (Jayachandran, 2006; Colmer, 2021).

We begin by examining how agricultural producers adjust their use of production inputs in the short run. Since these adjustments occur during the growing season, we estimate the contemporaneous effect of exposure to extreme temperature at time $t$ on the use of production

inputs following model (1). We estimate the effect of extreme temperature on a principal component index (PCI) based on four types of inputs (column 1), as well as on each input separately (columns 2-6). Additionally, we estimate the effect on the logarithm of the total cultivated area and the logarithm of the cultivated area dedicated to corn production.[11]

Table 2 reports these estimates. Column 1 shows the effect on the PCI and columns 2 to 6 show the effects on the likelihood of employing each input. Extreme temperature has a negative impact on the use of input materials across most categories, driven mostly by post-harvest chemicals (used for crop protection). This finding contrasts with existing literature. For instance, Jagnani et al. (2020) observed an increase in pesticide use and weeding labor due to a rise in pests from higher temperatures, while fertilizer use declined because of financial constraints faced by farmers. The difference in our results may partly be attributed to two main factors. First, farmers may be reducing their overall investment in inputs to finance migration after a poor growing season. Second, Jagnani et al. (2020) identified extreme temperatures early in the growing season, while our analysis spans the entire season, limiting the farmers' ability to adjust. This is particularly evident as the main reduction comes from chemical agents employed after harvest.

The results in columns 7 and 8 suggest an increase in land use, but the effect is not significantly different from zero. Although the inclusion of cumulative exposure to extreme temperature in previous seasons does not influence the significance and magnitude of the contemporaneous event, it is interesting to find a significant effect of the cumulative exposure on the use of land, column 6.[12] An additional week of exposure to extreme temperatures during the previous four growing seasons increases land use by 1.5 percent. Aragón et al. (2021) explain that if the increase in land use comes at the expense of planting fallow land, this response could have persistent effects in the medium term and long term. While we do

[11]The sample size corresponds to households that produced corn during the main growing season without missing values in inputs or land use (16,983 out of 19,325).

[12]While the coefficient's sign indicates an increase in land use, we find no evidence of short-term diversification in the production of other staple crops.

not test the effect on the use of fallow land directly, the negative coefficient of the cumulative exposure in Panel B of Table 1 are consistent with their hypothesis.

### 4.3 Labor Markets

We next study how agricultural producers adjust their labor demand when facing extreme temperatures. We start by estimating equation (1) for the number of workers allocated to agricultural production. Since some households only have either household or hired workers, we have households with zeros in one of these categories. To avoid dropping zeros, we use the Poisson fixed effects model. Columns 1 and 2 in Table 3 show the effect on the total number of workers, columns 3 and 4 on non-household workers, and columns 5 and 6 on household workers.

Extreme temperatures decrease the total number of workers in corn-producing households, and this effect is driven by non-household workers. We find that one week with extreme temperature during the main growing season decreases the number of total workers by 1.4 percent and the number of non-household workers by 2.6 percent.[13] As expected, the coefficient estimate for household workers is positive but it is not statistically significant. At face value, the results suggest a substitution of household workers for non-household workers. These results, with the effects on agricultural production, imply that income is negatively affected and households adjust to the shock by reducing their demand for non-household workers.[14]

When analyzing the effect of extreme temperatures at the extensive margin (Table A5), we find that an additional week with extreme temperatures increases the likelihood of having a household worker by 0.89 percentage points (pp), and reduces the likelihood of having a

[13] These percentages are calculated as $e^{\beta}$

[14] We also estimate this model using the inverse hyperbolic sine transformation, and the number of workers with no transformation. Although the estimates lose significance without transforming the dependent variable, the signs of the effects are consistent with those presented using the preferred Poison estimator, and the Inverse Hyperbolic Sine transformation.

non-household worker by 0.22 pp, however this effect is not statistically significant. These results are consistent with the effect shown on the number of workers hired on the farm in Table 3.

Table 3 reports negative and significant effects of lagged extreme temperatures on hired agricultural workers, indicating that agricultural units are adjusting their labor demand. Similarly, Table 2 shows negative but not significant effects on other agricultural inputs, suggesting that agricultural units may be reducing their capacity to invest in inputs with increased exposure to extreme temperatures.

To provide a comprehensive understanding of the impact on labor outcomes, we estimate the effect of extreme temperature on employment shares and hourly wages by sector at the municipality level. These models are estimated using individual-level data from the EHPM (2009-2018), aggregated at the municipality-year level.[15] Table 4 shows the average share of the working-age population that is employed in different sectors across municipalities. On average, half of the population age 10 to 65 is employed, 15 percent is employed in the agricultural sector, and 35 percent work in non-agricultural sectors.[16]

The analysis at the municipality level helps eliminate potential selection bias, as changes in the composition of workers remaining in El Salvador could skew estimates on labor market outcomes at the individual level. By focusing on the municipality level, our estimations capture the overall effect on the number of individuals working in the municipality, including those who migrate out and those who stay but exit the labor force. Specifically,

[15]We estimate similar models at the individual level, and the results are qualitatively the same. Section A3 in the Appendix includes a detailed analysis of the individual-level estimations.

[16]These statistics are similar to the ones reported by the ILO (2021) for El Salvador, which reported an employment share of 57.4% for 2018.

we estimate the following model:[17]

$$l_{jts} = \alpha + \delta_1 T_{jt} + \delta_2 \sum_{k=t-4}^{k=t-1} T_{jk} + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{jts}. \quad (2)$$

where $l_{jts}$ represents the employment share of municipality $j$ in year $t$ and sector $s$ (agricultural and non-agricultural), using the same controls as in equation (1).[18]

The odd-numbered columns of Table 4 show the results without controlling for cumulative exposure to extreme temperatures in previous seasons, while the even-numbered columns include this control.[19] Overall, we find that including this control does not affect the magnitude or significance of the contemporary exposure to extreme temperatures, consistent with previous model results. Focusing on our preferred specification in the even-numbered columns in Panel A, we find a significant negative effect on the employment share in the agricultural sector. An additional week of extreme temperatures during the growing season reduces the employment share in the agricultural sector by 1.79 percent relative to the baseline mean, with a larger effect observed in the corn sector (2.74 percent). The results in column 10 suggest an increase in the employment share of the non-agricultural sector, although these effects are not statistically significant. Nevertheless, the magnitude of the positive effect in the non-agricultural sector is smaller compared to the negative effect found in the agricultural sector. This indicates that, even if the effect is positive, it is not substantial enough to conclude that the non-agricultural sector can absorb all the displaced labor supply from the agricultural sector in the short term. Instead, the results suggest that the drop in the agricultural employment share is accompanied by a decrease in the overall employment share (column 2).[20]

[17] For the EHPM, we have data from 2009–2018, but the earliest year in the ENAMP is 2013. We estimate the labor and migration models for 2013–2018, and the results are robust for this sample.

[18] Employment Share in Sector $s$ and municipality $j$=$\frac{\#Workers_{sj}}{WorkingAgePop_j}$.

[19] The sample size changes across columns because some municipalities do not have observations for some sectors. The results are robust when estimating all the models for a balanced sample of municipalities.

[20] We estimate the effects in the non-agricultural sector by specific industries, and the null results persist

When interpreting both contemporaneous and lagged extreme temperatures together, it appears that both negatively impact the likelihood of being employed and the resulting wages in the agricultural sector. This suggests a contraction in demand, with repeated exposure to temperature shocks reinforcing this adjustment. There is no evidence that a contraction in labor supply offsets this negative wage effect.

Barriers to absorbing agricultural workers into the non-agricultural sector could explain these patterns, as discussed in Section 4.5. An alternative explanation might be the broader impact of extreme temperatures on the country's economy. Sarsons (2015) highlights that weather shocks can have widespread effects on an economy. If income losses in the agricultural sector are substantial, these negative shocks can affect the national income, leading to a reduction in labor demand across industries and labor reallocation across economic sectors. Although our results are reduced-form and do not perfectly disentangle the effects of overall economic decline from sector-specific barriers, the findings in Table 4 suggest that sector-specific barriers are the primary mechanism. We find no evidence of negative impacts or significant wage effects in the non-agricultural sector. The effects on non-agricultural wages are not only insignificant but also economically small.

To understand, if the effects on shares are coming from the numerator or the denominator, we estimate the effect of extreme temperature on the number of working age individuals in municipality $j$ and year $t$. Table A7 shows these effects. In columns 1 to 4, the dependent variable is the logarithm of the number of working-age individuals in the municipality, defined as ages 10 to 65 (columns 1 and 2) and ages 18 to 65 (columns 3 and 4). In columns 5 and 6, the dependent variable is the migration rate, estimated as the ratio between the number of international migrants at time $t$ and the working-age population aged 10 to 65.[21] The results show no evidence of an effect of extreme temperature on the total number of

across all sectors. Results not shown for sake of brevity.

[21]The number of migrants in year $t$ is based on households reporting a migrant for that year. Since we cannot determine the exact number of migrants per year, we assume only one migrant per household, which conservatively estimates the migration rate at the municipality level.

working-age individuals or overall migration rates at the municipality level. This indicates that the effects on employment shares are not driven by population changes or by entire households migrating out of El Salvador. Additionally, it reinforces our main finding that extreme temperatures influence the decision to migrate internationally only among a specific segment of the population: agricultural workers who grow weather-dependent crops.

Panel B of Table 4 shows the effect on average hourly wages. According to Jayachandran (2006), the effect on wages depends on the availability of risk-management mechanisms. Without access to financial markets or the ability to save or borrow, wage effects may intensify. The results in columns 5 to 8 in Panel B support this hypothesis. The results show negative and significant effects on the wages of agricultural corn-producers.

Overall, the findings in this section suggest that declines in corn production are felt in agricultural labor markets. Corn producers reduce their demand for hired workers and use household workers instead. Laid-off agricultural workers can potentially switch to other agricultural activities or to the non-agricultural sector, but we find no evidence of this in El Salvador. The transmission of the effect of temperature spikes into labor markets might be the consequence of incomplete financial markets to manage risk and low levels of integration between local labor markets. We provide suggestive evidence about these mechanisms in the next sections.

## 4.4 International Migration

Without access to risk-management mechanisms or a non-agricultural sector that can absorb displaced workers, international migration could become a key response to the income loss caused by extreme temperature when financially feasible. We explore this hypothesis by estimating the effect of extreme temperature in $t-1$ on the probability of international

migration in time $t$, using data from the EHPM with the following regression model:

$$m_{ijt} = \alpha + \delta_1 T_{jt-1} + \delta_2 \sum_{k=t-5}^{k=t-2} T_{jk} + X'_{ijt}\gamma + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{ijt} \quad (3)$$

where $m_{ijt}$ is a dummy variable equal to 1 if a member of household $i$ living in municipality $j$ in year $t$ migrated from El Salvador in year $t$, and equal to zero otherwise.[22] The variable $T_{jt-1}$ and the controls are the same as those in the previous models. It is critical to note that in this specification, extreme temperatures are lagged by one period. This design choice reflects the realistic constraints associated with international migration. Migrating internationally involves significant costs and complexities, making it unlikely for individuals to respond instantaneously to such shocks. The decision to migrate typically requires substantial planning and resources, which naturally delays the response time. By lagging the measure of extreme temperature, we account for the realistic lag in human decision-making and logistical execution, aligning our model more closely with the observed behaviors in migration dynamics.

Results with the fully controlled models are shown in Table 5.[23] We estimate this model using household-level information from 2009–2018 EHPM for all households (panel A), all agricultural households (panel B), agricultural households that cultivate seasonal crops including corn (panel C), agricultural households that cultivate corn (panel D), and non-agricultural households (panel E). We categorize households based on the occupation of the household head and the occupation of working-age members. A household is considered agricultural if the household head and at least 50 percent of the working-age members work in this sector. A potential concern is that the occupation of household members might be endogenous. In Appendix Table A9, we classify households based on alternative specifications. Method (1) is our preferred specification; Method (2) only considers the occupation

[22] In the empirical regressions, we multiply the dummy variable by 100 to ease the interpretation.
[23] In Table A8, we test the robustness of our results by including one set of controls at a time.

of the household head, and Methods (3) and (4) only consider other working-age members as a criterion to classify them in each panel. The results on the probability of migration are robust overall to the different classifications.

A negative effect on agricultural production is one mechanism through which high temperatures can affect migration decisions. If this is the main mechanism in El Salvador, we would expect to see a larger response to these shocks among agricultural households, especially producers of corn or other seasonal crops sensitive to extreme weather. The results in Table 5 indicate significant effects of extreme temperatures on the probability of migration for agricultural households working with seasonal crops, particularly corn (Panel D).[24] This result is expected, as seasonal crops are more sensitive to extreme temperature changes. Corn producers, who represent 88.7 percent of agricultural seasonal households, are likely driving this effect.[25] Not only are the effects statistically significant for this sample, but the magnitude of the coefficient is almost 10 times larger than that for all households. The coefficient for non-agricultural households is not only insignificant but also has a sign opposite to that of agricultural households.

The results in our preferred specification with the full set of controls for agricultural households that grow corn (column (2), panel D) show that one additional week with extreme temperature at time $t-1$ increases the probability of international migration by 0.18 pp, or 27.6 percent relative to the mean.[26] To put this magnitude in context, Mueller et al. (2020) finds that a 1 SD increase in precipitation caused a decline in migration of 10 and 11 percent in Kenya and Botswana, while causing an increase in migration as large as 24 percent in Zambia. For Central America, Baez et al. (2017) finds that 1 SD deviation in heat exposure doubles and quadruples the probability of young unskilled women to migrate to

[24] We estimate these effects for agricultural households producing non-seasonal crops. These non-seasonal households do not show any significant or positive effect on the probability of migration.

[25] The effect on other seasonal crops is also negative, although not significantly different from zero.

[26] Consistent with our results in the main specification, we find a significant positive effect of the interaction of the extreme temperature in t-1 with the dummy indicating if the observation is a seasonal or corn agricultural household (Table A10).

the provincial and national capital, respectively. Mueller et al. (2014) finds that exposure to extreme temperatures implies that male are 11 times more likely to move out of the village in Pakistan. Jessoe et al. (2016) estimates that increases in extreme temperature induces a 1.4 percent increase in migration from rural to urban areas and 0.25 percent in migration to the United States.

Similar to Kleemans (2023), our findings indicate that households increase the probability of migration in response to extreme temperatures during the previous growing season. However, the negative coefficient of the cumulative effect from previous seasons suggests that migration may also rise as an investment decision following one or more positive income shocks. To better understand the lagged and contemporaneous effects of extreme temperatures, Table A11 presents a model that interacts these two metrics. The results in this table support the investment interpretation from the conceptual framework. Specifically, the non-significant lagged cumulative coefficient in Panel A suggests that when households experience favorable temperatures, they may decide not to invest in technology to mitigate future production shocks, or they may lack the knowledge to prepare for these shocks. Additionally, the interaction between contemporaneous and lagged metrics, though small, is positive and significant. This indicates that repeated exposure to extreme temperatures might help corn producers prepare for contemporaneous shocks. However, the small magnitude of this interaction suggests it is not sufficient to significantly reduce the impact of the contemporaneous shock. Thus, households exposed to favorable temperatures might accumulate wealth for migration rather than invest in local production. As previously noted, our data does not distinguish between permanent and temporary migration. Future research should investigate whether the duration of migration varies when it serves as a risk-management response (the contemporaneous effect) versus an investment response (the lagged cumulative effect).

The results from Table A11 are also methodologically relevant. The robustness of the contemporaneous (or $t-1$ for migration) exposure to extreme temperatures, even when

including the interaction term, and the small or non-significant magnitude of the interaction, reassure us that we can separate between the cumulative and contemporaneous effects of extreme temperature when both are included in the empirical model.

Two forces are at play in El Salvador that could potentially explain the significant migration response from agricultural households. First, a push factor: El Salvador's apparent limited labor market capacity to absorb unemployment aligns with the large migration results, indicating that migration is an alternative adaptive measure. Second, a pull factor: the long history of migration to the U.S. has established migrant networks that can reduce migration costs.

Given the patterns of migration in El Salvador and the fact that we measure migration based on reports from households that remain, it is reasonable to believe that temporary migration constitutes a substantial portion of our results.[27] In the next section, we provide suggestive evidence highlighting the role of local labor markets and migrant networks in explaining our findings.

## 4.5 The Role of Migrant Networks and Local Labor Markets

We propose that two key characteristics of El Salvador contribute to the significant international migration response to income loss due to extreme temperatures. First, there is limited labor mobility from the agricultural sector to the non-agricultural sector for displaced workers. Second, an established migration corridor between the U.S. and El Salvador reduces the costs associated with international migration. This raises an important question: is the combination of limited reallocation opportunities between sectors and the presence of a substantial emigrant destination contribute to generate weather-induced migration? Although we cannot empirically distinguish the relative influence of these two factors, this section explores the role each plays in explaining the migratory response to the U.S. when extreme

[27] Approximately 66% of Salvadorian migrants in the U.S. aim to stay permanently, according to a survey of recent immigrants (Abuelafia et al., 2019).

temperatures occur.

### 4.5.1 Migrant Networks

We begin by investigating the role of migrant networks in the decision to migrate. Access to remittances and migrant networks can help households mitigate negative income shocks, thereby reducing their need to resort to more costly mitigation mechanisms such as distress migration. Simultaneously, these networks may lower migration costs by funding the relocation process, potentially *increasing* the likelihood of migration. The impact of these variables on migration is particularly relevant for countries with large migrant networks in destination countries. In the case of El Salvador, personal remittances constitute 23.7 percent of the GDP (WB, 2024), playing a crucial role in supporting family members who remain in the country.

We estimate two complementary models. First, we begin by disaggregating the migration analysis by the number of migrants in the family to test whether migrant networks render a response through migration more feasible. We estimate equation (3) interacting our measure of exposure to extreme temperature with the number of additional migrants reported in the household (Table A12). The results suggest that the magnitude of the effect on migration from extreme temperatures in agricultural households is higher as households have more migrants, or networks abroad.[28]

Second, we estimate differential effects of exposure to extreme temperature on agricultural production, labor outcomes, and migration by access to remitances and migrants' networks. To do this we construct: (i) the share of the population with access to remittances in 2007, according to the population Census, and (ii) the share of the migrant population, estimated as the number of migrants per municipality in 2007 over the total population in the municipality in 2007, using Census data. We then classify municipalities into quartiles based

[28] See section A4 for a more detailed explanation of the empirical model.

on these measures and interact the extreme temperature variable with dummy variables representing the second to fourth quartiles (municipalities in the bottom quartile are the omitted category). We employ the municipal shares in 2007 rather than individual outcomes to assuage endogeneity concerns. However, potential issues may still arise, as municipalities with varying levels of access to migrants and remittances might differ in unobserved ways that correlate with the outcomes of interest. Although we include a comprehensive set of municipality-level controls and municipality-fixed effects, unobserved time-variant characteristics of the municipalities could still be related to both the dependent and main explanatory variables. Households and municipalities with more access to remittances are likely different from others along many dimensions. Thus, the results in this section should be interpreted as associations rather than causal relationships.

Table 6 shows the results. The results in panel A suggest that access to migrant networks or remittances does not shield farmers from the effects of extreme temperatures. Farmers are probably not using these to protect themselves *ex ante* through insurance. This is consistent with a review of the literature discussed in Huckstep and Clemens (2023). These results also support the exogeneity assumption of our measure of extreme temperature. In this context, it is important to investigate whether farmers decide not to invest in weather-resistant seeds, appropriate fertilizer, and irrigation systems due to liquidity constraints or lack of information.

Panel B suggests that more access to remittances is associated with a lower response in the labor market. The results show that the reduction in the employment share is driven by municipalities with lower access to remittances. In these municipalities, households might need to resort more to labor markets to cope with the income shocks caused by extreme temperatures. Importantly, although the sign of the interaction is the same when looking at the interactions with the share of migrants (column 2), the effects are not significantly different from zero.

Finally, although the effects in Panel C are noisily estimated, the sign of the interaction coefficients suggests that municipalities with greater access to remittances and migrant networks exhibit a higher probability of migration. However, the absence of significant differences among the quartiles may be attributed to the two opposing effects that access to remittances can have on migratory decisions.

### 4.5.2 Local Labor Markets

In addition to the evidence presented in the previous section, certain characteristics of labor markets in El Salvador may create obstacles to reallocating workers between economic sectors. These barriers help explain why displaced agricultural workers might struggle to transition to the non-agricultural sector, marking a significant difference from the findings of Colmer (2021). Caria et al. (2024) reviews empirical evidence on labor markets in low and lower-middle-income countries, highlighting barriers to reallocation in urban labor markets. Key findings emphasize the role of information frictions, search costs, social networks, and recruitment costs.

El Salvador likely faces similar barriers for workers in urban settings. Additionally, the high levels of violence experienced in the country since the 1980s impose further challenges for reallocating workers into urban labor markets. This context is particularly relevant when comparing El Salvador with the Indian context studied by Colmer (2021). Colmer (2021) estimates the economic effects of temperature shocks in India and uses firm-level data to provide evidence of reallocation of agricultural workers in the manufacturing sector. The author suggest that this reallocation occurs in small and informal firms that absorb agricultural workers as casual workers. In El Salvador, this might not be the case due to territorial control of gangs. During our period of study, gangs were present in all large cities and imposed mobility limitations, extortion and violent crimes on firms and individuals within and outside of their territory (Melnikov et al., 2020). The widespread presence of gangs implied that citizens were not able to fully avoid contact with the gangs unless they

were willing to move to a remote part of the country (Melnikov et al., 2020). Our data corroborates this pattern since the level of homicides per capita is negatively correlated with the percentage of workers employed in the agricultural sector, which is a proxy of lower levels of urbanization (Figure A6). We hypothesize that gangs impose friction in the labor markets, particularly in the urban sector. This may partially explain why agricultural workers in El Salvador were not absorbed by labor markets in urban areas and why agricultural producers might opt to migrate internationally instead of internally. Although we cannot perfectly test this hypothesis, we estimated the main specification predicting international migration by including interactions between our measure of extreme temperatures and the homicide rate in 2008 (Table A13).[29] While the interaction coefficient is not significant, it does have the expected sign: as the homicide rate in the municipality of origin increases, the response to extreme temperatures through international migration becomes more pronounced.

This discussion is crucial, as high levels of violence are prevalent not only in El Salvador but also throughout the Latin American region. Latin America and the Caribbean has the highest rate of homicide worldwide, as well as the highest prevalence of homicidal violence due to organized crime (UNODC, 2023). In 2018, while the rate of victims of intentional homicide per 100,000 population in Latin America was 23.2, and even more concerning, 53.3 in El Salvador, in India this rate was only 3.0 (UNODC, 2024). Consequently, the presence of organized crime as a push factor plausibly extends to other Latin American contexts.

An additional potential barrier to reallocation is explained by the lack of integrated markets. We use road networks as a proxy for integration into other markets. Access to the non-agricultural sector may alleviate the negative effect on labor markets. We estimate the effects on labor markets, leveraging data on the national road network of El Salvador. We classify municipalities based on the distribution of the road network and interact our measure of extreme temperature with a dummy representing each quartile of the distribution, being

[29] We also estimate this model using the homicide rate in $t-1$, and the results remain consistent.

the bottom quartile the omitted category. It is important to highlight that municipalities with a better road network are different along many other dimensions, so these results should not be given a causal interpretation.

We hypothesize that a more integrated local labor market would facilitate reallocation into the non-agricultural sector, decreasing the effect of extreme temperatures on labor outcomes. The results support this hypothesis. The effects on the employment share in the agricultural sector are stronger for the least integrated municipalities (bottom quartile in the distribution of roads' network) (Table A14). In this context, it is crucial to comprehend integration of local labor markets and sectoral reallocation. These findings highlight the need for further research on these subjects.[30]

## 4.6 Robustness Checks

### 4.6.1 Definition of Extreme Temperature

We test our definition of extreme temperatures by varying the seasons within a year when the extreme temperatures are measured, as shown in Table A15, and by adjusting the cut-off definitions for extreme temperatures, as presented in Table A16. First, Table A15 estimates the results based on the number of weeks with extreme temperatures during the main growing season (our primary specification), throughout the year, during the *apante* season (November and December), and the lean season (August-September). As expected, significant effects are observed only with extreme temperatures during the main growing season. Additionally, this table shows that the results are robust across two periods: (i) for 2013–2018, aligning with the agricultural survey period; and (ii) excluding 2015, the year of the most intense drought. The coefficient estimates remain robust across different periods and consistent across all specifications.[31]

[30] See section A4.3 for further details of this model.

[31] For all results, it is important to note that Figure A5 suggests an underestimation of migration rates due to the migration of entire households.

Second, Table A16 tests the cut-off and definition of what constitutes a week with extreme temperatures. Columns 1 and 2 define the shock as the number of weeks during winter with temperatures higher than 1 and 1.5 standard deviations above the mean, respectively. Columns 3 and 4 define extreme temperature as weeks with temperatures above 29 and 35 degrees Celsius, respectively. Column 5 defines extreme temperature using Harmful Degree Weeks (HDW), where every 1-degree Celsius increase in the average temperature above 32 degrees Celsius corresponds to a one-unit increase in HDWs. Overall, the results are robust across these different measures.

Additionally, we conduct a placebo test to measure the likelihood of obtaining our estimates by chance. To do this, we randomly assign temperature levels to each municipality/week observation 1,000 times and reestimate the regression models using these alternative measures. We plot the kernel density of the estimated $\delta$s from each iteration in Figure A7 for the probability of migration, and in Figure A8 for agricultural production. Our baseline coefficients from Tables 1 and 5 are indicated by the red vertical lines. These analyses suggest that the estimated effects we find are very unlikely to be due to chance.

### 4.6.2 Standard Errors

We check the robustness of our results when estimating the standard errors to account for both spatial correlation and multiple hypothesis testing. Columns (2) to (4) of Table A17 in the Appendix present the results for all of the main outcomes using Conley standard errors to account for spatial correlation. We use different distance cutoffs (25Km, 50KM, 100KM) to account for different ranges of spatial correlation between observations. Using Conley standard errors does not change the significance of our results in corn production (Panel A). The results of employment share do not change significance with cutoffs of 25KM and 50KM and gain significance with a cutoff of 100 KM (Panel B). The results of migration likelihood still evidence statistical significance but at a lower level (Panel C). Columns (5) and (6) present the results of our main outcomes using Family Wise Error Rate (FWER)

adjusted p-values to control for the probability of Type I error in the estimations. While in Column (5) we use the Bonferroni method, considered as the most conservative, Column (6) presents the Holm method, which is considered a more powerful modification of the Bonferroni estimation. The FWER correction does not change the significance of our results in corn production and migration likelihood. Moreover, our results on employment share gain significance using these methods. Altogether, these estimations evidence the robustness of our results by adjusting for spatial correlation and multiple hypothesis testing.

#### 4.6.3 Controlling for Violence

In addition to natural disasters and extreme weather events, high levels of violence have historically been an additional push factor behind migration from El Salvador (Stanley, 1987; Halliday, 2006; Yang, 2008; Clemens, 2021), and recent evidence shows weather shocks may intensify violence (Dell et al., 2014; Carleton and Hsiang, 2016). To control for this, in Table A18 we estimate our main specification for all the main outcomes adding a variable of homicides per 1000 inhabitants by municipality in $t$ or $t-1$, depending on the timing of extreme temperature. While the effect of extreme temperature is robust for all our main outcomes, we do not find a significant effect of the homicide rates.

Since gangs are the main perpetrators of violence and operate mainly in urban areas (Melnikov et al., 2020), we also estimate the effect of extreme temperature and homicide rates among different groups of households, differentiating by urban and rural areas (Table A19). The effect of extreme temperature on migration among agricultural households that produce seasonal crops and corn are robust when including homicides per 1000 inhabitants by municipality in $t-1$. Consistent with the evidence that violence is mainly in urban areas due to the presence of gangs, the probability of migration increases with homicide rates for households living in urban areas, and particularly, non agricultural households.

# 5 Conclusions

We examine the response of corn producers to extreme temperatures in El Salvador. Our results show that exposure to extreme temperatures during the main growing season reduces the agricultural production of seasonal crops, particularly corn. In response, farmers adjust by cutting labor demand for hired workers. In a context like El Salvador, where barriers to reallocate to the non-agricultural sector exist and there are established migrant networks in the U.S., international migration becomes a crucial response to the income losses generated by extreme temperatures. Additionally, we find that international migration serves as an investment decision when farmers are exposed to repeated positive income shocks.

We find no evidence of displaced agricultural workers reallocating to the non-agricultural sector. Factors contributing to this may include inadequate market integration and unfavorable labor conditions due to high levels of criminal violence. Identifying the conditions in local labor markets that facilitate cross-sector reallocation to mitigate income losses from extreme weather is an important area for future research.

Our results also highlight the role of migrant networks and remittances. In municipalities with greater access to migrant networks and remittances, we observe a smaller adjustment through labor markets. However, access to remittances and networks does not differentially affect the probability of migration, indicating the dual role of remittances: easing the liquidity constraint to fund migration and mitigating the need to rely on decreasing labor demand of agricultural workers to offset income losses.

Policies should address both types of migration. To prevent distress migration where agricultural production is still feasible, policies should promote access to insurance and financial markets to address the negative income effects and extend irrigation and technical assistance to help rural households adjust their agricultural practices to a changing climate (e.g., resistant seeds). Humanitarian aid, which is rarely offered in response to extreme weather events (Baez et al., 2017; Mueller et al., 2014), should be available as well.

Policies should additionally aim to facilitate migration when seen as an investment strategy that can provide a pathway out of poverty. Credit market access and other mechanisms to fund migration costs are some examples of this (Bryan et al., 2014; Kleemans, 2023). Although there is growing evidence of the impact of insurance mechanisms on the welfare and productivity of small rural farmers,[32] we still lack proof of how these mechanisms influence migration responses. Our paper makes important contributions on these regards by showing that access to remittances might alleviate the need to rely on reducing the labor demand of non-household workers. In this context it makes sense to think about policies designed to reduce transaction fees and provide adequate infrastructure of formal channels to send remittances (WB, 2023).

[32] See, e.g., Carter and Lybbert (2012).

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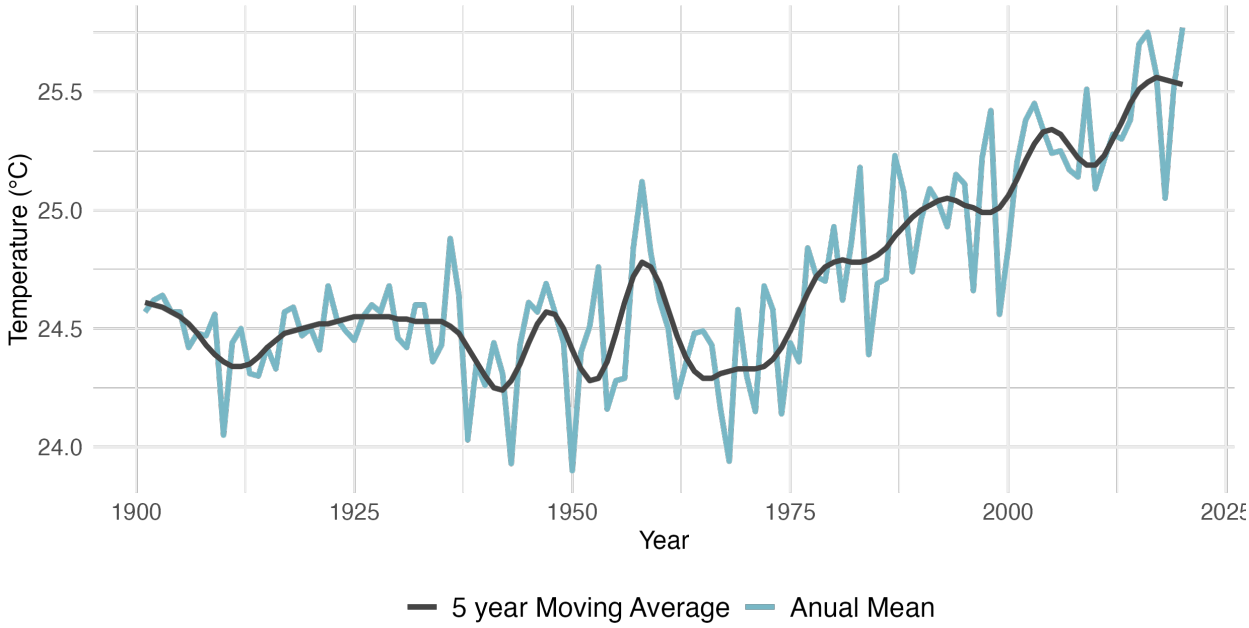
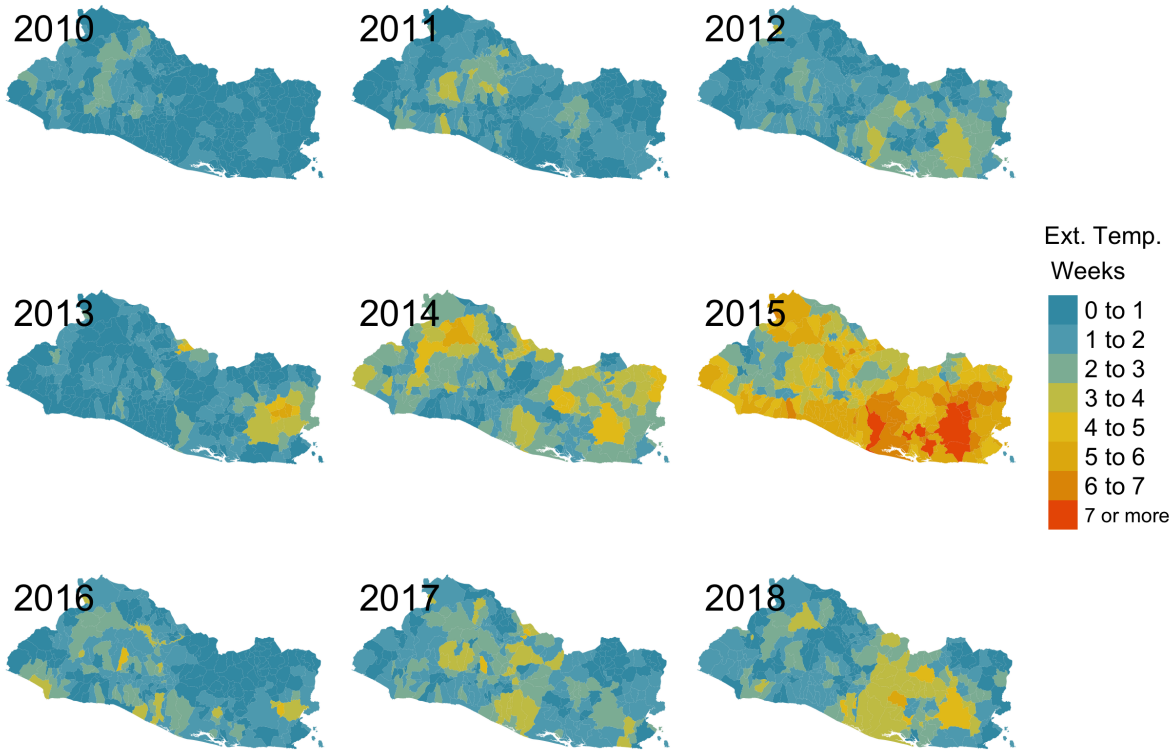
# 6 Figures

**Figure 1:** Average Temperature in El Salvador




Source: World Bank (2022). Data from Climatic Research Unit (CRU) of the University of East Anglia.

**Figure 2:** Extreme Temperatures at the Municipality and Year Level




Source: Own elaboration based on NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. Each map represents the number of weeks with an extreme temperature (two SD above the historic mean) during the main growing season.

# 7 Main Tables

**Table 1:** Impact of Extreme Temperatures on Corn Agricultural Outcomes

| | (1) | (2) |
|---|---|---|
| *Panel A: Log(Corn Production)* | | |
| Extreme Temperature$_t$ | −0.040*** | −0.041*** |
| | (0.012) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.001 |
| | | (0.006) |
| Mean | 1.915 | 1.915 |
| Observations | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.238 | 0.238 |
| *Panel B: Log(Production of Corn per Ha.)* | | |
| Extreme Temperature$_t$ | −0.053*** | −0.060*** |
| | (0.017) | (0.015) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.015 |
| | | (0.010) |
| Mean | 2.339 | 2.339 |
| Observations | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.271 | 0.272 |
| *Panel C: Log(Production of Corn per Ha. Cultivated in Corn)* | | |
| Extreme Temperature$_t$ | −0.046*** | −0.051*** |
| | (0.011) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.010 |
| | | (0.010) |
| Mean | 2.781 | 2.781 |
| Observations | 18,680 | 18,680 |
| Adjusted $R^2$ | 0.449 | 0.449 |
| *Panel D: TFP(Log Production)* | | |
| Extreme Temperature$_t$ | −0.044*** | −0.045*** |
| | (0.011) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.002 |
| | | (0.008) |
| Mean | -0.000 | -0.000 |
| Observations | 16,548 | 16,548 |
| Adjusted $R^2$ | 0.291 | 0.291 |
| *Panel E: Log(Labor Productivity)* | | |
| Extreme Temperature$_t$ | −0.019 | −0.018 |
| | (0.014) | (0.015) |
| Extreme Temperature$_{t-1}^{t-4}$ | | 0.001 |
| | | (0.007) |
| Mean | 0.447 | 0.447 |
| Observations | 18,847 | 18,847 |
| Adjusted $R^2$ | 0.173 | 0.173 |
| **Controls** | | |
| Extreme Rainfall$_t$ | x | x |
| Household | x | x |
| Municipal Socio*Year | x | x |
| Geographic*Year | x | x |
| Year and Municipal Fixed Effects | x | x |

Notes: We use data from El Salvador's Agricultural Household Survey (ENAMP) for corn-producing households from 2013–2018. Each panel has a different dependent variable: Panel A uses the logarithm of corn production from the main harvest season; Panel B, the logarithm of corn production per hectare from the main harvest season; Panel C, the logarithm of corn-specific production per hectare from the main harvest season; Panel D, the Total Factor Productivity (TFP) of corn calculated as the logarithm of corn production from the main harvest season using area, labor, and inputs; Panel E, the logarithm of corn production per worker from the main harvest season. The independent variable Extreme Temperature$_t$ is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season in the same year. The independent variable Extreme Temperature$_{t-1}^{t-4}$ is the sum of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season from year t-1 to t-4. Extreme Rainfall controls are the number of weeks with heavy rainfall shocks (2 SD higher than that week's historic value in that municipality during the main growing season) and drought shocks (2 SD lower than that week's historic value in that municipality) in the same year. Household controls are household head's education, number of household members, and access to irrigation for corn. Municipal socioeconomic controls at baseline correspond to poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal migrants and emigrants, and percentage of population under 18 and 18–60 years old, all from 2005 and interacted with year trends. Geographic controls correspond to the municipality' elevation and geographic extension, interacted with year trends. All regressions have municipality and year fixed effects. The means shown in the table correspond to the variables without transformations like logarithms. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table 2:** Impact of Extreme Temperatures on the Inputs to Corn Production

| | Input | | | | | | Land | |
|---|---|---|---|---|---|---|---|---|
| | PCI | Planting Material | Fertilizer | Pesticide Fungicide | Post Harvest Chemical Agents | Agro-Ecological | Log(Total Area) | Log(Corn Area) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Extreme Temperature$_t$ | −0.026*** | −0.061 | 0.020 | −0.270* | −2.266*** | 0.011 | 0.015 | 0.006 |
| | (0.009) | (0.048) | (0.071) | (0.142) | (0.830) | (0.238) | (0.016) | (0.009) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.011 | 0.027 | −0.051 | −0.034 | −1.171 | −0.057 | 0.010 | 0.006 |
| | (0.013) | (0.044) | (0.051) | (0.096) | (1.088) | (0.210) | (0.007) | (0.006) |
| Mean | 0.147 | 99.623 | 99.576 | 99.323 | 92.916 | 1.896 | 1.420 | 0.711 |
| Observations | 16,983 | 16,983 | 16,983 | 16,983 | 16,983 | 16,983 | 16,983 | 16,983 |
| Adjusted $R^2$ | 0.056 | 0.012 | 0.009 | 0.028 | 0.097 | 0.045 | 0.168 | 0.186 |
| **Controls** | | | | | | | | |
| Extreme Rainfall$_t$ | x | x | x | x | x | x | x | x |
| Household | x | x | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x | x |
| Year and Municipal Fixed Effects | x | x | x | x | x | x | x | x |

Notes: We use data from El Salvador's Agricultural Household Survey (ENAMP) for corn-producing households from 2013–2018. Each column has a different dependent variable. Columns 1 to 6 correspond to agricultural inputs: In Column 1 the dependent variable is an input index estimated with principal components analysis of the four input categories: planting material, agro-chemicals (including fertilizer and pesticide fungicide), post-harvest chemical agents, and agro-ecological inputs; Columns 2 to 6 are the likelihood (0-100) to employ each input. Column 2 corresponds to planting material such as seeds and plants; Column 3 and 4 correspond to agro-chemicals employed during the growing season: Column 3 to fertilizers and Column 4 to fungicides, bactericides, pesticides, and insecticides; Column 5 corresponds to chemical agents such as post-harvest product protection agents; and Column 6 corresponds to agro-ecological inputs such as compost, fertilizer, bioinsecticides, biopesticides, and biofungicides. Columns 7 and 8 correspond to land use: In Column 7 is the logarithm of the total cultivated area and in Column 8 is the logarithm of the cultivated area dedicated to corn production. The means shown in the table correspond to the variables without transformations like logarithms. The sample size corresponds to households that produced corn during the main growing season without missing values in inputs or land use (16,983 out of 19,325). Regressions have the same controls and independent variables as Table 1. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table 3:** Impact of Extreme Temperatures on Number of Agricultural Workers

| | Total Workers | | Non Household Workers | | Household Workers | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Extreme Temperature$_t$ | −0.009** | −0.014*** | −0.017*** | −0.026*** | 0.001 | 0.005 |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.007) | (0.007) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.010*** | | −0.019*** | | 0.008 |
| | | (0.003) | | (0.004) | | (0.006) |
| Mean workers | 5.407 | 5.407 | 3.700 | 3.700 | 1.707 | 1.707 |
| Observations | 18,908 | 18,908 | 18,908 | 18,908 | 18,908 | 18,908 |
| Log Likelihood | −58,754.330 | −58,749.100 | −63,972.560 | −63,959.000 | −29,656.300 | −29,655.240 |
| **Controls** | | | | | | |
| Extreme Rainfall$_t$ | x | x | x | x | x | x |
| Household | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Year and Municipal Fixed Effects | x | x | x | x | x | x |

Notes: We use data from El Salvador's Agricultural Household Survey (ENAMP) for corn-producing households from 2013–2018. Columns 1 and 2 correspond to the dependent variable of total workers in the corn-producing households. Columns 3 and 4 correspond to non-household workers, or hired workers. Columns 5 and 6 correspond household workers, or non hired workers. Estimations were done employing Poisson fixed effects within municipality and year. Regressions have the same controls and independent variables as in Table 1. The number of observations falls from 19,325 to 18,908 because of missing values in the variable of total workers. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table 4:** Impact of Extreme Temperatures on Municipal Labor Outcomes

| | **Employed** | | **Agricultural** | | **Agricultural (Seasonal)** | | **Agricultural (Corn)** | | **Non Agricultural** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Panel A: Employment Share* | | | | | | | | | | |
| Extreme Temperature$_t$ | −0.063 | −0.114 | −0.227* | −0.268** | −0.183 | −0.205* | −0.222** | −0.246** | 0.164 | 0.153 |
| | (0.145) | (0.149) | (0.131) | (0.133) | (0.114) | (0.116) | (0.111) | (0.113) | (0.145) | (0.150) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.145 | | −0.116 | | −0.065 | | −0.070 | | −0.029 |
| | | (0.097) | | (0.088) | | (0.073) | | (0.071) | | (0.100) |
| Mean | 50.083 | 50.083 | 14.957 | 14.957 | 9.749 | 9.749 | 8.981 | 8.981 | 35.127 | 35.127 |
| Observations | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.387 | 0.387 | 0.724 | 0.724 | 0.708 | 0.708 | 0.724 | 0.724 | 0.767 | 0.767 |
| *Panel B: Sectoral Wages per hour (log)* | | | | | | | | | | |
| Extreme Temperature$_t$ | 0.001 | −0.003 | 0.010 | 0.002 | −0.034* | −0.041* | −0.059*** | −0.061*** | −0.001 | −0.004 |
| | (0.010) | (0.010) | (0.017) | (0.017) | (0.021) | (0.021) | (0.022) | (0.023) | (0.010) | (0.010) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.010* | | −0.022* | | −0.019 | | −0.005 | | −0.009 |
| | | (0.005) | | (0.011) | | (0.015) | | (0.015) | | (0.006) |
| Mean | 2.161 | 2.161 | 0.961 | 0.961 | 0.945 | 0.945 | 0.927 | 0.927 | 2.399 | 2.399 |
| Observations | 2,239 | 2,239 | 2,073 | 2,073 | 1,857 | 1,857 | 1,782 | 1,782 | 2,237 | 2,237 |
| Adjusted $R^2$ | 0.342 | 0.343 | 0.389 | 0.390 | 0.499 | 0.499 | 0.541 | 0.540 | 0.273 | 0.273 |
| **Controls** | | | | | | | | | | |
| Extreme Rainfall$_t$ | x | x | x | x | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x | x | x | x |
| Year and Municipal Fixed Effects | x | x | x | x | x | x | x | x | x | x |

Notes: We use municipal-level data of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old from 2009–2018. The dependent variable of Panel A is the share of the working-age population employed per sector (multiplied by 100). In Panel B is the average wage per sector (in logs) defined as the last salary or wage received converted to salary per hour worked. Columns 1 and 2 show the overall share of employed people over the working-age population in Panel A, and the average wage per hour in logarithms in Panel B. Columns 3 and 4 display the share of employed people in the agricultural sector over the working-age population in Panel A, and the average wage per hour in the agricultural sector in Panel B. Columns 5 and 6 correspond to those employed in the agriculture of seasonal crops, including cereals, corn, rice, beans, seeds, and tubers, over the working-age population in Panel A, and the average wage per hour in this specific agricultural sector in Panel B. Columns 7 and 8 present data for those employed in the agriculture of corn over the working-age population in Panel A, and the average wage per hour in the corn agriculture sector in Panel B. Columns 9 and 10 correspond to those employed in any sector other than agriculture over the working-age population in Panel A, and the average wage per hour in these non-agricultural sectors in Panel B. The independent variable Extreme Temperature$_t$ is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season in the same year. The independent variable Extreme Temperature$_{t-1}^{t-4}$ is the sum of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season from year t-1 to t-4. The means correspond to the mean of the dependent variable. Controls are at the municipal level. Rainfall, municipal, and geographical controls are the same as in Table 1. The number of observations varies due to municipalities lacking wage information on certain sectors. Standard errors are robust to heteroskedasticity and are adjusted by sample size. *p<0.1; **p<0.05; ***p<0.01

**Table 5:** Impact of Extreme Temperatures on Migration

| | (1) | (2) |
|---|---|---|
| *Panel A: All Households* | | |
| Extreme Temperature$_{t-1}$ | 0.020 | 0.009 |
| | (0.031) | (0.034) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.030* |
| | | (0.016) |
| Mean | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.005 | 0.005 |
| *Panel B: Agricultural Households (all)* | | |
| Extreme Temperature$_{t-1}$ | 0.111*** | 0.096*** |
| | (0.019) | (0.018) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.057* |
| | | (0.031) |
| Mean | 0.743 | 0.743 |
| Observations | 23,960 | 23,960 |
| Adjusted $R^2$ | 0.004 | 0.004 |
| *Panel C: Agricultural Households (seasonal)* | | |
| Extreme Temperature$_{t-1}$ | 0.190*** | 0.159*** |
| | (0.040) | (0.028) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.120*** |
| | | (0.033) |
| Mean | 0.620 | 0.620 |
| Observations | 15,173 | 15,173 |
| Adjusted $R^2$ | 0.002 | 0.002 |
| *Panel D: Agricultural Households (corn)* | | |
| Extreme Temperature$_{t-1}$ | 0.213*** | 0.180*** |
| | (0.030) | (0.012) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.125*** |
| | | (0.036) |
| Mean | 0.654 | 0.654 |
| Observations | 13,454 | 13,454 |
| Adjusted $R^2$ | 0.0005 | 0.001 |
| *Panel E: Non Agricultural Households* | | |
| Extreme Temperature$_{t-1}$ | −0.014 | −0.017 |
| | (0.028) | (0.031) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.009 |
| | | (0.020) |
| Mean | 0.611 | 0.611 |
| Observations | 118,070 | 118,070 |
| Adjusted $R^2$ | 0.003 | 0.003 |
| **Controls** | | |
| Extreme Rainfall$_{t-1}$ | x | x |
| Household | x | x |
| Municipal Socio*Year | x | x |
| Geographic*Year | x | x |
| Year and Municipal Fixed Effects | x | x |

Notes: We use household-level data of El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable Extreme Temperature$_{t-1}$ is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season in the year before the survey. The independent variable Extreme Temperature$_{t-2}^{t-5}$ is the sum of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season from year t-2 to t-5. Panel A corresponds to all households. Panel B corresponds to agricultural households, defined if the household head and at least 50 percent of the members of working age are employed in agriculture. Panel C corresponds to seasonal agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing seasonal crops including cereals, corn, rice, beans, seeds, and tubers. Panel D corresponds to corn agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing corn. Panel E corresponds to non agricultural households defined if the household head or at least 50 percent of the members of working age are employed in a non-agricultural sector. Extreme Rainfall controls are the number of weeks with heavy rainfall shocks (2 SD higher than that week's historic value in that municipality during the main growing season) and drought shocks (2 SD lower than that week's historic value in that municipality) in the year before the survey. Household controls are the household head's gender and age, and the number of household's members. Municipal socioeconomic controls and geographic controls are the same as in Table 1. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table 6:** Heterogeneity by Access to Risk-Management Mechanisms: Labor and Migration Outcomes

| | Remittances (per capita %) (1) | Migrant (share %) (2) |
|---|---|---|
| *Panel A: Log(Corn Production)* | | |
| Extreme Temperature$_t$ | −0.051* | −0.032 |
| | (0.028) | (0.025) |
| Extreme Temperature$_t \times Q2$ | 0.024 | −0.007 |
| | (0.029) | (0.025) |
| Extreme Temperature$_t \times Q3$ | 0.007 | −0.011 |
| | (0.030) | (0.022) |
| Extreme Temperature$_t \times Q4$ | −0.001 | −0.018 |
| | (0.038) | (0.034) |
| Extreme Temperatures$_{t-1}^{t-4}$ | −0.001 | −0.001 |
| | (0.005) | (0.005) |
| Mean | 1.915 | 1.915 |
| Observations | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.238 | 0.238 |
| *Panel B: Employment Share of Agricultural Sector (Corn)* | | |
| Extreme Temperature$_t$ | −0.497*** | −0.443* |
| | (0.164) | (0.248) |
| Extreme Temperature$_t \times Q2$ | 0.255* | −0.004 |
| | (0.143) | (0.314) |
| Extreme Temperature$_t \times Q3$ | 0.374** | 0.362 |
| | (0.154) | (0.276) |
| Extreme Temperature$_t \times Q4$ | 0.290 | 0.293 |
| | (0.230) | (0.262) |
| Extreme Temperatures$_{t-1}^{t-4}$ | −0.080 | −0.080 |
| | (0.066) | (0.067) |
| Mean | 8.981 | 8.981 |
| Observations | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.724 | 0.725 |
| *Panel C: Migration likelihood in Agricultural Households (Corn)* | | |
| Extreme Temperature$_{t-1}$ | 0.024 | 0.040 |
| | (0.180) | (0.133) |
| Extreme Temperature$_{t-1} \times Q2$ | 0.244 | 0.086 |
| | (0.199) | (0.101) |
| Extreme Temperature$_{t-1} \times Q3$ | 0.321 | 0.169*** |
| | (0.198) | (0.056) |
| Extreme Temperature$_{t-1} \times Q4$ | 0.0003 | 0.207 |
| | (0.198) | (0.243) |
| Extreme Temperatures$_{t-2}^{t-5}$ | −0.113* | −0.127*** |
| | (0.062) | (0.045) |
| Mean | 0.654 | 0.654 |
| Observations | 13,454 | 13,454 |
| Adjusted $R^2$ | 0.001 | 0.001 |
| **Controls** | | |
| Extreme Rainfall$_{t \text{ or } t-1}$ | x | x |
| Household* | x | x |
| Municipal Socio*Year | x | x |
| Geographic*Year | x | x |
| Year and Municipality Fixed Effects | x | x |

Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main harvest season using ENAMP dataset. Panel B corresponds to the share of working age population working in corn agriculture, using EHPM dataset at the municipal level. Panel C corresponds to the likelihood of migration in corn agricultural households using the EHPM dataset at the household level. The independent variable across these panels is the interaction of Extreme Temperature with the municipality-level quartiles for each covariate. In Column 1, the covariate is the amount of remittances per capita per municipality, estimated using the 2005 Poverty Map of El Salvador. In Column 2, it is the share of migrants, also derived from the 2005 Poverty Map. Extreme Temperature is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season. Extreme Rainfall controls are the number of weeks with heavy rainfall shocks (2 SD higher than that week's historic value in that municipality during the main growing season) and drought shocks (2 SD lower than that week's historic value in that municipality). For Panel A and B, Extreme Rainfall controls are contemporaneous. For Panel C, Extreme Rainfall controls are lagged one year. Household controls are estimated for Panel A and C, but not Panel B as it corresponds to the municipality level. In Panel A (ENAMP), controls include household head's education, household size, and access to irrigation for corn. Panel C (EHPM) controls include household head's age and gender, and household size. Municipal socioeconomic controls and geographic controls are the same as in Table 1. Standard errors are robust in all panels and are clustered by municipality and year in Panel A and C. *p<0.1; **p<0.05; ***p<0.01

# Online Appendix

## A1 Background

### A1.1 Extreme Weather in El Salvador

The frequency of extreme weather events in El Salvador, particularly droughts and high temperatures, has intensified during recent decades with three extreme droughts in the last 10 years alone. In 2012, a severe and prolonged drought reduced coffee production by 70 percent. Between 2014 and 2015, more than 100,000 farmers suffered losses from another drought and the onset of *El Niño* (IFRC, 2016). In 2018, a new drought struck the country before it had recovered from the previous one. This led to a sharp loss of staple crops such as corn and to the declaration of a "red alert" by the government.[33]

Recurring droughts and extreme temperatures are driving incomes down while pushing food insecurity and migration up. This is particularly worrying for small countries like El Salvador, where one quarter of the labor force works in agriculture and most agricultural producers are small family farms dedicated to subsistence farming largely dependent on the rain cycle (WB, 2024; FAO, 2016).

### A1.2 Migration from El Salvador to the United States

Migration from El Salvador started in the 1980s due to the civil war and the migratory flows have persisted since then. Migrant networks have supported newly arrived families with financial assistance, shelter, and connections to labor markets. This aid has helped to attract new waves of migrants (Donato and Sisk, 2015; Clemens, 2021).[34] By 2021, 2.5 million Hispanics of Salvadorean origin lived in the United States—the third-largest group of Hispanic-origin immigrants in the country (**?**).

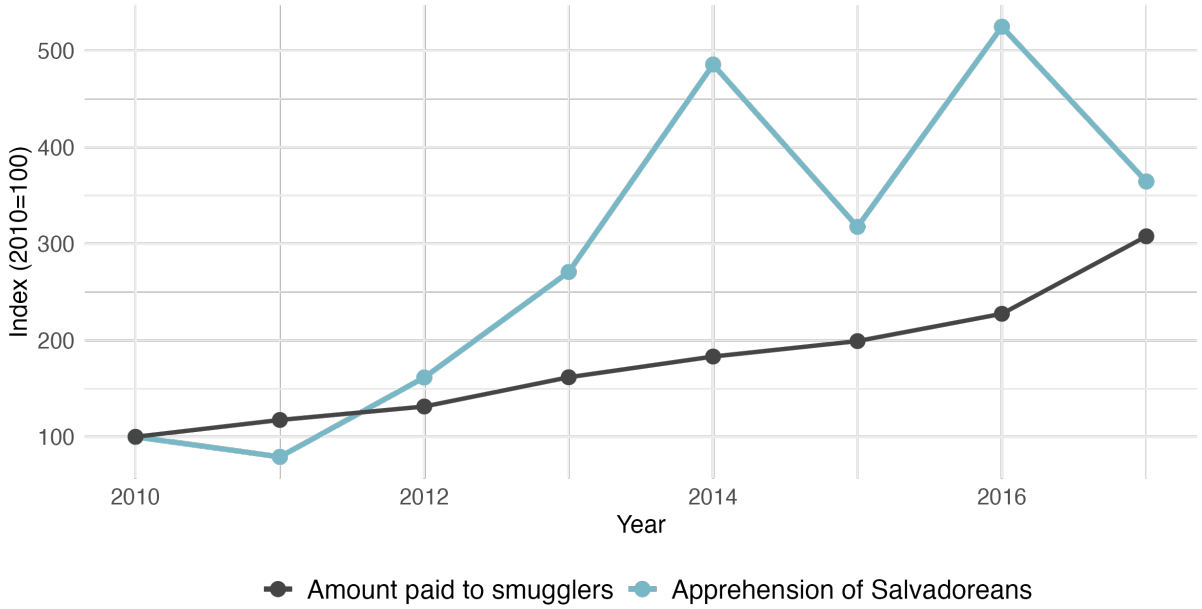
The costs of migration from Central America to the United States have risen significantly in the past decade.[35] Figure A1 depicts the rising costs of migrant smugglers and apprehensions at the border, illustrating that suppressive measures have not succeeded.

[33] https://www.reuters.com/article/us-el-salvador-drought/el-salvador-declares-emergency-to-ensure-food-supply-in-severe-drought-idUSKBN1KE338

[34] Clemens (2021) finds that past migration flows explain one-third of the current flows caused by violence.

[35] This article provides an example of the decision to migrate in spite of high migration costs: https://www.nytimes.com/interactive/2020/07/23/magazine/climate-migration.html retrieved on June 28, 2024.

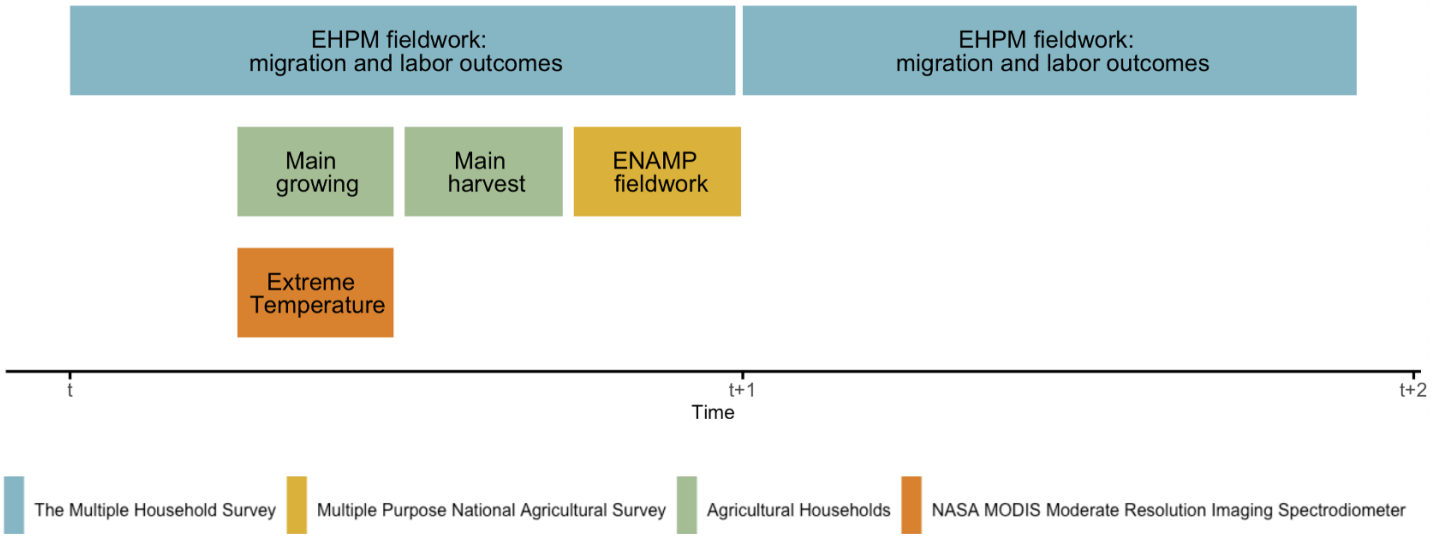
**Figure A1:** Border Apprehension of Salvadoreans and Cost of Smugglers




Notes: Own elaboration based on American Community Survey (ACS) and Customs and Border Protection (CBP). The figure shows the time series of an index (2010=100) on border apprehensions of Salvadorean and cost of smugglers. In 2010, the number of border apprehensions was 11,696 and the cost was USD 1,881

# A2 Data

**Figure A2:** Timeline of Data



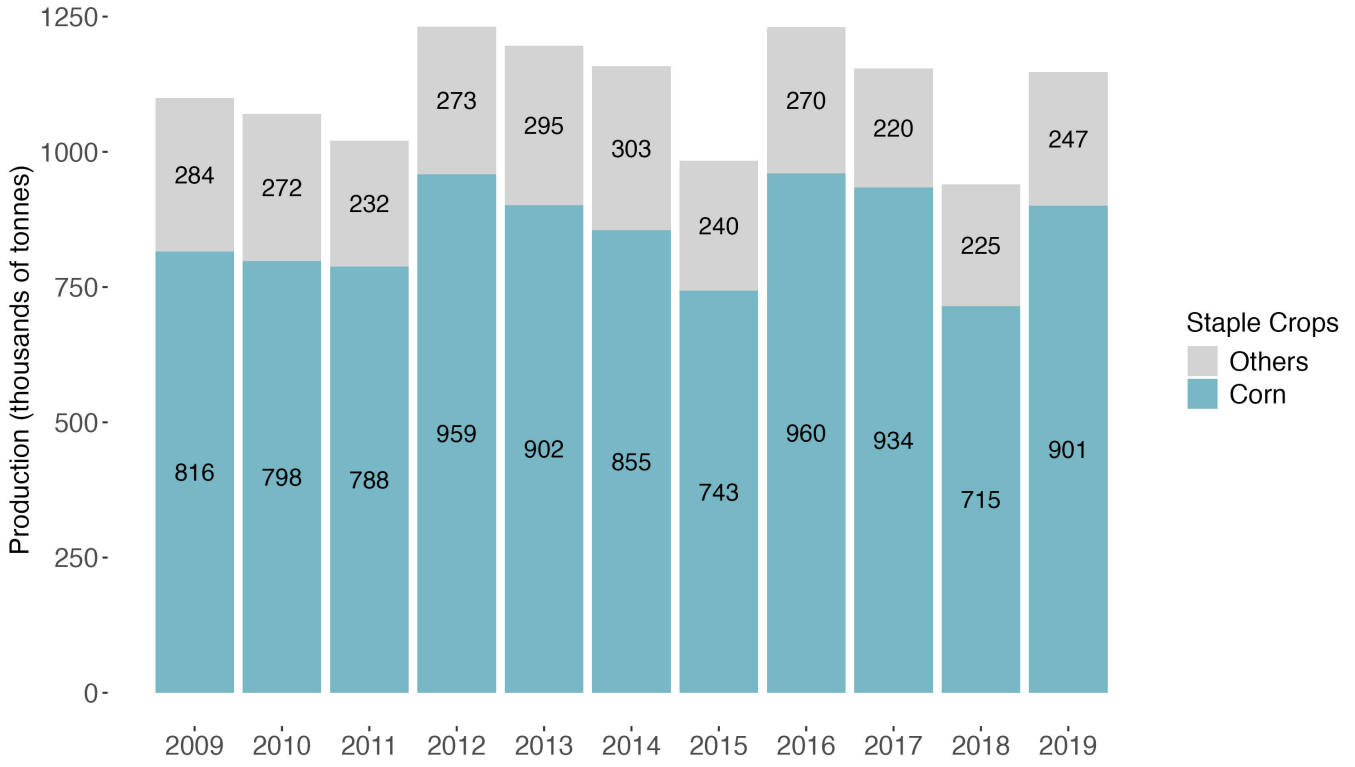

Notes: Own elaboration based on El Salvador's Multiple Purpose Household Survey (EHPM), El Salvador's Agricultural Household Survey (ENAMP) and NASA – Moderate Resolution Imaging Spectroradiometer (MODIS). The figure depicts that our main specification leverages extreme temperatures during the main growing season. We use three main sources of data: The Multiple Household Survey for migration and labor outcomes, which is collected throughout the whole year; the Multiple Purpose National Agricultural Survey for agricultural outcomes such as harvest production, use of inputs, land size, among others, and is collected the last quarter of the year (after main harvest); and NASA - Moderate Resolution Imaging Spectroradiometer (MODIS) for temperatures.

## A2.1 Agricultural Production

The Multiple Purpose National Agricultural Survey (ENAMP) is a survey representative at provincial level for grain crops such as corn. For the other items, is representative at national level. Within each of the 14 provinces in El Salvador, there was two-stage random selection process: first at cluster and then at individual level. Our sample includes 19,325 agricultural producers of corn. The total number of agricultural producers in El Salvador in 2007 was 395,588, according to the latest agricultural census "IV Censo Agropecuario".

We focus on corn production as it is the main staple crop in El Salvador as well as in the rest of Central America (Figure A3).

**Figure A3:** Production of Corn versus Other Staple Crops in El Salvador



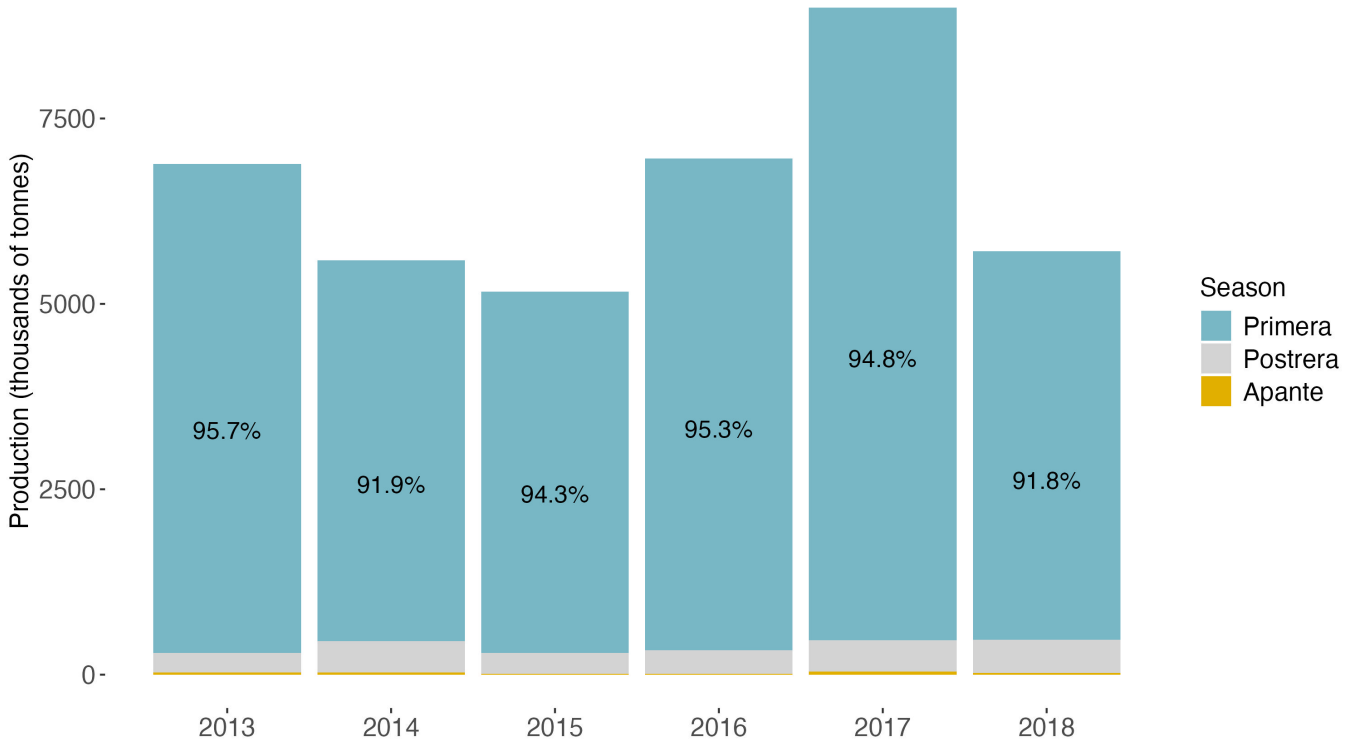

Notes: Own elaboration based on FAOSTAT. Staple crops include corn (maize), rice, sorghum, and beans. The numbers in black indicate the production of each category in thousands of tonnes.

Corn is a primary source of caloric intake for rural households and its production is widespread (Nawrotzki, 2015; WB, 2018). Across survey years, between 83 percent and 90 percent of the sample produces corn. An average agricultural producer has a yield per hectare of 2.3 tons, and a land plot of 1.5 hectares, of which 0.7 hectares are cultivated with corn. (See Tables A2 and A3). Access to irrigation—crucial for managing periods of drought and extreme temperatures—is practically nonexistent (0.4 percent). (Tables A2 and A3). In addition, other papers have found a significant association between temperature and corn production.[36]

The corn production calendar is as follows: *primera*, the main growing season (June and July), *postrera* (August and September), and *apante* (November and December). The survey is administered during the last quarter of the year once the harvest has occurred for the first two seasons, *primera* and *postrera*, as shown in Figure A2. At that time, respondents are asked to predict the third harvest of the year, *apante*. Figure A4 illustrates the yearly contributions of the three seasons for our period of analysis. Corn production occurs mostly in the main growing season, so our estimates measure the effect of extreme temperature during *primera*. In addition, we perform robustness tests using the other seasons (*postrera* and *apante*) and the lean season, when we would expect a weak effect or no effect of extreme weather on production.

[36]See Deschênes and Greenstone (2007), Schlenker and Roberts (2009), Schlenker and Lobell (2010), Feng et al. (2010), Roberts and Schlenker (2011), Ortiz-Bobea et al. (2019), and Burke and Emerick (2016). Most of these papers study the effects of weather shocks on crop-yield use data for developed countries that also produce corn.

**Figure A4:** Corn Production across Yearly Seasons in El Salvador




Notes: Own elaboration based on ENAMP 2013–2018. *Primera* corresponds to the main growing season (June-July). *Postrera* or lean season corresponds to August and September, and *apante* to November and December. The numbers in black represent the percentage of the total production or *primera* or the main growing season over the total yearly production of corn.

### A2.2 Labor Markets and Migration

To study labor outcomes and migration, we use the Multiple Purpose Household Survey (EHPM). The survey is representative at the national level and for 50 self-represented municipalities. Self-represented municipalities are the provincial capitals and other municipalities that are significantly relevant and distinctive within their providence due to their sociodemographic characteristics. Municipalities that are not self-represented are classified as co-represented. The latter indicates the group of municipalities that share similar sociodemographic characteristics within a province and are represented jointly.

Labor outcomes are constructed based on the labor module of the survey for the working-age population aged 10–65 years. Labor outcomes include employment, hourly wages, weekly hours, and monthly wages.[37] The module also enables us to identify an occupational sector for each working member of the household.

Migration outcomes are identified using the migration module, which collects information on household members who live abroad, their year of migration, and their destination country. To measure migration we use a question that asks: "Currently, is there any current or past member of this household that resides abroad?" followed by questions: "Since how long? (Register the most recent

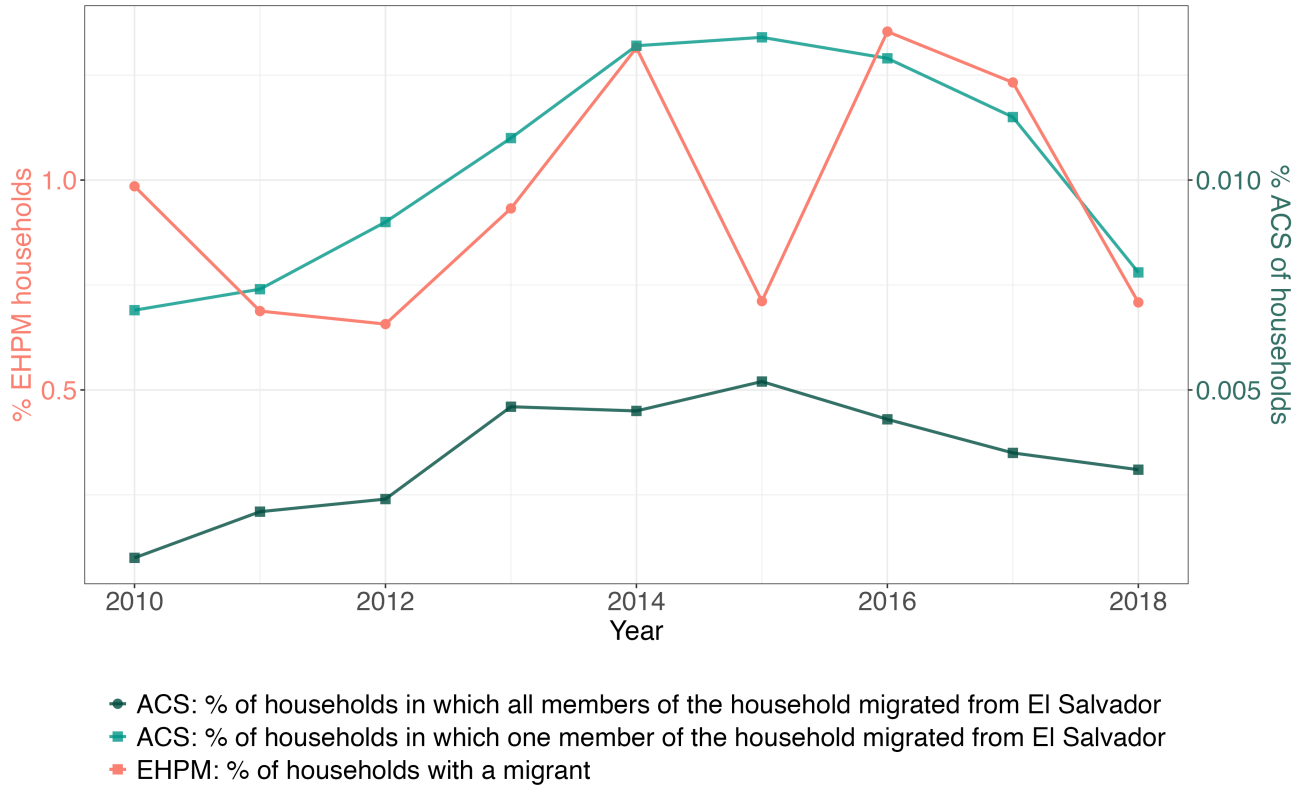
[37] Variables in Salvadorean Colons (SVC$) are deflated using the deflator of Banco Central de Reserva de El Salvador in https://www.bcr.gob.sv/bcrsite/?cdr=123.

one)" and "Country of residence". Therefore, even if the household reports more than one migrant, we don't have information about the year of migration of every member. We only have information of the last member(s) that migrated. In our period of interest, between 93 percent and 95 percent of household members living abroad resided in the United States. Our outcome variable is a dummy equal to one when at least one household member migrated abroad one year prior to the survey. Therefore, this analysis is conducted at the household level.

Ideally, we would measure migration using data on migrants rather than households with migrants. The latter may underestimate the number of migrants as, in some cases, all household members may migrate together, especially following intense temperature shocks. On the other hand, data collected in the United States regarding Salvadorean migrants may underreport undocumented ones (Halliday, 2006). To evaluate potential underreporting of entire-household migration, we compare migration trends from the EHPM and the American Community Survey (ACS).[38] Using the ACS, we calculate the percentage of households in the United States with at least one or all members who migrated from El Salvador the previous year. Figure A5 shows similar trends for both surveys for most years except for 2015. That year, the percentage of entire-household migration reported in the ACS spiked while in the EHPM, households reporting migrant members fell sharply. This suggests 2015 might have been a year when international migration was more common for entire Salvadorean households than for individuals. Reassuringly, our results are robust with and without the 2015 data.

[38]The ACS is a repeated cross-sectional dataset that covers a one percent random sample of the US population (Ruggles et al., 2017).

**Figure A5:** Migration Trends of Salvadoreans – EHPM and ACS




Notes: Own elaboration based on American Community Survey (ACS) and El Salvador's Multiple Purpose Household Survey (EHPM). The lighter green line indicates the percentage of households with a member who was living in El Salvador a year earlier, and the darker green line indicates the percentage of households in which all the members were living in El Salvador a year earlier. The red line indicates the percentage of households surveyed in El Salvador that have a member living outside the country who migrated in the same year.

### A2.3 Extreme Temperature

Temperature data come from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature, a data grid of one km resolution that features eight-day temperature averages for 2000–2018. Alternative sources to measure temperature are the daily MODIS and the ERA5. The MODIS at the weekly level is our preferred dataset for two main reasons: first, it is the dataset with the most disaggregated information (one km x one km grids). Second, it has temperature information for all the years and all the municipalities in our Household and Agricultural Surveys. In contrast, the MODIS data available on a daily basis contains missing values due to cloud coverage on each specific day, whereas ERA5 compiles information on a 30 km grid. We aggregate the grid to the municipal level with a weighted mean using the area covered.

Our primary measure of extreme temperatures is the number of weeks during the main growing season in which the temperature was 2 SD above its historic mean during that same week. To create our "Extreme Temperature" variable we follow the following steps: first, we estimate historic means and standard deviations for temperature for the main growing period between 2000 and 2003. Second, we standardize the temperature of municipality $j$, during week $w$ of year $y$ using the historic mean $\mu_{j,w,2001-06}$ and standard deviation $\sigma_{j,w,2000-03}$ of municipality $j$, during week $w$, between 2000 and

2003 (McKee et al., 1993; Marchiori et al., 2012):[39]

$$\frac{\text{Temperature}_{j,w,y} - \mu_{j,w,2001-2006}}{\sigma_{j,w,2001-2006}}$$

where $Temperature_{j,w,y}$ is the temperature of municipality $j$ and time $w$ (week) during the main growing season of year $y$. Third, we define "Extreme Temperature" as being 2 SD above the mean.[40]

$$\text{Extreme Temperature}_{j,w,y} = \mathbb{1}\left[\frac{\text{Temperature}_{j,w,y} - \mu_{j,w,2000-2003}}{\sigma_{j,w,2000-2003}} >= 2\right]$$

Using our main definition of extreme temperature, on average, there were 1.25 weeks out of 8 weeks during the main growing season of the year with temperatures 2 SD above the historic mean in the period 2010-2018.

### A2.4 Controls

Table A1 shows the controls used for each specification, including municipality controls, fixed effects, extreme rainfall, and household or individual controls when not in municipality regressions.

**Extreme Rainfall** $Z_{jt}$: Number of months of extreme rainfall during main growing season, estimated as 2 SD above and below the historic mean (2003-2006). Precipitation data were extracted from the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR), with a resolution of 0.25 degree with monthly periodicity and available from 2003.

**Baseline municipality controls** $\times$ **year** $W'_{j2005} * t$: It includes variables form the 2005 Poverty Map of El Salvador[41] and the 2007 Nacional Census[42]. From the 2005 Poverty Map of El Salvador we employ the following variables: poverty and extreme poverty rates, income per capita, percentage of households with no access to drinking water, percentage of people employed in agriculture, and percentage of young adults (16 and 18 years of age) who are not enrolled in school. From the 2007 census, we estimate the percentage of the population below 19 years of age, the percentage of the population above 60 years of age, population density, the number of internal migrants and emigrants[43], and the percentage of households with members living abroad. Lastly, we also include linear time trends interacted with the municipality's elevation calculated at the grid level and averaged for the municipality. This information is extracted from ASTER Global Digital Elevation Model NetCDF V003, NASA EOSDIS.

**Household controls** $X'_{ijt}$**:** Household controls vary by source of information and specification.

[39] This is similar to the method implemented by McKee et al. (1993) to estimate SPI (standardized precipitation index) and the definition of weather anomaly by Marchiori et al. (2012).

[40] McKee et al. (1993) uses this method to classify extreme droughts using the SPI.

[41] http://www.fisdl.gob.sv/temas-543/mapa-de-pobreza, retrieved in July 2019.

[42] https://onec.bcr.gob.sv/servers/redatam/htdocs/CPV2007S/index.html

[43] The number of internal migrants is estimated by the difference in birthplace and residence place

| Outcomes | Agricultural | Municipal Labor | Migration |
|---|---|---|---|
| Specification | (1) | (2) | (3) |
| Main data source | ENAMP | EHPM | EHPM |
| Extreme temperatures $T_{jk}$ | $t$ | $t$ | $t-1$ |
| Lagged temperatures $\sum_{k=t-4}^{k=t-1} T_{jk}$ | $t-1$ to $t-4$ | $t-1$ to $t-4$ | $t-2$ to $t-5$ |
| *Controls:* | | | |
| Extreme rainfall $Z_{jt}$ | $t$ | $t$ | $t-1$ |
| Baseline municipality controls $\times$ year $W'_{j2005} * t$ | Yes | Yes | Yes |
| Municipality and year fixed effects $\mu_j + \phi_t$ | Yes | Yes | Yes |
| Household controls $X'_{ijt}$ | Household head's education, number of household members, and irrigation for corn | | Household head's gender and age, and number of household's members |

**Table A1:** Controls employed for each specification

Household controls for agricultural outcomes are the household heads' education, number of household members and access to irrigation for corn. Household controls for migration outcomes are the household head's gender and age and number of household members. There are no household controls for outcomes at the municipality level.

Tables A2 and A3 present descriptive statistics for the variables employed in our study. Table A2 consists of three panels: Panel A provides individual-level labor outcome statistics from the EHPM survey, Panel B presents the migration outcome that is measured at the household level, and Panel C shows agricultural outcome statistics at the producer level from the ENAMP survey. Table A3 provides descriptive statistics of the control variables. Panel A shows household-level data from EHPM, and Panel B shows the aggregated data at the municipal level on weather shocks, geographical controls, and baseline socioeconomic characteristics.

**Table A2:** Descriptive Statistics: Outcome Variables

| Variable | N | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| *Panel A: EHPM Individual level* | | | | | |
| Employed | 639412 | 51.342 | 49.982 | 0.000 | 100.000 |
| Employed in agricultural sector | 328288 | 24.064 | 42.747 | 0.000 | 100.000 |
| Employed in agricultural sector (seasonal) | 328288 | 15.492 | 36.182 | 0.000 | 100.000 |
| Employed in agricultural sector (corn) | 328288 | 13.935 | 34.631 | 0.000 | 100.000 |
| Employed in the non agricultural sector | 328288 | 75.936 | 42.747 | 0.000 | 100.000 |
| Weekly hours worked | 328288 | 40.742 | 16.417 | 1.000 | 84.000 |
| Hourly wage ($SCV) | 265442 | 2.260 | 10.376 | 0.003 | 2072.144 |
| *Panel B: EHPM Household level* | | | | | |
| =100 if at least one migrant member last year | 207249 | 0.790 | 8.800 | 0.000 | 100.000 |
| *Panel C: ENAMP Agricultural unit level* | | | | | |
| Corn production (ton.) | 19325 | 1.900 | 1.900 | 0.001 | 59.000 |
| Corn - productivity (ton. per ha) | 19325 | 2.300 | 1.200 | 0.000 | 19.000 |
| Corn - productivity (ton. per ha cultivated in corn) | 18680 | 2.800 | 1.000 | 0.006 | 8.500 |
| TFP production | 16548 | -0.000 | 0.690 | -22.000 | 1.500 |
| Corn - productivity (ton. per worker) | 18847 | 0.450 | 0.410 | 0.000 | 9.700 |
| Total workers | 18908 | 5.400 | 7.300 | 0.000 | 494.000 |
| Hired workers | 18908 | 3.700 | 7.400 | 0.000 | 494.000 |
| Household workers | 18908 | 1.700 | 1.600 | 0.000 | 43.000 |
| PCA index of inputs | 17625 | 0.140 | 0.380 | -7.300 | 0.300 |
| Planting material (=100 if used) | 17625 | 1.000 | 0.065 | 0.000 | 1.000 |
| Agrochemicals (=100 if used) | 17625 | 1.000 | 0.038 | 0.000 | 1.000 |
| Chemical agents (=100 if used) | 17625 | 0.920 | 0.270 | 0.000 | 1.000 |
| Agroecological (=100 if used) | 17625 | 0.019 | 0.140 | 0.000 | 1.000 |
| Land Size (Ha) | 19325 | 1.500 | 4.800 | 0.077 | 210.000 |
| Land Size cultivated in corn (Ha) | 18680 | 0.700 | 0.690 | 0.056 | 46.000 |

Notes: Panel A shows descriptive statistics for El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018 at the individual level. Panel B presents the migration outcome that is measured at the household level. Panel C shows data from 2013–2018 of El Salvador's Agricultural Household Survey at the producer level.

**Table A3:** Descriptive Statistics: Control Variables

| Variable | N | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| *Panel A: EHPM Individual level* | | | | | |
| Years of education | 639412 | 5.869 | 4.488 | 0.000 | 25.000 |
| Male | 639412 | 0.469 | 0.499 | 0.000 | 1.000 |
| Age | 639412 | 30.758 | 15.173 | 10.000 | 65.000 |
| *Panel B: EHPM Household level* | | | | | |
| Male head | 207249 | 0.647 | 0.478 | 0.000 | 1.000 |
| Age of head | 207249 | 48.893 | 16.760 | 14.000 | 98.000 |
| Household size | 207249 | 3.848 | 1.973 | 1.000 | 24.000 |
| Has agricultural credit | 207249 | 0.033 | 0.178 | 0.000 | 1.000 |
| *Panel C: ENAMP Agricultural unit level* | | | | | |
| Highest education level of the household | 19325 | 2.500 | 0.930 | 0.000 | 6.000 |
| Has irrigation | 19325 | 0.004 | 0.067 | 0.000 | 1.000 |
| Household size | 19325 | 4.300 | 2.100 | 1.000 | 16.000 |
| *Panel D: Municipalities* | | | | | |
| Number of weeks temperature 2sd > historic mean | 244 | 1.200 | 0.550 | 0.000 | 3.500 |
| Number of accumulated weeks temperature 2sd > historic mean | 244 | 0.730 | 0.280 | 0.000 | 1.000 |
| Number of weeks rainfall 2sd > historic mean | 244 | 0.033 | 0.086 | 0.000 | 0.500 |
| Number of weeks rainfall 2sd < historic mean | 244 | 0.110 | 0.210 | 0.000 | 1.000 |
| Historic mean temperature in main growing season | 244 | 29.000 | 1.700 | 23.000 | 32.000 |
| Mean elevation | 244 | 498.000 | 279.000 | 9.700 | 1522.000 |
| Extension | 244 | 84.000 | 88.000 | 5.400 | 668.000 |
| Poverty rate (2005) | 244 | 51.000 | 15.000 | 10.000 | 88.000 |
| Extreme poverty (2005) | 244 | 26.000 | 13.000 | 4.200 | 60.000 |
| Income per capita (2005) | 244 | 561.000 | 266.000 | 213.000 | 2764.000 |
| % employed in agriculture (2005) | 244 | 40.000 | 29.000 | 0.520 | 394.000 |
| % young adults (16 and 18) not enrolled in school (2005) | 244 | 52.000 | 14.000 | 5.500 | 84.000 |
| % households with no access to drinking water (2005) | 244 | 35.000 | 20.000 | 0.100 | 99.000 |
| % people less than 19 years old (2007) | 244 | 48.000 | 4.100 | 31.000 | 57.000 |
| % people more than 60 years old (2007) | 244 | 9.900 | 2.000 | 5.400 | 19.000 |
| % Internal immigrants (2007) | 244 | 19.000 | 14.000 | 1.200 | 108.000 |
| % External immigrants (2007) | 244 | 30.000 | 26.000 | 3.900 | 235.000 |

Notes: Panel A shows descriptive statistics for El Salvador's Multiple Purpose Household Survey (EHPM) at the individual level from 2009–2018, while Panel B shows descriptive statistics at the household level. Panel C shows data of El Salvador's Agricultural Household Survey at the producer level from 2013 – 2018. Panel D shows municipality-level statistics for 2009–2018. The temperature statistics are calculated using the municipal average. The historic mean and standard deviation are calculated for the period between 2000 and 2003.

**Table A4:** Impact of Extreme Temperatures on Corn Agricultural Outcomes - Varying Controls

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: Log(Corn Production)* | | | | | | |
| Extreme Temperature$_t$ | −0.032 | −0.044*** | −0.047*** | −0.042*** | −0.040*** | −0.041*** |
| | (0.028) | (0.011) | (0.012) | (0.013) | (0.012) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.042** | −0.003 | −0.006 | 0.001 | 0.001 | −0.001 |
| | (0.020) | (0.009) | (0.010) | (0.011) | (0.006) | (0.006) |
| Mean | 1.915 | 1.915 | 1.915 | 1.915 | 1.915 | 1.915 |
| Observations | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.026 | 0.222 | 0.223 | 0.223 | 0.225 | 0.238 |
| *Panel B: Log(Production of Corn per Ha.)* | | | | | | |
| Extreme Temperature$_t$ | −0.063*** | −0.065*** | −0.065*** | −0.061*** | −0.061*** | −0.060*** |
| | (0.023) | (0.015) | (0.017) | (0.017) | (0.015) | (0.015) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.035* | −0.016 | −0.018 | −0.015 | −0.016 | −0.015 |
| | (0.018) | (0.012) | (0.012) | (0.013) | (0.010) | (0.010) |
| Mean | 2.339 | 2.339 | 2.339 | 2.339 | 2.339 | 2.339 |
| Observations | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.024 | 0.264 | 0.264 | 0.266 | 0.266 | 0.272 |
| *Panel C: Log(Production of Corn per Ha. Cultivated in Corn)* | | | | | | |
| Extreme Temperature$_t$ | −0.062*** | −0.061*** | −0.057*** | −0.054*** | −0.051*** | −0.051*** |
| | (0.021) | (0.011) | (0.012) | (0.013) | (0.012) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.033* | −0.010 | −0.012 | −0.009 | −0.011 | −0.010 |
| | (0.019) | (0.014) | (0.014) | (0.014) | (0.010) | (0.010) |
| Mean | 2.781 | 2.781 | 2.781 | 2.781 | 2.781 | 2.781 |
| Observations | 18,680 | 18,680 | 18,680 | 18,680 | 18,680 | 18,680 |
| Adjusted $R^2$ | 0.050 | 0.443 | 0.444 | 0.447 | 0.449 | 0.449 |
| *Panel D: TFP(Log Production)* | | | | | | |
| Extreme Temperature$_t$ | −0.050** | −0.049*** | −0.053*** | −0.049*** | −0.045*** | −0.045*** |
| | (0.021) | (0.010) | (0.012) | (0.013) | (0.011) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.042** | −0.001 | −0.006 | −0.00001 | −0.002 | −0.002 |
| | (0.019) | (0.012) | (0.013) | (0.014) | (0.008) | (0.008) |
| Mean | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| Observations | 16,548 | 16,548 | 16,548 | 16,548 | 16,548 | 16,548 |
| Adjusted $R^2$ | 0.040 | 0.282 | 0.283 | 0.283 | 0.285 | 0.291 |
| *Panel E: Log(Labor Productivity)* | | | | | | |
| Extreme Temperature$_t$ | −0.030 | −0.012 | −0.024 | −0.022 | −0.018 | −0.018 |
| | (0.032) | (0.012) | (0.015) | (0.017) | (0.015) | (0.015) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.021 | 0.009 | 0.002 | 0.005 | 0.001 | 0.001 |
| | (0.017) | (0.011) | (0.012) | (0.010) | (0.007) | (0.007) |
| Mean | 0.447 | 0.447 | 0.447 | 0.447 | 0.447 | 0.447 |
| Observations | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 | 18,847 |
| Adjusted $R^2$ | 0.008 | 0.167 | 0.169 | 0.169 | 0.172 | 0.173 |
| **Controls** | | | | | | |
| Year and Municipality Fixed Effects | | x | x | x | x | x |
| Extreme Rainfall$_t$ | | | x | x | x | x |
| Geographic*Year | | | | x | x | x |
| Municipal Socio*Year | | | | | x | x |
| Household | | | | | | x |

Notes: We use data from El Salvador's Agricultural Household Survey (ENAMP) for corn-producing households from 2013–2018. Each panel has a different dependent variable: Panel A uses the logarithm of corn production from the main harvest; Panel B, the logarithm of corn production per hectare from the main harvest season; Panel C, the logarithm of the corn-specific production per hectare from the main harvest season; Panel D, the Total Factor Productivity (TFP) of corn calculated as the logarithm of production from the main harvest season using area, labor, and inputs; Panel E, the logarithm of production per worker from the main harvest. Regressions have the same controls and independent variables as Table 1. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table A5:** Impact of Extreme Temperatures on the Likelihood of Having Household and Non-Household Workers

| | **Any workers Probability** | | **Non Household Workers Probability** | | **Household Workers Probability** | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Extreme Temperature$_t$ | 0.031 | 0.040 | −0.400 | −0.217 | 0.217 | 0.886** |
| | (0.051) | (0.054) | (0.376) | (0.399) | (0.346) | (0.367) |
| Extreme Temperature$_{t-1}^{t-4}$ | | 0.020 | | 0.400 | | 1.460*** |
| | | (0.039) | | (0.292) | | (0.268) |
| Probability | 99.677 | 99.677 | 75.428 | 75.428 | 77.613 | 77.613 |
| Observations | 18,908 | 18,908 | 18,908 | 18,908 | 18,908 | 18,908 |
| Adjusted $R^2$ | 0.023 | 0.023 | 0.069 | 0.069 | 0.162 | 0.163 |
| **Controls** | | | | | | |
| Extreme Rainfall$_t$ | x | x | x | x | x | x |
| Household | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Year and Municipal Fixed Effects | x | x | x | x | x | x |

Notes: We use data from El Salvador's Agricultural Household Survey (ENAMP) for corn-producing households from 2013–2018. Columns 1 and 2 correspond to the dependent variable of the likelihood (0 to 100) of having workers in the corn-producing households. Columns 3 and 4 correspond to the likelihood of having non-household workers, or hired workers. Columns 5 and 6 correspond to the likelihood of having household workers, or non hired workers. Regressions have the same controls and independent variables as Table 1. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

## A3 Labor Outcomes: Individual Level Analysis

We estimate the relationship between extreme temperature and individual labor outcomes using the EHPM data following the model below:

$$l_{ijt} = \alpha + \delta_1 T_{ijt} + \delta_2 \sum_{k=t-4}^{k=t-1} T_{ijk} + X'_{ijt}\gamma + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{ijt}. \quad (4)$$

where $l_{ijt}$ represents the labor outcomes of individual $i$ living in municipality $j$ in year $t$, using the same controls as in equation (1).[44] Labor outcomes include whether the person is employed, whether is employed in the agricultural or non-agricultural sector, hourly wage, and weekly hours worked.

The results in Table A6 suggest there is a negative effect on the probability of being employed. In the short term we expect the effects to be driven by individuals working in the agricultural sector, particularly those growing crops that are the most vulnerable to temperature shocks, such as corn. We explore this hypothesis in columns (3) to (8). As expected, the results are negative and significant for agricultural producers of seasonal crops and corn, which is consistent with the effects estimated in Table 3[45] and Table 4. Columns (5) and (6) show a significant and negative effect on the probability of employment in the agricultural sector, which is driven by workers growing corn (columns (7) and (8)). Since an employed individual may be either on the agricultural sector or the non agricultural sector, the results in columns (9) and (10) are symmetrical with columns (3) and (4). These results show positive but non-statistically significant effects on the probability of working in the non-agricultural sector, which suggests there is no perfect reallocation towards the non-agricultural sector.

[44] The only difference to equation (1) is that we do not include household controls for labor outcome estimations. Instead, we include age, gender and years of education as individual controls.

[45] It is worth mentioning that Table 3 and Table A6 use different databases and calculate the effect of extreme temperature on labor outcomes using different approximations. Table 3 uses information from ENAMP and reports the effect on the number of workers employed, as reported by agricultural corn-producers. In contrast, Table A6 uses the EHPM and reports the effect on the probability of employment reported by individuals.

**Table A6:** Impact of Extreme Temperatures on Individual Labor Outcomes

| | **Employed** | | **Agricultural** | | **Agricultural (Seasonal)** | | **Agricultural (Corn)** | | **Non Agricultural** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Extreme Temperature$_t$ | −0.097 | −0.138* | −0.094 | −0.083 | −0.212* | −0.176 | −0.218** | −0.200** | 0.094 | 0.083 |
| | (0.066) | (0.083) | (0.117) | (0.118) | (0.114) | (0.110) | (0.096) | (0.098) | (0.117) | (0.118) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.133* | | 0.038 | | 0.118* | | 0.059 | | −0.038 |
| | | (0.077) | | (0.056) | | (0.065) | | (0.059) | | (0.056) |
| Mean | 51.342 | 51.342 | 24.064 | 24.064 | 15.492 | 15.492 | 13.935 | 13.935 | 75.936 | 75.936 |
| Observations | 639,412 | 639,412 | 328,288 | 328,288 | 328,288 | 328,288 | 328,288 | 328,288 | 328,288 | 328,288 |
| Adjusted $R^2$ | 0.211 | 0.211 | 0.284 | 0.284 | 0.205 | 0.205 | 0.204 | 0.204 | 0.284 | 0.284 |
| **Controls** | | | | | | | | | | |
| Extreme Rainfall$_t$ | x | x | x | x | x | x | x | x | x | x |
| Individual | x | x | x | x | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x | x | x | x |
| Year and Municipality Fixed Effects | x | x | x | x | x | x | x | x | x | x |

Notes: We use individual-level data of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old from 2009–2018. The dependent variable of Columns 1 and 2 corresponds to the likelihood of being employed. Columns 3 and 4 correspond to the likelihood of being employed in agriculture including cereals, fruits, coffee, sugar, among others. Columns 5 and 6 correspond to the likelihood of being employed in agriculture of seasonal crops including cereals, corn, rice, beans, seeds and tubers. Colums 7 and 8 correspond to the likelihood of being employed in the agriculture of corn. Columns 9 and 10 correspond to the likelihood of being employed in any sector but in agriculture. All dependent variables are multiplied by 100 (=100 if employed, =0 if not). The independent variable Extreme Temperature$_t$ is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season in the same year. The independent variable Extreme Temperature$_{t-1}^{t-4}$ is the sum of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season from year t-1 to t-4. Individual controls are education years, gender, and age. Rainfall, municipal, and geographic controls are the same as in Table 1. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table A7:** Impact of Extreme Temperatures on Municipal Demographics

| | **Working Age 10-65 (log)** | | **Working Age 18-65 (log)** | | **Migration Rate** | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Extreme Temperature$_t$ | 0.004 | 0.002 | 0.005 | 0.002 | −0.001 | −0.058 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.219) | (0.221) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.007 | | −0.009** | | −0.160 |
| | | (0.004) | | (0.004) | | (0.134) |
| Mean | 285.579 | 285.579 | 216.040 | 216.040 | 18.686 | 18.686 |
| Observations | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.942 | 0.942 | 0.942 | 0.942 | 0.605 | 0.605 |
| **Controls** | | | | | | |
| Extreme Rainfall$_t$ | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Year and Municipality Fixed Effects | x | x | x | x | x | x |

Notes: We use municipal-level data of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old from 2009–2018. In columns 1 to 4, the dependent variable is the logarithm of the number of working-age individuals in the municipality, defined as ages 10 to 65 (columns 1 and 2) and ages 18 to 65 (columns 3 and 4). In columns 5 and 6, the dependent variable is the migration rate, estimated as the ratio between the number of international migrants at time $t$ and the working-age population aged 10 to 65. Independent variables and controls are the same as Table 4. Standard errors are robust to heteroskedasticity and are adjusted by sample size. *p<0.1; **p<0.05; ***p<0.01

**Table A8:** Impact of Extreme Temperatures on Migration - Varying Controls

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: All Households* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.060 | 0.013 | 0.001 | 0.002 | 0.009 | 0.009 |
| | (0.059) | (0.036) | (0.035) | (0.033) | (0.034) | (0.034) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.013 | −0.038** | −0.039*** | −0.039*** | −0.030* | −0.030* |
| | (0.027) | (0.016) | (0.015) | (0.014) | (0.016) | (0.016) |
| Mean | 0.788 | 0.788 | 0.788 | 0.788 | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 | 207,249 | 207,249 | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.0001 | 0.004 | 0.004 | 0.004 | 0.004 | 0.005 |
| *Panel B: Agricultural Households (all)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.102*** | 0.057* | 0.055* | 0.059** | 0.092*** | 0.096*** |
| | (0.024) | (0.032) | (0.032) | (0.029) | (0.021) | (0.018) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.077*** | −0.098*** | −0.097*** | −0.098*** | −0.058* | −0.057* |
| | (0.012) | (0.024) | (0.026) | (0.027) | (0.031) | (0.031) |
| Mean | 0.743 | 0.743 | 0.743 | 0.743 | 0.743 | 0.743 |
| Observations | 23,960 | 23,960 | 23,960 | 23,960 | 23,960 | 23,960 |
| Adjusted $R^2$ | 0.0005 | −0.00003 | −0.0001 | −0.0001 | 0.0001 | 0.004 |
| *Panel C: Agricultural Households (seasonal)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.180*** | 0.155*** | 0.147*** | 0.141*** | 0.153*** | 0.159*** |
| | (0.007) | (0.023) | (0.032) | (0.035) | (0.034) | (0.028) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.076*** | −0.115*** | −0.122*** | −0.125*** | −0.119*** | −0.120*** |
| | (0.024) | (0.028) | (0.027) | (0.028) | (0.034) | (0.033) |
| Mean | 0.620 | 0.620 | 0.620 | 0.620 | 0.620 | 0.620 |
| Observations | 15,173 | 15,173 | 15,173 | 15,173 | 15,173 | 15,173 |
| Adjusted $R^2$ | 0.001 | −0.002 | −0.002 | −0.002 | −0.002 | 0.002 |
| *Panel D: Agricultural Households (corn)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.201*** | 0.169 | 0.167*** | 0.158*** | 0.177*** | 0.180*** |
| | (0.006) | | (0.023) | (0.026) | (0.024) | (0.012) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.074*** | −0.126*** | −0.133*** | −0.139*** | −0.125*** | −0.125*** |
| | (0.025) | (0.030) | (0.030) | (0.031) | (0.036) | (0.036) |
| Mean | 0.654 | 0.654 | 0.654 | 0.654 | 0.654 | 0.654 |
| Observations | 13,454 | 13,454 | 13,454 | 13,454 | 13,454 | 13,454 |
| Adjusted $R^2$ | 0.001 | −0.002 | −0.002 | −0.003 | −0.003 | 0.001 |
| *Panel E: Non Agricultural Households* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.043 | −0.003 | −0.017 | −0.020 | −0.017 | −0.017 |
| | (0.050) | (0.033) | (0.031) | (0.030) | (0.031) | (0.031) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.005 | −0.007 | −0.009 | −0.012 | −0.009 | −0.009 |
| | (0.016) | (0.015) | (0.016) | (0.016) | (0.020) | (0.020) |
| Mean | 0.611 | 0.611 | 0.611 | 0.611 | 0.611 | 0.611 |
| Observations | 118,070 | 118,070 | 118,070 | 118,070 | 118,070 | 118,070 |
| Adjusted $R^2$ | 0.00003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 |
| **Controls** | | | | | | |
| Year and Municipality Fixed Effects | | x | x | x | x | x |
| Extreme Rainfall$_{t-1}$ | | | x | x | x | x |
| Geographic*Year | | | | x | x | x |
| Municipal Socio*Year | | | | | x | x |
| Household | | | | | | x |

Notes: We use data from El Salvador's Agricultural Household Survey (ENAMP) for corn-producing households from 2013–2018. The dependent variable is 100 if a household member migrated in the surveyed year. Panel A corresponds to all households. Panel B corresponds to agricultural households, defined if the household head and at least 50 percent of the members of working age are employed in agriculture. Panel C corresponds to seasonal agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing seasonal crops including cereals, corn, rice, beans, seeds and tubers. Panel D corresponds to corn agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing corn. Panel E corresponds to non agricultural households defined if the household head or at least 50 percent of the members of working age are employed in a non-agricultural sector. Regressions have the same controls and independent variables as Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table A9:** Impact of Extreme Temperatures on Migration - Heterogeneity by Working-Age Household Members Characteristics

| | Method 1: Preferred specification | Method 2: Household head works in Agro (Corn) | | Method 3: At least 50 % of working-age members work in Agro (Corn) | | Method 4: At least one of the working-age members works in Agro (Corn) | |
|---|---|---|---|---|---|---|---|
| | | No | Yes | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Extreme Temperature$_{t-1}$ | 0.180*** | −0.021 | 0.143*** | 0.012 | 0.145*** | 0.013 | 0.091** |
| | (0.012) | (0.041) | (0.012) | (0.041) | (0.012) | (0.041) | (0.041) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.125*** | −0.001 | −0.118*** | −0.025 | −0.078** | −0.014 | −0.098*** |
| | (0.036) | (0.022) | (0.036) | (0.022) | (0.036) | (0.022) | (0.022) |
| Mean | 0.654 | 0.610 | 0.784 | 0.794 | 0.707 | 0.771 | 0.855 |
| Observations | 13,454 | 127,148 | 23,594 | 159,237 | 19,651 | 148,823 | 30,065 |
| Adjusted $R^2$ | 0.001 | 0.003 | 0.004 | 0.006 | −0.001 | 0.006 | 0.003 |
| **Controls** | | | | | | | |
| Extreme Rainfall$_{t-1}$ | x | x | x | x | x | x | x |
| Household | x | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x |
| Year and Municipality Fixed Effects | x | x | x | x | x | x | x |

Notes: We use household-level data of El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. Method 1 uses the preferred specification to define corn agricultural households, in which the household head works in agriculture and at least 50 percent of the members of working age are employed producing corn. Method 2 defines a corn agricultural household considering if the head of the household is employed producing corn. Method 3 defines a corn agricultural household considering if at least 50 percent of the working-age members are employed producing corn. Method 4 defines a corn agricultural household considering if at least one working-age member is employed producing corn. Regressions have the same controls and independent variables as Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table A10:** Impact of Extreme Temperatures on Migration Likelihood

| | (1) | (2) |
|---|---|---|
| *Panel A: Interaction with Agricultural Households (all)* | | |
| Extreme Temperature$_{t-1}$ × Agricultural household | 0.009 | 0.024 |
| | (0.045) | (0.047) |
| Extreme Temperature$_{t-2}^{t-5}$ × Agricultural household | | −0.029 |
| | | (0.025) |
| Extreme Temperature$_{t-1}$ | 0.019 | 0.007 |
| | (0.025) | (0.025) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.027* |
| | | (0.015) |
| Agricultural household | −0.122 | −0.048 |
| | (0.085) | (0.108) |
| Mean | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.005 | 0.005 |
| *Panel B: Interaction with Agricultural Households (seasonal)* | | |
| Extreme Temperature$_{t-1}$ × Agricultural household (seasonal) | 0.097* | 0.110* |
| | (0.054) | (0.056) |
| Extreme Temperature$_{t-2}^{t-5}$ × Agricultural household (seasonal) | | −0.023 |
| | | (0.031) |
| Extreme Temperature$_{t-1}$ | 0.013 | 0.001 |
| | (0.024) | (0.025) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.029* |
| | | (0.015) |
| Agricultural household (seasonal) | −0.413*** | −0.354*** |
| | (0.103) | (0.132) |
| Mean | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.005 | 0.005 |
| *Panel C: Interaction with Agricultural Households (corn)* | | |
| Extreme Temperature$_{t-1}$ × Agricultural household (corn) | 0.120** | 0.131** |
| | (0.058) | (0.060) |
| Extreme Temperature$_{t-2}^{t-5}$ × Agricultural household (corn) | | −0.020 |
| | | (0.033) |
| Extreme Temperature$_{t-1}$ | 0.012 | 0.0001 |
| | (0.024) | (0.025) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.030** |
| | | (0.015) |
| Agricultural household (corn) | −0.437*** | −0.388*** |
| | (0.108) | (0.138) |
| Mean | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.005 | 0.005 |
| **Controls** | | |
| Extreme Rainfall$_{t-1}$ | x | x |
| Household | x | x |
| Municipal Socio*Year | x | x |
| Geographic*Year | x | x |
| Year and Municipality Fixed Effects | x | x |

Notes: We use household-level data of El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable Extreme Temperature$_{t-1}$ is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season in the year before the survey. The independent variable Extreme Temperature$_{t-2}^{t-5}$ is the sum of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season from year t-2 to t-5. Panel A presents the interaction of the independent variables with a dummy indicating if the observation corresponds to an agricultural household, defined if the household head and at least 50 percent of the members of working age are employed in agriculture. Panel B presents the interaction of the independent variables with a dummy indicating if the observation corresponds to seasonal agricultural household, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing seasonal crops including cereals, corn, rice, beans, seeds and tubers. Panel C presents the interaction of the independent variables with a dummy indicating if the observation corresponds to an agricultural household that produces corn, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing corn. Controls are the same as Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

**Table A11:** Impact of Extreme Temperatures in Main Outcomes with Contemporaneous and Lag Interactions

| | (1) | (2) |
|---|---|---|
| *Panel A: Log(Corn Production)* | | |
| Extreme Temperature$_t$ | $-0.041^{***}$ | $-0.068^{***}$ |
| | (0.012) | (0.018) |
| Extreme Temperature$_{t-1}^{t-4}$ | $-0.001$ | $-0.009$ |
| | (0.006) | (0.009) |
| Extreme Temperature $t \times \sum_{t-1}^{t-4}$ | | $0.005^{**}$ |
| | | (0.003) |
| Mean | 1.915 | 1.915 |
| Observations | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.238 | 0.238 |
| *Panel B: Employment Share of Agricultural Sector (Corn)* | | |
| Extreme Temperature$_t$ | $-0.246^{**}$ | $-0.331^{*}$ |
| | (0.113) | (0.182) |
| Extreme Temperature$_{t-1}^{t-4}$ | $-0.070$ | $-0.095$ |
| | (0.071) | (0.081) |
| Extreme Temperature $t \times \sum_{t-1}^{t-4}$ | | 0.018 |
| | | (0.029) |
| Mean | 8.981 | 8.981 |
| Observations | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.724 | 0.724 |
| *Panel C: Migration Likelihood in Agricultural Household (Corn)* | | |
| Extreme Temperature$_{t-1}$ | $0.180^{***}$ | 0.184 |
| | (0.012) | (0.160) |
| Extreme Temperature$_{t-2}^{t-5}$ | $-0.125^{***}$ | $-0.123$ |
| | (0.036) | (0.080) |
| Extreme Temperature $t-1 \times \sum_{t-2}^{t-5}$ | | $-0.001$ |
| | | (0.029) |
| Mean | 0.654 | 0.654 |
| Observations | 13,454 | 13,454 |
| Adjusted $R^2$ | 0.001 | 0.001 |
| **Controls** | | |
| Extreme Rainfall$_{t,t-1}$ | x | x |
| Household* | x | x |
| Municipal Socio*Year | x | x |
| Geographic*Year | x | x |
| Year and Municipal Fixed Effects | x | x |

Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main harvest season using ENAMP dataset. Panel B corresponds to the share of working age population working in corn agriculture, using EHPM dataset at the municipal level. Panel C corresponds to the likelihood of migration in corn agricultural households using the EHPM dataset at the household level. Extreme Temperature is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season). In Panel A and B, Extreme Temperature $t \times \sum_{t-1}^{t-4}$ is the interaction of the contemporaneous and cumulative Extreme Temperature variable. In Panel C, Extreme Temperature $t-1 \times \sum_{t-2}^{t-5}$ is the interaction of the lagged and the cumulative Extreme Temperature variable. Controls are the same as Table 6. Standard errors are clustered by municipality and year in Panel A and C. In Panel B, standard errors are robust. *p<0.1; **p<0.05; ***p<0.01

## A4 The Role of Local Labor Markets and Migrant Networks

### A4.1 Migrant Networks

Section 4.5 discussed the role of migrant networks and remittances as a potential pull-factor that renders feasible migrating internationally in El Salvador. We provide additional details of the empirical models discussed in that section.

We begin by estimating a model that interacts our measure of exposure to extreme temperature with the number of additional migrants reported in the household (Table A12), following the model below:

$$m_{ijt} = \alpha + \delta_1 T_{jt-1} + \sum_{k=1}^{k=3} \delta_{2,k} T_{jt-1} \times \Gamma_k + \delta_3 \sum_{k=t-5}^{k=t-2} T_{jk} + X'_{ijt}\gamma + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{ijt} \tag{5}$$

Where $T_{jt-1} \times \Gamma_k$ is the interaction of the extreme temperatures measured with three indicators $\Gamma_k$ which are equal to 1 if the household contains two migrants, three migrants, or more than three migrants, proxy of migrant networks of the household. $\delta_{2,k}$ gives the additional effect of extreme temperatures by having a larger number of migrants.

Although we can not distinguish if two or more migrants within a household migrated at the same time, information from the U.S. Border Patrol (USBP) and Office of Field Operations (OFO) reports that between 2021-2023, 66.3% of individuals of the southwest land border encounters were single adults or accompanied minors. This suggests that most of the migrants who go to the United States through the Mexican border do it by themselves. If we assume that households with more than one migrant are households who had a member living abroad prior to year *t-1*, the previous table evidences the importance of migration networks in the decision of migrating since we find a higher effect of a extreme temperature in the probability of migration for households with more than one migrant. This is suggestive evidence as, with our available data, we are unable to discern whether migrants within each household households migrated at the same time or not.

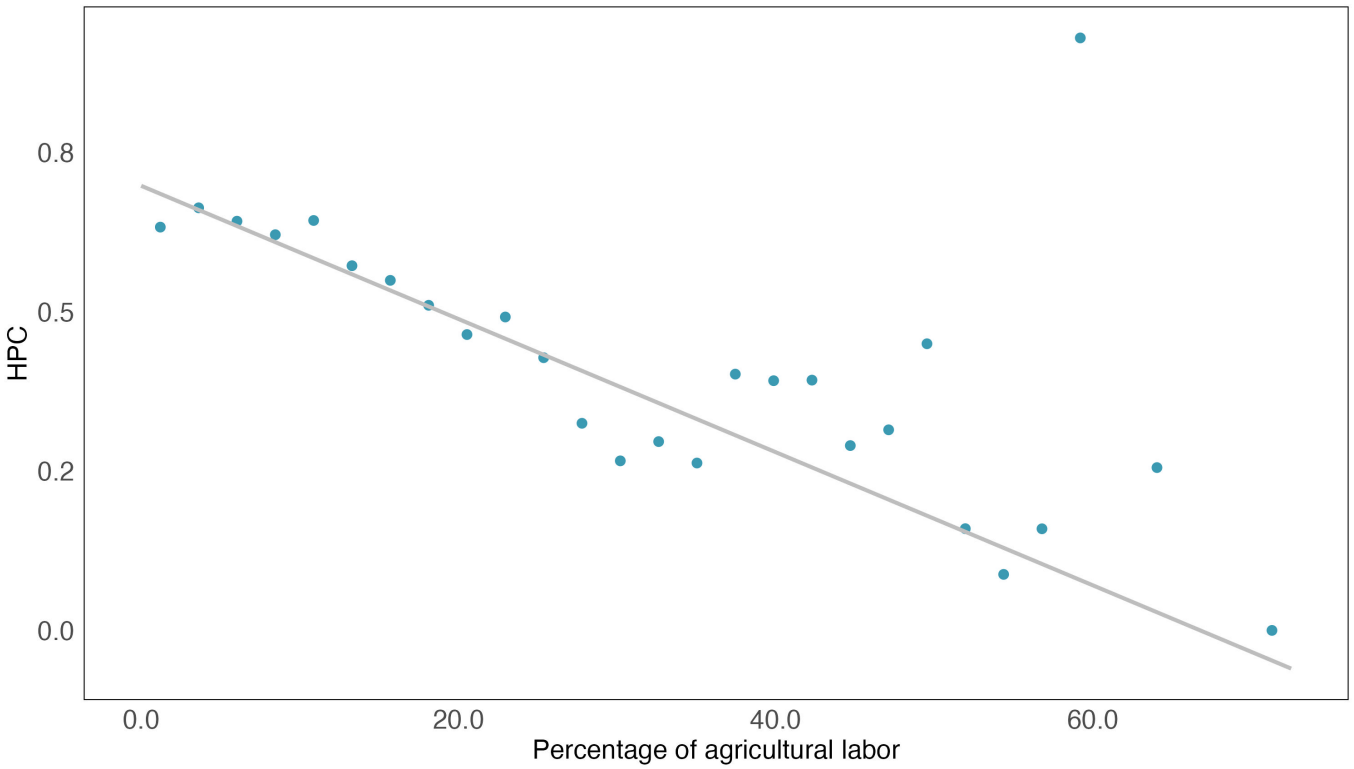
**Table A12:** Heterogeneity by Access to Networks: Migration

| | Agricultural Households (Corn) |
|---|---|
| Extreme Temperature$_{t-1}$ | 0.019 |
| | (0.092) |
| Extreme Temperature$_{t-1}$ × two migrants | 2.636** |
| | (1.135) |
| Extreme Temperature$_{t-1}$ × three migrants | 2.612*** |
| | (0.819) |
| Extreme Temperature$_{t-1}$ × more than three migrants | 2.501 |
| | (1.581) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.135 |
| | (0.084) |
| Ftest: extreme temp = extreme temp × two migrants | 0.000 |
| Ftest: extreme temp = extreme temp × three migrants | 0.000 |
| Ftest: extreme temp = extreme temp × more migrants | 0.000 |
| Mean | 0.654 |
| Observations | 13,454 |
| Adjusted $R^2$ | 0.021 |
| **Controls** | |
| Extreme Rainfall$_{t-1}$ | x |
| Household | x |
| Municipal Socio*Year | x |
| Geographic*Year | x |
| Year and Municipal Fixed Effects | x |

Notes: Household-level data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated in the surveyed year. The sample corresponds to corn agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing corn. The independent variable Extreme Temperature$_{t-1}$ is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season in the year before the survey. We interact this variable with the number of migrants within each household. Controls are the same as Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

## A4.2 Local Labor Markets and Violence

**Figure A6:** Correlation Between Homicides per Capita and Percentage of Employed Individuals in the Agricultural Sector




Source: Own elaboration based on Data from El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018 at the individual level and the National Police of El Salvador (Policia Nacional Civil). It shows the bin scatter plot between homicides per 1,000 people and the percentage of agricultural workers from total workers at the municipality level. Each dot represents 75 observations at the municipality-year level. The line is estimated using simple OLS.

**Table A13:** Heterogeneity by Crime on Migration

| | (1) |
|---|---|
| *Agricultural households (Corn)* | |
| Extreme Temperature$_{t-1}$ | 0.106 |
| | (0.133) |
| Extreme Temperature$_{t-1}$× Hom Rate$_{2008}$ | 0.209 |
| | (0.252) |
| Mean | 0.657 |
| Observations | 13,396 |
| Adjusted $R^2$ | 0.001 |
| **Controls** | |
| Extreme Rainfall$_{t-1}$ | x |
| Household | x |
| Municipal Socio*Year | x |
| Geographic*Year | x |
| Year and Municipality Fixed Effects | x |

Notes: We use household-level data of El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The sample corresponds to corn agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing corn. The independent variable Extreme Temperature$_{t-1}$ is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season in the year before the survey. Controls are the same as Table 5. We interact extreme temperature with the homicide rate at municipal level in 2008. There is a reduction in observations from 13,454 to 13,396 because two municipalities are missing homicides per capita information. Standard errors are clustered by municipality and year.*p<0.1; **p<0.05; ***p<0.01

### A4.3 Integration to Other Markets

To study the heterogeneous effects through access to non-agricultural sectors, we use road networks as a proxy for integration into other markets. Road network information was provided by the Transport Division of the Infrastructure and Energy Sector (INE) of the Inter-American Development Bank (IADB), which uses data from Open Street Maps in 2022.[46] We use the National road network, which contains 95,410 roads in El Salvador comprising highways, avenues, and streets among 27 different road types.

[46]We do not anticipate significant changes in the road infrastructure of El Salvador between 2008 and 2022. The main road network expanded during the 90s and has been maintained since then by the national road fund, FOVIAL (WB, 2006) Between 2000 y 2015, the construction of roads has been limited: 303 km (2.4% of the total 12,493 KM) (Rendón et al., 2020)

**Table A14:** Heterogeneity by Access to Risk-Management Mechanisms: Labor Outcomes

| | National Roads (1) | Main Roads (2) |
|---|---|---|
| *Employment Share of Agricultural Sector (Corn)* | | |
| Extreme Temperature$_t$ | $-0.612^{***}$ | $-0.626^{***}$ |
| | (0.191) | (0.182) |
| Extreme Temperature$_t \times Q2$ | 0.380 | $0.715^{***}$ |
| | (0.239) | (0.211) |
| Extreme Temperature$_t \times Q3$ | $0.651^{***}$ | $0.403^{**}$ |
| | (0.203) | (0.200) |
| Extreme Temperature$_t \times Q4$ | $0.478^{**}$ | $0.468^{**}$ |
| | (0.193) | (0.217) |
| Extreme Temperatures$_{t-1}^{t-4}$ | $-0.058$ | $-0.071$ |
| | (0.071) | (0.071) |
| Mean | 8.981 | 8.981 |
| Observations | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.725 | 0.726 |
| **Controls** | | |
| Extreme Rainfall$_t$ | x | x |
| Municipal Socio*Year | x | x |
| Geographic*Year | x | x |
| Year and Municipality Fixed Effects | x | x |

Notes: The outcome variable is the share of working age population working in corn agriculture, using EHPM dataset at the municipal level. The independent variable across these panels is the interaction of Extreme Temperature with the municipality-level quartiles for each covariate. In Column 1, the covariate is the share of national roads by area. In Column 2 it is the share of main roads by area. Regressions have the same controls and Extreme Temperature independent variables as in Table 4. Standard errors are robust to heteroskedasticity and are adjusted by sample size. *p<0.1; **p<0.05; ***p<0.01

**Table A15:** Impact of Extreme Temperatures on Migration – Varying Seasons

| | Main Growing Season (1) | All Year (2) | Apante Season (3) | Lean Season (4) | 2013–2018 (5) | Excluding 2015 (6) |
|---|---|---|---|---|---|---|
| *Panel A: Log(Corn Production)* | | | | | | |
| Extreme Temperature$_t$ | −0.041*** | −0.028*** | −0.013 | −0.064** | −0.041*** | −0.033*** |
| | (0.012) | (0.008) | (0.013) | (0.031) | (0.012) | (0.008) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.001 | 0.006** | 0.010 | 0.043*** | −0.001 | 0.001 |
| | (0.006) | (0.002) | (0.010) | (0.011) | (0.006) | (0.007) |
| Mean | 1.915 | 1.915 | 1.915 | 1.915 | 1.915 | 1.930 |
| Observations | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 | 16,648 |
| Adjusted $R^2$ | 0.238 | 0.239 | 0.237 | 0.238 | 0.238 | 0.233 |
| *Panel B: Employment Share of Agricultural Sector (Corn)* | | | | | | |
| Extreme Temperature$_t$ | −0.246** | −0.103* | −0.279** | 0.510** | −0.243* | −0.227* |
| | (0.113) | (0.060) | (0.120) | (0.220) | (0.138) | (0.136) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.070 | −0.052 | −0.032 | −0.108 | 0.026 | −0.093 |
| | (0.071) | (0.039) | (0.086) | (0.142) | (0.094) | (0.075) |
| Mean | 8.981 | 8.981 | 8.981 | 8.981 | 8.568 | 9.024 |
| Observations | 2,239 | 2,239 | 2,239 | 2,239 | 1,361 | 2,010 |
| Adjusted $R^2$ | 0.724 | 0.724 | 0.724 | 0.724 | 0.747 | 0.718 |
| *Panel C: Migration Likelihood in Agricultural Households (Corn)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.180*** | 0.046 | −0.032 | −0.047 | 0.184*** | 0.146 |
| | (0.012) | (0.050) | (0.117) | (0.152) | (0.066) | (0.103) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.125*** | −0.025 | 0.020 | 0.015 | −0.241*** | −0.126 |
| | (0.036) | (0.061) | (0.094) | (0.079) | (0.027) | (0.094) |
| Mean | 0.654 | 0.654 | 0.654 | 0.654 | 0.824 | 0.673 |
| Observations | 13,454 | 13,454 | 13,454 | 13,454 | 7,283 | 11,890 |
| Adjusted $R^2$ | 0.001 | 0.0001 | −0.00003 | −0.00004 | −0.005 | 0.001 |
| **Controls** | | | | | | |
| Extreme Rainfall$_{t,t-1}$ | x | x | x | x | x | x |
| Household | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Year and Municipal Fixed Effects | x | x | x | x | x | x |

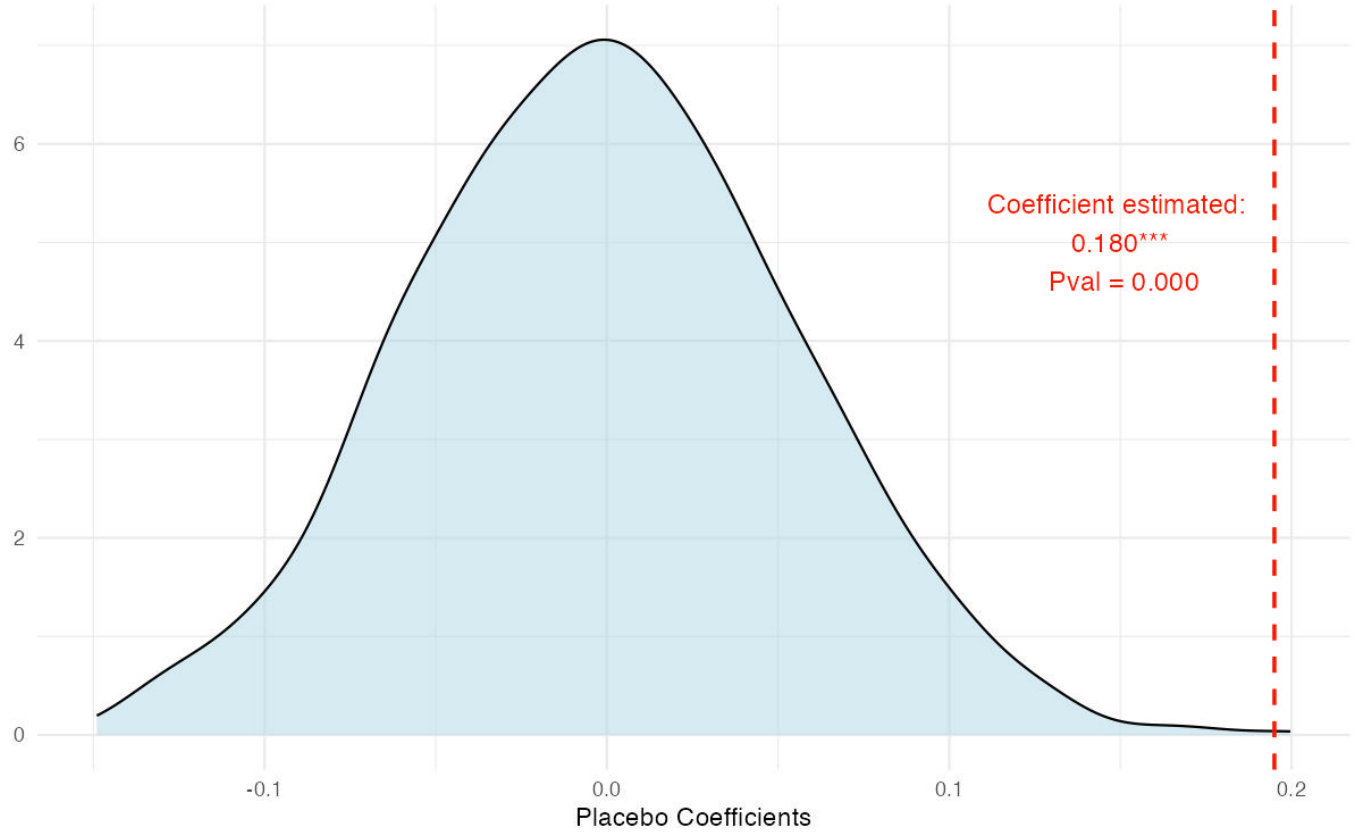
Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main harvest season using ENAMP dataset. Panel B corresponds to the share of working age population working in corn agriculture, using EHPM dataset at the municipal level. Panel C corresponds to the likelihood of migration in corn agricultural households using the EHPM dataset at the household level. Column 1 corresponds to our main specification, in which Extreme Temperature is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season (June - July). Columns 2 to 4 estimate Extreme Temperature (number of weeks with a temperature 2 SD higher than that week's historic value in that municipality) for different seasons: Column 2 estimates it for the whole year, Column 3 for *apante* season (November-December), and Column 4 for lean season or *postrera* (August - September). Columns 5 and 6 estimate the main specification (number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season) through different periods: Column 5 estimates the results for 2013-2018 (years where ENAMP and EHPM overlap), and column 5 excluding 2015 (a particularly hot year). Controls are the same as Table 6. Standard errors are clustered by municipality and year in Panel A and C. In Panel B, standard errors are robust. *p<0.1; **p<0.05; ***p<0.01

**Table A16:** Impact of Extreme Temperatures in Main Outcomes - Varying Definitions of Extreme Temperatures

| | 1 SD (1) | 1.5 SD (2) | Higher 29 (3) | Higher 35 (4) | HDW (5) |
|---|---|---|---|---|---|
| *Panel A: Log(Corn Production)* | | | | | |
| Extreme Temperature$_t$ | −0.029** | −0.031** | −0.033*** | −0.027 | −0.005 |
| | (0.014) | (0.012) | (0.012) | (0.021) | (0.003) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.006 | −0.001 | 0.006 | 0.017 | 0.004 |
| | (0.006) | (0.007) | (0.011) | (0.018) | (0.003) |
| Mean | 1.915 | 1.915 | 1.915 | 1.915 | 1.915 |
| Observations | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.238 | 0.238 | 0.238 | 0.237 | 0.237 |
| *Panel B: Employment Share of Agricultural Sector (Corn)* | | | | | |
| Extreme Temperature$_t$ | −0.127 | −0.227** | −0.169* | −0.221 | −0.038 |
| | (0.097) | (0.104) | (0.094) | (0.147) | (0.025) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.035 | −0.067 | 0.025 | −0.227** | −0.028 |
| | (0.054) | (0.061) | (0.055) | (0.106) | (0.018) |
| Mean | 8.981 | 8.981 | 8.981 | 8.981 | 8.981 |
| Observations | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.724 | 0.724 | 0.724 | 0.724 | 0.724 |
| *Panel C: Migration Likelihood in Agricultural Household (Corn)* | | | | | |
| Extreme Temperature$_{t-1}$ | 0.145 | 0.167** | 0.061 | 0.246 | 0.045 |
| | (0.094) | (0.067) | (0.052) | (0.160) | (0.032) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.047** | −0.057 | −0.095*** | 0.043 | 0.008 |
| | (0.022) | (0.035) | (0.028) | (0.147) | (0.029) |
| Mean | 0.654 | 0.654 | 0.654 | 0.654 | 0.654 |
| Observations | 13,454 | 13,454 | 13,454 | 13,454 | 13,454 |
| Adjusted $R^2$ | 0.0004 | 0.0004 | 0.0005 | 0.0002 | 0.0002 |
| **Controls** | | | | | |
| Extreme Rainfall$_{t,t-1}$ | x | x | x | x | x |
| Household* | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x |
| Year and Municipal Fixed Effects | x | x | x | x | x |

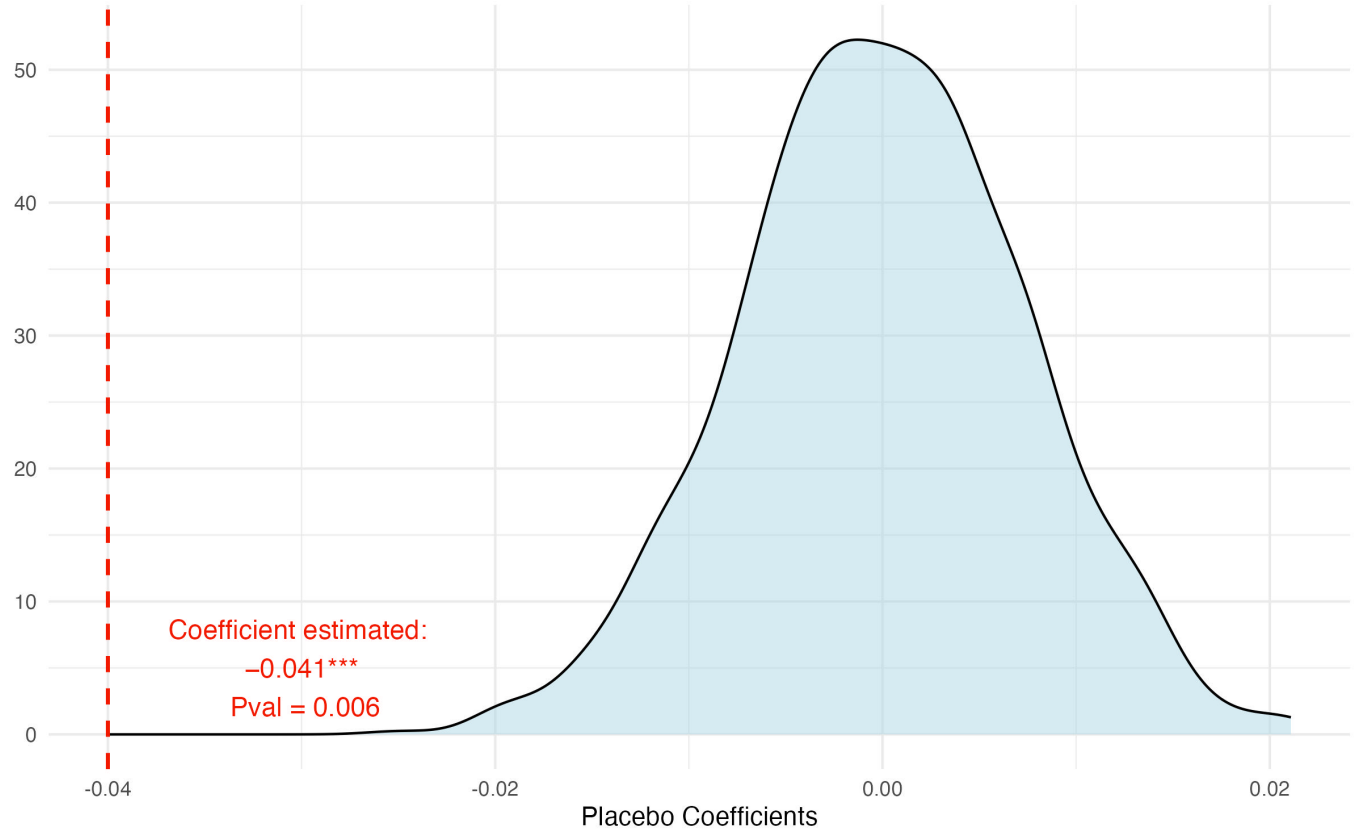
Notes: Each column estimates the independent variable with a different specification. Column 1 and 2 modify our main specification to different cutoffs. Column 1 specification is the number of weeks with a temperature 1 SD higher than that week's historic value in that municipality during main growing season. Column 2 corresponds to the number of weeks with a temperature 1.5 SD higher than that week's historic value in that municipality during main growing season. Column 3 and 4 define the independent variable as the number of weeks during main growing season with a temperature higher than 29 and 35 Celsius. Column 5 estimates armful Degree Weeks (HDW) during main growing season, where every 1-degree Celsius increase in the average temperature above 32 degrees Celsius corresponds to a one-unit increase in HDWs. Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main harvest using ENAMP dataset. Panel B corresponds to the share of working age population working in corn agriculture, using EHPM dataset at the municipal level. Panel C corresponds to the likelihood of migration in corn agricultural households using the EHPM dataset at the household level. Controls are the same as Table 6. Standard errors are clustered by municipality and year in Panel A and C. In Panel B, standard errors are robust. *p<0.1; **p<0.05; ***p<0.01

**Figure A7:** 1,000 Permutations of Extreme Temperature by Geography: Coefficients on Migration Likelihood




Notes: Own elaboration based on Household-level data of El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The figure shows the density of placebo coefficients of Extreme Temperature on migration likelihood, employing the same controls and independent variables as Table 5 for corn agricultural households. The red dotted line shows our main specification's coefficient of Extreme Temperature on migration likelihood for corn agricultural households. P-values are estimated based on the share of placebo T-statistics as extreme as the main specification.

**Figure A8:** 1,000 Permutations of Extreme Temperature by Geography: Coefficients on Agricultural Productivity




Notes: Own elaboration based on Data from 2013–2018 of El Salvador's Agricultural Household Survey (ENAMP). The figure shows the density of placebo coefficients of Extreme Temperature on the log of corn production employing the same controls and independent variables as Table 1. The red dotted line shows our main specification's coefficient of Extreme Temperature on corn production (in logarithms). P-values are estimated based on the share of placebo T-statistics as extreme as the main specification.

**Table A17:** Impact of Extreme Temperatures on Migration – Varying Standard Errors

| | Main specification (1) | Conley (25 KM) (2) | Conley (50 KM) (3) | Conley (100 KM) (4) | FWER Bonferroni (5) | FWER Holm (6) |
|---|---|---|---|---|---|---|
| *Panel A: Log(Corn Production)* | | | | | | |
| Extreme Temperature$_t$ | −0.041*** | −0.041*** | −0.041*** | −0.041*** | −0.041*** | −0.041*** |
| | (0.011) | (0.012) | (0.012) | (0.011) | (0.011) | (0.011) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 | −0.001 |
| | (0.006) | (0.008) | (0.008) | (0.008) | (0.006) | (0.006) |
| Mean | 1.915 | 1.915 | 1.915 | 1.915 | 1.915 | 1.915 |
| Observations | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.238 | 0.238 | 0.238 | 0.238 | 0.238 | 0.238 |
| *Panel B: Employment Share of Agricultural Sector (Corn)* | | | | | | |
| Extreme Temperature$_t$ | −0.246** | −0.246** | −0.246** | −0.246*** | −0.246*** | −0.246*** |
| | (0.113) | (0.109) | (0.099) | (0.089) | (0.087) | (0.087) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.070 | −0.070 | −0.070 | −0.070 | −0.070 | −0.070 |
| | (0.071) | (0.063) | (0.063) | (0.044) | (0.068) | (0.068) |
| Mean | 8.981 | 8.981 | 8.981 | 8.981 | 8.981 | 8.981 |
| Observations | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.724 | 0.724 | 0.724 | 0.724 | 0.724 | 0.724 |
| *Panel C: Migration Likelihood in Agricultural Households (Corn)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.180*** | 0.180* | 0.180** | 0.180** | 0.180*** | 0.180*** |
| | (0.012) | (0.101) | (0.075) | (0.074) | (0.012) | (0.012) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.125*** | −0.125** | −0.125*** | −0.125*** | −0.125*** | −0.125*** |
| | (0.036) | (0.049) | (0.043) | (0.035) | (0.036) | (0.036) |
| Mean | 0.654 | 0.654 | 0.654 | 0.654 | 0.654 | 0.654 |
| Observations | 13,454 | 13,454 | 13,454 | 13,454 | 13,454 | 13,454 |
| Adjusted $R^2$ | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| **Controls** | | | | | | |
| Extreme Rainfall$_{t,t-1}$ | x | x | x | x | x | x |
| Household | x | x | x | x | x | x |
| Municipal Socio*Year | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Year and Municipal Fixed Effects | x | x | x | x | x | x |

Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main harvest using ENAMP dataset. Panel B corresponds to the share of working age population working in corn agriculture, using EHPM dataset at the municipal level. Panel C corresponds to the likelihood of migration in corn agricultural households using the EHPM dataset at the household level. Extreme Temperature is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season. Controls are the same as in Table 6. All regressions include municipality and year fixed effects. In Column 1, standard errors are clustered by municipality and year in Panel A and C. In Panel B, standard errors are robust. In Columns 2-4 we use Conley standard errors to account for spatial correlation. In Columns 4-5 we use Family Wise Error Rate (FWER) adjusted p-values. *p<0.1; **p<0.05; ***p<0.01

**Table A18:** Impact of Extreme Temperatures and Homicide Rate in Main Outcomes

| | (1) |
|---|---|
| *Panel A: Log(Corn Production)* | |
| Extreme Temperature$_t$ | $-0.041^{***}$ |
| | (0.011) |
| Extreme Temperature$_{t-1}^{t-4}$ | $-0.002$ |
| | (0.005) |
| Homicide per capita$_t$ | $-0.021$ |
| | (0.020) |
| Mean | 1.915 |
| Observations | 19,261 |
| Adjusted $R^2$ | 0.238 |
| *Panel B: Employment Share of Agricultural Sector (Corn)* | |
| Extreme Temperature$_t$ | $-0.245^{**}$ |
| | (0.113) |
| Extreme Temperature$_{t-1}^{t-4}$ | $-0.071$ |
| | (0.071) |
| Homicide per capita$_t$ | $-0.125$ |
| | (0.294) |
| Mean | 8.981 |
| Observations | 2,239 |
| Adjusted $R^2$ | 0.724 |
| *Panel C: Migration Likelihood in Agricultural Households (Corn)* | |
| Extreme Temperature$_{t-1}$ | $0.182^{***}$ |
| | (0.007) |
| Extreme Temperature$_{t-2}^{t-5}$ | $-0.120^{***}$ |
| | (0.031) |
| Homicide per capita$_{t-1}$ | 0.176 |
| | (0.149) |
| Mean | 0.654 |
| Observations | 13,454 |
| Adjusted $R^2$ | 0.001 |
| **Controls** | |
| Extreme Rainfall$_{t,t-1}$ | x |
| Household* | x |
| Municipal Socio*Year | x |
| Geographic*Year | x |
| Year and Municipal Fixed Effects | x |

Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main harvest using ENAMP dataset. Panel B corresponds to the share of working age population working in corn agriculture, using EHPM dataset at the municipal level. Panel C corresponds to the likelihood of migration in corn agricultural households using the EHPM dataset at the household level. Extreme Temperature is the number of weeks with a temperature 2 SD higher than that week's historic value in that municipality during the main growing season. Homicides per capita is the number of recorded homicides per 1000 habitants by municipality. The source of information is the National Police of El Salvador (Policia Nacional Civil). Controls are the same as Table 6. Standard errors are clustered by municipality and year in Panel A and C. In Panel B, standard errors are robust. *p<0.1; **p<0.05; ***p<0.01

**Table A19:** Impact of Extreme Temperatures and Homicide Rate on Migration Likelihood by Area

| | Rural | Urban |
|---|---|---|
| | (1) | (2) |
| *Panel A: All Households* | | |
| Extreme Temperature$_{t-1}$ | 0.054 | −0.020 |
| | (0.059) | (0.022) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.035*** | −0.015 |
| | (0.012) | (0.019) |
| Homicides per capita$_{t-1}$ | 0.078 | 0.212*** |
| | (0.055) | (0.059) |
| Mean | 0.909 | 0.680 |
| Observations | 97,645 | 109,604 |
| Adjusted $R^2$ | 0.005 | 0.004 |
| *Panel B: Agricultural Households (all)* | | |
| Extreme Temperature$_{t-1}$ | 0.134** | 0.052 |
| | (0.055) | (0.069) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.053 | −0.027 |
| | (0.040) | (0.057) |
| Homicides per capita$_{t-1}$ | −0.098 | −0.261 |
| | (0.083) | (0.319) |
| Mean | 0.708 | 0.817 |
| Observations | 16,246 | 7,714 |
| Adjusted $R^2$ | 0.002 | −0.00004 |
| *Panel C: Agricultural Households (seasonal)* | | |
| Extreme Temperature$_{t-1}$ | 0.152*** | 0.063 |
| | (0.052) | (0.087) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.126*** | 0.009 |
| | (0.029) | (0.089) |
| Homicides per capita$_{t-1}$ | 0.252 | 0.025 |
| | (0.197) | (0.284) |
| Mean | 0.603 | 0.657 |
| Observations | 10,454 | 4,719 |
| Adjusted $R^2$ | −0.001 | −0.007 |
| *Panel D: Agricultural Households (corn)* | | |
| Extreme Temperature$_{t-1}$ | 0.182*** | 0.052 |
| | (0.050) | (0.093) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.138*** | −0.005 |
| | (0.031) | (0.110) |
| Homicides per capita$_{t-1}$ | 0.100 | 0.048 |
| | (0.205) | (0.292) |
| Mean | 0.623 | 0.725 |
| Observations | 9,315 | 4,139 |
| Adjusted $R^2$ | −0.003 | −0.011 |
| *Panel E: Non Agricultural Households* | | |
| Extreme Temperature$_{t-1}$ | 0.031 | −0.031 |
| | (0.070) | (0.027) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.027 | 0.021 |
| | (0.021) | (0.021) |
| Homicides per capita$_{t-1}$ | −0.031 | 0.231** |
| | (0.160) | (0.100) |
| Mean | 0.729 | 0.527 |
| Observations | 48,846 | 69,224 |
| Adjusted $R^2$ | 0.004 | 0.002 |
| **Controls** | | |
| Extreme Rainfall$_{t-1}$ | x | x |
| Household | x | x |
| Municipal Socio*Year | x | x |
| Geographic*Year | x | x |
| Year and Municipal Fixed Effects | x | x |

Notes: We use household-level data of El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable Homicides per capita$_{t-1}$ is the number of recorded homicides per 1,000 habitants by municipality in the year before the survey. The source of information is the National Police of El Salvador (Policia Nacional Civil). Column 1 corresponds to households in rural areas, while Column 2 to urban areas. Panel A corresponds to all households. Panel B to agricultural households, defined if the household head and at least 50 percent of the members of working age are employed in agriculture. Panel C to seasonal agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing seasonal crops including cereals, corn, rice, beans, seeds and tubers. Panel D to corn agricultural households, defined if the household head works in agriculture and at least 50 percent of the members of working age are employed producing corn. Panel E to non agricultural households defined if the household head or at least 50 percent of the members of working age are employed in a non-agricultural sector. Regressions have the same controls and Extreme Temperature independent variables as in Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01