# Responses to Extreme Temperatures: Migrant Networks and International Migration from El Salvador *

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**Abstract**

We show that exposure to extreme temperatures significantly increases international migration from El Salvador, where nearly a quarter of the population lives in the United States. Extreme temperatures reduce corn yields, leading producers to decrease their use of post-harvest inputs and demand for agricultural workers. These income losses, combined with established U.S. migration networks, increase emigration. Our findings highlight how international migration serves as a response to extreme temperatures when destination networks are strong and migration remains financially feasible. This pattern is not unique to El Salvador: roughly 30 million farms globally are in low-income settings with access to remittances.

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# 1 Introduction

The frequency and length of heat waves have increased since the middle of the last 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 hamper global efforts to reduce rural poverty.[2]

The effects of extreme temperatures can be especially significant in regions with rain-fed agriculture and for small agricultural producers in lower- and middle-income countries, who have less access to mechanisms that manage risk. Incomplete financial markets 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 like asset sales, changes in agricultural practices, greater use of household labor (including children), 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).

We contribute to the literature by measuring the effects of extreme temperatures on agricultural production and examining how 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 demand that prompt farm workers to migrate abroad with support from large migrant networks that ease relocation costs.

[1] The following papers, among others, show the impact of extreme temperatures 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 anomalies: 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).

El Salvador is a particularly interesting setting to explore these relationships for several reasons. First, a large percentage of the population still earns income from agriculture, especially compared to other Latin American countries. Most agricultural producers are subsistence farmers who work small land plots, largely depend 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 in recent decades, with three extreme droughts in the last 10 years alone. Figure 1 illustrates the trend of these increasing temperatures. Finally, El Salvador has a history of continuous migration to the United States that began during the civil war in the 1980s. In 2017, more than one-quarter of its population was estimated to be living in the United States (Abuelafia et al., 2019). The large Salvadoran migrant network there may significantly reduce migration costs, making international migration financially feasible.[3]

Using annual agricultural data from 2013 to 2018, 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 annual corn production by 3.0 percent and corn production per hectare by 3.9 percent. Corn producers adjust in the short run by reducing their demand for hired agricultural workers. One additional week with extreme temperatures decreases the number of hired workers by 3.6 percent for corn producers. Using household surveys from 2009 to 2018, we show that this contraction in labor demand is consistent with a decrease in the probability of being employed in the agricultural sector, growing corn.

These negative effects on agricultural production and employment may contribute to an increase in the probability of international migration. We find that this is the case in El Salvador. One additional week with extreme temperatures during the main growing season

[3]For a more detailed discussion about extreme weather trends in El Salvador and migration from El Salvador to the United States, see online Appendix section A1.

causes yearly migration from corn-based agricultural households to rise by 0.15 percentage points (pp) (23 percent relative to the mean). Our results are generally robust across a variety of alternative specifications. In addition, we find evidence of spillover effects for households with no members in the labor force. This may be driven by increases in food prices. Interestingly, these households are more likely to receive remittances compared to households with working-age individuals in the labor force, suggesting a high degree of dependence on these transfers.

Importantly, because our data do not allow us to distinguish between temporary and permanent migration, our analysis includes both types of migration responses. The results highlight that international migration plays a key role in *ex post* responses to climate shocks in settings with incomplete insurance and credit markets like El Salvador. In particular, informal migrant networks play a crucial role in informal risk-coping mechanisms by facilitating international migration. (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 agriculture in incomplete risk markets with strong migrant networks, 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 would expect extreme temperatures to have different effects in countries where farmers can access financial and insurance markets.[4] In response to a drop in agricultural production, our results suggest that corn producers in El Salvador protect their household income by adjusting input use. As some decisions regarding short-term input use are irreversible, corn producers adjust labor demand mainly by hiring fewer agricultural workers and substituting household workers

[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).

who increase their hours of farm work (Jayachandran, 2006; Bastos et al., 2013; Jessoe et al., 2016; Aragón et al., 2021). Agricultural workers who lose their jobs may move to the non-agricultural sector or migrate to offset income losses. In contexts where migration costs are lower, particularly due to established migrant networks, migration can become a more viable coping strategy. (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 dynamics of these relationships, we examine access to migrant networks as a pull factor in migration responses. Most of the previous literature relies on a reduced-form strategy to determine the effects of weather anomalies on migration but rarely delves into the mechanisms. Some papers explore agriculture as a mechanism but use aggregate data 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 noteworthy exceptions. We offer evidence that agricultural producers, when faced with extreme temperatures that reduce agricultural production, cut their demand for hired workers. With help from the strong migrant networks linking El Salvador and the United States, these workers pursue international migration to cope with the income losses. This situation is not unique to El Salvador. Globally, many agricultural producers operate in similar settings. Of the 570 million farms worldwide in 2016, 49% were located in low-income countries. Among these, 38% were in areas where remittance inflows were above the global median, and 5% were in areas within the top quartile of the global remittance distribution. Understanding how migrant networks facilitate international migration in response to extreme temperatures is, therefore, highly relevant from a policy perspective.

Second, 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 these interactions in order to design policies to prevent distress migration and facilitate intentional migration from regions where agriculture may no longer be feasible. Migration might produce better short-term *and* long-term outcomes if it is voluntary and not for lack of coping mechanisms. Financial and insurance mechanisms should be tailored to the specific needs of small farmers 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). These findings suggest two responses to extreme temperatures: an increase in migration following a negative wage shock caused by adverse temperatures (an ex post risk-coping strategy), and migration driven by the accumulation of prior favorable wage draws resulting from good temperature conditions (an 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, and section 4 explains our empirical strategy and presents our results. We discuss conclusions in section 5.

# 2 Conceptual Framework

This section explores how extreme temperatures influence migration decisions, drawing on the framework developed by Kleemans (2023). Kleemans's model presents migration as a dynamic decision shaped by income fluctuations and liquidity constraints. Households receive unpredictable wage draws each period and decide whether to migrate based on economic circumstances. In this framework, migration can be an immediate response to negative income shocks or a longer-term investment enabled by accumulated positive shocks.

Kleemans's model clarifies how to interpret the effects of contemporaneous and cumula-

tive exposure to extreme temperatures on migration outcomes. When extreme temperatures hurt agricultural productivity in a given year, households may suffer an immediate income shortfall. Absent alternative income sources such as employment in the non-agricultural sector, migration may emerge as a necessary coping strategy. This migration is likely driven by economic distress rather than by long-term planning. The estimated effect of contemporaneous exposure to extreme temperatures in our analysis thus captures the extent to which migration serves as an *ex post* risk-coping strategy in response to economic hardship.

Beyond these short-term effects, cumulative exposure to extreme temperatures over multiple years may influence migration decisions through a different channel. If households experience a sequence of favorable wage draws (resulting from favorable weather conditions), they may be better positioned to finance migration as an investment rather than as a necessity. In this case, migration is not a reaction to immediate hardship but a strategic decision to access higher expected earnings elsewhere. An ongoing sequence of positive wage draws would allow households to accumulate wealth, thereby covering migration costs to an international destination with higher expected wages. Unlike short-term distress migration, these moves are more likely to be longer-term ones that involve relocation to destinations with greater income potential. In our empirical analysis, the coefficient on cumulative temperature exposure reflects the extent to which prior exposure to extreme temperatures enables migration as a planned economic decision rather than as a risk-coping strategy.

We extend Kleemans's model by incorporating two key dimensions that are relevant in El Salvador: migrant networks and local labor markets. Migrant networks shape migration responses by reducing movement costs and facilitating migration in response to economic shocks. At the same time, these networks increase access to remittances, which can ease liquidity constraints and thus reduce the need to migrate despite income fluctuations. The net effect of migrant networks on migration decisions depends on whether they primarily lower barriers to movement or provide financial aid that enables households to remain.

Local labor market conditions also mediate migration responses to extreme temperatures. When non-agricultural employment is available, households may adjust by shifting sectors rather than relocating. However, if local labor markets are weak—with low wages, high unemployment, or barriers to sectoral mobility—migration is more viable.

We seek to provide suggestive evidence on whether migration responses to extreme temperatures are primarily driven by short-term economic distress or longer-term financial planning. In doing so, we extend Kleemans's framework to international migration, where established migrant networks play a central role in shaping decisions.

# 3 Data

Our empirical analysis draws on several data sources to study the effects of extreme temperatures on agricultural production, labor markets, and migration. Agricultural production data come from El Salvador's Multiple Purpose National Agricultural Survey (ENAPM) from 2013 to 2018 conducted by General Directorate of Agricultural Economics of the Ministry of Agriculture and Livestock of El Salvador (2013–2018).[5] The ENAPM is an annual cross-sectional survey providing provincial-level representative data on agricultural units, defined as land holdings dedicated to agricultural production.[6] These include two types of producers: commercial and subsistence. 77 percent identify as subsistence producers, henceforth "corn producers". Our sample includes 19,325 corn producers in all 14 provinces and 169 municipalities during our period of study (2013–2018). The ENAPM has detailed data on crop yields, land size, and agricultural inputs.

We focus on corn production for several reasons. First, corn is the country's main staple crop, a primary source of caloric intake that is produced by 83 to 90 percent of the

[5] At the time of writing this paper, the 2019 survey was not publicly available.

[6] El Salvador is administratively divided into 14 departments (provinces), which are the largest subnational entities. Each department is further divided into 44 districts that encompass 262 municipalities, which are the smallest administrative units.

surveyed sample (WB, 2018; Nawrotzki, 2015). 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 extreme temperatures and corn production.[7]

El Salvador has three corn-producing seasons: *primera* (June–July), *postrera* (August–September), and *apante* (November–December). We measure the effect of extreme temperatures during *primera* (the main season), which yields 94 percent of all corn production.

Labor and migration outcomes are measured using the Multiple Purpose Household Survey (EHPM), a nationally representative annual cross-sectional survey, covering 207,249 households from 2009 to 2018 and conducted by Central Reserve Bank of El Salvador (2009–2018).[8] It includes data on 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, the likelihood of migration, is a dummy equal to one when at least one household member migrated abroad in the year surveyed. We multiply the dummy by 100 to ease interpretation. Data from the EHPM shows that 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. Twelve percent of individuals worked in the agricultural sector and seven percent worked in the agricultural sector producing corn (Tables A1 and A2).

The sample includes households in the agricultural and non-agricultural sectors. Households in the agricultural sector may include landholders or landless agricultural workers. A household is considered agricultural if the household head and at least 50 percent of the working-age members work in this sector. Because the sectors in which household members

[7] 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).

[8] The EHPM has been conducted since 2009, with publicly available data from 2009 to 2021. Data for 2022 and 2023 remain preliminary at the time of writing. The 2020 dataset has geographic limitations due to fieldwork interruptions during the Covid-19 pandemic. While we could have included data from 2019 and 2021, we restrict our analysis to 2018 to ensure consistency with the ENAPM.

work may be endogenous, we classify households using alternative specifications. Our results are robust to these definitions, as discussed in the next section. When using the EHPM, it is important to note that the classification of corn producers includes individuals who may not have direct access to land. As a result, the category includes not only household producers, but also agricultural workers.

Temperature data come from two sources: NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature for 2000 to 2018 (MOD11)[9], and the ERA5-Land dataset for 1980 to 2018 (ECMWF ERA5)[10]. MODIS provides higher spatial resolution with a data grid of $1 \times 1$ $KM$ and reports temperatures in eight-day averages, while ERA5 offers daily measurements at a coarser spatial resolution of approximately $9 \times 9$ $KM$ at the equator—as a reference, the average size of a municipality in El Salvador is 80 $KM^2$ (21,040 $KM^2$ divided by 262 municipalities). Consequently, while MODIS provides the fine spatial granularity needed for our analysis, its limited temporal coverage prevents us from constructing a historical mean temperature over at least 10 years, as is standard in the literature. To address this, we leverage ERA5-Land data to extend the historical baseline while preserving MODIS-level resolution. Specifically, we use available MODIS and ERA5 data to impute historical temperatures at the $1 \times 1$ $KM$ grid level for 1980 to 1999. The methodology employed for this conversion is described in Appendix Section A2.3.

Our primary measure of extreme temperature is the number of weeks during the main growing season in which the temperature was two standard deviations above its historic mean for that same week.[11] To create this, we first estimate historical means and standard deviations for temperature for the main growing season (eight weeks from June to July) from 1980 to 2003. Second, we standardize the temperature for each district by comparing it with these means and standard deviations; and third, we define extreme temperatures as being

[9] Wan et al. (2021)
[10] Muñoz Sabater et al. (2024)
[11] For ease of interpretation, we define a "week" as an eight-day period.

two standard deviations above the mean (McKee et al., 1993).[12]

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 can be stored and replaced by groundwater resources (Colmer, 2021); average temperatures have 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 temperatures affect staple crops more 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 distributions of our measure, showing that extreme temperatures vary widely across municipalities. For example, in 2015, some southeastern municipalities experienced five weeks of such temperatures, whereas some northwestern municipalities experienced zero weeks. Second, some municipalities experienced prolonged exposure to these temperatures. This type of exposure, alongside the theoretical rationale for distinguishing between contemporaneous and cumulative exposures in our model, underscores the need to treat these measures separately. One concern is the correlation level between the two, which could introduce multicollinearity and thereby limit our ability to identify separate effects (the correlation coefficient is 0.35). We discuss the interpretation of both contemporaneous and lagged effects in section 4.[13]

[12] In section 4.6, we test our results using alternative definitions and thresholds.

[13] For additional information on our three main data sources, the definition of all variables, descriptive statistics, and other details, see the online appendix section (A2).

# 4 Empirical Strategy and Results

## 4.1 Agricultural Production

We start by estimating the effect of extreme temperatures on agriculture. Our empirical model exploits both temporal and spatial variations in extreme temperatures during corn-growing seasons from 2013 to 2018 in El Salvador. We estimate the effect of extreme temperatures on agricultural outcome $y_{ijt}$ for corn producer $i$ in municipality $j$ in year $t$ . The agricultural survey collects information during the last quarter of the year. Therefore, a producer interviewed during survey year $t$ reports production for the last growing and harvest seasons in year $t$. Specifically, we estimate the following model:

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

Where $T_{jt}$ represents the number of weeks of extreme temperatures 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 for the previous four years. Including the latter term follows the conceptual framework from section 2 and ensures that $\hat{\delta}_1$ does not capture the effects of extreme temperatures from previous seasons.

This specification controls for time-variant characteristics of the corn producer's household and the land plot ($X'_{ijt}$) 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 ($Z'_{jt}$). Given that temperature might correlate highly with other climatic variables, we follow previous literature (Jessoe et al., 2016; Auffhammer, 2018; Ortiz-Bobea et al., 2019; Colmer, 2021) and include measures of extreme rainfall and droughts, defined as the number of months with rainfall levels two standard deviations below or above

the historic mean (1980–2003) during the main growing season.[14] We include municipality fixed effects ($\mu_j$) that account for any time-invariant unobserved heterogeneity at the municipality level to absorb geographic characteristics such as historic level of rainfall and historic mean of temperatures in municipality $j$. Our specification also includes year fixed effects ($\phi_t$) to account for national shocks such as prices that would impact migration decisions. Therefore, the model exploits within-municipality variation of the shock (Deschênes and Greenstone, 2007; Feng et al., 2010; Dell et al., 2014; Jagnani et al., 2020).

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.[15] Our model's validity relies on the assumption that, conditional on previous controls, there were no unobserved time-varying differences within municipalities that correlated with extreme temperatures. All models are estimated using double-clustered standard errors by municipality and year. Since we measure the effect of extreme temperatures rather than the effect of climate change, our results should be considered short-term effects rather than long-term adjustments by agricultural producers.

Table 1 reports results for equation (1) with the full set of controls. As a robustness check, Table A7 adds controls across columns. 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), the logarithm of Total Factor Productivity (TFP) (Panel C), and labor productivity (Panel D). Column (1) shows the effect of the contemporaneous measure of extreme temperature without controlling for such temperatures in previous years, and column (2) adds those controls.

The results reveal a consistent and significant negative effect of exposure to contem-

[14]The results are robust to these controls and to controls for the level of soil moisture and extreme soil moisture during the main growing season (Ortiz-Bobea et al., 2019). Soil moisture information comes from the 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 cm underground.

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

poraneous extreme temperatures on all agricultural outcomes. Column (2) shows that one week with extreme temperatures during the main growing season cuts corn production by 3.0 percent (Panel A), while yield per hectare falls by 3.9 percent (Panel B) and TFP drops by 3.2 percent (Panel C). These effects are expected as exposure to extreme temperatures causes production losses since corn producers have limited capacity for short-term adjustments.

The magnitude and significance of the contemporaneous effects do not change across specifications, which aligns with the fact that our identification strategy captures within-season, short-term temperature effects. While the effect of cumulative exposure on corn production is positive, it is not statistically significant across specifications. Moreover, the net effect of exposure to extreme temperatures remains negative: the contemporaneous coefficient indicates a 3.0 percent drop in production, while the cumulative coefficient suggests a 0.9 percent gain, resulting in an overall decline.

In general, we find strong evidence that extreme temperatures reduce corn production in El Salvador. This may prompt corn producers to respond by adjusting inputs such as land and workers at the intensive margin. We investigate these responses in the next section.

## 4.2 Input Adjustments

Given that we measure responses in the short term, corn producers have a limited margin to adjust production inputs. Two key features influence these adjustments. First, when exposed to extreme temperatures during the growing season, most production inputs are fixed since decisions have already been made. Second, producers with little or no access to financial markets employ other strategies to offset income losses and smooth consumption. One strategy is to lay off hired workers and substitute them with household workers, thereby protecting the producer's 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 assessing how corn producers adjust their use of production inputs in the short run following model (1). We estimate the effect of extreme temperatures on a principal component index (PCI) based on four types of inputs, on each input separately and on the logarithm of the total cultivated area and area dedicated to corn production.[16]

Table 2 reports these estimates using the agricultural survey. Column (1) shows the effect on the PCI and columns (2) – (6) show the effects on the likelihood of using each input. Extreme temperatures hinder the use of input materials (the PCI), driven mostly by post-harvest chemicals used for crop protection. It is important to note that the magnitude of the effects is small, albeit significantly different from zero. Pesticide use decreased by 0.2 percent and use of post-harvest chemicals fell by 1.7 percent. The lack of responses in planting material and fertilizer is unsurprising since most of these investments had already occurred prior to the extreme temperatures. Nonetheless, these findings contrast with existing literature. For instance, Jagnani et al. (2020) observe gains in pesticide use and weeding labor due to an increase in pests related to higher temperatures, while fertilizer use fell because of financial constraints among farmers. The difference in our results may be partly attributable to two factors. First, corn producers may trim their overall input investment to finance migration after a poor growing season. Second, Jagnani et al. (2020) identify extreme temperatures early in the growing season, while our analysis spans the entire season, limiting the ability to adjust. This is particularly meaningful as the main reduction in our analysis comes from chemical agents employed after harvest.

The results in columns (7) and (8) suggest an increase in land used for corn production from contemporaneous extreme temperatures, and an overall increase in land use from past cumulative exposure: An additional week of exposure to extreme temperatures during the previous four growing seasons increases land use by 1.8 percent. Aragón et al. (2021) explain

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

that if the rise in land use comes through planting fallow land, it could have persistent effects in the medium and long terms. Although we do not directly test the effect on the use of fallow land, the negative coefficient of the cumulative exposure in Panel B of Table 1 is consistent with their hypothesis.[17]

## 4.3 Labor Markets

We next study how corn producers adjust their labor input when facing extreme temperatures. We start by estimating equation (1) for the number of workers allocated to agricultural production. Since some producers 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. Using the ENAPM data, we present columns (1) and (2) in Table 3 that show the effect on the total number of workers, columns (3) and (4) on hired workers, and columns (5) and (6) on household workers.

Extreme temperatures cut total demand for workers in corn production, driven by hired workers. We find that one week with extreme temperatures during the main growing season decreases total workers by 2.5 percent and hired workers by 3.6 percent. These results and the effects on agricultural production imply that income is negatively affected and that producers partly adjust to this by reducing their demand for hired workers.[18]

Table 3 reports negative and significant effects of both contemporaneous and lagged extreme temperatures on the demand for hired agricultural workers. This finding, together with the results in Table 1, supports the idea that corn producers offset production losses through cost-cutting strategies, including reductions in labor and adjustments to input use. These patterns suggest that, when repeatedly exposed to extreme temperatures, producers

[17] 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.

[18] We also estimate this model using the inverse hyperbolic sine transformation and the number of workers with no transformation. The results are overall quantitatively robust, losing significance only when using the dependent variable without transformation.

do not adopt adaptive strategies that require additional labor. Instead, they may adapt by relying more heavily on non-labor-intensive inputs, which is consistent with the positive (albeit insignificant) cumulative effects on production observed in Table 2.

We also find a positive and significant effect of lagged extreme temperatures on the demand for household workers, although it is marginally significant at the 10 percent level. Similarly, our analysis of the effect of extreme temperatures on the extensive margin (Table A8) shows that an additional week with such temperatures increases the probability of having a household worker by 0.4 percentage points (pp) and reduces the likelihood of employing a hired worker by 0.8 pp, although the former effect is not statistically significant. All these results consistently show that corn producers are reducing the number of hired workers, with suggestive evidence of substitution toward household labor.

Next, we provide evidence on individual labor outcomes and local labor market outcomes– complementary dimensions of effects on the labor market– using EHPM data from 2009 to 2018 for both analyses. We estimate the relationship between extreme temperatures and individual labor outcomes following the model below:

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

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).[19] Labor outcomes include whether the person is employed, whether they are employed in the agricultural or non-agricultural sector, and hourly wage. We measure the effect of extreme temperatures at time $t$ to avoid estimating the impact on a selected sample of non-migrants. By capturing the effect at $t$, we mitigate potential selection biases that could arise if migration were influencing labor market outcomes.

[19]The only difference from 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.

Column (1) shows the effect on the probability of being employed; Columns (2) to (10) show the unconditional probability of being employed in different sectors. Since an individual may be unemployed or employed in the agricultural or non-agricultural sector, the results in columns (9) and (10) do not mirror those in columns (3) and (4).

The results in Table 4 suggest a negative effect on the probability of being employed in the agricultural sector. 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 extreme temperatures, such as corn. We explore this hypothesis in columns (3) to (8). As expected, the results are negative for individuals working in seasonal crops and corn, which is consistent with the effects estimated in Table 3.[20] In particular, the results in column (7) indicate that an additional week of extreme temperatures decreases the probability of being employed in the agricultural sector growing corn by 1.37 percent relative to the mean. However, these effects lose significance when controlling for cumulative exposure to extreme temperatures. While the results in Table 3 point to a negative effect of cumulative exposure on the demand for hired workers, the individual-level estimates in Table 4 show a positive, yet not statistically significant, effect of cumulative exposure on the probability of working in the agricultural sector. Although this may appear contradictory at first glance, a potential explanation lies in changes to the structure of agricultural labor: as producers adjust their practices and stabilize production, they may reduce reliance on hired labor while maintaining or increasing reliance on household or self-employed workers. This interpretation is consistent with the findings in Table 1. Unfortunately, the EHPM does not allow us to distinguish between household and hired workers within the agricultural sector, limiting our ability to explore this mechanism directly. Finally, the positive but not statistically significant effects on the probability of working in the non-agricultural sector, as shown

[20] Tables 3 and 4 rely on different data sources and employ different methodological approaches to estimate the effect of extreme temperatures on labor outcomes. Table 3 uses ENAPM data and shows the effect on the number of employed workers as reported by corn producers. In contrast, Table 4 uses EHPM data and measures the probability of employment as reported by individuals.

in columns (9) and (10), suggest there is some reallocation of displaced agricultural workers into non-agricultural jobs. However, the results are noisily estimated and do not allow us to draw firm conclusions.

Panel B of Table 4 shows the effect on the log of hourly wages. Jayachandran (2006) documents that this effect depends on the availability of risk-coping mechanisms. Without access to financial markets or the ability to save or borrow, wage effects may intensify. The negative effects in columns (7) and (8) of Panel B align with this hypothesis, though the coefficient estimates for both the contemporaneous and cumulative effects are not statistically significant.

Although we take steps to minimize the risk of sample selection bias when estimating individual probabilities, some concerns may remain. Therefore, we estimate the effect of extreme temperatures on sector-specific employment shares and hourly wages at the municipality level. These models are estimated using individual-level data from the EHPM (2009–2018), aggregated to the municipality-year level in Table A9.[21]

The analysis at the municipality level helps mitigate potential selection bias, as changes in the composition of workers remaining in El Salvador could distort individual-level estimates of labor market outcomes. By aggregating to the municipality level, our estimations capture the overall effect on the number of individuals employed within a given municipality, accounting for both those who migrate and those who remain but exit the labor force. However, this approach comes at the cost of reduced precision in our coefficient estimates. It is important to interpret these municipality-level results with caution, as the EHPM is not designed to be representative at this level of aggregation. While we mitigate this limitation by applying survey weights, some caution is still warranted when interpreting the findings.

[21] On average, 51 percent of the population aged 10 to 65 are employed, 12 percent are employed in the agricultural sector, and 39 percent work in non-agricultural sectors. These statistics are similar to those reported by the ILO (2021) for El Salvador, which recorded an employment share of 57.4 percent for 2018.

Consistent with the patterns observed in Table 4, we find a negative effect on the employment share in the corn agricultural sector and an increase in the non-agricultural sector, although neither effect is statistically significant (Table A9). The results do not provide evidence of full absorption or partial reallocation into non-agricultural activities. Yet, they show suggestive evidence of a decline on average salaries among the agricultural sector growing corn. To address the concern that migration may be driving population changes in aggregate employment, Table A10 show no evidence of an effect of extreme temperature on the total number of working-age individuals or overall migration rates at the municipality level. This indicates that the suggestive evidence on employment shares is not driven by population changes or by entire households migrating out of El Salvador.

Overall, our findings suggest that declines in corn production affect agricultural labor markets, with corn producers reducing their demand for hired workers. However, we do not have robust evidence to assess the extent to which the non-agricultural sector can absorb these workers.

## 4.4 International Migration

Without access to risk-coping mechanisms but with the advantage of strong networks that reduce relocation costs, international migration—when financially feasible—could become a key response to income loss caused by extreme temperatures. We explore this hypothesis by estimating the effect of extreme temperatures at $t-1$ on the probability of international migration at time $t$, using data from the EHPM with the following regression model:

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

where $m_{ijt}$ is a dummy variable equal to one 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 in the previous models.[23] It is critical to note that in this specification, extreme temperatures are lagged by one period. This design choice reflects the realistic constraints of international migration, which involves significant costs and complexities. Therefore, it is unlikely that individuals can respond instantaneously to these temperature spikes. The migration decision typically requires substantial planning and resources, which naturally delay the response time. By lagging the extreme temperature measure, we account for a realistic lag in human decision-making and logistic execution, making our model more similar to observed behaviors in migration dynamics.

Results for the fully controlled model are in Table 5.[24] We use household-level EHPM data from 2009 to 2018 for all households (Panel A), all agricultural households (Panel B), agricultural households employed in seasonal crops including corn (Panel C), those employed only in corn (Panel D), and non-agricultural households (Panel E). This classification is based on the employment sector of the household head and working-age household members.

A negative effect on agricultural production is one mechanism through which extreme temperatures can affect migration decisions. If this is one of the main mechanisms in El Salvador, we would expect to see a larger response to these temperatures among agricultural households, especially those employed in corn or other seasonal crops sensitive to extreme weather. The results in Table 5 show significant effects of extreme temperatures on the probability of migration for agricultural households employed in seasonal crops, especially corn (Panel D).[25] We expected this result, as seasonal crops are more sensitive to extreme temperature changes. Households employed in corn, who represent 88.7 percent of seasonal

[22] In the empirical regressions, we multiply the dummy variable by 100 to ease the interpretation.

[23] The difference from equation (1) is that household controls are now: household head's age and gender, and the number of household members.

[24] In Table A11, we test the robustness of our results by including one set of controls at a time.

[25] We estimate these effects for agricultural households employed in non-seasonal crops. These households do not show any significant or positive effect regarding the probability of migration.

agricultural households, are likely responsible for this effect.[26] Not only are the effects statistically significant for this sample, but the magnitude of the coefficient is twice as large than that for all households. The coefficient for non-agricultural households is not statistically significant.[27]

The results for agricultural households employed in corn (Panel D, column (2)) show that one additional week with extreme temperatures at time $t-1$ increases the probability of international migration by 0.15 pp, or 23 percent relative to the mean. To contextualize this magnitude, Mueller et al. (2020) find that an increase of one standard deviation in precipitation causes migration to fall 10 and 11 percent in Kenya and Botswana, respectively, but to rise as much as 24 percent in Zambia. For Central America, Baez et al. (2017) find that a gain of one standard deviation in heat exposure doubles and quadruples the probability of young unskilled women to migrate to the provincial and national capitals, respectively. In Pakistan, Mueller et al. (2014) find that exposure to extreme temperatures implies that males are 11 times more likely to leave their villages. Finally, Jessoe et al. (2016) estimate that increases in extreme temperatures induce a 1.4 percent rise in migration from rural to urban areas and a 0.25 percent rise in migration to the United States.

Similar to Kleemans (2023), our findings indicate that the probability of migration increases in response to extreme temperatures during the previous growing season. Yet, we also find that the cumulative effect of extreme temperatures during previous *seasons* makes migration *less* likely. Specifically, an additional week of extreme temperatures during the years from $t-5$ to $t-2$ reduces the likelihood of migration by 0.08 percentage points, representing a 12 percent decrease relative to the mean. This too corresponds to Kleemans (2023) because households exposed to one or more consecutive negative income shocks may lack the necessary resources to finance migration investments in the longer term.

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

[27]In Appendix Table A12 we assess the robustness of our definition of agricultural households, and the results are overall robust. Using Method 3 and 4, we find significant effects among non agricultural households. As we will discuss later, this effect is driven by ''unemployed households".

The magnitude of the coefficients suggests that one additional week with extreme temperatures leads to a significantly larger increase in short-term migration than the decrease from past cumulative exposure among households employed in corn. Since the short-term effect outweighs the cumulative one, the overall net effect is an increase in migration for households with equal exposure to both cumulative and contemporaneous extreme temperatures, launched primarily by immediate responses to economic distress rather than by long-term investments. The overall effect across households varies on their specific exposure levels.

To better understand the lagged and contemporaneous effects of extreme temperatures, Table A13 presents a model that interacts with these two metrics. In Panel A and B, the small and insignificant coefficients for both lagged cumulative extreme temperatures and their interaction with the contemporaneous extremes indicates that repeated exposure to extreme temperatures is insufficient to meaningfully reduce the impact of contemporaneous extreme temperatures on production and employment. Thus, households exposed to favorable temperatures may prioritize wealth accumulation for migration rather than invest in local production, a pattern consistent with the results in Panel C. As noted above, our data do not distinguish between temporary and permanent migration. Future research should explore whether the duration of migration differs when it is a risk-coping response (driven by contemporaneous exposure) instead of an investment response (driven by cumulative exposure).

These findings are also methodologically significant. The contemporaneous effects remain robust even with the inclusion of the interaction term. Moreover, the small and statistically insignificant magnitude of the interaction provides reassurance that the contemporaneous and cumulative effects can be meaningfully disentangled when both are incorporated into the empirical model.

As an additional robustness check, we estimate the model in Equation 3 on the full

sample, fully interacted with a dummy indicating whether the household is classified as a seasonal or corn-producing agricultural household (Appendix Table A14). Consistent with our main specification, we find a significant positive effect of the interaction between lagged extreme temperature ($t$–1) and the agricultural household growing corn dummy.

However, results in Panel C indicate a positive effect on the probability of migration for households not engaged in corn production. As discussed in Table 5, we find no significant effects for households with members working in the non-agricultural sector. These effects are driven by a distinct group of households in which no working-age individuals report labor force participation. These "unemployed" households tend to be smaller, have a higher proportion of elderly members (over age 65), and report lower per capita income. Notably, they also display a stronger connection to migration: 41 percent receive remittances, compared to just 16 percent among other households. In addition, they are more likely to reside in districts with a higher concentration of migrants and greater remittance inflows per capita—underscoring their reliance on international migration and remittance income.

Section A6 and Table A15 examine potential mechanisms underlying migratory responses among these households. The evidence suggests that, for unemployed households, extreme temperatures influence migration through two channels: reduced food access and greater reliance on remittances. This group is the only one to experience a significant decline in per capita food consumption, and they are more likely to depend on remittances and reside in areas with strong migrant networks. Some may be out of the labor force precisely because remittances are their primary source of income. These findings highlight that extreme temperatures can drive migration even among households not directly engaged in agriculture, an important dimension for future research.

## 4.5 The Role of Migrant Networks

Two forces could potentially explain the significant migration response among agricultural households. First, a pull factor: El Salvador's established migration corridor with the U.S. lowers the cost of international mobility. Second, the extent of labor mobility from the agricultural to the non-agricultural sector for displaced workers. However, in El Salvador, the role of local labor markets does not appear to be as salient as in other contexts (Colmer, 2021). As shown in the previous section, although agricultural employment declines following extreme temperatures, the evidence is not robust enough to suggest that limited absorption or partial reallocation into non-agricultural activities is a primary driver of international migration.[28] Therefore, in this section, we focus on examining whether migrant networks amplify migration responses to extreme temperatures.

Access to remittances and migrant networks can help households mitigate negative income losses, thereby reducing the need for more costly mitigation mechanisms such as distress migration. At the same time, these networks may actually lower migration costs by funding relocation, potentially *increasing* the likelihood of migration. The impact of these variables 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 GDP (WB, 2024), offering crucial support to family members who remain there.

We estimate two complementary models. First, we disaggregate the migration analysis by the number of migrants in the household to test whether migrant networks make a migration response more feasible. We estimate equation (3), interacting our measure of extreme temperature with the number of additional migrants in the household (Table A17). The results suggest that the magnitude of the effect on migration from extreme temperatures

[28] We also examine the role of municipality-level connectivity using road network data but find no robust evidence that this form of connectivity influences migration responses. However, we do find that violence may constrain reallocation across sectors, consistently with Melnikov et al. (2020). Specifically, as the homicide rate in the municipality of origin increases, the response to extreme temperatures through international migration becomes more pronounced.

in agricultural households is higher as they have more migrants and networks abroad.[29]

Second, we estimate differential effects of exposure to extreme temperatures on agricultural production, labor outcomes, and migration by access to remittances and migrant networks at baseline. 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 each municipality in 2007, using census data. We then classify municipalities into quartiles based 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). To address endogeneity concerns, we include a comprehensive set of municipality-level controls and municipality fixed effects. 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. Households and municipalities with more access to remittances are likely different from others in many dimensions. Thus, the results in this section should be interpreted as associations rather than causal relationships.

Table 6 shows the results. Panel A suggests that access to remittances and migrant networks does not shield farmers from the effects of extreme temperatures, so corn producers are probably not using them to protect themselves *ex ante* through insurance, consistent with a literature review in Huckstep and Clemens (2023). These results support the exogeneity assumption of our measure of extreme temperature. In this context, further study is needed to understand how corn producers utilize remittances and why they are not used to prepare for seasons of extreme temperatures. Panel B, column (1) suggests that greater access to remittances does not imply different responses in the labor market when exposed to extreme temperatures. This suggests that networks or remittances are not being used for reallocation

[29] See section A7 for a more detailed explanation of the empirical model.

in the labor markets.

Panel C provides strong evidence of a significant relationship between migrant networks and the probability of migration. Individuals residing in municipalities with the lowest share of migrants do not exhibit a significant likelihood of migration, whereas this probability increases progressively across higher quartiles. The sign of the interaction coefficients further implies that municipalities with greater access to these networks experience a higher probability of migration. These findings underscore the crucial role these networks play in prompting international migration from El Salvador.

## 4.6 Robustness Checks

### 4.6.1 Definition of Extreme Temperatures

We test our definition of extreme temperatures by varying the seasons within a year when these temperatures are measured (Table A18) and by adjusting the cutoff definitions for extreme temperatures (Table A19). First, Table A18 estimates 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–December), and in the lean season (August–September). Although there are significant effects on corn production and the likelihood of employment in the agricultural sector growing corn during extreme temperatures throughout the year and during apante season, migration significant effects emerge only from extreme temperatures during the main growing season. The table also shows that results are quantitatively similar across the period from 2013 to 2018, aligning with the agricultural survey period. The results are statistically significant when excluding 2015, the year of the most intense drought.[30]

Second, Table A19 tests the cutoff and definition of a week with extreme temperatures

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

to: the number of weeks during winter with temperatures higher than 1 and 1.5 standard deviations above the mean, weeks with temperatures above 29 and 35 degrees Celsius, and Harmful Degree Weeks (HDW), where every one-degree-Celsius increase in the average temperature above 32 degrees Celsius corresponds to a gain of one unit in HDWs. Overall, the results are quantitative similar 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 2,000 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 A9 for the probability of migration, and in Figure A10 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 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 in Table A20. We estimate the effects on corn production and migration likelihood with Conley standard errors to account for spatial correlation using the distance cutoffs of 25KM, 50KM, and 100KM. In addition, we estimate our main outcomes using Family Wise Error Rate (FWER) adjusted p-values to control for the probability of Type I error. We apply the Bonferroni method, considered the most conservative, and the Holm method, which is considered a more powerful modification of the Bonferroni estimation. Our results remain significant across all standard error adjustments. These estimations demonstrate 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 A21, we estimate our main specification for all the main outcomes, adding a variable of homicides per 1,000 inhabitants by municipality at $t$ or $t-1$, depending on the timing of extreme temperatures. While the effect of extreme temperatures is robust for all our main outcomes, we do not find a significant effect from the homicide rates.

# 5 Conclusions

We examine the response of corn producers to extreme temperatures in El Salvador and find that exposure to such temperatures during the main growing season decreases the production of seasonal crops, particularly corn. In response, farmers adjust by cutting labor demand for hired workers. In a nation like El Salvador, which boasts strong migrant networks in the United States, international migration is an immediate coping response to income losses caused by extreme temperatures. Yet, we find that it becomes an investment decision when farmers are exposed to repeated positive income shocks. Our results highlight the roles of migrant networks and remittances. In areas with more access to such resources, the migratory response to extreme temperatures is stronger.

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 negative income effects, as well as 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 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,[31] we still lack proof of how these mechanisms influence migration responses. 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).

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

# References


**Abuelafia, Emmanuel, Giselle Del Carmen, and Marta Ruiz-Arranz**, *Tras los pasos del migrante: Perspectivas y experiencias de la migración de El Salvador, Guatemala y Honduras en Estados Unidos*, Vol. 775, Inter-American Development Bank, 2019.

**Albert, Christoph, Paula Bustos, and Jacopo Ponticelli**, "The Effects of Climate Change on Labor and Capital Reallocation," 2024. Unpublished.

**Aragón, Fernando, Francisco Oteize, and Juan Pablo Rud**, "Climate change and agriculture: Subsistence farmers' response to extreme heat," *American Economic Journal: Economic Policy*, 2021, *13* (1), 1–35.

**Auffhammer, Maximilian**, "Quantifying economic damages from climate change," *Journal of Economic Perspectives*, 2018, *32* (4), 33–52.

**Auffhammer, Maximilian, Veerabhadran Ramanathan, and Jeffrey R Vincent**, "Climate change, the monsoon, and rice yield in India," *Climatic change*, 2012, *111*, 411–424.

**Baez, Javier, German Caruso, Valerie Mueller, and Chiyu Niu**, "Heat Exposure and Youth Migration in Central America and the Caribbean," *American Economic Review*, May 2017, *107* (5), 446–50.

**Bastos, Paulo, Matías Busso, and Sebatián Miller**, "Adapting to Climate Change: Long-Term Effects of Drought on Local Labor Markets," 2013.

**Blakeslee, David S and Ram Fishman**, "Weather shocks, agriculture, and crime evidence from India," *Journal of Human Resources*, 2018, *53* (3), 750–782.

**Briones, C., J. R. Castro, and O. A. López**, *Mapa de pobreza: Indicadores para el manejo social del riesgo a nivel municipal: Tomo II*, 1st ed., Social Investment Fund for Local Development (Fondo de Inversión Social para el Desarrollo Local), 2005.

**Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak**, "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, 2014, *82* (5), 1671–1748.

**Burke, Marshall and Kyle Emerick**, "Adaptation to Climate Change: Evidence from US Agriculture," *American Economic Journal: Economic Policy*, August 2016, *8* (3), 106–40.

**Cai, Ruohong, Shuaizhang Feng, Michael Oppenheimer, and Mariola Pytlikova**, "Climate variability and international migration: The importance of the agricultural linkage," *Journal of Environmental Economics and Management*, 2016, *79*, 135–151.

**Carleton, Tamma A. and Solomon M. Hsiang**, "Social and economic impacts of climate," *Science*, 2016, *353*, aad9837.

**Carter, Michael R. and Travis J. Lybbert**, "Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso," *Journal of Development Economics*, 2012, *99* (2), 255–264.

**Cattaneo, Cristina and Giovanni Peri**, "The migration response to increasing temperatures," *Journal of Development Economics*, 2016, *122*, 127–146.

**Central Reserve Bank of El Salvador**, "Multiple Purpose Household Survey (EHPM) [Encuesta de Hogares de Propósitos Múltiples]," 2009–2018.

**Clemens, Michael A.**, "Violence, development, and migration waves: Evidence from Central American child migrant apprehensions," *Journal of Urban Economics*, 2021, *124*, 103355.

**Colmer, Jonathan**, "Temperature, Labor Reallocation, and Industrial Production: Evidence from India," *American Economic Journal: Applied Economics*, October 2021, *13* (4), 101–24.

**Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken**, "What Do We Learn from the Weather? The New Climate–Economy Literature," *Journal of Economic Literature*, 2014, *52* (3), 740–798.

**Deschênes, Olivier and Michael Greenstone**, "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, 2007, *97* (1), 354–385.

**Donato, Katharine and Blake Sisk**, "Children's Migration to the United States from Mexico and Central America: Evidence from the Mexican and Latin American Migration Projects," *Journal of Migration and Human Security*, 2015, *3* (1), 58–79.

**FAO**, "World Agriculture Watch," 2016. Retrieved on June 28, 2024.

**Feng, Shuaizhang, Alan Krueger, and Michael Oppenheimer**, "Linkages among climate change, crop yields and Mexico–US cross-border migration," *Proceedings of the National Academy of Sciences*, 2010, *107* (32), 14257–14262.

**Fishman, Ram**, "More uneven distributions overturn benefits of higher precipitation for crop yields," *Environmental Research Letters*, 2016, *11* (2), 024004.

**Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura Harrison, Andrew Hoell, and Joel Michaelsen**, "The Climate Hazards Infrared Precipitation with Stations—A New Environmental Record for Monitoring Extremes," *Scientific Data*, 2015, *2*, 150066.

**General Directorate of Agricultural Economics of the Ministry of Agriculture and Livestock of El Salvador**, "El Salvador's Multiple Purpose National Agricultural Survey (ENAPM) [Encuesta Nacional Agropecuaria de Propósitos Múltiples]," 2013–2018.

**General Directorate of Statistics and Census (DIGESTYC) of the Ministry of Economics of El Salvador**, *National Census: VI Population and V Housing Census, 2007. Volume IV: Municipalities. Volume I: General Population Characteristics*, San Salvador, El Salvador: DIGESTYC, 2007. Accessed May 8, 2025.

**Graff Zivin, Joshua and Matthew Neidell**, "Temperature and the allocation of time: Implications for climate change," *Journal of Labor Economics*, 2014, *32* (1), 1–26.

**Guiteras, Raymond**, "The impact of climate change on Indian agriculture," *Manuscript, Department of Economics, University of Maryland, College Park, Maryland*, 2009.

**Halliday, Timothy**, "Migration, Risk, and Liquidity Constraints in El Salvador," *Economic Development and Cultural Change*, 2006, *54* (4), 893–925.

**Hornbeck, Richard**, "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe," *American Economic Review*, June 2012, *102* (4), 1477–1507.

**Hornbeck, Richard and Suresh Naidu**, "When the Levee Breaks: Black Migration and Economic Development in the American South," *American Economic Review*, March 2014, *104* (3), 963–90.

**Huckstep, Sam and Michael Clemens**, *Climate Change and Migration An Omnibus Overview for Policymakers and Development Practitioners*, Center for Global Development Washington, DC, 2023.

**Hunter, Lori M., Sheena Murray, and Fernando Riosmena**, "Rainfall patterns and U.S. migration from Rural Mexico," *International Migration Review*, 2013, *47* (4), 874–909.

**IFRC**, "El Salvador: Drought Emergency Appeal no. MDRSV010 Operations Update," Technical Report 2016. Retrieved on June 28, 2024.

**ILO**, "Employment and Migration El Salvador 2021," Technical Report, International Labor Organization 2021.

**IPCC**, *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Vol. In Press, Cambridge University Press, 2021.

**Jagnani, Maulik, Christopher B. Barrett, Yanyan Liu, and Liangzhi You**, "Within-Season Producer Response to Warmer Temperatures: Defensive Investments by Kenyan Farmers," *The Economic Journal*, 05 2020, *131* (633), 392–419.

**Jayachandran, Seema**, "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries," *Journal of Political Economy*, 2006, *114* (3), 538–575.

**Jessoe, Katrina, Dale T. Manning, and J. Edward Taylor**, "Climate Change and Labour Allocation in Rural Mexico: Evidence from Annual Fluctuations in Weather," *Economic Journal*, 2016, *128* (608), 230–261.

**Kleemans, Marieke**, "Migration choice under risk and liquidity constraints," 2023.

**Lobell, David B. and Marshall B. Burke**, "Why Are Agricultural Impacts of Climate Change so Uncertain? The Importance of Temperature Relative to Precipitation," *Environmental Research Letters*, 2008, *3* (034007).

**Lowder, Sarah K., Jakob Skoet, and Terri Raney**, "The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide," *World Development*, 2016, *87*, 16–29.

**Mahajan, Parag and Dean Yang**, "Taken by Storm: Hurricanes, Migrant Networks, and US Immigration," *American Economic Journal: Applied Economics*, April 2020, *12* (2), 250–77.

**Marchiori, Luca, Jean-François Maystadt, and Ingmar Schumacher**, "The impact of weather anomalies on migration in sub-Saharan Africa," *Journal of Environmental Economics and Management*, 2012, *63* (3), 355–374.

**Massey, Douglas S., Rafael Alarcón, Jorge Durand, and Humberto González**, *Return to Aztlan. The Social Process of International Migration from Western Mexico* Studies in Demography, Oakland, California, USA: University of California Press, 1990.

**McKee, Thomas B, Nolan J Doesken, and John Kleist**, "The Relationship of Drought Frequency and Duration to the Time Scales," 1993.

**Melnikov, Nikita, Carlos Schmidt-Padilla, and Maria Micaela Sviatschi**, "Gangs, Labor Mobility and Development," Working Paper 27832, National Bureau of Economic Research September 2020.

**Mueller, Valerie, Christen M. Gray, and Katricia Kosec**, "Heat stress increases long-term human migration in rural Pakistan," *Nature Climate Change*, 2014, *4*, 182–185.

**Mueller, Valerie, Clark Gray, and Douglas Hopping**, "Climate-Induced Migration and Unemployment in Middle-Income Africa," 2020, *65*, 102183.

**Munshi, Kaivan**, "Networks in the modern economy: Mexican migrants in the US labor market," *The Quarterly Journal of Economics*, 2003, *118* (2), 549–599.

**Muñoz Sabater, J., E. Comyn-Platt, H. Hersbach, B. Bell, P. Berrisford, G. Biavati, A. Horányi, J. Muñoz Sabater, J. Nicolas, C. Peubey, R. Radu, I. Rozum, D. Schepers, A. Simmons, C. Soci, D. Dee, J.-N. Thépaut, C. Cagnazo, and M. Cucchi**, "ERA5-land post-processed daily-statistics from 1950 to present," https://doi.org/10.24381/cds.e9c9c792 2024.

**Nawrotzki, Raphael J.**, "Climate change as a migration driver from rural and urban Mexico," *Environmental Research Letters*, 2015, *10* (114023).

**Ortiz-Bobea, Ariel, , Toby R Ault, Carlos M Carrillo, Robert G. Chambers, and David B. Lobell**, "Anthropogenic climate change has slowed global agricultural productivity growth," *Environmental Research Letters*, 2021, *11* (4), 306–312.

**Ortiz-Bobea, Ariel, Haoying Wang, Carlos M. Carrillo, and Toby R. Ault**, "Unpacking the climatic drivers of US agricultural yields," *Environmental Research Letters*, 2019, *14* (6), 064003.

**Roberts, Michael and Wolfram Schlenker**, "The Evolution of Heat Tolerance of Corn: Implications for Climate Change," in "The Economics of Climate Change: Adaptations Past and Present," University of Chicago Press, 2011, pp. 225–251.

**Rosenzweig, Mark R. and Kenneth I. Wolpin**, "Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Bullocks in India," *Journal of Political Economy*, 1993, *101* (2), 223–244.

**Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek**, "Integrated Public Use Microdata Series: Version 7.0. [dataset]," 2017.

**Schlenker, Wolfram and David B. Lobell**, "Robust negative impacts of climate change on African agriculture," *Environmental Research Letters*, 2010, *5* (1).

**Schlenker, Wolfram and Michael J. Roberts**, "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 2009, *106* (37), 15594–15598.

**Stanley, William Deane**, "Economic Migrants or Refugees from Violence? A Time-Series Analysis of Salvadoran Migration to the United States," *Latin American Research Review*, 1987, *22* (1), 132–154.

**Wan, Z., S. Hook, and G. Hulley**, "MODIS/Terra Land Surface Temperature/Emissivity 8-Day L3 Global 1km SIN Grid V061 [Data set]," https://doi.org/10.5067/MODIS/MOD11A2.061 2021.

**WB**, "Groundswell: Preparing for Internal Climate Migration," Technical Report, World Bank 2018.

**WB**, *World Development Report 2023: Migrants, Refugees, and Societies*, World Bank, 2023.

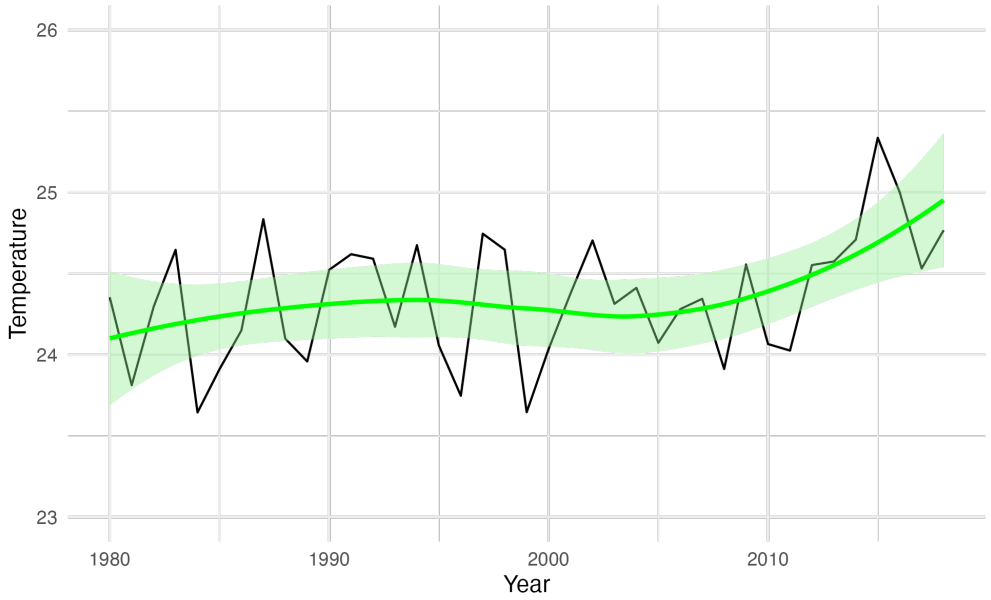
**WB**, "Agricultural irrigated land (% of total agricultural land)," 2024. Sourced from Food and Agriculture Organization. Data retrieved on June 28, 2024.

**WB**, "Personal remittances, received (% of GDP) - El Salvador," 2024. Sourced from World Bank. Data retrieved on June 28, 2024.

**Yang, Dean**, "Risk, Migration, and Rural Financial Markets: Evidence from Earthquakes in El Salvador," *Social Research*, 2008, *75* (3), 955–992.

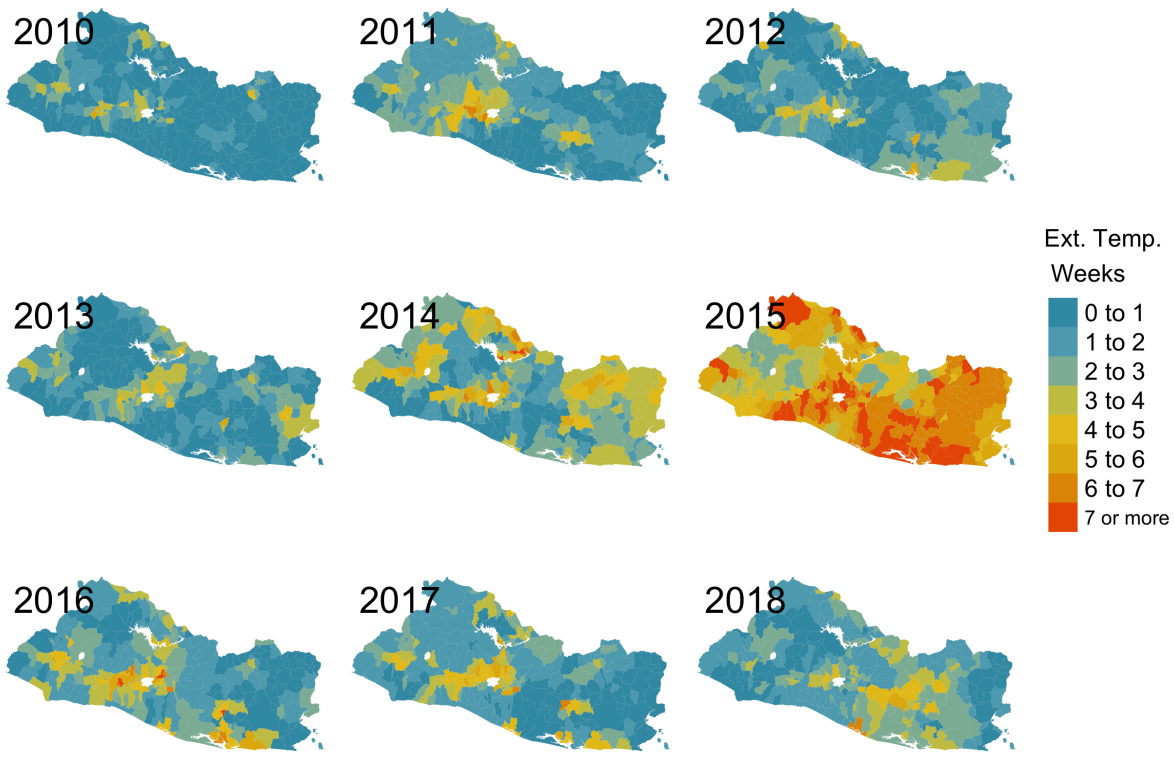
# 6 Figures

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




Source: ERA5-Land. Average per year weighted by area. The green line shows the LOESS (Locally Estimated Scatterplot Smoothing) trend.

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




Source: Own elaboration based on NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature and ERA5-Land temperature. Each map represents the number of weeks with an extreme temperature (two standard deviations 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(Total Production of Corn)* | | |
| Extreme Temperature$_t$ | $-0.034^{***}$ | $-0.030^{**}$ |
| | (0.010) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | | 0.009 |
| | | (0.009) |
| 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$_t$ | $-0.035^{**}$ | $-0.039^{**}$ |
| | (0.016) | (0.018) |
| Extreme Temperature$_{t-1}^{t-4}$ | | $-0.009$ |
| | | (0.007) |
| Mean | 2.339 | 2.339 |
| Observations | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.270 | 0.270 |
| *Panel C: TFP(Log Production)* | | |
| Extreme Temperature$_t$ | $-0.036^{***}$ | $-0.032^{***}$ |
| | (0.010) | (0.011) |
| Extreme Temperature$_{t-1}^{t-4}$ | | 0.008 |
| | | (0.008) |
| Mean | -0.000 | -0.000 |
| Observations | 16,548 | 16,548 |
| Adjusted $R^2$ | 0.290 | 0.290 |
| *Panel D: Log(Labor Productivity)* | | |
| Extreme Temperature$_t$ | $-0.013$ | $-0.007$ |
| | (0.012) | (0.015) |
| Extreme Temperature$_{t-1}^{t-4}$ | | 0.012 |
| | | (0.014) |
| Mean | 0.447 | 0.447 |
| Observations | 18,847 | 18,847 |
| Adjusted $R^2$ | 0.172 | 0.172 |
| **Controls** | | |
| Year Fixed Effects | x | x |
| Municipality Fixed Effects | x | x |
| Extreme Rainfall$_t$ | x | x |
| Geographic*Year | x | x |
| Baseline Municipality$_{2005}$*Year | x | x |
| Corn Producer Controls$_t$ | x | x |

Notes: Data from El Salvador's Agricultural Household Survey (ENAPM) for corn-producing agricultural units from 2013–2018. Each panel has a different dependent variable: Panel A uses the logarithm of corn production during the main growing season; Panel B, the logarithm of corn production per hectare during the main growing season; Panel C, the Total Factor Productivity (TFP) of corn calculated as the logarithm of corn production during the main growing season using area, labor, and inputs; Panel D, the logarithm of corn production per worker during the main growing season. The independent variable Extreme Temperature$_t$ is the number of weeks with a temperature two standard deviations 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 number of weeks with a temperature two standard deviations higher than that week's historic value in that municipality during the main growing season from year t-1 to t-4. All regressions have year and municipality fixed effects. Extreme Rainfall$_t$ controls are the number of weeks with heavy rainfall shocks (two standard deviations higher than that week's historic value in that municipality during the main growing season) and drought (two standard deviations lower than that week's historic value in that municipality) in the same year. Geographic*Year controls correspond to the municipality's elevation and geographic extension, interacted with year trends. Baseline Municipality$_{2005}$*Year controls 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. Corn producer controls are the household head's education, number of household members, and access to irrigation for corn. The means shown in the table correspond to the variables without transformations. The sample size corresponds to corn producers during the main growing season. 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$_t$ | −0.022*** | −0.120 | −0.001 | −0.166* | −1.701** | 0.072 | 0.012 | 0.020** |
| | (0.008) | (0.089) | (0.048) | (0.099) | (0.790) | (0.241) | (0.015) | (0.009) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.013 | 0.026 | 0.024 | −0.016 | −1.428 | 0.194 | 0.018** | 0.012 |
| | (0.012) | (0.033) | (0.062) | (0.054) | (0.972) | (0.122) | (0.007) | (0.009) |
| 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 | 0.008 | 0.028 | 0.096 | 0.045 | 0.168 | 0.186 |
| **Controls** | | | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x | x | x |
| Extreme Rainfall$_t$ | x | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x | x | x |
| Corn Producer Controls$_t$ | x | x | x | x | x | x | x | x |

Notes: Data from El Salvador's Agricultural Household Survey (ENAPM) for corn-producing agricultural units from 2013–2018. Each column has a different dependent variable. Columns (1) – (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 in columns (1) to (6), that show the likelihood (0–100) to employ each input. Column (2) corresponds to planting material such as seeds and plants; (3) and (4) agro-chemicals employed during the growing season: (3) fertilizers and (4) fungicides, bactericides, pesticides, and insecticides; (5) corresponds to chemical agents such as post-harvest product protection agents; and (6) agro-ecological inputs such as compost, fertilizer, bioinsecticides, biopesticides, and biofungicides. Columns (7) shows the logarithm of the total cultivated area and (8) the logarithm of the cultivated area dedicated to corn production. The means correspond to the variables without transformations. The sample size corresponds to agricultural units 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 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: Poisson Fixed Effects

| | Total Workers | | Hired Workers | | Household Workers | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Extreme Temperature$_t$ | −0.017*** | −0.025*** | −0.021*** | −0.036*** | −0.006 | −0.001 |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.016*** | | −0.027*** | | 0.009* |
| | | (0.003) | | (0.003) | | (0.005) |
| 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 | −58,778.030 | −58,761.550 | −64,009.240 | −63,976.160 | −29,656.840 | −29,655.010 |
| **Controls** | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x |
| Extreme Rainfall$_t$ | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x |
| Corn Producer Controls$_t$ | x | x | x | x | x | x |

Notes: Data from El Salvador's Agricultural Household Survey (ENAPM) for corn-producing agricultural units from 2013–2018. Columns (1) and (2) correspond to the dependent variable of total workers in these units; (3) and (4) to hired workers; (5) and (6) to household workers. 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 Individual Labor Outcomes

| | **Employed** | | **Agricultural** | | **Agricultural (Seasonal)** | | **Agricultural (Corn)** | | **Non-Agricultural** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Panel A: Employment Likelihood* | | | | | | | | | | |
| Extreme Temperature$_t$ | 0.024 | 0.012 | −0.091 | −0.065 | −0.085 | −0.054 | −0.099* | −0.080 | 0.108 | 0.071 |
| | (0.081) | (0.089) | (0.059) | (0.067) | (0.052) | (0.059) | (0.051) | (0.057) | (0.080) | (0.098) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.030 | | 0.070 | | 0.082** | | 0.049 | | −0.099 |
| | | (0.065) | | (0.045) | | (0.038) | | (0.035) | | (0.075) |
| Mean | 51.342 | 51.342 | 12.476 | 12.476 | 8.033 | 8.033 | 7.224 | 7.224 | 38.987 | 38.987 |
| Observations | 639,412 | 639,412 | 639,412 | 639,412 | 639,412 | 639,412 | 639,412 | 639,412 | 639,412 | 639,412 |
| Adjusted $R^2$ | 0.211 | 0.211 | 0.181 | 0.181 | 0.132 | 0.132 | 0.129 | 0.129 | 0.175 | 0.175 |
| *Panel B: Wages per hour (log)* | | | | | | | | | | |
| Extreme Temperature$_t$ | 0.001 | −0.002 | 0.002 | −0.006 | 0.015 | 0.008 | −0.012 | −0.014 | −0.001 | −0.003 |
| | (0.006) | (0.005) | (0.014) | (0.014) | (0.016) | (0.019) | (0.013) | (0.017) | (0.004) | (0.003) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.007** | | −0.020** | | −0.018 | | −0.007 | | −0.003 |
| | | (0.003) | | (0.010) | | (0.011) | | (0.011) | | (0.003) |
| Mean | 2.260 | 2.260 | 0.918 | 0.918 | 0.943 | 0.943 | 0.940 | 0.940 | 2.459 | 2.459 |
| Observations | 265,442 | 265,442 | 34,267 | 34,267 | 19,253 | 19,253 | 15,074 | 15,074 | 231,175 | 231,175 |
| Adjusted $R^2$ | 0.128 | 0.129 | 0.249 | 0.250 | 0.388 | 0.389 | 0.471 | 0.471 | 0.107 | 0.107 |
| **Controls** | | | | | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x | x | x | x | x |
| Extreme Rainfall$_t$ | x | x | x | x | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x | x | x | x |
| Individuals Controls$_t$ | x | x | x | x | x | x | x | x | x | x |

Notes: Individual-level data from El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old from 2009–2018. TPanel A reports results for the probability of employment. The dependent variable in columns (1)–(2) is the likelihood of being employed; columns (3)–(4) correspond to employment in agriculture (including cereals, fruits, coffee, sugar, and other crops); columns (5)–(6) to employment in seasonal crops (cereals, corn, rice, beans, seeds, tubers); columns (7)–(8) to employment in corn agriculture; and columns (9)–(10) to employment in non-agricultural sectors. All dependent variables are scaled by 100 (=100 if employed, =0 if not). Panel B reports results for monthly wages for employed individuals. The independent variable Extreme Temperature$_t$ is the number of weeks with a temperature two standard deviations higher than that week's historic value in that municipality during the main growing season in the same year. Extreme Temperature$_{t-1}^{t-4}$ is the number of weeks with a temperature two standard deviations higher than that week's historic value in that municipality during the main growing season from year t-1 to t-4. Fixed effects, rainfall, and geographic and municipality controls are the same as in Table 1. Individual controls are education years, gender, and age. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

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

| | (1) | (2) |
|---|---|---|
| *Panel A: All Households* | | |
| Extreme Temperature$_{t-1}$ | 0.067*** | 0.061*** |
| | (0.016) | (0.014) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.016 |
| | | (0.013) |
| Mean | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.005 | 0.005 |
| *Panel B: Agricultural Households (all)* | | |
| Extreme Temperature$_{t-1}$ | 0.073* | 0.066 |
| | (0.039) | (0.042) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.025 |
| | | (0.028) |
| Mean | 0.839 | 0.839 |
| Observations | 33,237 | 33,237 |
| Adjusted $R^2$ | 0.006 | 0.006 |
| *Panel C: Agricultural Households (seasonal)* | | |
| Extreme Temperature$_{t-1}$ | 0.157*** | 0.134*** |
| | (0.054) | (0.050) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.072** |
| | | (0.033) |
| Mean | 0.621 | 0.621 |
| Observations | 15,143 | 15,143 |
| Adjusted $R^2$ | 0.001 | 0.001 |
| *Panel D: Agricultural Households (corn)* | | |
| Extreme Temperature$_{t-1}$ | 0.173*** | 0.148*** |
| | (0.055) | (0.052) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.079** |
| | | (0.035) |
| Mean | 0.655 | 0.655 |
| Observations | 13,440 | 13,440 |
| Adjusted $R^2$ | −0.00003 | 0.00003 |
| *Panel E: Non Agricultural Households* | | |
| Extreme Temperature$_{t-1}$ | 0.038 | 0.037 |
| | (0.024) | (0.024) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.005 |
| | | (0.014) |
| Mean | 0.579 | 0.579 |
| Observations | 131,011 | 131,011 |
| Adjusted $R^2$ | 0.003 | 0.003 |
| **Controls** | | |
| Year Fixed Effects | x | x |
| Municipality Fixed Effects | x | x |
| Extreme Rainfall$_{t-1}$ | x | x |
| Geographic*Year | x | x |
| Baseline Municipality$_{2005}$*Year | x | x |
| Household Controls$_t$ | x | x |

Notes: Household-level data from El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The dependent variable equals 100 if a household member migrated in the survey year and 0 otherwise. Extreme Temperature$_{t-1}$ is the number of weeks during the main growing season in the year prior to the survey with temperatures two standard deviations above that week's historical average in the same municipality. Extreme Temperature$_{t-2}^{t-5}$ is defined analogously for the main growing seasons from years t–2 to t–5. Panel A includes all households. Panel B includes agricultural households, defined as those where the household head and at least 50% of working-age members are employed in agriculture. Panel C includes seasonal agricultural households, defined as those where the household head works in agriculture and at least 50% of working-age members are employed in seasonal crop production (cereals, corn, rice, beans, seeds, and tubers). Panel D includes corn agricultural households, where the household head works in agriculture and at least 50% of working-age members are employed in corn production. Panel E includes non-agricultural households, defined as those where neither the household head nor at least 50% of working-age members are employed in agriculture. Household controls$_t$ are the household head's gender and age, and the number of household members. Fixed effects and geographic and municipal 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(Total Production)* | | |
| Extreme Temperature$_t$ | −0.042 | −0.030 |
| | (0.030) | (0.022) |
| Extreme Temperatures$_{t-1}^{t-4}$ | 0.009 | 0.009 |
| | (0.009) | (0.009) |
| Extreme Temperature$_t \times Q2$ | 0.018 | 0.009 |
| | (0.028) | (0.021) |
| Extreme Temperature$_t \times Q3$ | 0.027 | −0.009 |
| | (0.022) | (0.013) |
| Extreme Temperature$_t \times Q4$ | −0.006 | 0.003 |
| | (0.046) | (0.036) |
| Observations | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.238 | 0.238 |
| *Panel B: Employed in Agricultural Sector (corn)* | | |
| Extreme Temperature$_t$ | −0.051 | −0.036 |
| | (0.110) | (0.085) |
| Extreme Temperatures$_{t-1}^{t-4}$ | 0.045 | 0.047 |
| | (0.035) | (0.035) |
| Extreme Temperature$_t \times Q2$ | −0.072 | −0.090 |
| | (0.093) | (0.071) |
| Extreme Temperature$_t \times Q3$ | −0.107 | −0.085 |
| | (0.114) | (0.079) |
| Extreme Temperature$_t \times Q4$ | 0.116 | 0.026 |
| | (0.140) | (0.104) |
| Observations | 639,412 | 639,412 |
| Adjusted $R^2$ | 0.129 | 0.129 |
| *Panel C: Migration Likelihood in Agricultural Households (corn)* | | |
| Extreme Temperature$_{t-1}$ | −0.031 | −0.044 |
| | (0.088) | (0.088) |
| Extreme Temperatures$_{t-2}^{t-5}$ | −0.079** | −0.086** |
| | (0.040) | (0.040) |
| Extreme Temperature$_{t-1} \times Q2$ | 0.247* | 0.156** |
| | (0.035) | (0.076) |
| Extreme Temperature$_{t-1} \times Q3$ | 0.259* | 0.199*** |
| | (0.133) | (0.076) |
| Extreme Temperature$_{t-1} \times Q4$ | 0.129 | 0.292* |
| | (0.148) | (0.176) |
| Observations | 13,440 | 13,440 |
| Adjusted $R^2$ | 0.0001 | 0.0001 |
| **Controls** | | |
| Year Fixed Effects | x | x |
| Municipality Fixed Effects | x | x |
| Extreme Rainfall | x | x |
| Geographic*Year | x | x |
| Baseline Municipality$_{2005}$*Year | x | x |
| Corn Producer$_t$ / Individual$_t$ / Household Controls$_t$ | x | x |

Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production during the main growing season, using the ENAPM dataset. Panel B corresponds to the likelihood of being employed in the agriculture of corn, using the EHPM dataset at the individual 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 El Salvador poverty map of 2005. In column (2), it is the share of migrants, also derived from the 2005 Poverty Map. Panel A uses the corn producer controls explained for Table 1, Panel B uses individual controls explained in Table 4, and Panel C uses household controls explained in Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

# Online Appendix

## Responses to Extreme Temperatures: Migrant Networks and International Migration from El Salvador

**Ana Maria Ibáñez, Juliana Quigua, Jimena Romero, Andrea Velásquez**

## 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.[32]

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; one-quarter of its labor force works in agriculture, and most agricultural producers are small family farms dedicated to subsistence farming that largely depend on the rain cycle (WB, 2024; FAO, 2016).

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

Migration to the United States from El Salvador started in the 1980s due to its civil war and migratory flows have persisted since then. Migrant network in the United States have provided 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).[33] By 2021, 2.5 million Hispanics of Salvadoran origin lived in the United States—the third-largest group of Hispanic-origin immigrants in the country. [34]

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

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

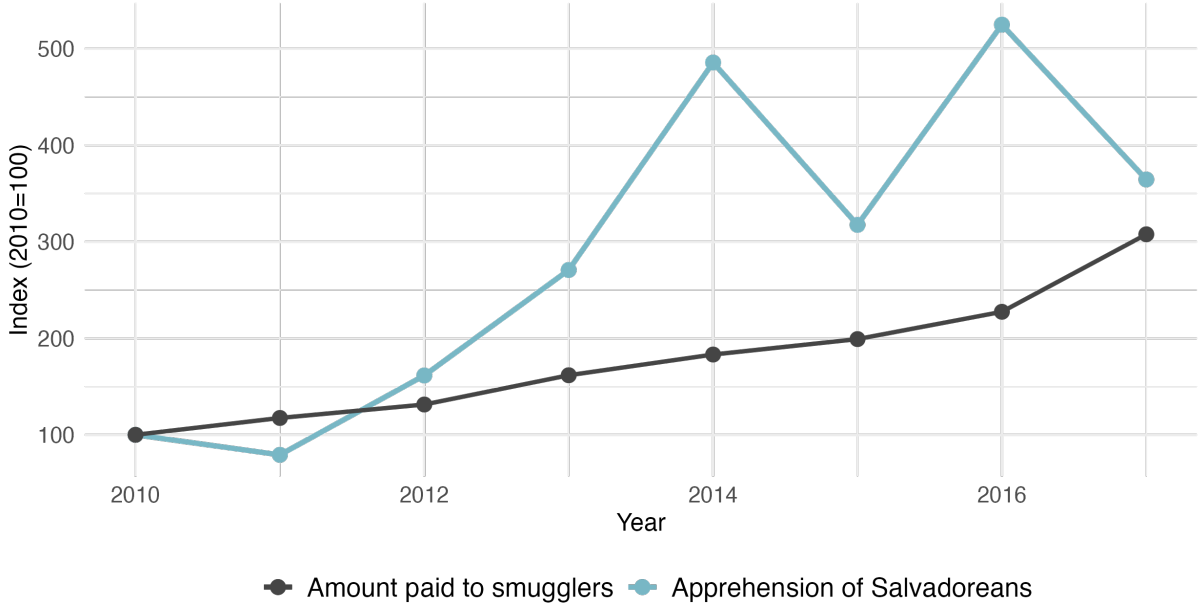
[33] Clemens (2021) finds that past migration flows explain one-third of the current flows caused by violence.

[34] https://www.pewresearch.org/race-and-ethnicity/fact-sheet/us-hispanics-facts-on-salvadoran-origin-latinos/

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

at the border, illustrating that suppressive measures have not succeeded.

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

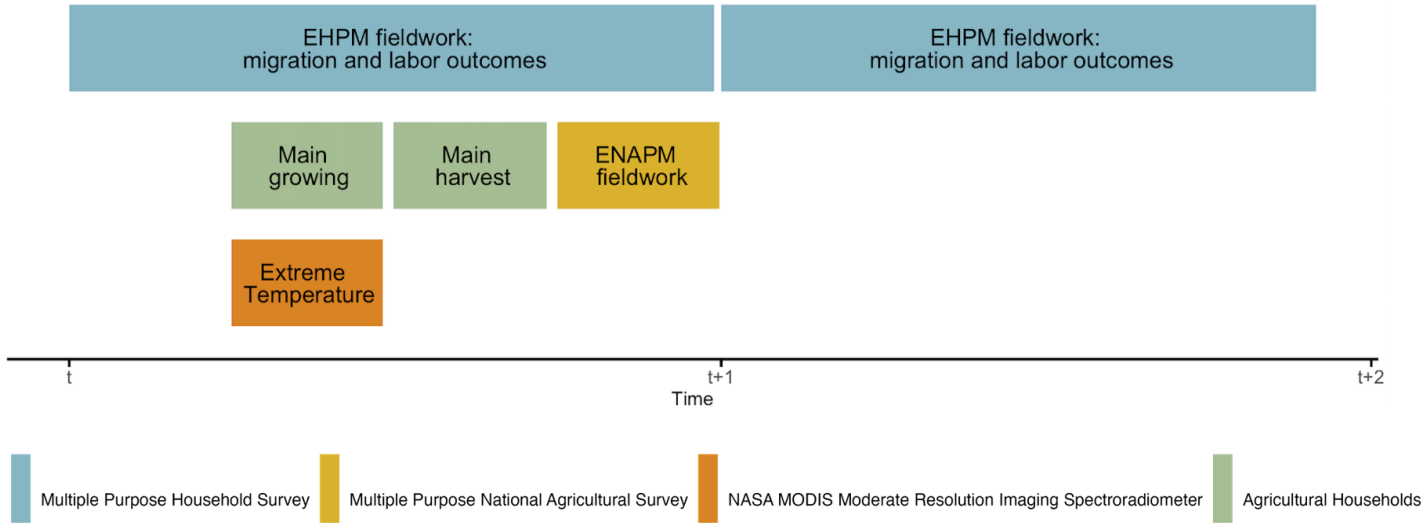



Notes: Own elaboration based on American Community Survey (ACS) and Customs and Border Protection (CBP). The figure shows the time series of an index (2010=100) on border apprehensions of Salvadorans and the cost of smugglers. In 2010, the number of border apprehensions was 11,696 and the cost was USD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

## A2 Data

Figure A2 provides an overview of our three main data sources, the fieldwork calendar, and key outcomes.

**Figure A2:** Timeline of Data



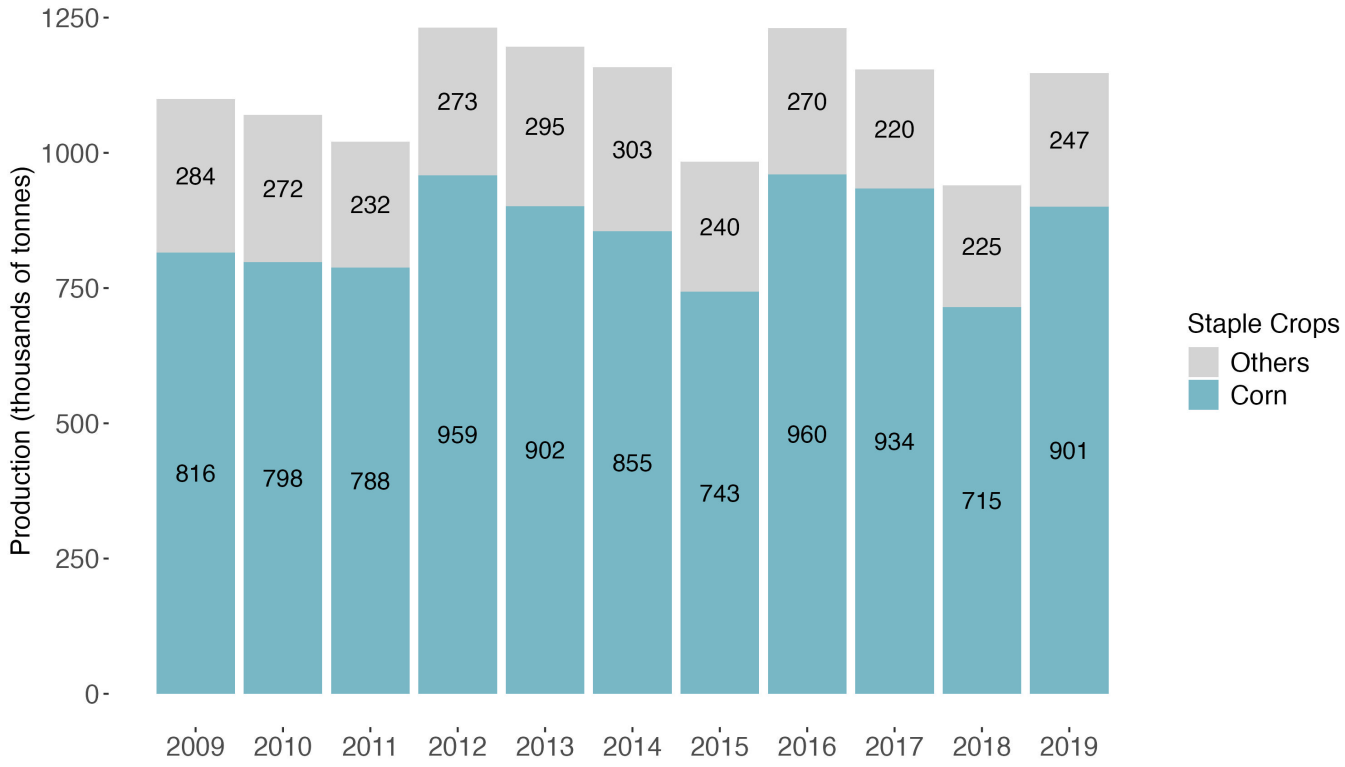

Notes: Own elaboration based on El Salvador's Multiple Purpose Household Survey (EHPM), El Salvador's Multiple Purpose National Agricultural Survey (ENAPM) and NASA – Moderate Resolution Imaging Spectroradiometer (MODIS). The figure depicts that our main specification leverages extreme temperatures during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

### A2.1 Agricultural Production

The Multiple Purpose National Agricultural Survey (ENAPM) is representative at the provincial level for grain crops such as corn. For the other items, it is representative at the national level. There was a two-stage random selection process within each of El Salvador's 14 provinces: first at the cluster level and then at the 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 because 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.

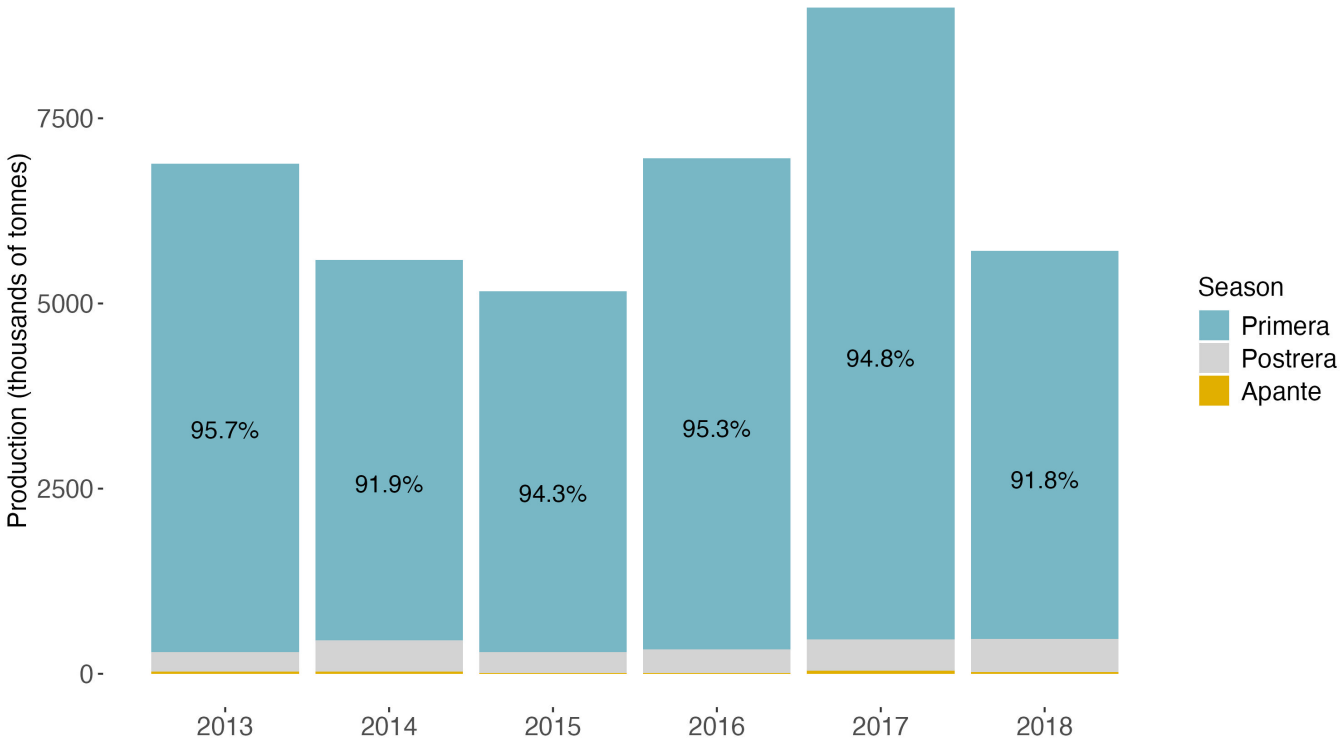
Corn is a primary source of caloric intake for rural households and its production is widespread (Nawrotzki, 2015; WB, 2018). Across survey years, between 83% and 90% of the sample produce corn. An average agricultural producer has a yield per hectare of 2.3 tons and a land plot of 1.5 hectares, of which 0.7 hectares are cultivated with corn. Access to irrigation—crucial for managing periods of drought and extreme temperatures—is practically nonexistent (0.4 percent). (Tables A1 and A2). 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–July), *postrera* (August–September), and *apante* (November–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

[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.

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 temperatures during *primera*. In addition, we perform robustness tests using the other seasons and only the lean season, when we would expect a weak effect or no effect of extreme temperatures on production.

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




Notes: Own elaboration based on El Salvador's Multiple Purpose National Agricultural Survey (ENAPM) data for 2013 to 2018. *Primera* corresponds to the main growing season (June–July). *Postrera* or the lean season corresponds to August and September, and *apante* corresponds to November and December. The numbers in black represent the percentage of the total production for *primera* 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 due to their sociodemographic characteristics. Municipalities that are not self-represented are classified as co-represented. The latter term indicates a 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.

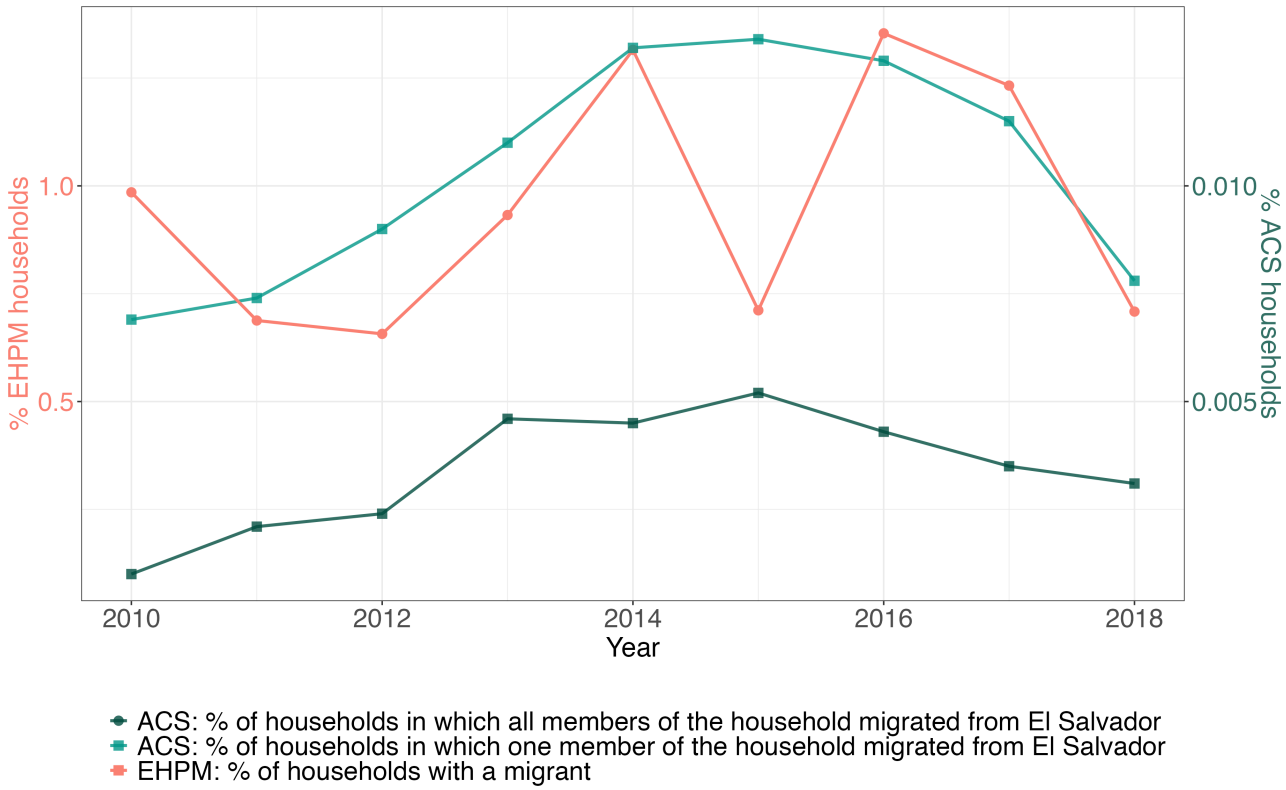
Migration outcomes are identified using the migration module, which collects information on household members who live abroad, their year of migration, and their destination country. To measure migration, we use a question that asks: "Currently, is there any current or past member of this household who resides abroad?" followed by questions: "For how long? (Register the most recent 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 for each, only for the last one(s) who 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 on households with migrants. The latter may underestimate the number of migrants as, in some cases, all household members may migrate together, especially following extreme temperatures. On the other hand, US data on Salvadoran 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 Salvadoran households than for individuals. Reassuringly, our results are robust with and without the 2015 data.

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

[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 Salvadorans – EHPM and ACS




Notes: Own elaboration based on the 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 members were living in El Salvador a year earlier. The red line indicates the percentage of households surveyed in El Salvador with a member living outside the country who migrated in the same year.

Tables A1 and A2 present descriptive statistics for the variables employed in our study. Table A1 consists of three panels. Panel A provides individual-level labor outcome statistics from the EHPM survey, Panel B presents the migration outcome measured at the household level, and Panel C shows agricultural outcome statistics at the producer level from the ENAPM survey. Table A2 provides descriptive statistics of the control variables. Panel A shows household-level data from the EHPM, and Panel B shows aggregated data at the municipal level on temperature, rainfall, geographical controls, and baseline socioeconomic characteristics.

**Table A1:** 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 | 639412 | 12.476 | 33.045 | 0.000 | 100.000 |
| Employed in agricultural sector (seasonal) | 639412 | 8.033 | 27.180 | 0.000 | 100.000 |
| Employed in agricultural sector (corn) | 639412 | 7.224 | 25.888 | 0.000 | 100.000 |
| Employed in the non agricultural sector | 639412 | 38.987 | 48.772 | 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: EHPM Municipal level* | | | | | |
| Share of working age population | 2239 | 0.974 | 0.0785 | 0.560 | 1.000 |
| Share of working age population that is employed | 2239 | 50.046 | 7.528 | 8.696 | 75.163 |
| Share of working age population that is employed in corn | 2239 | 18.454 | 17.071 | 0.000 | 85.714 |
| Mean municipal salary per hour | 2239 | 2.171 | 1.336 | 0.167 | 28.072 |
| Mean municipal salary per hour in corn | 1782 | 0.927 | 0.881 | 0.0201 | 13.579 |
| *Panel D: ENAPM Agricultural unit level* | | | | | |
| Corn production (ton.) | 19325 | 1.915 | 1.890 | 0.001 | 58.880 |
| Corn - productivity (ton. per ha) | 19325 | 2.339 | 1.209 | 0.000 | 19.189 |
| TFP production | 16548 | -0.000 | 0.694 | -21.823 | 1.545 |
| Corn - productivity (ton. per worker) | 18847 | 0.447 | 0.414 | 0.000 | 9.660 |
| Total workers | 18908 | 5.407 | 7.326 | 0.000 | 494.000 |
| Hired workers | 18908 | 3.700 | 7.380 | 0.000 | 494.000 |
| Household workers | 18908 | 1.707 | 1.571 | 0.000 | 43.000 |
| Principal Component Index of inputs (PCI) | 16983 | 0.147 | 0.367 | -7.259 | 0.299 |
| Planting material (=100 if used) | 16983 | 99.623 | 6.127 | 0.000 | 100.000 |
| Fertilizer (=100 if used) | 16983 | 99.576 | 6.498 | 0.000 | 100.000 |
| Pesticide and Fungicide (=100 if used) | 16983 | 99.323 | 8.201 | 0.000 | 100.000 |
| Post Harvest Chemical agents (=100 if used) | 16983 | 92.916 | 25.656 | 0.000 | 100.000 |
| Agroecological (=100 if used) | 16983 | 1.896 | 13.639 | 0.000 | 100.000 |
| Land Size (Ha) | 16983 | 1.420 | 4.163 | 0.077 | 210.000 |
| Land Size cultivated in corn (Ha) | 16983 | 0.711 | 0.711 | 0.056 | 45.500 |

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 descriptive statistics for the EHPM aggregated at the municipal level using municipal weights. Panel D shows data from 2013–2018 of El Salvador's Agricultural Household Survey at the agricultural unit level.

**Table A2:** 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 | 2.465 | 0.925 | 0.000 | 6.000 |
| Has irrigation | 19325 | 0.004 | 0.067 | 0.000 | 1.000 |
| Household size | 19325 | 4.285 | 2.064 | 1.000 | 16.000 |
| *Panel D: Municipalities* | | | | | |
| Weeks temperature 2sd > historic mean during main growing season | 244 | 1.838 | 0.991 | 0.000 | 4.400 |
| Weeks rainfall 2sd > historic mean during main growing season | 244 | 0.335 | 0.162 | 0.000 | 1.000 |
| Weeks rainfall 2sd < historic mean during main growing season | 244 | 7.632 | 0.516 | 0.000 | 8.000 |
| Mean temperature during main growing season | 244 | 29.246 | 2.206 | 22.417 | 35.959 |
| Mean rainfall during main growing season | 244 | 66.148 | 21.634 | 0.000 | 130.660 |
| Mean elevation | 244 | 498.362 | 278.794 | 9.677 | 1522.368 |
| Extension | 244 | 83.733 | 88.237 | 5.400 | 668.360 |
| Poverty rate (2005) | 244 | 50.632 | 14.944 | 10.370 | 88.500 |
| Extreme poverty (2005) | 244 | 25.751 | 12.596 | 4.200 | 60.400 |
| Income per capita (2005) | 244 | 561.074 | 266.001 | 212.600 | 2763.520 |
| % employed in agriculture (2005) | 244 | 38.471 | 18.494 | 0.520 | 78.510 |
| % young adults (16 and 18) not enrolled in school (2005) | 244 | 52.183 | 13.539 | 5.500 | 84.270 |
| % households with no access to drinking water (2005) | 244 | 34.707 | 20.223 | 0.100 | 98.600 |
| % people less than 19 years old (2007) | 244 | 47.541 | 4.145 | 30.800 | 57.300 |
| % people more than 60 years old (2007) | 244 | 9.879 | 1.954 | 5.400 | 19.000 |
| % internal immigrants | 244 | 19.031 | 13.552 | 1.245 | 108.087 |
| % external immigrants | 244 | 29.947 | 26.330 | 3.862 | 234.916 |

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.

### A2.3 Extreme Temperature

Temperature data come from two sources: NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature for 2000–2018 (MOD11)[39], and the ERA5-Land dataset for 1980 to 2018 (ECMWF ERA5)[40]. MODIS provides higher spatial resolution with a data grid of one kilometer and reports temperatures in eight-day averages, while ERA5 offers daily measurements at a coarser spatial resolution of approximately nine kilometers at the equator. Consequently, while MODIS offers superior spatial granularity, ERA5-Land allows us to establish a longer historical baseline for identifying temperature anomalies. To construct our measure of extreme temperature, we follow several steps. First, to ensure consistency between the datasets, we aggregate ERA5's daily measurements into eight-day averages to match MODIS's temporal structure. Second, we aggregate both datasets to the district level using weighted means based on the area covered. Third, we implement a conversion procedure to leverage the advantages of both datasets while maintaining consistency. Specifically, we transform earlier ERA5 data (1980–1999) to match MODIS-equivalent values during their common period (2000–2018):

$$\begin{aligned} T^{MODIS}i,t =& \beta_0 + \beta_1 T^{ERA5}i,t + \sum_{m=1}^{12} \gamma_m (T^{ERA5}i,t \times Month_m) + \\ \sum_{i=1}^{N} \delta_i (T^{ERA5}i,t \times District_i) + & \sum_{m=1}^{12} \alpha_m Month_m + \sum_{i=1}^{N} \phi_i District_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

where $T^{MODIS}i,t$ and $T^{ERA5}i,t$ represent temperature measurements from MODIS and ERA5, respectively, for district $i$ at time $t$. $Month_m$ and $District_i$ are indicator variables for each month and district, respectively. The model includes interactions between ERA5 temperatures and month fixed effects, district fixed effects, and month-by-month interactions to capture both spatial and temporal patterns in the relationship between the two datasets.

[39] Wan et al. (2021)
[40] Muñoz Sabater et al. (2024)

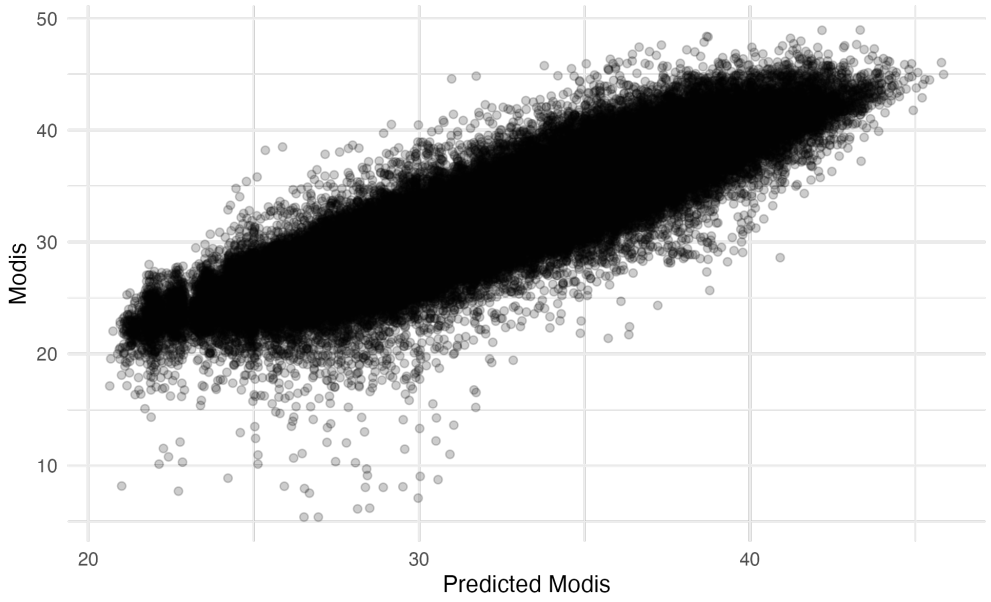
The following table shows the result for $\beta_1$ from regression 4:

**Table A3:** MODIS and ERA5 temperatures correlation

| | *Dependent variable:* |
|---|---|
| | MODIS |
| ERA5-Land | 1.030*** |
| | (0.057) |
| Constant | 7.581*** |
| | (1.341) |
| Observations | 215,132 |
| $R^2$ | 0.818 |
| Adjusted $R^2$ | 0.817 |
| Residual Std. Error | 1.823 (df = 214588) |
| F Statistic | 1,770.576*** (df = 543; 214588) |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 |

Using the resulting coefficients, we predict MODIS-equivalent temperatures for the ERA5 data from 1980 to 2000, effectively creating a harmonized dataset with MODIS-level resolution for the entire 1980–2018 period. The following image shows the correlation between MODIS and the predicted MODIS using ERA5-Land for the years 2000–2018. The coefficient of correlation is 0.904.

**Figure A6:** Correlation between MODIS and the Predicted MODIS temperatures



The statistics for MODIS and predicted MODIS temperatures are:

**Table A4:** Summary Statistics for MODIS and predicted MODIS temperatures

| Statistic | MODIS | Predicted MODIS |
|---|---|---|
| Mean | 30.852 | 30.859 |
| Median | 29.956 | 30.123 |
| Standard Deviation | 4.258 | 3.854 |

Our primary measure of extreme temperatures is the number of weeks during the main growing season in which the temperature was two standard deviations above its historic mean during that same week. To create our "Extreme Temperature" variable, we follow the next steps: first, we estimate historical means and standard deviations for temperature for the main growing season from 1980 to 2003. Second, we standardize the temperature of municipality $j$ during week $w$ of year $y$ using the historic mean $\mu_{j,w,1980-2003}$ and standard deviations $\sigma_{j,w,1980-2003}$ of municipality $j$ during week $w$, between 1980 and 2003 (McKee et al., 1993; Marchiori et al., 2012):[41]

$$\frac{\text{Temperature}_{j,w,y} - \mu_{j,w,1980-2003}}{\sigma_{j,w,1980-2003}}$$

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 two standard deviations above the mean.[42]

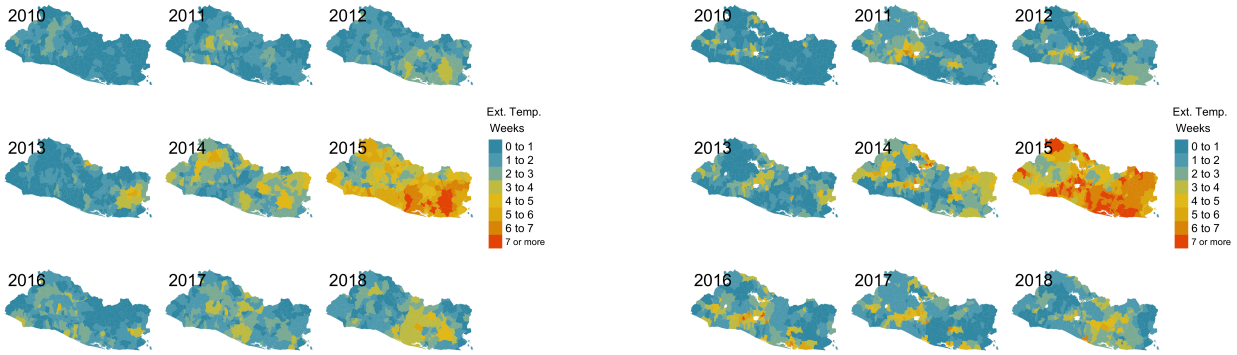
$$\text{Extreme Temperature}_{j,w,y} = \mathbb{1}\left[\frac{\text{Temperature}_{j,w,y} - \mu_{j,w,1980-2003}}{\sigma_{j,w,1980-2003}} >= 2\right]$$

[41] 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).

[42] McKee et al. (1993) use this method to classify extreme droughts, using the SPI.

The following map shows the number of extreme temperature weeks with the predicted MODIS temperature:

**Figure A7:** Extreme Temperature Weeks with Distinct Historic Bases




**(a)** MODIS with Short Historic Base

**(b)** Predicted MODIS with Long Historic Base

The statistics on the number of extreme temperature weeks per municipality and year are:

**Table A5:** Extreme Temperature Weeks using MODIS and Predicted MODIS

| Statistic | Shorter Period (MODIS) | Longer Period (Predicted MODIS) |
|---|---|---|
| Mean | 0.985 | 1.590 |
| Median | 1.00 | 1.00 |
| Standard Deviation | 1.233 | 1.679 |

### A2.4 Extreme Rainfall

Precipitation information comes from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS)[43], which provides high-resolution satellite data at 0.05 degrees, covering the period from 1981 to the current date. To construct our measures of extreme rainfall (high rainfall and low rainfall), we implemented the following process.

First, to ensure consistency between the rainfall and temperature data sets, we aggregated the daily measurements into eight-day averages to match the frequency of MODIS. Second, we aggregated the data to the district level using weighted means based on the area covered. Third, we estimate historical means and standard deviations for rainfall for the main growing season from 1980 to 2003. Finally, we standardize the rainfall of municipality $j$ during week

[43] Funk et al. (2015)

$w$ of year $y$, using the historic mean $\mu_{j,w,1980-2003}$ and standard deviations $\sigma_{j,w,1980-2003}$ of municipality $j$, during week $w$, between 1980 and 2003:

$$\frac{\text{Rainfall}_{j,w,y} - \mu_{j,w,1980-2003}}{\sigma_{j,w,1980-2003}}$$

where $Rainfall_{j,w,y}$ is the rainfall of municipality $j$ and time $w$ (week) during the main growing season of year $y$. Third, we define "High Extreme Rainfall" as being two standard deviations above the mean and "Low Extreme Rainfall" as being two standard deviations below the mean. We include these two measures as controls for Extreme Rainfall.

### A2.5 Controls

Table A6 shows the controls used for each specification, including municipality controls, fixed effects, extreme rainfall, and corn producer, individual or household controls.

**Table A6:** Controls employed for each specification

| Outcomes | Agricultural | Individual Labor | Migration |
|---|---|---|---|
| Specification | (1) | (5) | (3) |
| Main data source | ENAPM | 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 |
| Corn Producer, Individual or Household Controls $X'_{ijt}$ | Household head's education, number of household members, and irrigation for corn | Age, gender and years of education | Household head's gender and age, and number of household's members |

**Extreme Rainfall** $Z_{jt}$: This is the number of months of extreme rainfall during the main growing season, estimated as two standard deviations above and below the historic mean (1981–2003). Precipitation data were extracted from CHIRPS daily Rainfall Data[44], with a resolution of 0.05 degree with daily periodicity and available from 1981.

**Baseline municipality controls** $\times$ **year** $W'_{j2005} * t$: This includes variables from the 2005 Poverty Map of El Salvador[45] and the 2007 Nacional Census.[46] 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 (16–18 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,[47] 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. We extract this information from ASTER Global Digital Elevation Model NetCDF V003, NASA EOSDIS.

**Corn producer, individual or household controls** $X'_{ijt}$**:** Household controls vary by source of information and specification. Household controls for agricultural outcomes estimated using the ENAPM are the household head's education, number of household members, and access to irrigation for corn. Household controls for migration outcomes estimated using the EHPM are the household head's gender, and age and number of household members. There are no household controls for outcomes at the municipality level.

[44] Funk et al. (2015)
[45] Briones et al. (2005)
[46] General Directorate of Statistics and Census (DIGESTYC)
[47] The number of internal migrants is estimated by the difference in birthplace and place of residence.

# A3 Agricultural Outcomes

**Table A7:** Impact of Extreme Temperatures on Corn Agricultural Outcomes Varying Controls

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: Log(Corn Production)* | | | | | | |
| Extreme Temperature$_t$ | −0.063*** | −0.027** | −0.027** | −0.024* | −0.027** | −0.030** |
| | (0.023) | (0.012) | (0.011) | (0.013) | (0.013) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.0004 | 0.017** | 0.018** | 0.019** | 0.010 | 0.009 |
| | (0.016) | (0.008) | (0.008) | (0.009) | (0.010) | (0.009) |
| 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 $R^2$ | 0.018 | 0.223 | 0.223 | 0.223 | 0.225 | 0.238 |
| *Panel B: Log(Production of Corn per Ha.)* | | | | | | |
| Extreme Temperature$_t$ | −0.056*** | −0.045** | −0.045** | −0.042** | −0.041** | −0.039** |
| | (0.017) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.025* | −0.009* | −0.008 | −0.008 | −0.009 | −0.009 |
| | (0.014) | (0.005) | (0.005) | (0.006) | (0.007) | (0.007) |
| 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 $R^2$ | 0.022 | 0.262 | 0.262 | 0.264 | 0.264 | 0.270 |
| *Panel C: TFP(Log Production)* | | | | | | |
| Extreme Temperature$_t$ | −0.064*** | −0.034*** | −0.034*** | −0.031*** | −0.032*** | −0.032*** |
| | (0.015) | (0.011) | (0.010) | (0.011) | (0.011) | (0.011) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.015 | 0.014** | 0.015** | 0.016** | 0.009 | 0.008 |
| | (0.015) | (0.006) | (0.006) | (0.007) | (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 $R^2$ | 0.026 | 0.282 | 0.282 | 0.283 | 0.285 | 0.290 |
| *Panel D: Log(Labor Productivity)* | | | | | | |
| Extreme Temperature$_t$ | −0.044** | −0.006 | −0.006 | −0.006 | −0.007 | −0.007 |
| | (0.021) | (0.014) | (0.014) | (0.015) | (0.014) | (0.015) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.001 | 0.021 | 0.019 | 0.019 | 0.012 | 0.012 |
| | (0.014) | (0.014) | (0.017) | (0.018) | (0.014) | (0.014) |
| 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 $R^2$ | 0.009 | 0.168 | 0.168 | 0.168 | 0.171 | 0.172 |
| **Controls** | | | | | | |
| Year Fixed Effects | | x | x | x | x | x |
| Municipality Fixed Effects | | x | x | x | x | x |
| Extreme Rainfall$_t$ | | | x | x | x | x |
| Geographic*Year | | | | x | x | x |
| Baseline Municipality$_{2005}$*Year | | | | | x | x |
| Corn Producer Controls$_t$ | | | | | | x |

Notes: We use data from El Salvador's Multiple Purpose National Agricultural Survey (ENAPM) for corn-producing agricultural units for 2013 to 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 growing season; Panel C, the Total Factor Productivity (TFP) of corn calculated as the logarithm of production from the main growing season, using area, labor, and inputs; Panel D, the logarithm of production per worker from the main harvest. Regressions have the same controls and independent variables as in Table 1. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.0

**Table A8:** Impact of Extreme Temperatures on the Probability of Having Household and Hired Workers in the Agricultural Producer Unit

| | **Any workers** | | **Hired Workers** | | **Household Workers** | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Extreme Temperature$_t$ | −0.056 | −0.073 | −1.167*** | −0.815** | 0.002 | 0.430 |
| | (0.046) | (0.049) | (0.343) | (0.366) | (0.315) | (0.336) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.034 | | 0.698*** | | 0.848*** |
| | | (0.034) | | (0.254) | | (0.233) |
| 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 | 0.162 |
| **Controls** | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x |
| Extreme Rainfall$_t$ | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x |
| Corn Producer Controls$_t$ | x | x | x | x | x | x |

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

## A4 Labor Outcomes at the Municipality Level

At the municipality level, we estimate the following model:[48]

$$l_{jts} = \alpha + \delta_1 T_{jt} + \delta_2 \sum_{k=t-4}^{k=t-1} T_{jk} + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{jts}. \quad (5)$$

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).[49]

The odd-numbered columns of Table A9 show results without controlling for cumulative exposure to extreme temperatures in previous seasons, while the even-numbered columns include this control.[50] Regarding our preferred specification in the even-numbered columns in Panel A, we find that the share of workers in the agricultural sector falls. Due to the lack of significance, we refrain from drawing strong conclusions based on the magnitude of the coefficients. At face value, though, we find that the effect on the agricultural sector is a drop of 0.8 p.p., similar in magnitude to the effect on the nonagricultural sector.

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 A10 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. 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. This indicates that the effects on employment shares are not driven by population changes or by entire households migrating out of El Salvador.

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

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

[50] 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.

**Table A9:** 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$_t$ | 0.068 | 0.052 | 0.003 | 0.021 | −0.001 | 0.006 | −0.008 | −0.014 | 0.065 | 0.032 |
| | (0.127) | (0.129) | (0.115) | (0.117) | (0.100) | (0.101) | (0.098) | (0.099) | (0.131) | (0.134) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.043 | | 0.049 | | 0.019 | | −0.017 | | −0.087 |
| | | (0.083) | | (0.073) | | (0.062) | | (0.059) | | (0.086) |
| Mean | 50.046 | 50.046 | 15.103 | 15.103 | 9.864 | 9.864 | 9.080 | 9.080 | 35.078 | 35.078 |
| Observations | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.385 | 0.384 | 0.736 | 0.736 | 0.716 | 0.716 | 0.731 | 0.731 | 0.773 | 0.773 |
| *Panel B: Sectoral Wages per hour (log)* | | | | | | | | | | |
| Extreme Temperature$_t$ | 0.001 | 0.0004 | −0.007 | −0.013 | −0.013 | −0.018 | −0.031 | −0.035* | 0.002 | 0.003 |
| | (0.008) | (0.008) | (0.015) | (0.015) | (0.019) | (0.020) | (0.021) | (0.021) | (0.008) | (0.009) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.002 | | −0.015 | | −0.013 | | −0.010 | | 0.001 |
| | | (0.005) | | (0.011) | | (0.013) | | (0.014) | | (0.005) |
| Mean | 2.171 | 2.171 | 0.965 | 0.965 | 0.945 | 0.945 | 0.927 | 0.927 | 2.413 | 2.413 |
| Observations | 2,239 | 2,239 | 2,073 | 2,073 | 1,857 | 1,857 | 1,782 | 1,782 | 2,237 | 2,237 |
| Adjusted $R^2$ | 0.348 | 0.348 | 0.391 | 0.392 | 0.499 | 0.499 | 0.540 | 0.540 | 0.274 | 0.273 |
| **Controls** | | | | | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x | x | x | x | x |
| Extreme Rainfall$_t$ | x | x | x | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x | x | x | x | x |

Notes: We use municipality-level data from El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old from 2009–2018. The dependent variable in Panel A is the share of the working-age population employed per sector (multiplied by 100). The dependent variable in Panel B is the logarithm of the average wage per sector. It is calculated by converting the most recent salary or wage received into an hourly rate. 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 two standard deviations 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 number of weeks with a temperature two standard deviations 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 without transformation. Controls are at the municipal level. Fixed effects, rainfall, and geographic and municipal controls are the same as in Table 1. The number of observations varies due to a lack of municipal wage information in certain sectors. We include sample weights in the estimations. Standard errors are robust to heteroskedasticity and are adjusted by sample size. *p<0.1; **p<0.05; ***p<0.01

**Table A10:** 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$_t$ | −0.0002 | 0.00001 | 0.001 | 0.001 | 0.191 | 0.217 |
| | (0.0004) | (0.0004) | (0.001) | (0.001) | (0.183) | (0.187) |
| Extreme Temperature$_{t-1}^{t-4}$ | | 0.001* | | 0.00003 | | 0.069 |
| | | (0.0003) | | (0.001) | | (0.122) |
| Mean | 97.414 | 97.414 | 73.405 | 73.405 | 18.696 | 18.696 |
| Observations | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 | 2,239 |
| Adjusted $R^2$ | 0.957 | 0.957 | 0.650 | 0.650 | 0.603 | 0.602 |
| **Controls** | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x |
| Extreme Rainfall$_t$ | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | 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 A9. Standard errors are robust to heteroskedasticity and are adjusted by sample size. *p<0.1; **p<0.05; ***p<0.01

# A5 Additional Tables

**Table A11:** Impact of Extreme Temperatures on Migration Likelihood – Varying Controls

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel A: All Households* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.046 | 0.057*** | 0.057*** | 0.057*** | 0.060*** | 0.061*** |
| | (0.039) | (0.013) | (0.013) | (0.013) | (0.014) | (0.014) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.053*** | −0.023* | −0.023* | −0.024* | −0.016 | −0.016 |
| | (0.015) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| 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 $R^2$ | 0.001 | 0.004 | 0.004 | 0.004 | 0.004 | 0.005 |
| *Panel B: Agricultural Households (all)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.072*** | 0.049 | 0.050 | 0.052 | 0.064 | 0.066 |
| | (0.022) | (0.035) | (0.034) | (0.037) | (0.041) | (0.042) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.079*** | −0.031 | −0.031 | −0.039 | −0.026 | −0.025 |
| | (0.019) | (0.032) | (0.032) | (0.031) | (0.029) | (0.028) |
| Mean | 0.839 | 0.839 | 0.839 | 0.839 | 0.839 | 0.839 |
| Observations | 33,237 | 33,237 | 33,237 | 33,237 | 33,237 | 33,237 |
| Adjusted $R^2$ | 0.001 | 0.003 | 0.003 | 0.003 | 0.003 | 0.006 |
| *Panel C: Agricultural Households (seasonal)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.135*** | 0.119** | 0.122** | 0.123** | 0.134*** | 0.134*** |
| | (0.030) | (0.055) | (0.054) | (0.053) | (0.050) | (0.050) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.076*** | −0.081** | −0.082** | −0.082** | −0.070* | −0.072** |
| | (0.029) | (0.040) | (0.041) | (0.041) | (0.036) | (0.033) |
| Mean | 0.621 | 0.621 | 0.621 | 0.621 | 0.621 | 0.621 |
| Observations | 15,143 | 15,143 | 15,143 | 15,143 | 15,143 | 15,143 |
| Adjusted $R^2$ | 0.001 | −0.002 | −0.002 | −0.002 | −0.002 | 0.001 |
| *Panel D: Agricultural Households (corn)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.147*** | 0.126** | 0.129** | 0.131** | 0.147*** | 0.148*** |
| | (0.036) | (0.057) | (0.056) | (0.055) | (0.051) | (0.052) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.079** | −0.099** | −0.100** | −0.099** | −0.079** | −0.079** |
| | (0.033) | (0.048) | (0.048) | (0.048) | (0.039) | (0.035) |
| Mean | 0.655 | 0.655 | 0.655 | 0.655 | 0.655 | 0.655 |
| Observations | 13,440 | 13,440 | 13,440 | 13,440 | 13,440 | 13,440 |
| Adjusted $R^2$ | 0.001 | −0.003 | −0.003 | −0.003 | −0.003 | 0.00003 |
| *Panel E: Non-Agricultural Households* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.034 | 0.038* | 0.037* | 0.037* | 0.037 | 0.037 |
| | (0.040) | (0.022) | (0.023) | (0.023) | (0.024) | (0.024) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.035*** | −0.007 | −0.007 | −0.007 | −0.005 | −0.005 |
| | (0.011) | (0.016) | (0.016) | (0.016) | (0.014) | (0.014) |
| Mean | 0.579 | 0.579 | 0.579 | 0.579 | 0.579 | 0.579 |
| Observations | 131,011 | 131,011 | 131,011 | 131,011 | 131,011 | 131,011 |
| Adjusted $R^2$ | 0.0004 | 0.002 | 0.002 | 0.002 | 0.002 | 0.003 |
| **Controls** | | | | | | |
| Year Fixed Effects | | x | x | x | x | x |
| Municipality Fixed Effects | | x | x | x | x | x |
| Extreme Rainfall$_{t-1}$ | | | x | x | x | x |
| Geographic*Year | | | | x | x | x |
| Baseline Municipality$_{2005}$*Year | | | | | x | x |
| Household Controls$_t$ | | | | | | x |

Notes: Same notes as Table 5.

**Table A12:** Impact of Extreme Temperatures on Migration Likelihood – Heterogeneity by Working-Age Household Members Characteristics

| | Method 1: Preferred specification | Method 2: Household head works in agriculture (corn) | | Method 3: At least 50 % of working-age members work in agriculture (corn) | | Method 4: At least one of the working-age members works in agriculture (corn) | |
|---|---|---|---|---|---|---|---|
| | | No | Yes | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Extreme Temperature$_{t-1}$ | 0.148*** | 0.046*** | 0.150*** | 0.078*** | 0.121* | 0.066*** | 0.140* |
| | (0.052) | (0.013) | (0.051) | (0.017) | (0.070) | (0.013) | (0.074) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.079** | −0.012 | −0.038 | −0.022 | −0.009 | −0.023 | −0.011 |
| | (0.035) | (0.015) | (0.034) | (0.019) | (0.035) | (0.020) | (0.034) |
| Mean | 0.655 | 0.782 | 0.826 | 0.794 | 0.716 | 0.760 | 0.892 |
| Observations | 13,440 | 178,810 | 28,439 | 158,904 | 19,984 | 145,587 | 33,301 |
| Adjusted $R^2$ | 0.00003 | 0.005 | 0.005 | 0.006 | 0.0001 | 0.006 | 0.004 |
| **Controls** | | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x | x |
| Extreme Rainfall$_{t-1}$ | x | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x | x |
| Household Controls$_t$ | x | x | x | x | x | x | x |

Notes: 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 corn agricultural households as those in which the head of the household is employed producing corn. Method 3 defines corn agricultural households as those in which at least 50 percent of the working-age members are employed producing corn. Method 4 defines corn agricultural households as those in which 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 A13:** Impact of Extreme Temperatures in Main Outcomes with Contemporaneous and Lag Interactions

| | (1) | (2) |
|---|---|---|
| *Panel A: Log(Corn Production)* | | |
| Extreme Temperature$_t$ | −0.030** | −0.035** |
| | (0.012) | (0.014) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.009 | 0.007 |
| | (0.009) | (0.009) |
| Extreme Temperature $t \times \sum_{t-1}^{t-4}$ | | 0.001 |
| | | (0.002) |
| Mean | 1.915 | 1.915 |
| Observations | 19,325 | 19,325 |
| Adjusted $R^2$ | 0.238 | 0.238 |
| *Panel B: Employed in Agricultural Sector (corn)* | | |
| Extreme Temperature$_t$ | −0.080 | −0.125 |
| | (0.059) | (0.079) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.049 | 0.037 |
| | (0.038) | (0.042) |
| Extreme Temperature $t \times \sum_{t-1}^{t-4}$ | | 0.006 |
| | | (0.006) |
| Mean | 7.224 | 7.224 |
| Observations | 639,412 | 639,412 |
| Adjusted $R^2$ | 0.129 | 0.129 |
| *Panel C: Migration Likelihood in Agricultural Household (corn)* | | |
| Extreme Temperature$_{t-1}$ | 0.148*** | 0.228 |
| | (0.052) | (0.146) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.079** | −0.045 |
| | (0.035) | (0.067) |
| Extreme Temperature $t \times \sum_{t-1}^{t-4}$ | | −0.019 |
| | | (0.018) |
| Mean | 0.655 | 0.655 |
| Observations | 13,440 | 13,440 |
| Adjusted $R^2$ | 0.00003 | 0.0001 |
| **Controls** | | |
| Year Fixed Effects | x | x |
| Municipality Fixed Effects | x | x |
| Extreme Rainfall | x | x |
| Geographic*Year | x | x |
| Baseline Municipality$_{2005}$*Year | x | x |
| Corn Producer$_t$ / Individual$_t$ / Household Controls$_t$ | x | x |

Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main growing season using ENAPM dataset. Panel B corresponds to the likelihood of being employed in the employed in the agriculture of corn, using the EHPM dataset at the individual 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 standard deviations 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

**Table A14:** Impact of Extreme Temperatures on Migration Likelihood

| | (1) | (2) |
|---|---|---|
| *Panel A: Interaction with Agricultural Households (all)* | | |
| Extreme Temperature$_{t-1}$ × Agricultural Household | 0.005 | 0.009 |
| | (0.032) | (0.034) |
| Extreme Temperature$_{t-2}^{t-5}$ × Agricultural Household | | −0.006 |
| | | (0.016) |
| Extreme Temperature$_{t-1}$ | 0.066*** | 0.059*** |
| | (0.021) | (0.022) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.016 |
| | | (0.014) |
| Agricultural Household | 0.030 | 0.050 |
| | (0.075) | (0.093) |
| 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) | 0.073 | 0.074 |
| | (0.046) | (0.047) |
| Extreme Temperature$_{t-2}^{t-5}$ × Agricultural Household (seasonal) | | −0.002 |
| | | (0.024) |
| Extreme Temperature$_{t-1}$ | 0.062*** | 0.056*** |
| | (0.021) | (0.021) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.016 |
| | | (0.014) |
| Agricultural Household (seasonal) | −0.394*** | −0.387*** |
| | (0.101) | (0.128) |
| 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) | 0.088* | 0.089* |
| | (0.048) | (0.050) |
| Extreme Temperature$_{t-2}^{t-5}$ × Agricultural Household (corn) | | −0.001 |
| | | (0.026) |
| Extreme Temperature$_{t-1}$ | 0.062*** | 0.055*** |
| | (0.021) | (0.021) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.017 |
| | | (0.014) |
| Agricultural Household (corn) | −0.416*** | −0.413*** |
| | (0.106) | (0.135) |
| Mean | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.005 | 0.005 |
| **Controls** | | |
| Year Fixed Effects | x | x |
| Municipality Fixed Effects | x | x |
| Extreme Rainfall$_{t-1}$ | x | x |
| Geographic*Year | x | x |
| Baseline Municipality$_{2005}$*Year | x | x |
| Household Controls$_t$ | x | x |

Notes: Household-level data of EHPM: 2009–2018. Dependent variable is 100 if household member migrated in the surveyed year. Following household definitions from Table 5, Panel A shows interactions with a dummy indicating if the observation corresponds to an agricultural household; Panel B interactions with a dummy indicating if the observation corresponds to seasonal agricultural household; Panel C interactions with a dummy indicating if the observation corresponds to an agricultural household that produces 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

## A6 Spillover Effects

Table A15 shows the estimated effect of extreme temperatures on households in which no working-age individuals report labor force participation. Panel A shows that an additional week of extreme temperatures increases the probability of migration by 0.2 percentage points.

Panel B focuses on the subgroup of households with some connection to agriculture—either because a member is currently out of work while awaiting the start of the agricultural cycle, or because their most recent employment was in the agricultural sector. While these households are not classified as agricultural in our main definition (which requires current employment in agriculture), their exposure to agricultural income cycles makes them vulnerable to extreme temperatures. The coefficient for this group is sizable and statistically significant, consistent with the mechanism discussed for agricultural households in the main analysis.

More unexpected are the results in Panel C. For these households, we observe significant increases in the likelihood of migration among unemployed households with no apparent connection to the agricultural sector. These effects are surprising and raise important questions about the channels through which extreme temperatures influence migration decisions in this group.

In Panel D, we present the effects on households with undefined sector, which are those with at least one employed individual that can not be clearly categorized as agricultural or non-agricultural. While contemporaneous extreme temperatures do not have a significant effect on migration likelihood, lagged cumulative exposure reduces it.

One possibility is that these households are indirectly affected by higher food prices. This is a reasonable mechanism in El Salvador given that national trends show a positive correlation between corn and bean prices and average extreme temperatures during the corn agricultural season, as shown in Figure A8. This suggests that food availability may be affected by extreme temperatures. Food insecurity in El Salvador has been widely documented, where more than half of households had some degree of chronic food insecurity between 2015 and 2020.[51] Food insecurity is worsen by extreme temperatures.[52]

[51] Source: IPC

[52] Source: Humanitarian Action, World Food Program

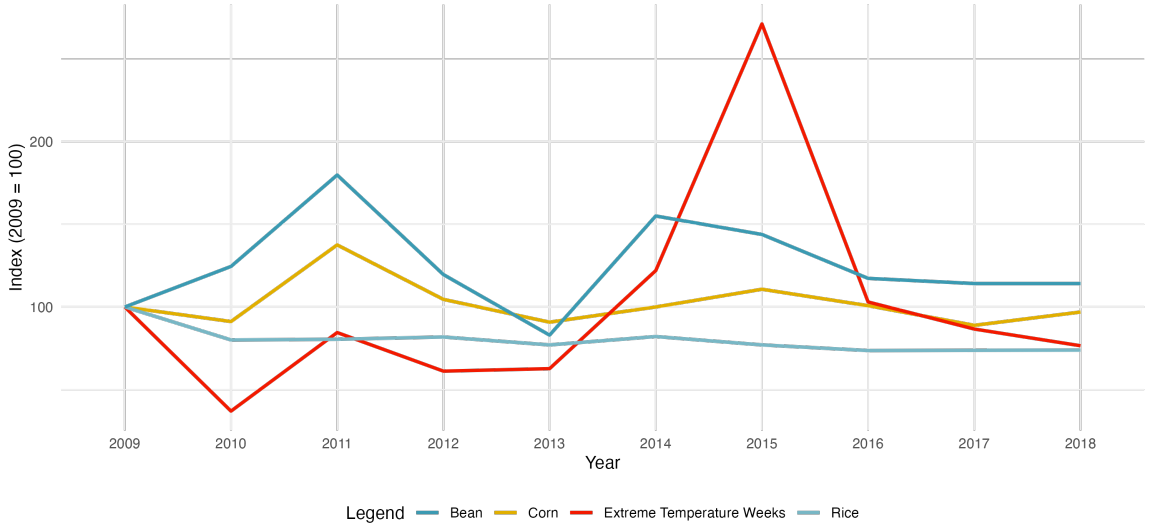



**Figure A8:** Trends in food prices and extreme temperatures

Notes: We use consumption prices from the El Salvador's Ministry of Agriculture and Livestock on beans ("Frijol Rojo de Seda"), corn ("Maiz Blanco"), and rice ("Arroz Oro"). Extreme Temperature Weeks are the number of weeks with a temperature two standard deviations higher than that week and municipality's historic value during the main growing season in the same year. All variables are indexed to 100 in 2009.

In order to explore this mechanism, we estimate the effect of extreme temperatures on food expenditure per capita using a similar identification strategy as in equation 3, with the key difference that we examine contemporaneous effects—estimating the impact of extreme temperatures in time $t$ on food consumption in the same period. It is important to note that we cannot disentangle whether changes in food expenditure are driven by price fluctuations or changes in quantity purchased. The results in Panel D of Table A16 support this hypothesis. We find a significant reduction in food expenditure among unemployed households. Among households with undefined sector, the results also suggest a reduction in food expenditure, yet results are not statistically significant. In this sense, the evidence suggests that unemployed and undefined sector households may have fewer options to adjust to income shocks and rising food prices during years of extreme temperatures, making them particularly vulnerable. They may substitute towards cheaper items or reduce the quantity purchased. Further research is needed to better disentangle the effects on food consumption and food availability. In contrast, corn-agricultural households do not experience a significant change in per capita food expenditure.

**Table A15:** Impact of Temperature Shocks on Migration Likelihood - Unemployed Households

| | (1) | (2) |
|---|---|---|
| *Panel A: Unemployed Households* | | |
| Extreme Temperature$_{t-1}$ | 0.152* | 0.155* |
| | (0.078) | (0.080) |
| Extreme Temperature$_{t-2}^{t-5}$ | | 0.007 |
| | | (0.049) |
| Mean | 1.547 | 1.547 |
| Observations | 31,277 | 31,277 |
| Adjusted $R^2$ | 0.012 | 0.012 |
| *Panel B: Unemployed Households - Agricultural link* | | |
| Extreme Temperature$_{t-1}$ | 0.252* | 0.285** |
| | (0.134) | (0.144) |
| Extreme Temperature$_{t-2}^{t-5}$ | | 0.079 |
| | | (0.088) |
| Mean | 1.158 | 1.158 |
| Observations | 4,059 | 4,059 |
| Adjusted $R^2$ | 0.001 | 0.001 |
| *Panel C: Unemployed Households - Non agricultural link* | | |
| Extreme Temperature$_{t-1}$ | 0.146* | 0.145* |
| | (0.085) | (0.084) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.004 |
| | | (0.056) |
| Mean | 1.562 | 1.562 |
| Observations | 28,417 | 28,417 |
| Adjusted $R^2$ | 0.013 | 0.013 |
| *Panel D: Households with Undefined Sector* | | |
| Extreme Temperature$_{t-1}$ | 0.087 | 0.055 |
| | (0.153) | (0.145) |
| Extreme Temperature$_{t-2}^{t-5}$ | | −0.077* |
| | | (0.043) |
| Mean | 0.955 | 0.955 |
| Observations | 11,724 | 11,724 |
| Adjusted $R^2$ | 0.003 | 0.003 |
| **Controls** | | |
| Year Fixed Effects | x | x |
| Municipality Fixed Effects | x | x |
| Extreme Rainfall$_{t-1}$ | x | x |
| Geographic*Year | x | x |
| Baseline Municipality$_{2005}$*Year | x | x |
| Household Controls$_t$ | x | x |

Notes: We use household-level data from 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 two standard deviations 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 number of weeks with a temperature two standard deviations higher than that week's historic value in that municipality during the main growing season from year $t-2$ to $t-5$. Panel A represents households that do not have any member employed (from the question "Have you worked last week?"). Panel B includes unemployed households with a connection to agriculture, either because a member did not work but is waiting for the agricultural season to begin or because their previous employment was in agriculture. Panel C comprises unemployed households with no agricultural ties. Panel D comprises households with at least one employed individual that can not be clearly categorized as agricultural or non-agricultural. This typically occurs when information about the household head's occupation is missing, incomplete, or does not align with the defined sector categories. Consequently, these households are economically active but cannot be confidently assigned to a specific employment sector. 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 A16:** Impact of Extreme Temperatures on Food Expenditure

| | (1) | (2) |
|---|---|---|
| *Panel A: All Households* | | |
| Extreme Temperature$_t$ | 0.015 | −0.011 |
| | (0.081) | (0.081) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.066 |
| | | (0.052) |
| Mean | 0.788 | 0.788 |
| Observations | 207,249 | 207,249 |
| Adjusted $R^2$ | 0.261 | 0.261 |
| *Panel B: Agricultural Households* | | |
| Extreme Temperature$_t$ | 0.099 | 0.075 |
| | (0.112) | (0.113) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.065 |
| | | (0.075) |
| Mean | 0.839 | 0.839 |
| Observations | 33,237 | 33,237 |
| Adjusted $R^2$ | 0.284 | 0.284 |
| *Panel C: Non-Agricultural Households* | | |
| Extreme Temperature$_t$ | 0.095 | 0.078 |
| | (0.095) | (0.095) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.043 |
| | | (0.072) |
| Mean | 0.579 | 0.579 |
| Observations | 131,011 | 131,011 |
| Adjusted $R^2$ | 0.231 | 0.231 |
| *Panel D: Unemployed Households* | | |
| Extreme Temperature$_t$ | −0.472*** | −0.463*** |
| | (0.148) | (0.139) |
| Extreme Temperature$_{t-1}^{t-4}$ | | 0.024 |
| | | (0.107) |
| Mean | 1.547 | 1.547 |
| Observations | 31,277 | 31,277 |
| Adjusted $R^2$ | 0.281 | 0.281 |
| *Panel E: Households with Undefined Sector* | | |
| Extreme Temperature$_t$ | −0.184 | −0.227 |
| | (0.242) | (0.233) |
| Extreme Temperature$_{t-1}^{t-4}$ | | −0.109 |
| | | (0.102) |
| Mean | 0.955 | 0.955 |
| Observations | 11,724 | 11,724 |
| Adjusted $R^2$ | 0.291 | 0.291 |
| **Controls** | | |
| Year Fixed Effects | x | x |
| Municipality Fixed Effects | x | x |
| Extreme Rainfall$_{t-1}$ | x | x |
| Geographic*Year | x | x |
| Baseline Municipality$_{2005}$*Year | x | x |
| Household Controls$_t$ | x | x |

Notes: We use household-level data from El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018. The dependent variable is the food expenditure per capita. The independent variable Extreme Temperature$_t$ is the number of weeks with a temperature two standard deviations higher than that week's historic value in that municipality during the main growing season in the year of the survey. The independent variable Extreme Temperature$_{t-1}^{t-4}$ is the number of weeks with a temperature two standard deviations higher than that week's historic value in that municipality during the main growing season from year $t-1$ to $t-4$. Panel A corresponds to all households. Panel B corresponds to agricultural households, defined as those in which the household head and at least 50 percent of the working-age members are employed in agriculture. Panel C corresponds to non-agricultural households defined as those in which neither the household head nor less than 50 percent of the members of working age are employed in an agricultural sector. Panel D represents households that do not have any member employed (from the question "Have you worked last week?"). Panel E comprises households with at least one employed individual that can not be clearly categorized as agricultural or non-agricultural. This typically occurs when information about the household head's occupation is missing, incomplete, or does not align with the defined sector categories. Consequently, these households are economically active but cannot be confidently assigned to a specific employment sector. Controls are the same as Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Moreover, given that unemployed households are more likely to receive remittances, relative to other households, we test whether migrant networks play a significant role in their migration decisions. In Section A7, we show in Table A17 that the migration effect among unemployed households is driven by those with stronger networks, proxied by the total number of household members who have migrated, both contemporaneously and in the past.

## A7 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 A17), following the model below:

$$m_{ijt} = \alpha + \delta_1 T_{jt-1} + \sum_{k=1}^{k=3} \delta_{2,k} T_{jt-1} \times \Gamma_k + \delta_3 \sum_{k=t-5}^{k=t-2} T_{jk} + X'_{ijt}\gamma + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{ijt} \tag{6}$$

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 A17:** Heterogeneity by Access to Networks: Migration

| | Corn Agricultural Households | Non Agricultural Households | Unemployed Households |
|---|---|---|---|
| | (1) | (2) | (3) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.078** | −0.002 | 0.013 |
| | (0.039) | (0.013) | (0.049) |
| Extreme Temperature$_{t-1}$ | 0.066 | 0.032 | 0.091 |
| | (0.048) | (0.020) | (0.081) |
| Extreme Temperature$_{t-1}$ × two migrants | 1.077*** | 0.087 | 0.769** |
| | (0.765) | (0.226) | (0.303) |
| Extreme Temperature$_{t-1}$ × more than two migrants | 1.617 | 0.144 | 0.093 |
| | (0.415) | (0.260) | (0.216) |
| Share household with two migrants | 0.030 | 0.026 | 0.075 |
| Share household with more than two migrants | 0.026 | 0.021 | 0.082 |
| F-test: Extreme Temp = Extreme Temp × Two Migrants | 0.179 | 0.813 | 0.042 |
| F-test: Extreme Temp = Extreme Temp × More Migrants | 0.001 | 0.666 | 0.994 |
| Observations | 13,440 | 131,011 | 31,277 |
| Adjusted $R^2$ | 0.026 | 0.015 | 0.021 |
| **Controls** | | | |
| Year Fixed Effects | x | x | x |
| Municipality Fixed Effects | x | x | x |
| Extreme Rainfall$_{t-1}$ | x | x | x |
| Geographic*Year | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x |
| Household Controls$_t$ | x | x | 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 in column 1) 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, in column 2) corresponds to non agricultural households, defined if the household head does not work in agriculture and less than 50 percent of the members of working age are employed producing corn, and column 3) to households that do not have an employed member (from the question "Have you worked last week?"). The independent variable and 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 A18:** Impact of Extreme Temperatures on Migration Likelihood – Varying Seasons and Time Frame

| | 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$_t$ | −0.030** | −0.018*** | −0.032** | −0.006 | −0.030** | −0.016 |
| | (0.012) | (0.006) | (0.013) | (0.019) | (0.012) | (0.014) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.009 | 0.003 | 0.009 | 0.006 | 0.009 | 0.009 |
| | (0.009) | (0.003) | (0.009) | (0.010) | (0.009) | (0.010) |
| Observations | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 | 16,648 |
| Adjusted $R^2$ | 0.238 | 0.239 | 0.238 | 0.236 | 0.238 | 0.233 |
| *Panel B: Employed in Agricultural Sector (corn)* | | | | | | |
| Extreme Temperature$_t$ | −0.080 | −0.054** | −0.116* | 0.055 | −0.091 | −0.073 |
| | (0.059) | (0.027) | (0.060) | (0.090) | (0.083) | (0.071) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.049 | 0.003 | 0.011 | 0.079 | 0.061 | 0.034 |
| | (0.038) | (0.019) | (0.047) | (0.072) | (0.073) | (0.038) |
| Observations | 639,412 | 639,412 | 639,412 | 639,412 | 356,980 | 573,366 |
| Adjusted $R^2$ | 0.129 | 0.129 | 0.129 | 0.129 | 0.126 | 0.130 |
| *Panel C: Migration Likelihood in Agricultural Households (corn)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.148*** | 0.026 | −0.062 | 0.062 | 0.097 | 0.140** |
| | (0.052) | (0.027) | (0.101) | (0.111) | (0.079) | (0.066) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.079** | −0.001 | 0.058 | −0.060 | −0.144** | −0.080* |
| | (0.035) | (0.018) | (0.046) | (0.060) | (0.071) | (0.043) |
| Observations | 13,440 | 13,440 | 13,440 | 13,440 | 7,229 | 11,871 |
| Adjusted $R^2$ | 0.00003 | −0.0004 | −0.0004 | −0.0004 | −0.007 | −0.0002 |
| **Controls** | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x |
| Extreme Rainfall | x | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x |
| Corn Producer$_t$ / Individual$_t$ / Household Controls$_t$ | x | x | x | x | x | x |

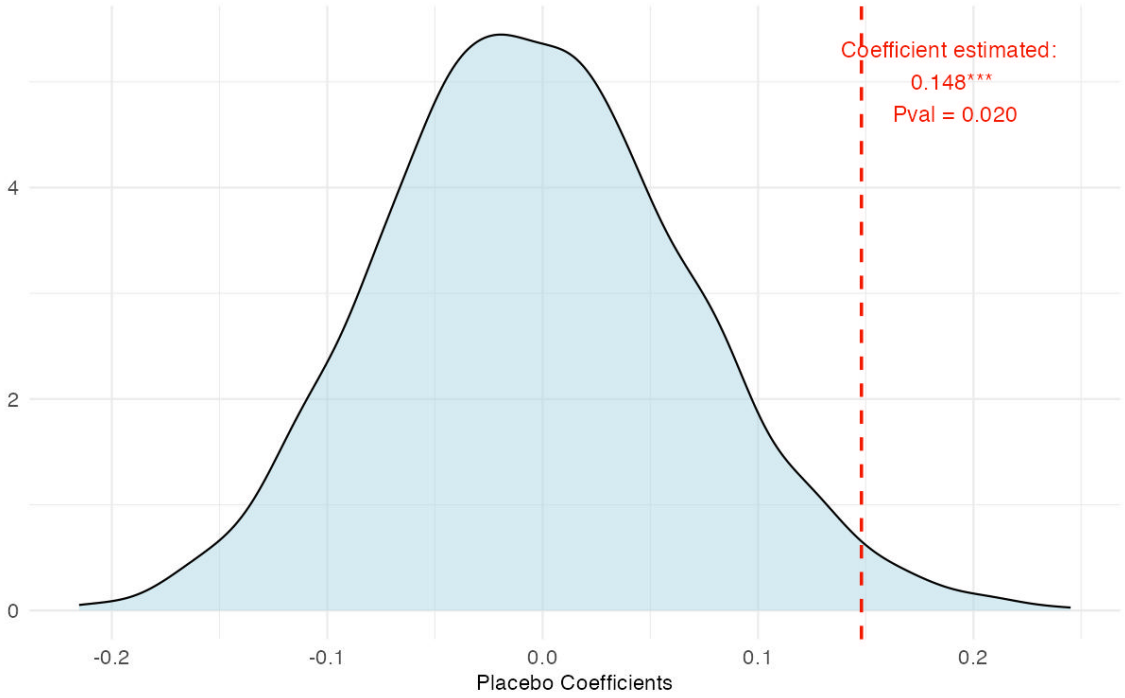
Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main growing season using ENAPM dataset. Panel B corresponds to the likelihood of being employed in the agriculture of corn, using the EHPM dataset at the individual level. Panel C corresponds 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 standard deviations higher than that week's historic value in that municipality during the main growing season (June - July). Columns (2) to (4) estimate Extreme Temperature for different seasons: Column (2) 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 standard deviations 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 ENAPM 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.*p<0.1; **p<0.05; ***p<0.01

**Table A19:** Impact of Extreme Temperatures in Main Outcomes - Varying Definitions of Extreme Temperatures

| | 1 SD | 1.5 SD | Higher 29 | Higher 35 | HDW |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: Log(Corn Production)* | | | | | |
| Extreme Temperature$_t$ | −0.029*** | −0.033*** | −0.033*** | −0.027 | −0.005 |
| | (0.010) | (0.010) | (0.011) | (0.022) | (0.004) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.008 | 0.008 | 0.007 | 0.021 | 0.005 |
| | (0.007) | (0.006) | (0.010) | (0.020) | (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: Employed in Agricultural Sector (corn)* | | | | | |
| Extreme Temperature$_t$ | −0.068* | −0.031 | −0.073 | −0.147*** | −0.029*** |
| | (0.038) | (0.047) | (0.059) | (0.046) | (0.011) |
| Extreme Temperature$_{t-1}^{t-4}$ | −0.001 | 0.046 | 0.008 | −0.073 | 0.001 |
| | (0.039) | (0.036) | (0.042) | (0.062) | (0.011) |
| Mean | 7.224 | 7.224 | 7.224 | 7.224 | 7.224 |
| Observations | 639,412 | 639,412 | 639,412 | 639,412 | 639,412 |
| Adjusted $R^2$ | 0.129 | 0.129 | 0.129 | 0.129 | 0.129 |
| *Panel C: Migration Likelihood in Agricultural Households (corn)* | | | | | |
| Extreme Temperature$_{t-1}$ | 0.112* | 0.083 | 0.077 | 0.245*** | 0.045* |
| | (0.061) | (0.071) | (0.065) | (0.088) | (0.024) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.067* | −0.109** | −0.084** | 0.051 | 0.009 |
| | (0.037) | (0.049) | (0.037) | (0.087) | (0.021) |
| Mean | 0.655 | 0.655 | 0.655 | 0.655 | 0.655 |
| Observations | 13,440 | 13,440 | 13,440 | 13,440 | 13,440 |
| Adjusted $R^2$ | 0.00003 | 0.0001 | −0.00000 | −0.0002 | −0.0002 |
| **Controls** | | | | | |
| Year Fixed Effects | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x |
| Extreme Rainfall | x | x | x | x | x |
| Geographic*Year | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x |
| Corn Producer$_t$ / Individual$_t$ / Household Controls$_t$ | x | x | x | x | x |

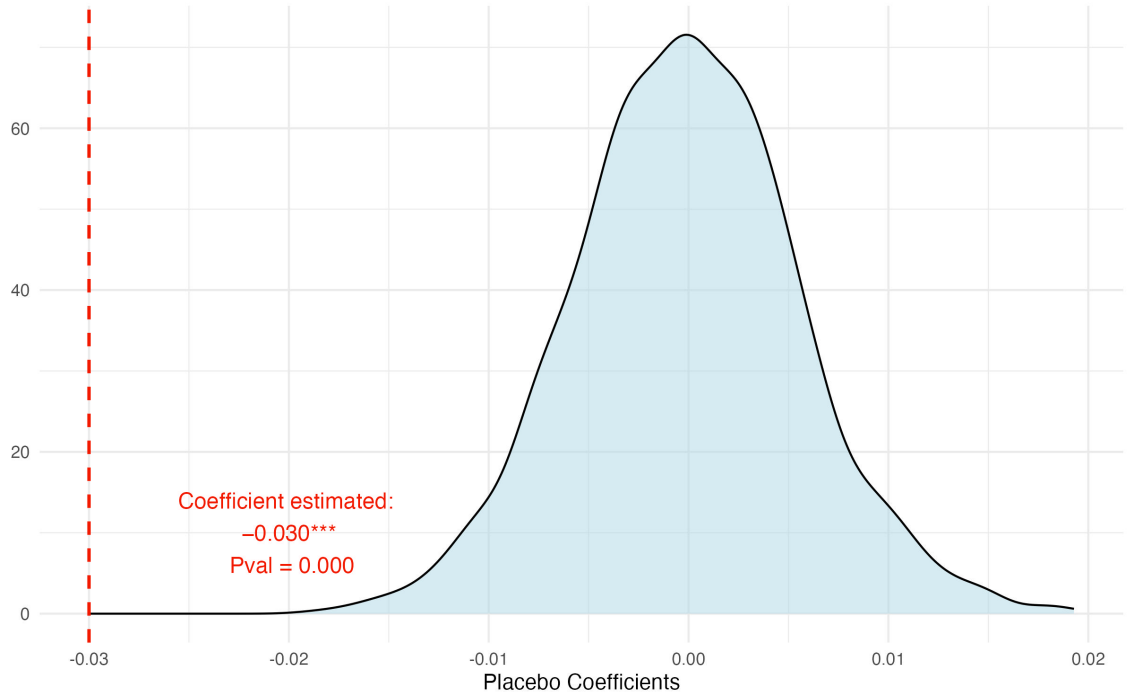
Notes: Each column estimates the independent variable with a different specification. Column (1) and (2) modify our main specification to different cutoffs. Column (1) specification is the number of weeks with a temperature 1 standard deviations higher than that week's historic value in that municipality during main growing season. Column (2) corresponds to the number of weeks with a temperature 1.5 standard deviations 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 ENAPM dataset. Panel B corresponds to the likelihood of being employed in the agriculture of corn, using the EHPM dataset at the individual 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 A9:** 2,000 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 A10:** 2,000 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 (ENAPM). 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 A20:** Impact of Extreme Temperatures on Labor and Migration Outcomes – Varying Standard Errors

| | Main specification | Conley (25 KM) | Conley (50 KM) | Conley (100 KM) | FWER Bonferroni | FWER Holm |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Log(Corn Production)* | | | | | | |
| Extreme Temperature$_t$ | −0.030** | −0.030*** | −0.030** | −0.030** | −0.030** | −0.030** |
| | (0.012) | (0.011) | (0.012) | (0.012) | (0.012) | (0.012) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 |
| | (0.009) | (0.009) | (0.011) | (0.013) | (0.009) | (0.009) |
| Observations | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 | 19,325 |
| $R^2$ | 0.245 | 0.245 | 0.245 | 0.245 | 0.245 | 0.245 |
| Adjusted $R^2$ | 0.238 | 0.238 | 0.238 | 0.238 | 0.238 | 0.238 |
| *Panel B: Migration likelihood in Agricultural Households (corn)* | | | | | | |
| Extreme Temperature$_{t-1}$ | 0.148*** | 0.148* | 0.148** | 0.148*** | 0.148*** | 0.148*** |
| | (0.052) | (0.088) | (0.061) | (0.051) | (0.052) | (0.052) |
| Extreme Temperature$_{t-2}^{t-5}$ | −0.079** | −0.079 | −0.079* | −0.079* | −0.079** | −0.079** |
| | (0.035) | (0.052) | (0.047) | (0.042) | (0.035) | (0.035) |
| Observations | 13,440 | 13,440 | 13,440 | 13,440 | 13,440 | 13,440 |
| $R^2$ | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 | 0.019 |
| Adjusted $R^2$ | 0.00003 | 0.00003 | 0.00003 | 0.00003 | 0.00003 | 0.00003 |
| **Controls** | | | | | | |
| Year Fixed Effects | x | x | x | x | x | x |
| Municipality Fixed Effects | x | x | x | x | x | x |
| Extreme Rainfall | x | x | x | x | x | x |
| Baseline Municipality$_{2005}$*Year | x | x | x | x | x | x |
| Corn Producer Controls$_t$ / Household Controls$_t$ | 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 ENAPM dataset. Panel B 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 standard deviations 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) to (4) we use Conley standard errors to account for spatial correlation. In columns (4) to (5) we use Family Wise Error Rate (FWER) adjusted p-values. *p<0.1; **p<0.05; ***p<0.01

**Table A21:** Impact of Extreme Temperatures and Homicide Rate in Main Outcomes

| | (1) |
|---|---|
| *Panel A: Log(Corn Production)* | |
| Extreme Temperature$_t$ | $-0.031^{**}$ |
| | (0.013) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.007 |
| | (0.009) |
| Homicide per capita$_t$ | $-0.014$ |
| | (0.026) |
| Mean | 1.91 |
| Observations | 19,261 |
| Adjusted $R^2$ | 0.238 |
| *Panel B: Employed in Agricultural Sector (corn)* | |
| Extreme Temperature$_t$ | $-0.080$ |
| | (0.059) |
| Extreme Temperature$_{t-1}^{t-4}$ | 0.049 |
| | (0.038) |
| Homicide per capita$_t$ | 0.006 |
| | (0.206) |
| Mean | 7.22 |
| Observations | 639,412 |
| Adjusted $R^2$ | 0.129 |
| *Panel C: Migration Likelihood in Agricultural Households (corn)* | |
| Extreme Temperature$_{t-1}$ | $0.148^{***}$ |
| | (0.052) |
| Extreme Temperature$_{t-2}^{t-5}$ | $-0.075^{**}$ |
| | (0.031) |
| Homicide per capita$_{t-1}$ | 0.165 |
| | (0.223) |
| Mean | 0.655 |
| Observations | 13,440 |
| Adjusted $R^2$ | $-0.00002$ |
| **Controls** | |
| Year Fixed Effects | x |
| Municipality Fixed Effects | x |
| Extreme Rainfall | x |
| Geographic*Year | x |
| Baseline Municipality$_{2005}$*Year | x |
| Corn Producer / Individual / Household Controls$_t$ | x |

Notes: Each panel corresponds to a different outcome. Panel A corresponds to the logarithm of corn production from the main harvest using ENAPM dataset. Panel B corresponds to the likelihood of being employed in the agriculture of corn, using the EHPM dataset at the individual 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 standard deviations 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. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01