Temperature Shocks, Labor Markets and Migratory Decisions in El Salvador*

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Abstract

The inflow of migrants from El Salvador to the United States has increased persistently since 1980. In spite of the intensification of immigration policies in the U.S. in the last decades, by 2017, 25% of people born in El Salvador were international migrants. This paper shows that the weather shocks the country has suffered has been an important push-factor. We find that temperature shocks affected agricultural production in El Salvador, which affected the labor market of agricultural workers. Our results suggest this is an important mechanism to explain rising international migration, despite the current anti-immigrant political climate. These results highlight that there should be a global responsibility relative to the consequences of climate change.

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1 Introduction

Since the middle of the 20^{th} century, the frequency and length of heat waves have increased. This trend will likely intensify in the coming decades (Seneviratne et al., 2012). Weather shocks reduce crop yield, agricultural productivity and agricultural income.[1] Farmers highly dependent on rain-fed agriculture and living in contexts with incomplete markets will struggle even further to mitigate the negative impacts of weather shocks, affecting a large number of households and hampering the worldwide efforts to reduce rural poverty. In 2016, there were 570 million farms in 167 countries, 89% of which were family farms and the great majority small farms (84% were under two hectares). Forty nine percent are located in lower-income countries (Lowder et al., 2016).

Incomplete markets limit the risk-coping mechanisms available to confront extreme weather events for rural households in many regions of the developing world. In the short-term, households cannot resort to financial markets to compensate for the income loss or cover *ex-ante* against risks through insurance markets. For protecting consumption, households rely on costly strategies such as selling assets, changing agricultural practices, expanding the use of domestic labor, including children, and working on subsistence activities (Rosenzweig and Wolpin, 1993; Jayachandran, 2006, Hornbeck, 2012; Carter and Lybbert, 2012; Aragón et al., 2021). In responding to long-term climate changes, farmers seem also to a have limited capacity to adapt (Carleton and Hsiang, 2016; Hornbeck, 2012). Even though agricultural producers in developed countries are better able to adapt to climate change, evidence for small farmers show that adjustments to these changes are not sufficient to cover the initial shock (Hornbeck, 2012, Dell et al., 2014).

Migration is a coping strategy that is becoming increasingly frequent as weather be-

[1] Evidence on the impact of weather shocks on agricultural production can be found in the following papers, among others: Deschênes and Greenstone (2007), Schlenker and Roberts (2009); Schlenker and Lobell (2010), Feng et al. (2010); Hornbeck (2012), Dell et al. (2014); Hornbeck and Naidu (2014), Carleton and Hsiang (2016), Ortiz-Bobea et al. (2019) and Aragón et al. (2021)

comes more unpredictable in some regions of the world.[2] Weather-driven migration is higher in countries more reliant on agriculture (Feng et al., 2010; Cai et al., 2016; Thiede et al., 2016). If carefully planned, migration is a viable strategy for households to geographically diversify risk or escape untenable conditions (Mahajan and Yang, 2020). Nonetheless, migration under stress might impose large social and economic costs to households by pushing them to make poor decisions that may compromise their long term prospects (Kleemans, 2015).

This paper examines the migratory responses of households to extreme weather events, and explores the mechanisms that explain this relationship. Importantly, we expect a negative effect on agricultural production can potentially affect both agricultural and non-agricultural workers. While the negative effect on agricultural production directly affects the income of workers in the agricultural sector, non-agricultural workers can be indirectly affected through labor markets. Negative weather shocks reduce crop yields and farmers adjust inputs accordingly to protect agricultural income (Aragón et al., 2021; Hornbeck, 2012). In the short-run, farmers have a small margin of adjustment as some decisions on input use are non-reversible. For example, if the planting season is over, farmers may not be able to switch land use or cut back the use of fertilizers. Therefore, farmers may hire less agricultural workers, relying more on domestic workers. Laid-off agricultural workers may move to the non-agricultural sector. If the expansion in labor supply for the non-agricultural sector is large, wages on the non-agricultural sector may decrease. Because domestic workers substitute for hired workers, their hours of on-farm work may increase (Jayachandran, 2006; Bastos et al., 2013; Jessoe et al., 2016;Aragón et al., 2021).

Incentives to migrate increase for landowners and agricultural workers. However, landowners face larger opportunity costs from migrating than agricultural workers and are better able to afford adjustment strategies (Kleemans, 2015; Kubik and Maurel, 2016; Catta-

[2]See Dell et al. (2014) and Carleton and Hsiang (2016) for a literature review

neo and Peri, 2016; Mahajan and Yang, 2020). Agricultural workers may hence resort more to migration to compensate for the income loss. Funding the migration process is costly and more so for households living near subsistence levels that recently suffered a negative income shock (Jayachandran, 2006; Feng et al., 2010; Hornbeck, 2012; Kleemans, 2015; Jessoe et al., 2016; Aragón et al., 2021). Households better able to fund the migration process, either because they have access to financial markets or migrant networks, will be more likely to migrate (Massey et al., 1990; Munshi, 2003; Hunter et al., 2013; Nawrotzki, 2015; Clemens, 2017; Mahajan and Yang, 2020).

We explore the effect of weather shocks on agricultural outputs and inputs, labor outcomes, and migration using household level data from El Salvador. El Salvador has several advantages for studying this topic. First, a large percentage of the population still gets their income from agriculture, specially compared to other countries in Latin America. Agriculture is the second largest employer in the country (17.6%) after the service sector.[3] Second, a large number of agricultural producers are subsistence farmers, 87%, with small land plots (on average 1.2 hectares) and living in contexts with incomplete markets.[4] In 2017, the rural poverty rate was 50%.[5] Third, the country is increasingly vulnerable to extreme weather events.[6] Lastly, El Salvador has a long history of migration to the United States that started during the civil war in the eighties and has persisted ever since. One quarter of the country's population lives abroad, the majority in the United States (Abuelafia et al., 2020).

Our empirical model exploits both temporal and geographic variation of temperature

[3]The percentage for the other sectors is: 15.6% manufacturing, social services 6.5%, construction 5.8%, financial services 5.6%, domestic workers 5.0% and others 11%. See https://www.mtps.gob.sv/wp-content/uploads/descargas/BoletinesEstadisticos/mtps-boletin-laboral-mujeres-2019.pdf

[4]http://www.fao.org/world-agriculture-watch/our-program/slv/en/retrievedJuly31,2020

[5]https://www.climatelinks.org/sites/default/files/asset/document/2017_USAID\%20ATLAS_Climate\%20Change\%20Risk\%20Profile_El\%20Salvador.pdf retrieved on July 31, 2020

[6]For example, the number of hurricanes in Central America rose to 39 between 2000 to 2009 from nine between 1990 and 1999. https://www.climatelinks.org/sites/default/files/asset/document/2017_USAID\%20ATLAS_Climate\%20Change\%20Risk\%20Profile_El\%20Salvador.pdf retrieved on July 31, 2020

shocks between 2009 and 2019 in El Salvador. Importantly, since we are measuring the effect of weather shocks and not the effect of climate change, our results should be interpreted as short-term effects and not long-term adjustments of agricultural producers. We measure temperature shocks as the deviation of the average temperature in a year and season relative to the historical mean weighted by the standard deviation, which can be interpreted as random draws from a climate distribution (Deschênes and Greenstone, 2007; Feng et al., 2010; Dell et al., 2014) and, exploit within-municipality variation of this shock. Our empirical model includes municipality fixed effects to absorb time invariant characteristics, year fixed effects to absorb national dynamics affecting agricultural households, and the interaction of baseline municipality characteristics with linear time trends to account for differential pre-trends at the municipality level. Moreover, we include time varying characteristics such as crime shocks, excessive rainfall and drought shocks as these are correlated with weather shocks and influence migration and agricultural decisions. Therefore, the validity of the identification strategy rests on the assumption that, conditional on observables and fixed effects, there are not time-varying differences within municipalities that are correlated with the temperature shock. We perform several robustness tests to rule out potential threats to our identification strategy.

The paper finds that weather shocks are a push factor for rural households in El Salvador. In responding to weather shocks, households living in rural areas migrate abroad as a strategy to mitigate the negative income shock. One additional week of the temperature shock increases migration for agricultural households and the impact is sizeable: 26.5% evaluated at the mean of the shock. The negative impact of the temperature shock on agricultural production is one mechanism explaining the effect on migration. The temperature shocks decreases corn production, the main staple crop in El Salvador. An additional week of the temperature shock evaluated at the mean reduces agricultural production by 2.8%. Agricultural producers adjust in the short-run by reducing the demand for hired agricultural workers and substituting those with domestic workers. Labor productivity for agricultural households decreases significantly, depressing agricultural wages. To compensate for the income loss, agricultural workers seek employment in non-agricultural occupations or migrate. The lack of access to risk-coping mechanisms imply that households restricted access to formal and informal sources to cope with the negative impact of the shock, and those less attached to the land in origin are the most likely to migrate.

We test the robustness of our results with different strategies. First, to probe that the effect of the shock on migration is indeed driven by a drop on agricultural production, we define the shock on different time windows unrelated to the harvest season. We find that the impact of the shock on migration only occurs during the harvest season. Second, the temperature could be capturing other correlates of migration or driven by chance. For gauging whether this is the case, we estimate a placebo test in which we randomly assign each temperature/week observation 1000 times and re-estimate the results. The estimations confirm that our results are not driven by chance or other correlates.

Our paper contributes to three strands of the economic literature. First, we add to the literature on migratory responses to weather shocks and natural disasters. This literature finds negative weather shocks, including natural disasters, cause an increase on internal[7] and international migration[8], mostly for middle income households who have lower opportunity costs from relocating and are less constrained to fund the migration process (Cattaneo and Peri, 2016). Most of these papers rely on reduced forms to identify the effect of negative weather shocks on migration and rarely delve into the potential mechanisms driving these results. Some papers explore agriculture as a potential mechanism, yet use aggregate data either at the country, state or county level (see for example Feng et al., 2010; Hornbeck,

[7]Examples of papers on internal migration are Dillon et al. (2011), Hornbeck and Naidu (2014), Bastos et al. (2013), Mueller et al. (2014) Kleemans (2015), Kubik and Maurel (2016), Thiede et al. (2016), Cai et al. (2016) and Baez et al. (2017)

[8]Examples of papers on the influence of weather shocks on international migration are Halliday (2006), Feng et al. (2010), Gray and Mueller (2012), Gröger and Zylberberg (2016), Marchiori et al., 2012, Gray and Bilsborrow (2013), Bohra-Mishra et al. (2014), Nawrotzki (2015), Cattaneo and Peri (2016), Jessoe et al. (2016), and Mahajan and Yang (2020)

2012; Hornbeck and Naidu, 2014; Cai et al., 2016; Cattaneo and Peri, 2016). Two noteworthy exceptions are Jayachandran (2006) and Aragón et al. (2021). We study the impact of negative weather shocks on agricultural production and document how these shocks reduce the demand for hired workers; leading thus to higher migration, mostly from workers in agricultural households who are those directly affected by the shock. Exploring the potential transmitting mechanisms and the factors facilitating migration is crucial to design policies that help prevent distressed migration and facilitate migration from regions in which agriculture may no longer be feasible.

Second, we provide evidence on the impact of negative weather shocks on agricultural production in developing countries and how incomplete markets may lead households to rely on migration. Evidence on the impact of extreme weather events on agriculture is mostly for developed countries[9] where farmers have access to financial and insurance markets and hence a larger array of alternatives to cope with shocks. Because developed and developing countries have such different contexts, it is not valid to extrapolate the effects of negative weather shocks on agricultural production and the responses of agricultural producers in developed countries to developing ones (Dell et al., 2014). Our paper provides evidence on how incomplete markets for agricultural producers in developing countries push rural households to rely on migration, in this case international migration, to compensate for the fall in income. Migration is a valid alternative to cope with negative shocks if voluntary and not driven by lack of better coping mechanism. Financial and insurance mechanisms, adjusted to the complexities of small farmers, need to be developed to mitigate the negative impacts of extreme weather events and prevent distressed migration.

Third, the findings in our paper on the migratory responses to drops on agricultural production and labor demand contributes to the literature on the consequences of climate

[9]Some examples are Deschênes and Greenstone (2007), Schlenker and Roberts (2009), Schlenker and Lobell (2010), Hornbeck (2012), Hornbeck and Naidu (2014), and Ortiz-Bobea et al. (2019)

change and the ensuing adaptation strategies used by households.[10] Even though the paper focuses on short-term effects and do not account for long-term adaptation strategies, the results provide evidence on the potential adaptative responses of farmers to the increasing frequency of extreme weather events. Climate change, which is caused by global emissions, affects mostly households in developing countries who are seeking refuge when possible in developed countries. Addressing the negative effects of climate change must therefore be a shared global responsibility.

2 Background

2.1 Migration from El Salvador to the U.S

The inflow of Salvadorean migrants to the United States started in the 1980 as a consequence of the civil war and it has persisted to this date. Migrant networks have supported newly arrived families with financial assistance, shelter and connection to labor markets, attracting new waves of migrants (Donato and Sisk, 2015; Clemens, 2017).[11] By 2017, 2.3 million Hispanics of Salvadorean origin lived in the United States -the third largest group of Hispanic origin immigrants in the country[12] - and overall twenty five percent of people born in El Salvador lived abroad (Abuelafia et al., 2020).

However, migration costs from Central American countries to the United States have risen significantly during the last decade. In the last 15 years the government of the United States has enacted stricter migratory regulations and enforced tighter border controls, which has intensified the number of detentions and deportations (East and Velásquez, 2020). These policies have particularly affected immigrants from El Salvador. While in 2007 more than

[10]See Dell et al. (2014) and Carleton and Hsiang (2016) for a literature review

[11]Clemens(2017) finds for example that past migration flows explain one third of the current flows caused by violence.

[12]https://www.pewresearch.org/hispanic/fact-sheet/u-s-hispanics-facts-on-salvadoran-origin-latinos/ retrieved on July 30, 2020

14,000 Salvadoreans were apprehended in the border, in 2018 this figure rose to almost 32,000.[13] As expected, stricter immigration policies in the U.S. have been accompanied by an increase in the price of services provided by migrant smugglers or *coyotes*. Surprisingly, this sharp increment on migration costs has not been an effective deterrent to stop migration (Massey et al., 2014). Figure 1 illustrates that the rising costs of migrant smugglers has not decreased migration, in spite of the high risks involved.[14]

Given the sustained increase in out migration from El Salvador, despite the stricter immigration policies in the U.S., a question remains: what are other potential drivers of the persistent migration flows from El Salvador? Evidence indicates that push-factors, such as, the deterioration of economic conditions, negative income shocks and violence are important determinants of the decision to migrate of Salvadoreans (Stanley, 1987; Halliday, 2006; Yang, 2008; Clemens, 2017). Extreme weather conditions are also a potential cause of international migration and is strongly related to internal migration in Central America (Baez et al., 2017; WFP, 2017; WB, 2018). In fact, newly arrived migrants from El Salvador to the U.S. have increasingly been from rural areas, who are more vulnerable to climate shocks (WFP, 2017; Abuelafia et al., 2020). Importantly, El Salvador is not only extremely vulnerable to climate conditions,[15] but also the frequency of weather shocks have been increasing in the country (ECLAC, 2010).

2.2 Weather Shocks in El Salvador

The recurrence of droughts in El Salvador is causing large crop losses, in particular of coffee, maize and beans, and exerting a heavy toll on vulnerable rural populations.[16] Most agricultural producers in the country are small family farms with average land sizes of 1.2

[13] `https://www.cbp.gov/newsroom/media-resources/statsretrievedontheJuly31,2020`

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

[15] `https://www.ifad.org/en/web/operations/country/id/el_salvador` retrieved on July 31, 2020

[16] `http://www.fao.org/americas/noticias/ver/en/c/1150344/` and `https://www.nytimes.com/interactive/2020/07/23/magazine/climate-migration.html` retrieved July 31, 2020

hectares[17] and dedicated to subsistence farming. Because only 1.4% of the land is irrigated,[18] agricultural production is highly dependent on the rain cycle (WB, 2018).

During the last decade, El Salvador experienced three extreme droughts. In 2012, a severe and prolonged drought reduced coffee production by 70%. Between 2014 and 2015, more than 100,000 farmers suffered losses as a consequence of another drought and the onset of *El Niño*.[19] A new drought hit the country in 2018, which had hardly recovered from the previous one, leading to a sharp loss of staple crops, such as maize, and to the declaration of a red alert by the government.[20] Droughts are causing severe drops in income, food insecurity and migration. The outlook for the future is grim as agricultural production in some areas may become unfeasible (WB, 2018). For example, in the Dry Corridor, a region with severe water shortages and persistent droughts, one third of households are food insecure and the main motivations to migrate are lack of food and drought shocks (WFP, 2017).

3 Data

Our empirical analysis uses several sources of data. To study migration, we use the Multiple Purpose Household Survey (EHPM from its acronym in Spanish), a yearly cross-sectional household survey collected by the Official Statistical Office of El Salvador. The sample employed in the estimations covers 186,856 households for the period 2009-2018 and collects information on household members' socio-demographic characteristics, housing, employment, agricultural outcomes, land tenure, household income, and household members' migratory status, among others. The survey is representative at the national level and for 50 municipalities. We dropped from the sample households with no information on the household's

[17]According to FAO, 87% of agricultural producers are small family farms. http://www.fao.org/world-agriculture-watch/our-program/slv/en/ retrieved July 31, 2020

[18]https://data.worldbank.org/indicator/AG.LND.IRIG.AG.ZS retrieved July 31, 2020

[19]https://reliefweb.int/report/el-salvador/el-salvador-drought-emergency-appeal-no-mdrsv010-operations-update, retrieved on August 4, 2020

[20]https://www.reuters.com/article/us-el-salvador-drought/el-salvador-declares-emergency-to-ensure-food-supply-in-severe-drought-idUSKBN1KE338 retrieved on August 4, 2020

head occupation and those located in municipalities for which weather information is not available.

The main dependent variable was identified using the migration module, which collects information on household members living abroad, the year of migration, and the country of destination. Our outcome variable is a dummy variable equal to one when at least one household member migrated abroad one year prior to the survey. Ideally, we should measure migration using data on migrants and not households with migrants. The latter may underestimate the number of migrants as, in some cases, all household members may migrate together. On the other hand, data on migrants from El Salvador collected in the United States may under-report undocumented immigrants (Halliday, 2006). To explore the potential of under-reporting from households migrating in its enterity, we compare the migration trends from the EHPM data and the American Community Survey (ACS). Using the ACS, we calculate the percentage of households in the United States with at least one or all members that migrated from El Salvador the previous year. Figure 2 shows similar trends for both surveys for most years but for 2015, year in which the percentage of complete household migration spiked in the ACS while households reporting migrant members dropped sharply in the EHPM. Therefore, we estimate the regressions with and without 2015 for checking the robustness of our results.

Labor outcomes are constructed based on the labor module of the survey. Labor outcomes include employment, weekly hours, monthly wages, and wage per hour. The module also allow us to identify the sector of occupation for each working member of the household. We define a household as agricultural when the head works in agriculture. We check the robustness of our results by defining a household as agricultural when 50% of its working members are employed in the agricultural sector.

Tables A1 to A3 in the appendix reports descriptive statistics for the total sample, by migratory status and by occupational group of the household head (unemployed and employed in the agricultural and non-agricultural sector). A little more than 0.9% of households had at least one member that migrated abroad the year previous to the survey, 17.2% of household heads are employed in the agricultural sector and, of those, 16.4%, own land. Migration rates are higher for agricultural households (0.9%) than for non-agricultural ones (0.7%). Agricultural households also live in regions with a more frequency of temperature shocks, higher poverty rates and less access to State services.

Data on agricultural production come from the Multiple Purpose National Agricultural Survey (ENAMP for its acronym in Spanish) collected by the Ministry of Agriculture for the period 2013-2018. The ENAMP is a yearly cross-sectional survey applied to agricultural producers with the purpose of collecting information on crop yield, land size, agricultural inputs, including labor, and prices. The sample, which includes 19,261 agricultural producers, is representative at the national level and, for grains crops, representative at the province level. The survey is applied during the last quarter of the year once the harvest for the first two seasons, (*invierno* and *postrera*), already took place. Respondents are requested to predict the third harvest (*apante*) of the year.

We focus on corn production. Corn is the main staple crop in El Salvador and Central American Countries (see Figure 3), one of the main sources of caloric intake for rural households, and its production is widespread across the country (Nawrotzki, 2015, WB, 2018). Corn is a short-cycle crop and the impacts of weather shocks can be traced back in the same period. Lastly, we may validate our results with other papers that estimate the impact of weather shocks on corn production.[21] Corn production occurs mostly on the first harvest (*invierno*) of the season. Figure 4 illustrates the yearly contribution of the first two harvests for our period of analysis. Therefore, our estimates use the first season, yet we perform robustness tests using the second season (*postrera*). Because respondents predict the yield

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

for the third harvest (*apante*) and may have a large measurement error, in particular in years with unexpected weather shocks, we do not use the data for this season.

The outcomes for agricultural production include yearly tons of corn yield per hectare, the value of corn yield per hectare,and the number of hired and domestic workers. An average agricultural producer produces 2.4 tons (SVC$736.000) of corn per hectare, has access to a land plot of 1.5 hectares, and employs 3.9 workers, 1.7 of which are domestic workers (See Table A1 in the Appendix).

Temperature data is extracted from NASA's MODIS Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature, a grid data of 1km resolution that contains 8-day temperature averages for the period 2001-2018. We aggregate the grid to the municipal level with a weighted mean using the area covered. We estimate historic means and standard deviations for temperature for the first harvest's period (*invierno*) between 2001 and 2006. Our main variable of interest is the temperature shock during the first harvest of the year. Temperature shocks measure the number of weeks during the first harvest season in which the temperature was two standard deviations (SD) above its historic mean. Evidence shows temperature is a stronger predictor of crop yields than precipitation as the effect of precipitation depends on several physical conditions of water inflows and outflows which are difficult to measure (Lobell and Burke, 2008, Ortiz-Bobea et al., 2019). In fact, recent studies find that temperature has a stronger effect on staple crops than precipitation (Schlenker and Lobell, 2010; Nawrotzki, 2015; Carleton and Hsiang, 2016; Jessoe et al., 2016; Aragón et al., 2021).

Nonetheless, we also control for excessive rainfall shocks during the first harvest season, measured as the number of weeks with rainfall 2SD above its historical means, and drought shocks, measured as the number of weeks with rainfall 2SD below its historical mean. Precipitation data was extracted from Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks- Climate Data Record (PERSIANN-CDR), with a resolution of 0.25 degree with monthly periodicity and available from 2003. Historic and standard deviation means are estimated for the period between 2003 and 2006.

The average number of weeks with temperature 2SD above the historic mean during the first harvest of the year is 1.2. Our empirical strategy exploits the large time and geographic variation of temperature shocks. During 2014 and 2015, the years with the strongest droughts, the number of weeks with excessive temperature was 1.9 and 4 respectively (see Figure 5). The temperature shock varied widely across municipalities such that during 2015 in some Southeastern municipalities it was five weeks whereas in the Northwestern region some municipalities did not face any week above 2SD (see Figure 6).

We use also municipal characteristics to control for initial conditions and estimate a measure of the migrants networks. For measuring violent shocks we use yearly data on homicides from the *Policia Nacional Civil*. We calculate the historic mean and standard deviation for homicides per capita between 2003 and 2006 and define crime shocks as the number of weeks during the year in which homicides were 2SD above the historic mean. For baseline municipality conditions, we use the following variables from the Poverty Map of El Salvador in 2005: poverty and extreme poverty rates, income per capita, percentage of households with no access to drinking water, percentage of people employed in agriculture, and percentage of young adults (16 and 18 years of age) that are not enrolled in school.[22]. Using data from the Census of 2007, 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 immigrants and emigrants, and the percentage of households with members living abroad. Lastly, we control for the municipality's elevation calculated at the grid level and then averaged for the municipality.[23]

[22] `http://www.fisdl.gob.sv/temas-543/mapa-de-pobreza` retrieved on July 2019

[23] Extracted from ASTER Global Digital Elevation Model NetCDF V003. NASA EOSDIS

4 Empirical Strategy

In order to measure the effects of weather shocks on the decision to migrate internationally from El Salvador, our identification strategy exploits temporal and geographic variation in temperature between 2009 and 2018. Our hypothesis is that the temperature shocks witnessed in El Salvador in the last decade have had negative effects on economic outcomes, which has been an important push-factor that has increased the likelihood of international migration. By focusing on temperature shocks this paper contributes to a wide literature studying the effects of temperature on economic growth, and particularly on agricultural production (for an extensive literature review see Dell et al., 2012 and Carleton and Hsiang, 2016).

The effects of temperature shocks on the probability of international migration are estimated using the household survey EHPM with the following regression model:

$$m_{ijt} = \alpha + \delta_1 T_{ijt-1} + X'_{ijt}\gamma + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{ijt} \tag{1}$$

Where m_{ijt} is a dummy variable equal to 1 if a member of household i, living in municipality j, in year t migrated out from El Salvador in year t, and equal to zero otherwise.[24] The variable T_{jt-1} is a measure of the variation of temperature in municipality j, the year before migration took place, $t-1$. This is measured as the number of weeks during the main harvest season with a temperature shock in $t-1$, where a shock is defined as an average temperature two standard deviations above its historical mean. The coefficient of interest, δ_1 should be interpreted as the effect of an additional week with high temperatures during the harvest season on the probability of migration.[25] Our main specification controls for time-variant household characteristics, X'_{ijt}, such as: age and gender of the household head, and number of household members. However, since these could potentially be en-

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

[25] In section 5.4 we test the robustness of the temperature shocks using alternative definitions.

dogenous we test that the results are robust to including these controls. We also include a vector with time-variant controls at the municipality level, Z'_{jt-1}. Importantly, to avoid including potential bad controls in our specification, these variables are measured in $t-1$. Given that temperature might be highly correlated to other climatic variables, this vector includes rainfall shocks and droughts (Auffhammer, 2018).[26] In addition to natural disasters, the high levels of violence have been historically an additional push factor that has driven international migration from El Salvador (Stanley, 1987; Halliday, 2006; Yang, 2008; Clemens, 2017). To control for this, we add a variable of a crime shock measured in $t-1$. We include fixed effects at the municipality level, μ_j, that account for any time-invariant unobserved heterogeneity at the municipality level, importantly this includes the historical level of rainfall and historical mean of temperatures in municipality j. Our specification also includes year fixed effects (ϕ_t) to account for national shocks that would impact migratory decisions, for example national shocks that could affect prices. Therefore, the validity of our identification strategy relies on the assumption that, conditional on observables, there are not time-varying differences within municipalities that are correlated with changes in temperature. To account for any pre-trend at the municipality level that could bias the results, we include interactions between socioeconomic variables measured at baseline (2005 and 2007) and linear time trends (W'_{j2005}).[27] All the models are estimated using double clustered standard errors by municipality and year.

[26] The results are also robust to controlling for level of soil moisture. Ortiz-Bobea et al. (2019) shows evidence of the importance of accounting for soil moisture when explaining historical yields. However, their models also find that temperature is the primary weather related driver of future yields. Following these results, our preferred specification does not add moisture as a control.

[27] The vector V'_{j2005} includes measures of poverty, average income per capita, access to drinking water, demographic structure of the population (% of the population below 19 years of age and above 60 years of school), the number of internal immigrant and emigrants, school dropout for young adults (16 and 18 years), % of people employed in agriculture, population density, and elevation of each municipality.

4.1 Mechanisms

Temperature shocks can affect the decision to migrate through different mechanisms. Dell et al. (2012) and Carleton and Hsiang (2016) provide an extensive literature review describing the effects of temperature on agricultural outcomes, mortality, physical and cognitive capacity, and crime, among others. In this section we explore the role of agricultural production as the main mechanism to explain the effect of temperature shocks on migration. We focus on agricultural production as the main mechanism, since previous evidence has found a strong correlation between temperature shocks and agricultural production, particularly in countries that are vulnerable to these shocks and have no mechanisms to smooth consumption. For example, Munshi (2003) finds a strong correlation between the probability of migration to the U.S. among individuals who live in agricultural regions in Mexico and rainfall; and, Feng et al. (2010) finds a significant relationship between climate-driven changes in crop production and net out-migration.

To test this mechanism we follow a number of empirical steps. First, we start by conducting an heterogeneity analysis by occupation of the household head. We expect households in the agricultural sector to be the most affected and that is indeed what we find.[28] Second, we estimate the direct effect of temperature shocks on agricultural production. The results show robust evidence of a negative effect of high temperature on agricultural production, specifically corn.

To estimate the direct effect of temperature shocks on agriculture productivity we use data from the ENAMP for the period between 2013 and 2018.[29] We follow a similar identification strategy as the one in model (1). Specifically we estimate the effect of temperature shocks on the production of corn, the main staple of El Salvador. We estimate the following

[28]The occupation of the household head can potentially be endogenous. To explore this concern in section 5.4 we estimate these heterogeneous effects in alternative ways.

[29]While for the EHPM we have information from 2009 to 2018, in the ENAMP the earlier year is 2013. We estimate the migration model for the period of 2013 to 2018 and the results are robust for this sample.

regression model:

$$log(y_{ijt}) = \alpha + \delta_2 T_{ijt} + X'_{ijt}\gamma + \beta Z_{jt} + \mu_j + \phi_t + W'_{j2005} * t\theta + e_{ijt} \tag{2}$$

In this case since we want to estimate the contemporaneous effect of a temperature shock on agricultural productivity, T_{ijt} represents the shock in the same year of production during the main season (*invierno*), measured as the number of weeks with 2 standard deviations above the historical mean.[30] Recall that the agricultural survey collects information from October to June, therefore a household interviewed during the survey year t (from October to June) reports their production during the last harvest season. In our model y_{ijt} represents different variables: crop productivity (total production in tons per hectare), total production of household i in municipality j in year t during the agricultural harvest season, and number of workers used (total, hired and domestic).

The controls included in the vectors W'_{j2005} and Z_{jt} are the same controls as in model (1). Since in this specification we use data from the ENAMP, the household controls are slightly different in this case. We include: household head education, number of household members, and access to irrigation for corn. Our results strongly suggest

We provide additional evidence of this mechanisms in a number of ways. First, we estimate a placebo test with the temperature shock defined as the number of weeks above the historical mean during the entire year, instead as defined as the number of weeks with a shock only during the main season. When looking at the effect of the temperature shock outside the main season we find no significant effects on agricultural production or migration. These rules out contemporaneous unobserved events are driving the negative effects on production, and suggests the main mechanism through which a temperature shock affects migration is through agricultural production. Second, we find evidence of a negative effect on the labor

[30]For corn this is the period between June and July, which is supposed to be the rainy season.

outcomes of individuals in agricultural households, who are the households for whom we find an increase in the probability of migration.

For the effects on the labor outcomes at the individual level we use the EHPM (same survey used to estimate effects on migration) to estimate the following model:

$$l_{ijt} = \alpha + \delta_3 T_{ijt} + \delta_4 T_{ijt-1} + X'_{ijt}\gamma + \beta Z_{jt-1} + \mu_j + \phi_t + W'_{j2005} * t + \epsilon_{ijt}. \tag{3}$$

The goal of this regression is to investigate whether temperature shocks affect labor outcomes, particularly of individuals in agricultural households who are those directly affected by the shock. The temperature shock may affect labor markets instantaneously or because of rigidity in the labor market, the effects might be delayed. To model these dynamics we control for both the shock during the harvest season in years t and $t-1$. Since the shock is defined during the harvest season, for these models we estimate the effects for households interviewed in the second half of the calendar year (August to December). Therefore, l_{ijt} represents the labor outcomes of individual i, living in muncipality j, in year t after the harvest season.

5 Results

We start our analysis by showing the results of equation (1) in Table 1. We estimate this model using household level information from the EHPM between 2009 and 2018 for all households (panel A), agricultural households (panel B), non-agricultural households (panel C) and unemployed households. We categorize households based on the occupation of the household head.

We estimate first the effect of temperature shocks for all households (Panel A). Column 1 shows the results when controlling only for time variant municipality characteristics (rainfall and crime shocks). Moving across columns we include additional controls: year fixed effects (column 2), municipality fixed effects (column 3), and an interaction of characteristics at the municipality level measured in 2005 interacted with a linear time trend (column 4). Column 5 adds time-variant household characteristics. These controls could be potentially endogenous, but the results in columns 4 and 5 show that the empirical model is robust to their inclusion. Overall, the results are robust to the inclusion of all the controls.

As discussed in the previous section, one of the mechanisms through which high temperature can affect the decision to migrate, is through an effect on agricultural production. If this is one of the main mechanisms, we would expect to see a larger response to these shocks among agricultural households. The results in Table 2 show that this is the case. The results show significant effects of the temperature shock on the probability of migration only for agricultural households (Panel B). Not only the effects are only significant for this sample, but the magnitude of the effects is also bigger relative to the estimated effect for non-agricultural or unemployed households.

The results in our preferred specification with the full set of controls (column 5) show that an additional week of high temperature increases the probability of migration by 0.2 percentage points, which relative to the mean is and increase by 25 percent in the probability of international migration from El Salvador. Evaluated at the mean of the temperature shock between 2007 and 2018 (1.06 weeks) this effect translates into an increase on the probability of migration of 26.5%.

There are two potential concerns with our classification of agricultural households. First, one concern is classifying households based only on the occupation of the household head. In table A4 we classify households as agricultural if more than 50% of their working-age household members work in an occupation in agriculture. The results on the probability of migration are robust. Second, since the occupation of the household head or other members might be endogenous to the temperature shock, we stratify using characteristics of the municipality at baseline. Table A5 shows the effect of the temperature shock for municipalities with a share of their population in agricultural occupations below and above the national median. Once again the results show that the there is a positive effect on the probability of international migration in municipalities with a higher share of individuals in agricultural occupations, while for those below the national mean the coefficient estimate is not statistically significant .

5.1 Mechanisms

The heterogeneity analysis in Table 1 provides suggestive evidence that the effect on agricultural production is an important mechanism through which temperature affects decisions about migration. In this section, we show additional evidence that supports this hypothesis. We start by estimating the direct effect of temperature shocks on agricultural production of corn, the main staple of El Salvador. Table 2 shows the results of estimating equation (2) using data from the ENAMP for 2013-2018. Similarly to table 1 we add controls across columns to test the robustness of the model. We estimate equation (2) for three different agricultural outcomes. The dependent variables are: in Panel A the logarithm of the ratio of corn production per hectare in the first harvest, in Panel B the logarithm of the total production per households in the first harvest, in Panel C the logarithm of the value sold per hectare in the main harvest, and in Panel D the logarithm of the price per tonne.

The results show consistently negative effects on corn production during the main season. Focusing on the results in column 5, Panel A shows that the production of corn per hectare diminishes by 5.4% for each additional week with a temperature shock, and this decrease in productivity translates into a negative effect on the total production of corn. Panel B shows that an additional week with a temperature shock during the harvest season of the contemporaneous year significantly decreases total production by 2.8%. Similarly to Aragón et al. (2021), households seem to be adjusting agricultural practices to reduce the impact of the shock on total production. Finally, the results in Panel C show the effects on the value of the production. The negative and significant effect suggest that in the short term, the lower supply does not affect the prices of corn, thereby the price does not compensate for the fall in production which decreases the income of agricultural households by 5.1%. The intuition is confirmed in Panel D. The results show no significant effect on prices. Figure **??** summarizes these results.

The results on prices shed additional light on potential spillover effects of the negative effect on agricultural production. A pathway through which a temperature shock could affect disposable income of non-agricultural households, is through an effect on prices. If this is the case, the disposable income of both agricultural an non-agricultural households would be affected. However, the results in Panel D of Table 2 suggest this is not the case.[31]

For agricultural households, which were directly impacted by the temperature shock, this suggests they are able to smooth consumption, either through migration or re-allocation in the labor market. In the next section we explore directly the effects of the temperature shock on the labor markets of El Salvador.

5.2 Local Labor Markets and Decisions about Migration

We first investigate how agricultural producers adjust their labor demand when facing a temperature shock. Table 3 shows the results from estimating equation (2) for the number of workers allocated for agricultural production using data from the agricultural survey ENAMP. Because some households only have either domestic or hired workers, we have households with zeros in one of these categories. To avoid dropping zeros we use the hyperbolic sine transformation. Column 1 shows the effect on the total number of workers, column 2 on hired workers and column 3 on domestic workers. The results show that a temperature shock decreases the number of workers, and this is driven by hired workers. The

[31] To provide additional evidence on this potential mechanism we estimate the effects of the temperature shock on food consumption per capita for agricultural and non-agricultural households. The results in Table A6 show no significant effects on food consumption, suggesting effects on income and therefore migration via changes in prices is unlikely for either agricultural or non-agricultural households.

coefficient estimate for domestic workers is positive, as expected as agricultural producers may substitute for hired workers with domestic ones, but not statistically significant. These results, together with the effects found on agricultural production, suggest that agricultural income is negatively affected and households adjust to the shock by reducing the demand for hired agricultural workers.

Since previous evidence shows that temperature shocks affect agricultural production at the household level, we assume the decisions to mitigate the impact of the shock are taken at the household level as well. As seen in Table 1 one of the responses of agricultural households is to increase international migration. We complement this analysis by estimating the effect of the temperature shock on individual labor markets stratified by whether the individual belongs to an agricultural or non-agricultural household, where the classification of type of household follows the model from Table 1. Because there are frictions in the labor market we estimate the effect of the temperature shock both in year $t-1$ and year t. These results provide additional evidence to understand whether the decision to migrate responds to the effects caused by the shock in the labor market.

We start by estimating the effect on the probability of being active in the labor force in Column 1 of Table 4.[32] The results in Panels A and B show that while the probability of working does not change for individuals living in agricultural households, it negatively affects the probability of working for individuals from non-agricultural households. This is consistent with the results of Table 3. Agricultural households might respond to the shock by replacing hired workers with domestic. The results in column 1 suggest that the displaced workers might belong to non-agricultural households.

Column 2 shows the effect of the shock at the intensive margin. On average, among workers who stay in the labor force there is a positive effect on working hours, and this effect is observed for individuals both in agricultural and non-agricultural households. On the one

[32]The question in the survey is whether the individual worked last week.

hand, given that individuals in agricultural households do not respond to the shock at the extensive margin, the effect on working hours is not driven by selection. These results suggest that among agricultural households individuals respond to the shock by working more hours. The evidence in column 4 suggests that the productivity of workers in agricultural households decreases, as expected but the coefficients are very noisily estimated. On the other hand, the positive effect on working hours of individuals in non-agricultural households might be driven by selection of those who stay in the labor force or by an increase in working hours given the higher competition in the labor market.

We further investigate these effects in Table 5 separately for households in municipalities below and above the median of the national production of corn in 2007. The results in column 4 of Panels A and B show that independently of the level of production of corn in the municipality, the productivity of individuals in agricultural households was significantly negatively impacted by the shock. However, for individuals in non-agricultural households (Panels c and D), the effects are mainly seen in regions with a higher production of corn. This is consistent with previous results showing that agricultural households substitute hired workers with domestic workers, pushing hired workers to seek employment in other sectors, which potentially depresses wages.

Overall the effects on the labor market show a robust negative effect on the productivity of workers in agricultural households, and evidence of a substitution of hired workers with domestic workers.

5.3 Migration Costs

Overall, so far the results show that the temperature shocks have been an important push factor that has increased the probability of international migration from El Salvador from 2009 to 2018, despite the increasing enforcement policies in the U.S. Although the temperature shocks increases the benefits of migrating, only those individuals who have the economic means to finance the costs of migration can actually leave the country. Access to assets, savings, credit, and networks may decrease the costs of migration. We explore whether this play an important role in the context of El Salvador to facilitate international migration.

Table 6 explores different hypothesis. First, owning land and other non-liquid assets might reduce the probability of migration. Because these are non-liquid assets, individuals might not easily sell them to finance the cost of migration. Columns 1 and 2 show the probability of migration by access to land. While the temperature shock does not have a significant effect on the probability of migration for households who own their land, it does increase the likelihood of migration for households who rent their land. Households who do not own their land might be less attached to their region of origin or face lower opportunity costs.

In addition to access to liquid assets to finance migration, access to credit also plays an important role. However, the role of access to credit on the probability of migration when exposed to a shock is an empirical question. On the one hand, access to credit may help to finance the costs of migration. On the other hand, it helps to smooth the negative weather shocks which diminished the need to migrate to diversify the sources of income. The results in columns 3 and 4 show that the latter is the dominant effect in El Salvador. Households without access to credit are probably the most affected ones by the shock and those that need to rely on international migration the most. Finally, agricultural households where the head is not an employer (columns 5 and 6) might be less attached to the labor markets in their communities of origin, which increases the likelihood of migration.

Similarly to the access to credit, access to migrant networks of migrants can either increase or decrease the likelihood of migration when exposed to a negative shock. Access to networks decreases the cost of migration, through remittances and access to information and potential help in the country of destination, yet also through remittances it can increase financial well-being of the household to smooth the negative effects of the shock. Table 7 shows the effect of the temperature shock on the likelihood of migration for agricultural households living in municipalities with a share of migrants below the national median (column 1) and above the national median (column 2).[33] The results suggest that receiving transfers might help to stay in the place of origin. While in both regions there is an increase on the probability of migration, in regions with a share of migrants below the median the increase is of about 37%, while in the regions above the median the increase is of about 19%.[34] This hypothesis is consistent with the results in Table 8, that disaggregates the results based on the share of remittances received at the municipality level at baseline. Once again the results show a larger increase in municipalities with a lower share of remittances.

The results from this section show that while temperature shocks are an important push-factor, not all agricultural households react to the shock by migrating internationally. Households with less access to formal and informal sources to finance the shock, and those less attached to the land in origin are the most likely to migrate.

5.4 Robustness Checks

In this section we estimate a number of robustness checks to test the validity of our identification strategy. Table A7 shows a robustness check that gives support to an effect on agricultural production as the main mechanism of the migration results. Column 1 mimics the main results in Table 1, columns 2 shows the results when using the number of weeks above the historic mean the entire year (including non-harvest seasons), and columns 3 shows the results when using only the *apante* season. As expected we find significant effects only when using the shock defined during the main harvest season.

Table A8 test the robustness to using different periods. Column 1 mimics the results from Table 1; column 2 uses only the sample oh households interviewed during August to December, which is the sample used for the analysis of the effects on labor outcomes;

[33] The share of migrants is measured in 2007.
[34] The share of migrants is measured in 2007.

column 3 uses only years from 2013 to 2018, which are the years used to estimate effects on agricultural production; and, column 4 excludes 2015 since it had one of the worst cases of high temperatures and drought. This seems to have driven migration of the entire household which may have caused an undereporting of migration in our data (See Figure 2). The results are consistently robust to all the different specifications.

Finally, we estimate a placebo test to measure the likelihood of getting the estimates we get due to chance. To do this, we randomly assign temperature levels to each municipality/week observation 1000 times and re-estimate the regression models using these alternative measures. We plot the kernel density of the estimated δs from each of these iterations in Figure 7, for the probability of migration, and Figure 8 for agricultural production. We plot our baseline coefficients from Tables 1 and 2 in the red vertical lines. These analysis suggest that the estimated effects we find are very unlikely to occur due to chance.

6 Conclusions

This paper studies the migratory responses of rural households to cope with an extreme rise in temperature. Based on household and agricultural producer data, we find that a sharp increase in temperature decreases agricultural productivity and total production. Farmers adjust by cutting back the demand for hired workers. Labor markets act as a transmission mechanism of the negative impact of weather shocks on agricultural workers, who react by migrating or switching to the non-agricultural sector.

The results of the paper adds to the literature on migratory responses to short-term weather shocks and long-term adaptation to climate change. We show that negative shocks to agricultural production are related with migration decisions. Two types of migration may emerge from this relation. First, rural households often lack access to risk-coping mechanisms and live in regions with a poor provision of public goods to mitigate the effects of weather shocks (i.e. irrigation structures). Migration becomes a strategy to survive and compensate for the income losses brought by negative weather shocks (Mueller et al., 2014; Kleemans, 2015). Second, migration might be a way out of poverty such that households can escape untenable conditions, including those caused by a changing climate, and improve their welfare (Dell et al., 2014; Mueller et al., 2014; Kleemans, 2015; Carleton and Hsiang, 2016).

Policies should address both type of migrations. In preventing distressed migration where agricultural production is still feasible, policies should promote access to insurance and financial markets for rural households to cope with the negative impacts of the shock, and technical assistance to adjust agricultural practices to a changing climate (i.e. resistant seeds). Humanitarian aid, an assistance hardly provided when extreme weather events hit (Baez et al., 2017; Mueller et al., 2014), should also be provided. Policies should also aim to remove obstacles to migration that provides a pathway out of poverty. Access to financial markets or others mechanisms to fund migration costs are an example (Bryan et al., 2014; Kleemans, 2015).

Several new avenues for future research to understand the mechanisms through which extreme weather events cause migration and policies to address it are worth exploring. First, studying how access to financial and insurance markets influence migration decisions, either to prevent it or facilitate it, would provide inputs for better policy design. Kleemans (2015) explores how financial mechanisms interact with migratory decisions and Munshi and Rosenzweig (2016) study how informal insurance mechanisms shape migration decisions. Also, there is growing evidence on the impact of insurance mechanisms on the welfare and productivity of small rural farmers.[35] However, evidence on how these mechanisms influence migration responses is lacking. Second, improved resilience to negative weather shocks, through better agricultural practices, resistant seeds or public goods such as irrigation, may also prevent distressed migration and evidence on this respect is practically non-existent.

[35] See for example Carter and Lybbert (2012)

Evidence on additional benefits of such policies may provide further arguments to increase investment on these public goods. Third, our paper, and most papers, study the effects of weather shocks, and not long-term changes on climate, on migration. The results of estimations on the short-term effects should not be extrapolated to long-term climate changes, as farmers may adapt to these gradual changes. The evidence on this respect is scarce. Additional research on the long-term agricultural responses to climate change is crucial to understand how to support rural households in adapting to climate change.

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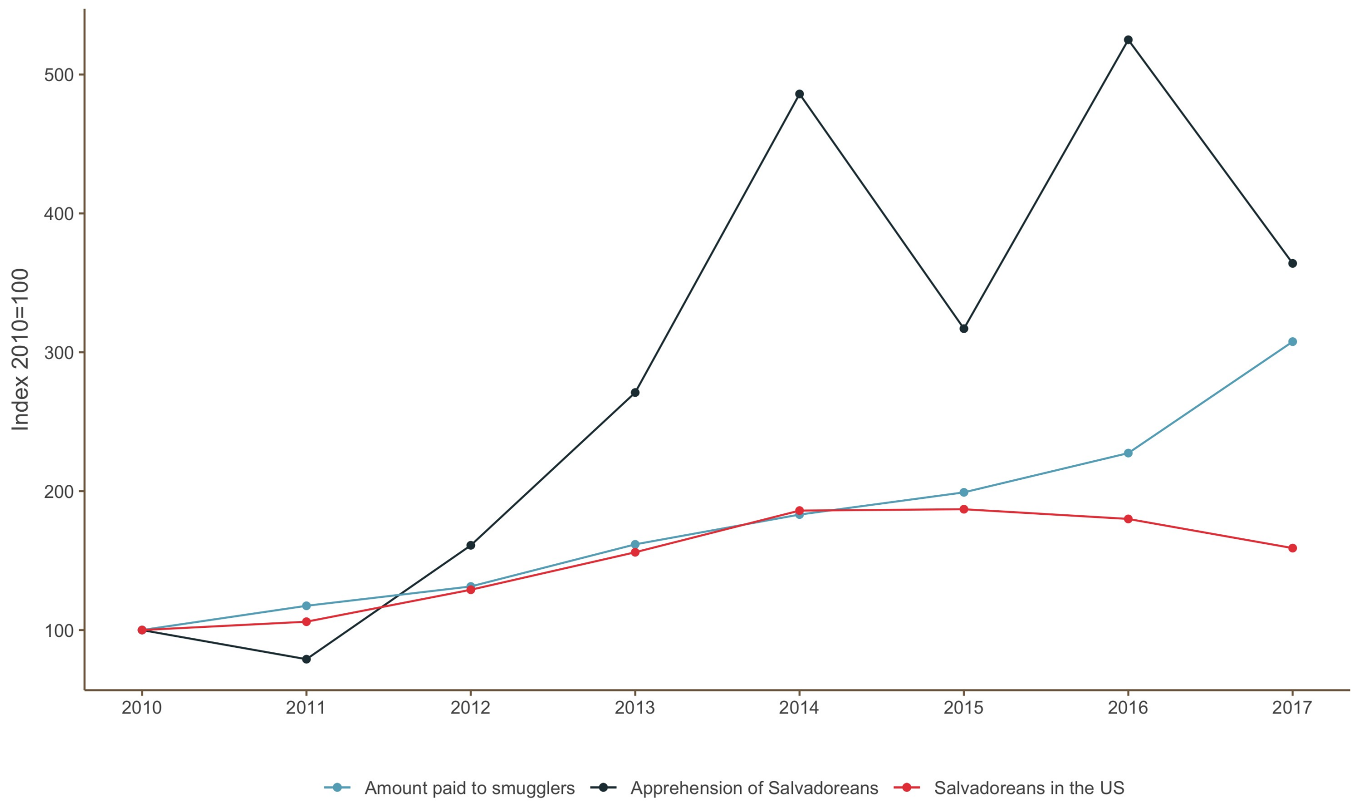
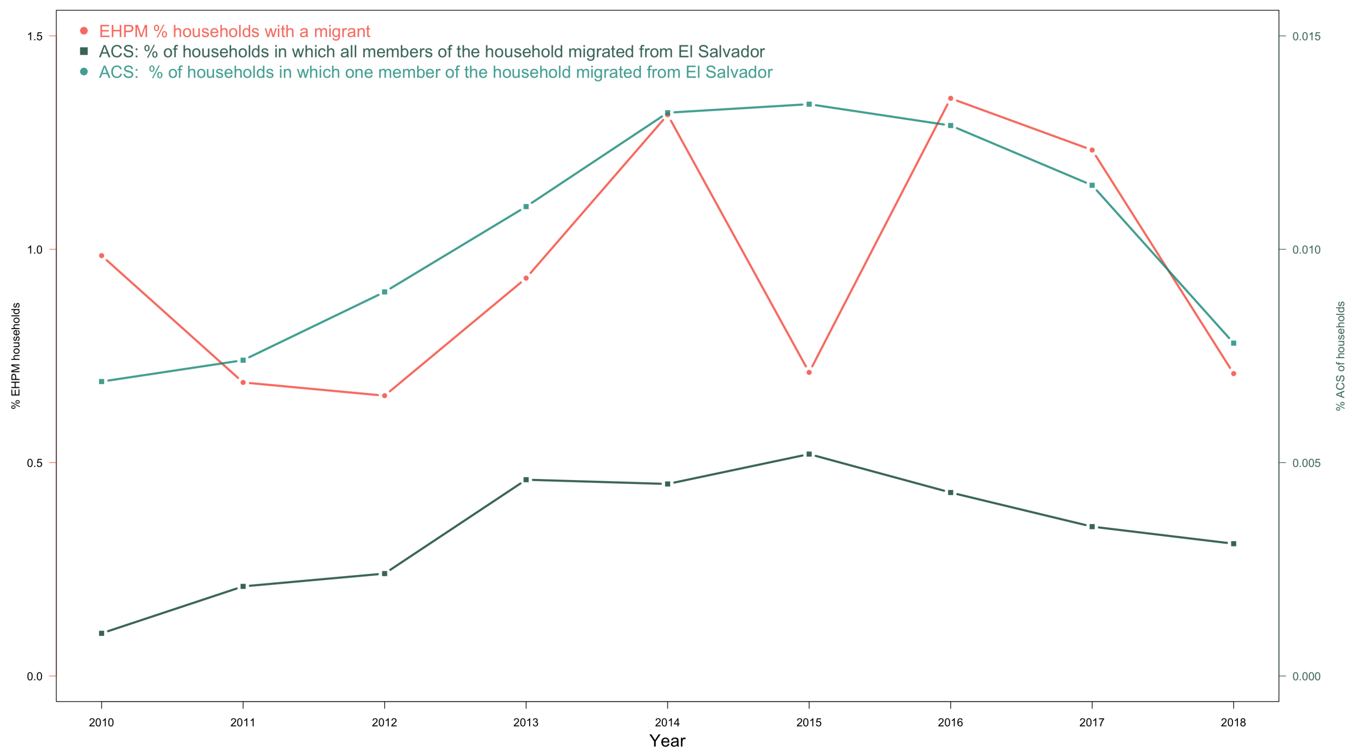
7 Figures

Figure 1: Border Apprehension of Salvadoreans and Cost of Smugglers



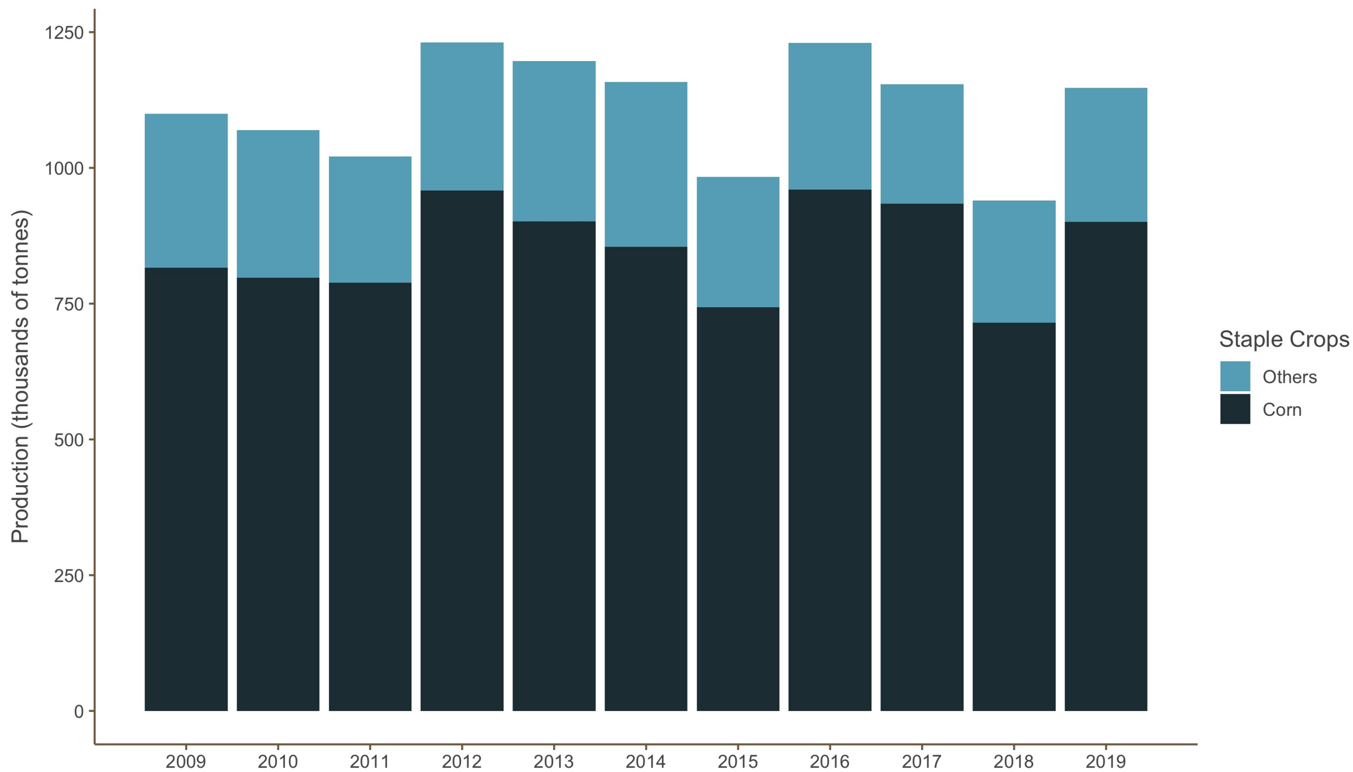
Source: American Community Survey (ACS) and Customs and Border Protection (CBP)

Figure 2: Migration trends of Salvadoreans - EHPM and ACS



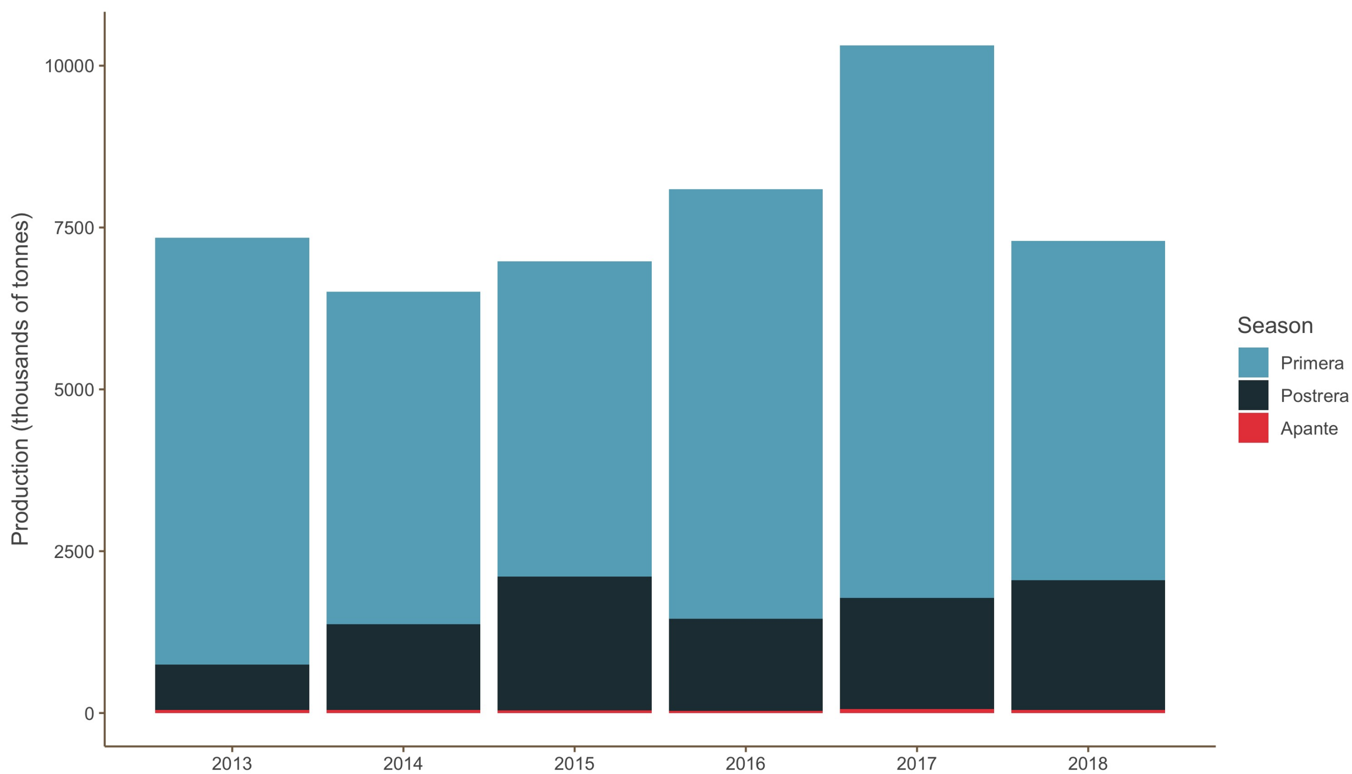
Source: American Community Survey (ACS) and Multiple Purpose Household Survey (EHPM). The lighter blue line indicates the percentage of households that have a member that was living in El Salvador a year earlier, and the darker blue line indicates the percentage in which all the members of the household were living in El Salvador a year earlier. The red line indicates the percentage of households surveyed in El Salvador that have a member living outside of the country that migrated in the same year.

Figure 3: Production of corn versus other staple crops in El Salvador



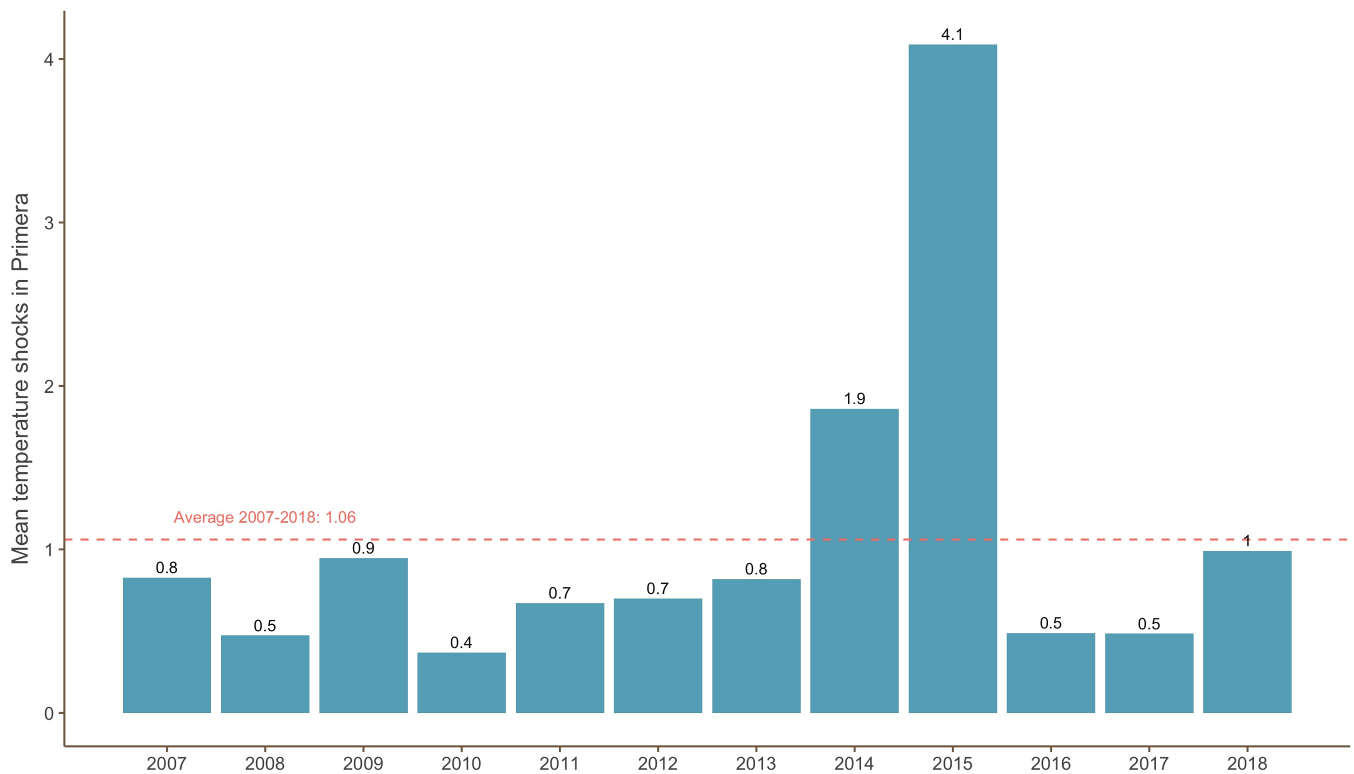
Source: FAOSTAT. Staple crops include corn (maize), rice, sorghum, and beans.

Figure 4: Corn production across yearly seasons in El Salvador



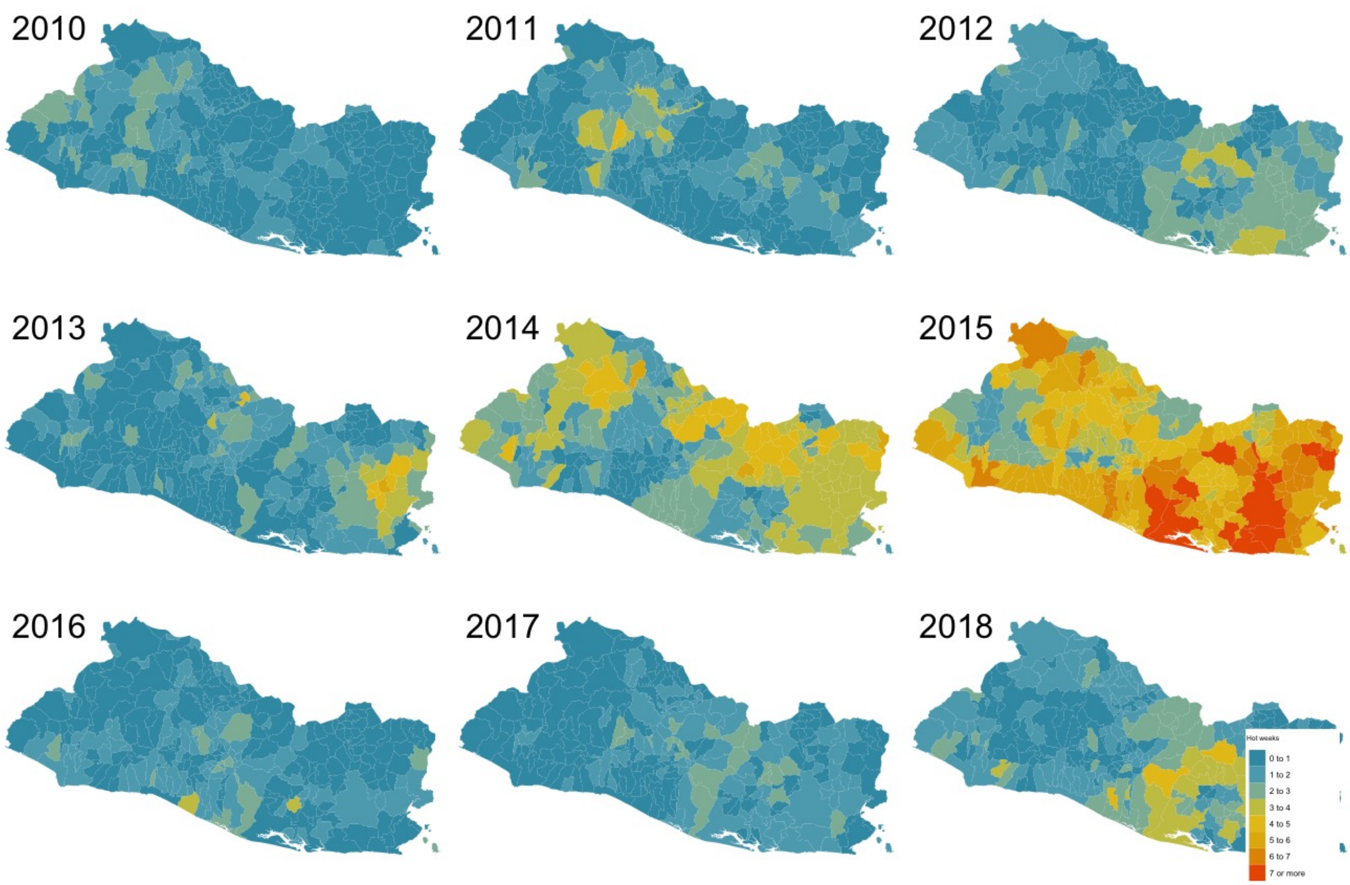
Source: ENAMP 2013-2018.

Figure 5: Average temperature shocks in winter per municipality



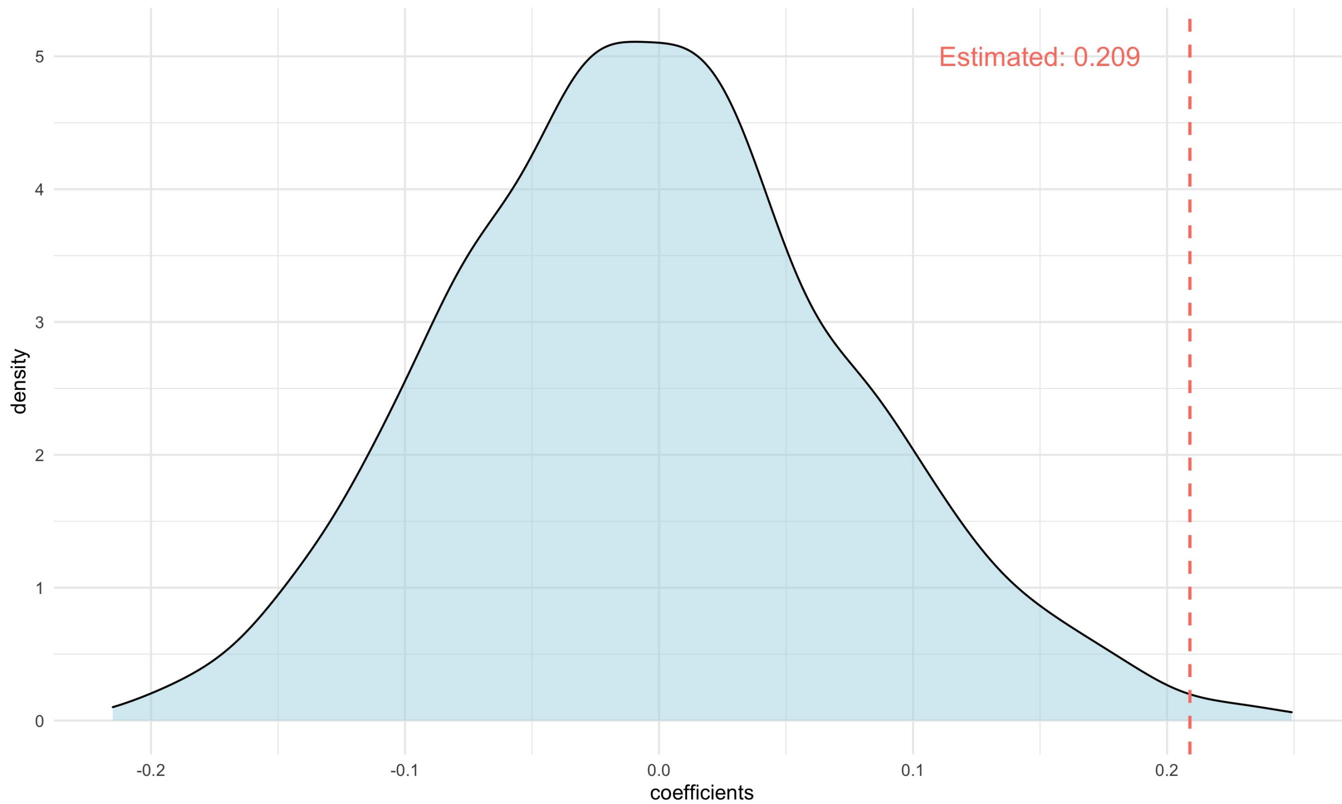
Source: NASA - MODIS Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. Temperature in Celsius. A temperature shock is defined if a week is 2 standard deviations higher than its historic mean (from 2001-2006).

Figure 6: Temperature shocks per municipality



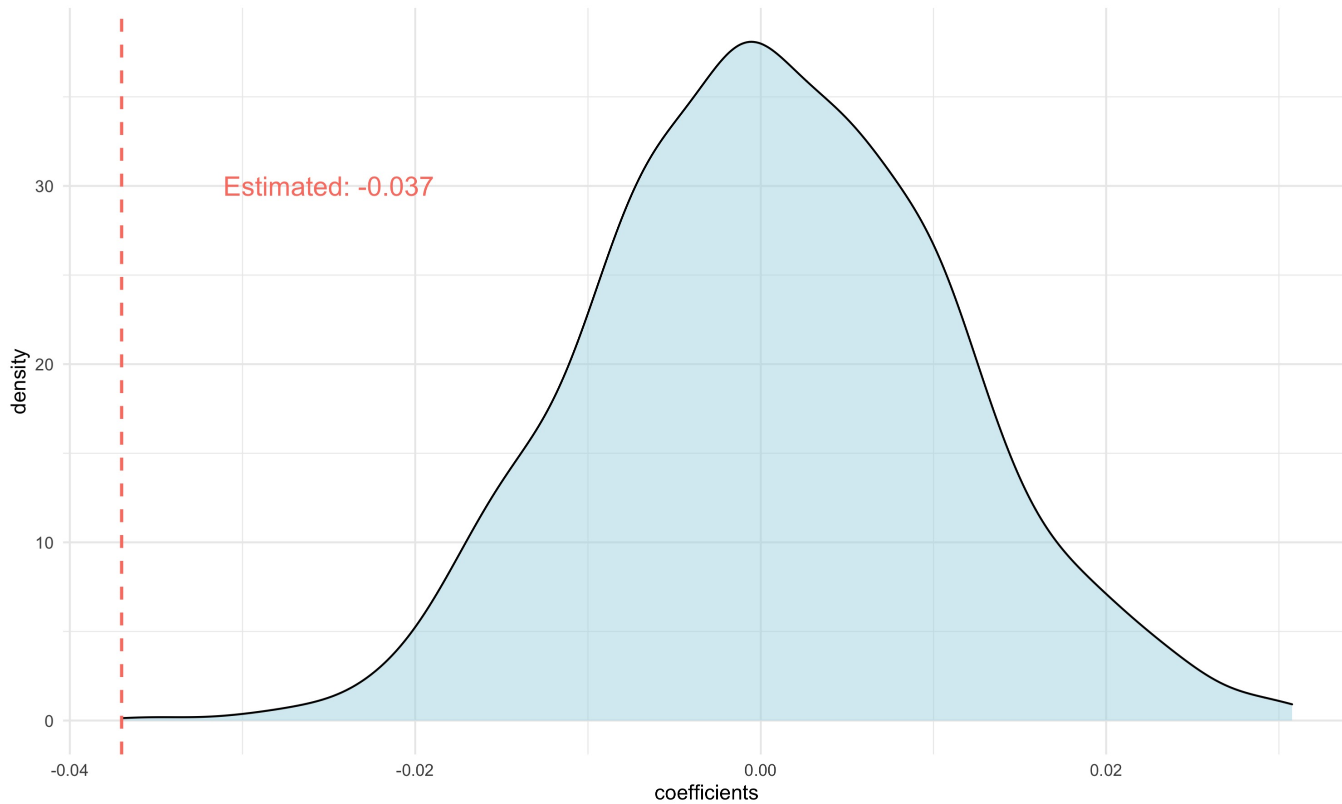
Source: NASA - MODIS Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. Each map represents the number of weeks in winter with a temperature shock (2 standard deviations above the historic mean).

Figure 7: 1,000 permutations of temperature shocks by geography:
Coefficients on migration likelihood



The red dotted line shows the coefficient with the corresponding temperature shocks

Figure 8: 1,000 permutations of temperature shocks by geography:
Coefficients on agricultural productivity



The red dotted line shows the coefficient with the corresponding temperature shocks

8 Tables

Table 1: Impact of Temperature Shocks during Harvest Season on Probability of International Migration

Population Group	(1)	(2)	(3)	(4)	(5)	Mean	Obs
A: All HHs							
Temperature shock year $t-1$	0.045	0.053	0.040	0.048	0.051	0.874	186,856
	(0.044)	(0.059)	(0.056)	(0.060)	(0.063)		
R^2	0.002	0.002	0.005	0.005	0.006		
B: Agricultural HHs							
Temperature shock year $t-1$	0.099	0.161	0.180	0.194	0.201	0.802	24,323
	(0.064)	(0.083)*	(0.084)**	(0.085)**	(0.089)**		
R^2	0.002	0.002	0.007	0.007	0.011		
C: Non-Agricultural HHs							
Temperature shock year $t-1$	0.031	0.021	-0.012	-0.008	-0.006	0.652	113,270
	(0.034)	(0.040)	(0.039)	(0.042)	(0.044)		
R^2	0.002	0.002	0.003	0.003	0.004		
D: Unemployed HHs							
Temperature shock year $t-1$	0.049	0.070	0.087	0.102	0.095	1.421	49,263
	(0.087)	(0.118)	(0.129)	(0.134)	(0.142)		
R^2	0.002	0.003	0.007	0.007	0.011		
Crime and Weather	X	X	X	X	X		
Year Fixed Effects		X	X	X	X		
Municipal Fixed Effects			X	X	X		
Municipal Socio*Year				X	X		
Geographic*Year				X	X		
Household					X		

Notes: Data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated on the surveyed year. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) of the previous year. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are age and gender of the household head, and number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. Standard errors are clustered by municipality and year.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2: Impact of Temperature Shocks on Corn Agricultural Outcomes in First-Harvest Season

Agricultural Outcome	(1)	(2)	(3)	(4)	Obs
A: Log(Corn Production per Hectare)					
Temperature shock year t	-0.092	-0.055	-0.054	-0.054	19,261
	(0.030)**	(0.029)*	(0.018)**	(0.015)***	
R^2	0.061	0.095	0.267	0.270	
B: Log(Total Production)					
Temperature shock year t	-0.070	-0.024	-0.030	-0.028	19,261
	(0.033)**	(0.016)	(0.013)**	(0.014)**	
R^2	0.060	0.105	0.234	0.237	
C: Log(Value per hectare)					
b Temperature shock year t	-0.024	-0.053	-0.051	-0.051	19,261
	(0.029)	(0.029)*	(0.019)**	(0.017)**	
R^2	0.032	0.064	0.226	0.229	
D: Log(Price per Tonne)					
Temperature shock year t	0.068	0.002	0.003	0.002	19,261
	(0.027)**	(0.003)	(0.002)	(0.003)	
R^2	0.212	0.671	0.699	0.702	
Crime, Weather and Household	X	X	X	X	
Year Fixed Effects		X	X	X	
Municipal Fixed Effects			X	X	
Municipal Socio*Year				X	
Geographic*Year				X	

Notes: Data from 2013-2018 of El Salvador Agricultural Household Survey (ENAMP). The dependent variable is in Panel A the logarithm of the ratio of corn production per hectare in the first harvest, in Panel B the logarithm of the total production per households in the first harvest, and in Panel C the logarithm of the value sold per hectare in the first harvest. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) of the same year. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are household head education, number of household members and access to irrigation for corn. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. Standard errors are clustered by municipality and year.
*p<0.1; **p<0.05; ***p<0.01

Table 3: Impact of Temperature Shocks during the Harvest Season on Composition of Workers in Agricultural Households (Hyperbolic Sine Model)

	Total Workers	Hired workers	Domestic Workers
	(1)	(2)	(3)
Temperature shock year t	-0.018^{*}	-0.029^{**}	0.015
	(0.011)	(0.012)	(0.015)
Mean workers	2.17	1.53	1.1
Crime, Weather and Household	X	X	X
Year Fixed Effects	X	X	X
Municipal Fixed Effects	X	X	X
Municipal Socio*Year	X	X	X
Geographic*Year	X	X	X
Observations	18,845	18,845	18,845
R^2	0.103	0.113	0.231

Data from 2013-2018 of El Salvador Agricultural Household Survey. The dependent variables correspond to the inverse hyperbolic sine of the number of worker and number of family workers. The independent variables are temperature shock (2 standard deviations higher than their historic value during the winter season of the previous year) in t. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are household head education, number of household members and access to irrigation for corn. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. Standard errors are clustered by municipality and year.
*p<0.1; **p<0.05; ***p<0.01

Table 4: Impact of Temperature Shocks during the Harvest Season on Labor Outcomes

Population Group	Worked Last Week (1)	Log(Weekly Hours) (2)	Log(Monthly Salary) (3)	Log(Salary Per Hour) (4)
A: Individuals in Agricultural HHs				
Temperature shock year t	0.002	0.004	-9.472	-0.005
	(0.02)	(0.003)	(7.505)	(0.005)
Temperature shock year $t-1$	0.000	0.011	5.660	-0.013
	(0.002)	(0.007)*	(13.731)	(0.008)
Mean	0.543	34.911	191.958	0.169
Obs	67,489	36,641	17,498	17,494
B: Individuals in Non-Agricultural HHs				
Temperature shock year t	-0.001	0.003	-2.642	-0.001
	(0.001)	(0.002)**	(2.042)	(0.002)
Temperature shock year $t-1$	-0.002	0.001	0.372	-0.003
	(0.001)**	(0.003)	(2.274)	(0.003)
Mean	0.501	41.586	344.957	0.160
Obs	318,434	159,657	134,824	134,780
Crime, Weather and Household	X	X	X	X
Year Fixed Effects	X	X	X	X
Municipal Fixed Effects	X	X	X	X
Municipal Socio*Year	X	X	X	X
Geographic*Year	X	X	X	X

Notes: Individual data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM) for people aged between 10 and 65. Sample of individuals surveyed from June to December. The dependent variable in Column 1 is a dummy if the person is employed, in Column 2 is the logarithm of hours worked per week, in Column 3 is the logarithm of the monthly salary (from dependent or independent work). Column 4 is the logarithm of hours worked per week. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historical value in that municipality during the winter season) of the same year and the previous year. Municipality controls are heavy rain and drought shocks (2 standard deviations higher or lower than their historical value during the winter season in this year and the previous year), and crime controls (2 standard deviations higher than their historical value the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are household head education, number of household members, and access to irrigation for corn. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include the mean extension and elevation of each municipality. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table 5: Impact of Temperature Shocks during the Harvest Season on Labor Outcomes Heterogeneity by Municipal Agricultural Production of Corn in 2007

Population Group	Worked Last Week (1)	Log(Weekly Hours) (2)	Log(Monthly Salary) (3)	Log(Salary Per Hour) (4)
	Individuals in Agricultural HHs			
A: Below Median Production				
Temperature shock year t	0.000	0.010	6.562	0.012
	(0.005)	(0.011)	(7.368)	(0.014)
Temperature shock year $t-1$	0.003	0.034	-3.703	-0.043
	(0.004)	(0.013)**	(8.858)	(0.019)**
Mean	0.505	34.192	179.690	0.171
Obs	12,500	6,715	3,139	3,138
B: Above Median Production				
Temperature shock year t	0.001	0.004	-13.542	-0.010
	(0.003)	(0.004)	(9.733)	(0.006)*
Temperature shock year $t-1$	-0.001	0.006	7.681	-0.007
	(0.002)	(0.007)	(16.367)	(0.009)
Mean	0.510	35.072	194.639	0.168
Obs	54,989	29,926	14,359	14,356
	Individuals in Non-Agricultural HHs			
C: Below Median Production				
Temperature shock year t	0.001	0.001	-3.317	0.004
	(0.002)	(0.006)	(6.551)	(0.005)
Temperature shock year $t-1$	0.001	0.003	11.002	-0.005
	(0.003)	(0.004)	(5.103)**	(0.005)
Mean	0.514	42.132	376.683	0.158
Obs	87,109	44,756	39,141	39,125
D: Above Median Production				
Temperature shock year t	-0.001	0.003	-2.760	-0.001
	(0.001)	(0.002)*	(1.172)**	(0.003)
Temperature shock year $t-1$	-0.002	0.000	-1.890	-0.002
	(0.001)	(0.003)	(2.339)	(0.004)
Mean	0.497	41.373	331.979	0.161
Obs	231,325	114,901	95,683	95,655
Crime, Weather and Household	X	X	X	X
Year Fixed Effects	X	X	X	X
Municipal Fixed Effects	X	X	X	X
Municipal Socio*Year	X	X	X	X
Geographic*Year	X	X	X	X

Notes: Individual data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM) for people aged between 10 and 65. Sample of individuals surveyed from June to December. The dependent variable in Column 1 is a dummy if the person is employed, in Column 2 is the logarithm of hours worked per week, in Column 3 is the logarithm of the monthly salary (from dependent or independent work). Column 4 is the logarithm of hours worked per week. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historical value in that municipality during the winter season) of the same year and the previous year. Municipality controls are heavy rain and drought shocks (2 standard deviations higher or lower than their historical value during the winter season in this year and the previous year), and crime controls (2 standard deviations higher than their historical value the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are household head education, number of household members, and access to irrigation for corn. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include the mean extension and elevation of each municipality. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table 6: Impact of Temperature Shocks during Harvest Season on Probability of International Migration
Heterogeneity by Household Characteristics

	Access to land		Access to Credit		Head is Employer	
	Own	Rent	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
A: Agricultural HHs						
Temperature shock year $t-1$	0.306	0.197**	−0.030	0.218**	0.365	0.196**
	(0.245)	(0.087)	(0.296)	(0.089)	(0.241)	(0.090)
Mean Migration Likelihood	1.256	0.706	1.078	0.767	1.354	0.766
Crime, Weather and Household	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X
Municipal Fixed Effects	X	X	X	X	X	X
Municipal Socio*Year	X	X	X	X	X	X
Geographic*Year	X	X	X	X	X	X
Observations	4,221	20,102	2,690	21,633	1,477	22,846
R^2	0.069	0.024	0.068	0.025	0.103	0.022

Data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated on the surveyed year. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) of the previous year. Column 1 and 2 corresponds to households that own or rent agricultural land, respectively. Column 3 corresponds to households that have agricultural credit, and Column 4 to those who don't have agricultural credit. Column 5 corresponds to households with a head that has an employer position, and Column 6 households with a head that does not have an employer position. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are age and gender of the household head, and number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. The sample is constrained to agricultural households (household head works in agriculture). Standard errors are clustered by municipality and year.
*p<0.1; **p<0.05; ***p<0.01

Table 7: Effects Temperature Shocks on Migration Likelihood
Heterogeneity by Share of Emigrants per District

	Below Median	Above Median
	(1)	(2)
Temperature Shock $t-1$	0.137*	0.217**
	(0.078)	(0.093)
Mean Migration Likelihood	0.368	1.121
Crime, Weather and Household	X	X
Year Fixed Effects	X	X
Municipal Fixed Effects	X	X
Municipal Socio*Year	X	X
Geographic*Year	X	X
Observations	10,314	14,009
R^2	0.035	0.019

Data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated on the surveyed year. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) of the previous year. Each column corresponds to households in districts ranked according to the share of their population abroad in 2007. Column 1 corresponds to households in districts in the bottom half and, Column 2 to the top half. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are age and gender of the household head, and number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. The sample is constrained to agricultural households (household head works in agriculture). Standard errors are clustered by municipality and year.
5*p<0.1; **p<0.05; ***p<0.01

Table 8: Effects Temperature Shocks in First-Season Harvest on Migration Likelihood Heterogeneity by Share of Population that Receives Remittances per District

	Below the Median	Above the Median
	(1)	(2)
Temperature Shock $t-1$	0.159**	0.216**
	(0.068)	(0.097)
Mean Migration Likelihood	0.414	1.169
Crime, Weather and Household	X	X
Year Fixed Effects	X	X
Municipal Fixed Effects	X	X
Municipal Socio*Year	X	X
Geographic*Year	X	X
Observations	11,836	12,487
R^2	0.029	0.020
Note:		*p<0.1; **p<0.05; ***p<0.01

Data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated on the surveyed year. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) of the previous year. Each column corresponds to households in districts ranked according to the share of their population that receives remittances in 2007. Column 1 corresponds to households in districts in the bottom half and, Column 2 to the top half. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are age and gender of the household head, and number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. The sample is constrained to agricultural households (household head works in agriculture). Standard errors are clustered by municipality and year.
*p<0.1; **p<0.05; ***p<0.01

9 Appendix

Table A1: Descriptive Statistics by Database

Variable	N	Mean	Std. Dev.	Min	Max
Panel A: EHPM					
=1 if at least one migrant member last year	173,946	0.009	9.649	0.000	100.000
Male head	173,946	0.615	0.487	0.000	1.000
Age of head	173,946	47.356	16.360	14.000	98.000
Household size	173,946	3.864	1.946	1.000	24.000
Employed head	173,946	0.752	0.432	0.000	1.000
Head employed in agriculture	133,793	0.172	0.377	0.000	1.000
Own lands	173,946	0.062	0.240	0.000	1.000
Panel B: ENAMP					
Corn - productivity (ton. per ha)	19,325	2.339	1.209	0.000	19.189
Corn - value of productivity per ha (SCV$)	19,325	708.899	377.079	0.062	5,487.429
Land size (Ha)	19,325	1.490	4.825	0.077	210.000
Corn price per ton (SCV$)	19,325	311.155	67.505	21.739	978.261
Number of workers	18,908	3.700	7.380	0.000	494.000
Number of family workers	18,908	1.707	1.571	0.000	43.000
Highest education level	19,325	2.465	0.925	0.000	6.000
Has irrigation	19,325	0.004	0.067	0.000	1.000
Household size	19,325	4.285	2.064	1.000	16.000
Panel C: Municipalities					
Number of weeks temperature 2sd > historic mean in winter	244	1.150	0.580	0.000	3.915
Number of weeks rainfall 2sd > historic mean in winter	244	0.108	0.144	0.000	0.729
Number of weeks rainfall 2sd < historic mean in winter	244	0.336	0.238	0.000	1.000
Crime shock	244	0.327	0.269	0.000	1.000
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	266.000	212.600	2,763.520
% employed in agriculture (2005)	244	39.903	29.319	0.520	393.870
% 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
Historic mean temperature	244	30.96	2.247	23.831	35.477
Historic mean rainfall	244	244.231	22.383	179.055	297.771
Historic standard deviation of rainfall	244	63.268	12.121	38.306	96.341
Mean elevation	244	498.362	278.794	9.677	1522.368
Extension (km^2)	244	83.733	88.237	5.4	668.36
% Internal immigrants (2007)	244	19.031	13.552	1.245	108.087
% Internationa immigrants (2007)	244	29.947	26.33	3.862	234.916

Note: Panel A shows descriptive statistics for El Salvador Multiple Purpose Household Survey (EHPM) from 2009 - 2018 to the household level. Panel B shows data from 2013-2018 of El Salvador Agricultural Household Survey to the household level. Panel C shows municipality-level statistics for the period 2009-2018. The historic mean and standard deviation is calculated for the period between 2001 and 2006.

Table A2: Summary Statistics by HH Migration Status

Variable	Non-migrant HHs Mean (1)	Migrant HHs Mean (2)	Test (3)
Male head	0.617	0.428	F= 244.573***
Age of head	47.351	47.883	F= 1.707
Household size	3.863	3.980	F= 5.878**
Employed head	0.753	0.572	F= 286.289***
Head employed in agriculture	0.172	0.204	F= 6.871***
Owns land	0.061	0.124	F= 109.911***
Number of weeks temperature 2sd > historic mean	1.168	1.234	F= 3.107*
Number of weeks rainfall 2sd > historic mean	0.104	0.168	F= 62.185***
Number of weeks rainfall 2sd < historic mean	0.280	0.330	F= 16.724***
Crime shock	0.281	0.324	F= 15.192***
Poverty rate (2005)	41.927	46.562	F= 184.32***
Extreme poverty (2005)	18.578	22.604	F= 234.987***
Income per capita (2005)	703.294	621.839	F= 98.267***
Employed in agriculture (2005)	28.259	37.620	F= 239.929***
Adolescents without school (2005)	48.329	53.201	F= 221.936***
Households without water (2005)	31.086	37.891	F= 216.21***
People less than 19 years old (2007)	45.962	47.826	F= 274.363***
People more than 60 years old (2007)	9.217	9.724	F= 167.033***
Historic mean temperature	31.127	31.513	F= 68.401***
Historic mean rainfall	239.854	245.227	F= 83.3***
Historic standard deviation of rainfall	64.049	61.445	F= 84.888***
Mean elevation	502.968	447.531	F= 70.635***
Extension	139.338	173.270	F= 95.605***
Internal immigrants (2007)	22.113	17.300	F= 176.126***
External immigrants (2007)	24.883	27.803	F= 32.735***

Note: Data from El Salvador Multiple Purpose Household Survey (EHPM) from 2009 - 2018 to the household level. Column 1 presents the average of each variable for households without a migrant member. Column 2 presents the average for households with a migrant member. Column 3 shows the F-statistic test of differences in mean.

Table A3: Summary Statistics

Variable	Agricultural HHs Mean (1)	Non Agricultural HHs Mean (2)	Unemployed HHs Mean (3)	Test (4)
=100 if at least one migrant member last year	0.802	0.652	1.421	F= 117.963***
Male head	0.872	0.647	0.377	F= 10468.01***
Age of head	46.796	43.486	58.039	F= 15853.766***
Household size	4.304	3.868	3.635	F= 960.116***
Owns land	0.174	0.0494	0.0541	F= 2636.474***
Number of weeks temperature 2sd > historic mean	1.232	1.147	1.174	F= 34.08***
Number of weeks rainfall 2sd > historic mean	0.152	0.100	0.116	F= 250.05***
Number of weeks rainfall 2sd < historic mean	0.310	0.268	0.288	F= 84.865***
Crime shock	0.325	0.270	0.284	F= 155.187***
Poverty rate (2005)	49.223	40.469	43.058	F= 4346.468***
Extreme poverty (2005)	24.502	17.384	19.550	F= 4853.724***
Income per capita (2005)	559.124	729.723	690.195	F= 2805.028***
employed in agriculture (2005)	39.167	26.129	30.527	F= 2926.031***
Adolescents without school (2005)	54.070	47.323	49.207	F= 2739.126***
households without water (2005)	36.715	30.055	32.468	F= 1366.702***
People less than 19 years old (2007)	48.273	45.542	46.279	F= 3830.925***
People more than 60 years old (2007)	9.427	9.162	9.391	F= 522.641***
Historic mean temperature	31.342	31.088	31.220	F= 225.954***
Historic mean rainfall	240.880	239.458	241.717	F= 164.961***
Historic standard deviation of rainfall	60.523	64.585	63.823	F= 1269.303***
Mean elevation	466.853	509.918	488.937	F= 311.329***
Extension	163.166	136.794	141.749	F= 351.88***
internal immigrants	16.708	23.119	21.092	F= 2068.572***
External immigrants	28.949	24.064	25.751	F= 598.183***

Data from El Salvador Multiple Purpose Household Survey (EHPM) from 2009 - 2018 to the household level. Column 1 presents the average for households that have a household head working in agriculture. Column 2 presents the average for households that have a household head working in other sectors. Column 3 presents the average for households that have a household head unemployed. Column 4 shows the F-statistic test of differences in mean.

Table A4: Impact of Temperature Shocks on Migration Likelihood
Heterogeneity on Working-Age Household Members Characteristics

	More than 50 % of HH Members in Agriculture	
	(Yes)	(No)
Temperature shock $t-1$	0.183*	0.006
	(0.100)	(0.046)
Crime, Weather and Household	X	X
Year Fixed Effects	X	X
Municipal Fixed Effects	X	X
Municipal Socio*Year	X	X
Geographic*Year	X	X
Mean mig	0.678	0.687
Observations	17,101	117,057
R^2	0.020	0.007

Data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated on the surveyed year. Column 1 corresponds to households that have more than 50% of their working-age members in agriculture. Column 2 corresponds to households that have less than 50% working in agriculture. that own or rent agricultural land, respectively. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) of the previous year. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are age and gender of the household head, and number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. The sample is constrained to agricultural households (household head works in agriculture). Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A5: Effects Temperature Shocks on Migration Likelihood
Heterogeneity by Share of Population of Municipalities in Agriculture

	Below the Median	Above the Median
	(1)	(2)
Temperature shock year $t-1$	0.084	0.320***
	(0.098)	(0.114)
Mean Migration Likelihood	0.59	1.028
Crime, Weather and Household	X	X
Year Fixed Effects	X	X
Municipal Fixed Effects	X	X
Municipal Socio*Year	X	X
Geographic*Year	X	X
Observations	12,550	11,773
R^2	0.020	0.025

Data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated on the surveyed year. The independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) of the previous year. Column 1 corresponds to households living in municipalities with a share of population working in agriculture below the median municipality, as of 2007. Column 2 corresponds to households living in municipalities with a share of population working in agriculture above the median municipality, as of 2007. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are age and gender of the household head, and number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. The sample is constrained to agricultural households (household head works in agriculture). Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A6: Effect on Log of Food Consumption per Capita

	Agricultural HHs	Non-Agricultural HHs
	(1)	(2)
Temperature shock year $t-1$	-0.009	-0.002
	(0.006)	(0.004)
Crime, Weather and Household	X	X
Year Fixed Effects	X	X
Municipal Fixed Effects	X	X
Municipal Socio*Year	X	X
Geographic*Year	X	X
Observations	24,323	113,264
R^2	0.354	0.300

Data from 2009-2018 of El Salvador Multiple Purpose Household Survey (EHPM). The dependent variable is the logarithm of food consumption per capita. Column 1 corresponds to households that have a household head working in agriculture, and Column 2 to a household head not working in agriculture. The independent variables are temperature shock (2 standard deviations higher than that week's historic value in that municipality during the winter season) in $t-1$, t, and $t+1$. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historic value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season, and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are age and gender of the household head, and number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include mean extension and elevation of each municipality. The sample is constrained to agricultural households (household head works in agriculture). Standard errors are clustered by municipality and year.
*p<0.1; **p<0.05; ***p<0.01

Table A7: Impact of Temperature Shocks on Migration Likelihood - Different Shocks

Population Group	Winter Shock (1)	All-year Shock (2)	Apante Shock (3)
A: All HHs			
Temperature shock year $t-1$	0.051	0.031	0.024
	(0.064)	(0.031)	(0.053)
R^2	0.006	0.006	0.006
B: Agricultural HHs			
Temperature shock year $t-1$	0.201	0.054	-0.086
	(0.088)**	(0.042)	(0.126)
R^2	0.011	0.010	0.010
C: Non-Agricultural HHs			
Temperature shock year $t-1$	-0.006	0.011	0.032
	(0.045)	(0.021)	(0.068)
R^2	0.004	0.004	0.004
D: Unemployed HHs			
Temperature shock year $t-1$	0.095	0.073	0.070
	(0.143)	(0.073)	(0.132)
R^2	0.011	0.012	0.011
Crime, Weather and Household	X	X	X
Year Fixed Effects	X	X	X
Municipal Fixed Effects	X	X	X
Municipal Socio*Year	X	X	X
Geographic*Year	X	X	X

Data from (EHPM). The dependent variable is 100 if a household member migrated on the surveyed year. Column 1's independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historical value in that municipality) of the previous year. Column 2's independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historical value in that municipality during the second-harvest (apante) season) of the previous year. Column 3's independent variable is the number of weeks with a temperature shock (2 standard deviations higher than that week's historical value in that municipality during the first-harvest season) of the previous year, and the sample is restricted to the 2013-2018 period. Municipality controls are crime, heavy rain, and drought shocks (2 standard deviations higher than their historical value during the winter season of the previous year). Historic weather controls are mean temperature from 2001-2006 during the winter season and mean and variance of precipitation from 2003-2006 during the winter season. Household controls are the age and gender of the household head and the number of household members. Baseline municipal controls are from 2005 and include poverty and extreme poverty prevalence, average income per capita, percentage of workers in agriculture, adolescents missing school, percentage of internal and migrants and emigrants, and percentage of population under 18 and between 18 and 60 years old. Geographic controls include the mean extension and elevation of each municipality. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A8: Impact of Temperature Shocks in First-Harvest Season on Migration Likelihood - Different Periods

Population Group	2009-2018 (1)	August-December (2)	2013-2018 (3)	Excluding 2015 (4)
A: All HHs				
Temperature shock year $t-1$	0.051	0.075	0.059	0.067
	(0.064)	(0.083)	(0.084)	(0.075)
R^2	0.006	0.006	0.006	0.007
B: Agricultural HHs				
Temperature shock year $t-1$	0.201	0.303	0.241	0.236
	(0.088)**	(0.132)**	(0.102)**	(0.094)**
R^2	0.011	0.010	0.012	0.012
C: Non-Agricultural HHs				
Temperature shock year $t-1$	-0.006	0.032	-0.011	0.021
	(0.045)	(0.096)	(0.063)	(0.045)
R^2	0.004	0.004	0.004	0.005
D: Unemployed HHs				
Temperature shock year $t-1$	0.095	0.048	0.111	0.079
	(0.143)	(0.134)	(0.190)	(0.179)
R^2	0.011	0.011	0.012	0.012
Crime and Weather	X	X	X	X
Year Fixed Effects	X	X	X	X
Municipal Fixed Effects	X	X	X	X
Municipal Socio*Year	X	X	X	X
Geographic*Year	X	X	X	X
Household	X	X	X	X