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Responses to Temperature Shocks: Labor Markets and Migration Decisions in El Salvador*

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April 22, 2022

Abstract

By 2017, one-quarter of people born in El Salvador were estimated to be living in the U.S. We show that extreme temperatures have negatively affected agricultural production and increased international migration from El Salvador. We find that labor markets act as a transmission mechanism of the negative effects of weather shocks on agricultural workers, who react by migrating internationally or reallocating within local labor markets. However, these responses differ by landownership status and access to risk-coping mechanisms. Our results suggest that, despite the current anti-immigrant political climate, there should be a global responsibility relative to the consequences of climate change.

JEL: Q54, O15, J43
Keywords: Migration, Temperature Shocks, El Salvador

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1 Introduction

The frequency and length of heat waves have escalated since the middle of the twentieth century, a trend that will likely intensify in the coming decades (Seneviratne et al., 2012). This has important implications for small farmers since evidence increasingly shows that extreme temperatures negatively affect crop yield, agricultural productivity, and agricultural income.[1] If these trends persist, subsistence farmers who grow crops that are highly sensitive to extreme temperatures will struggle even more to absorb these shocks, with negative consequences for hundreds of millions of people and global efforts to reduce rural poverty.[2]

Incomplete financial markets to manage risk in developing countries limit the ability of households to compensate for income losses caused by weather shocks and to protect themselves *ex ante* through insurance. Empirical evidence shows agricultural households respond in the short term to these shocks through costly strategies such as asset sales, changes in agricultural practices, an expansion in the use of household labor (including children), and participation in subsistence activities (Rosenzweig and Wolpin, 1993; Jayachandran, 2006; Hornbeck, 2012; Carter and Lybbert, 2012; Jessoe et al., 2016; Aragón et al., 2021). A lack of sustainable short-term responses to weather shocks has also prevented farmers from adapting to long-term climate change (Hornbeck, 2012; Carleton and Hsiang, 2016). Agricultural producers in developed countries are somewhat able to adapt to climate change, but the literature suggests that for small farmers, such adjustments are not sufficient to address the initial shock (Hornbeck, 2012; Dell et al., 2014; Burke and Emerick, 2016).

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

[2] In 2016, there were 570 million farms in 167 countries; 89 percent were family farms, and the great majority were small farms (84 percent under two hectares). Forty-nine percent were located in lower-income countries (Lowder et al., 2016).

Migration is an increasingly important coping strategy as weather becomes more unpredictable in some regions of the world.[3] In fact, weather-driven migration is more frequent in countries that rely more on agricultural production (Feng et al., 2010; Cai et al., 2016; Thiede et al., 2016). Intentional migration is a viable strategy that can help households to diversify risk or escape untenable conditions (Mahajan and Yang, 2020). Yet, migration due to stressful conditions ("distress migration") might impose large social and economic costs by pressuring households to make poor decisions that could compromise their long-term prospects (Kleemans, 2015).

This paper examines migration responses of households to extreme temperature events in El Salvador and provides novel evidence on the mechanisms underlying this relationship. Specifically, we study the effects of temperature on agricultural production and we examine the complex ways in which farmers respond to these shocks. Our results suggest labor markets transmit the negative impact of temperature shocks to agricultural workers, who react by migrating internationally or moving to the nonagricultural sector. Moreover, we show that the adjustment through labor markets differs by landownership and access to both formal and informal mechanisms to address risk (Jayachandran, 2006).

Our empirical model follows the conceptual framework of previous literature. Negative temperature shocks are expected to reduce crop yields. In response, farmers adjust inputs accordingly to protect agricultural income when mechanisms to address risk—such as credits or insurance—are absent (Hornbeck, 2012; Aragón et al., 2021). In the short run, farmers have a small margin of adjustment as some decisions on input use are irreversible. For example, farmers may adjust their use of land and fertilizer if the planting season is not over. In addition, they may adjust labor demand at the extensive and intensive margins by hiring fewer agricultural workers and instead substituting household workers who thus increase their hours of on-farm work (Jayachandran, 2006; Bastos et al., 2013; Jessoe et al., 2016; Aragón

[3]See Dell et al. (2014), Carleton and Hsiang (2016), and Šedová, Čizmaziová and Cook (2021) for a literature review.

et al., 2021). Agricultural workers who lose their jobs may move to the nonagricultural sector or migrate to offset income losses. If labor supply for the nonagricultural sector expands, wages in that sector may decrease, with negative consequences ultimately for those workers as well (Colmer, 2021).

Landowners and wage workers are likely to adjust differently to temperature shocks, and we provide evidence to support this hypothesis. Landowners face larger opportunity costs of migration (relative to agricultural wage workers) and cope better with negative income shocks due to their increased access to risk-management mechanisms such as credits (Kleemans, 2015; Kubik and Maurel, 2016; Cattaneo and Peri, 2016; Mahajan and Yang, 2020). Both dimensions reduce the need for distress migration. Nonetheless, it is costly to fund migration, and even more so for households living near subsistence levels that have recently suffered a negative income shock (Jayachandran, 2006; Feng et al., 2010; Hornbeck, 2012; Kleemans, 2015; Jessoe et al., 2016; Aragón et al., 2021). We provide evidence of these differential margins of adjustment for landowners and agricultural workers. We also test whether access to mechanisms such as credits or migrant networks prevent reliance on distress migration or, on the contrary, facilitate migration by lowering its costs (Massey et al., 1990; Munshi, 2003; Hunter et al., 2013; Nawrotzki, 2015; Clemens, 2017; Mahajan and Yang, 2020).

El Salvador has several advantages to study this topic. First, a large percentage of the population still earn income from agriculture, especially compared to other Latin American countries. Agriculture is the second-largest employer in the country (17.6 percent) after the service sector.[4] Second, a large number (87 percent) of agricultural producers are subsistence farmers who have small land plots (on average, 1.2 hectares) and live in contexts with

[4]Percentages for the other sectors are: manufacturing, 15.6 percent; social services, 6.5 percent; construction, 5.8 percent; financial services, 5.6 percent; domestic work, 5.0 percent; and other, 11 percent. See https://www.mtps.gob.sv/wp-content/uploads/descargas/BoletinesEstadisticos/mtps-boletin-laboral-mujeres-2019.pdf.

incomplete markets;[5] in 2017, the rural poverty rate was 50 percent.[6] Third, the country is increasingly vulnerable to extreme weather events.[7] Finally, El Salvador has a long history of migration to the United States that began during the civil war in the 1980s and has continued ever since. In 2017, over one-quarter of the country's population was estimated to be living in the United States (Abuelafia et al., 2019).

Our empirical model exploits both temporal and geographic variations in temperature shocks between 2009 and 2018 in El Salvador. We measure temperature shocks as the deviation of the average temperature in a year and season relative to the historic mean weighted by the historic standard deviation, which can be interpreted as random draws from a climate distribution. Next, we exploit within-municipality variation of this shock (Deschênes and Greenstone, 2007; Feng et al., 2010; Dell et al., 2014). Our empirical model includes municipality fixed effects to absorb time-invariant geographic characteristics, year fixed effects to absorb national-level shocks, and the interaction of baseline municipality characteristics with linear time trends to account for differential pre-trends at the municipality level. We control for time-varying characteristics such as crime shocks, excessive rainfall, and drought shocks as these are correlated with temperature shocks and may also influence migration and agricultural decisions. The validity of the identification strategy rests on the assumption that, conditional on observables and fixed effects, there are no 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. Since we measure the effect of temperature shocks rather than the effect of climate change, our results should be interpreted as short-term effects, not long-term adjustments of agricultural producers.

We show that the negative impact of temperature shocks on agricultural production

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

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

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

is an important mechanism that explains the effect on migration. Temperature shocks decrease production of corn (also known as maize, El Salvador's main staple crop) such that an additional one standard deviation (SD) of the temperature shock reduces total agricultural production by two percent and the value of corn production per hectare by 3.9 percent. Agricultural producers adjust in the short run by reducing demand for hired agricultural workers and substituting household workers for them; this contraction in labor demand depresses agricultural wages. Like Aragón et al. (2021) in Peru, we find that farmers respond to these shocks by increasing the area of land use and changing production inputs mainly in postharvest activities. Households living in rural areas seek employment in nonagricultural occupations or migrate abroad as strategies to mitigate the negative income shock. One additional week of the temperature shock increases international migration sizably for agricultural households: a one SD increase in the temperature shock causes migration to rise by 14.5 percent. These results suggest that temperature shocks are a significant push factor for rural Salvadorean households.

As predicted, we find important heterogeneity depending on land ownership and access to risk-management mechanisms. Landowners can respond to the shock by adjusting production costs, which diminishes their response through migration. Access to risk-management mechanisms also plays an important role in mitigating the effects of extreme temperatures. Migrant networks and credit provide funds to better cope with the drop in income caused by the negative shock, reducing the likelihood of distress migration for these households.

We test the robustness of our results via different strategies. First, to assess whether the effect of the shock on migration was indeed driven by a decline in agricultural production, we define the shock in different time windows unrelated to the harvest season. We find that the impact of extreme temperatures on migration only stems from shocks that occur during the harvest season. Second, the estimated effect of temperature shocks on migration could capture other correlates of migration or be driven by chance. To determine this, we

estimate a placebo test in which we randomly assign each temperature/week observation 1,000 times and re-estimate the results. The estimations confirm that our results are not found by chance. Third, we estimate effects for different definitions of temperature shocks, and the results hold. Finally, we gauge the robustness of our results by controlling for crime rates. By negatively impacting income, temperature shocks might also be strongly correlated with spikes in crime (Dell et al., 2014; Carleton and Hsiang, 2016), which have prompted migration from El Salvador and other countries (Stanley, 1987; Clemens, 2017; Bermeo and Leblang, 2021). The magnitude and significance of our coefficient estimates are robust to including these controls.

Our paper contributes to three strands of economics literature. First, we add to the work on migration responses to weather shocks and natural disasters. This literature finds that negative weather shocks, including natural disasters, increase internal migration[8] and emigration[9] mostly for middle-income households, which have lower opportunity costs of relocation and are less constrained in funding migration (Cattaneo and Peri, 2016). Most of these papers rely on a reduced-form strategy to identify the effects of negative weather shocks on migration and rarely delve into the potential mechanisms behind these results. Some papers explore agriculture as a mechanism but use aggregate data either at the country, state, or county level (see, for example, Feng et al., 2010; Hornbeck, 2012; Hornbeck and Naidu, 2014; Cai et al., 2016; and Cattaneo and Peri, 2016). Jayachandran (2006) and Aragón et al. (2021), which use microdata for agricultural producers, are two noteworthy exceptions. We bolster this literature by providing evidence of the role of labor markets as a transmission mechanism for the negative impact of temperature shocks on agricultural

[8]Examples of papers on internal migration are: Dillon et al. (2011), Clark Gray and Valerie Mueller (2012), 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), Baez et al. (2017), Quiñones et al. (2021), and Mullins and Bharadwaj (2021).

[9]Examples of papers on the influence of weather shocks on emigration are: Halliday (2006), Feng et al. (2010), Gray, Clark L. and Mueller, Valerie (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), Mahajan and Yang (2020), and Bermeo and Leblang (2021).

workers, some of who react by leaving El Salvador. In addition, we show that access to risk-management mechanisms (such as credits and migrant networks) reduces reliance on distress migration. It is vital to examine these elements in order to design policies to prevent distress migration and facilitate intentional migration from regions where agriculture may no longer be feasible.

Second, we provide evidence on how negative temperature shocks affect agricultural production in developing countries and how incomplete markets may pressure households to rely on migration. Evidence on the impact of extreme weather events on agriculture exists mostly for developed countries where farmers have access to financial and insurance markets and hence a larger array of coping alternatives.[10] Since developed and developing countries are such different contexts, it might not be valid to extrapolate results for developed countries to developing ones (Dell et al., 2014). Our paper demonstrates how incomplete markets in developing countries force rural households to rely on migration—in this case, international migration—to counteract declines in income. Migration might lead to better outcomes both in the short and long terms if it is voluntary and not for lack of better coping mechanisms. Under certain conditions, however, it can lead to persistent negative effects for both migrants and the households they leave behind. Financial and insurance mechanisms, adjusted for the specific conditions small farmers face, should be designed to mitigate the negative impacts of extreme weather events and prevent distress migration.

Third, our findings on migration responses to declines in agricultural production and labor demand contribute to the literature on the consequences of climate change and the strategies households use to address them. Even though we focus on short-term effects and do not consider long-term strategies, our results provide proof of the potential adaptive responses of farmers to increasingly frequent extreme weather events. Climate change,

[10]Some examples are Deschênes and Greenstone (2007), Schlenker, Wolfram and Roberts, Michael J. (2009), Schlenker and Lobell (2010), Hornbeck (2012), Hornbeck and Naidu (2014), Burke and Emerick (2016), and Ortiz-Bobea et al. (2019).

which is caused by global emissions, mostly affects households in developing countries that seek refuge, when possible, in developed countries. It must therefore be a shared global responsibility to address the harmful effects of climate change.

The rest of the paper proceeds as follows: the next section provides information about El Salvador. Section 3 describes our data, section 4 explains our empirical strategy, and section 5 presents our results. Section 6 concludes.

2 Background

2.1 Migration from El Salvador to the United States

The inflow of Salvadorean migrants to the United States started in the 1980s due to the civil war and has continued ever since. Migrant networks have supported newly arrived families with financial assistance, shelter, and connections to labor markets. This aid has helped to attract new waves of migrants (Donato and Sisk, 2015; Clemens, 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]— which accounts for 25 percent of the Salvadorean population (Abuelafia et al., 2020).

The costs of migration from Central America to the United States, however, have risen significantly in the past decade. In the last 15 years, the U.S. government has imposed stricter regulations and enforced tighter border controls, which have produced more detentions and deportations (East and Velásquez, Forthcoming). These policies have particularly affected immigrants from El Salvador. In 2018, nearly 32,000 Salvadoreans were apprehended at the border, compared with over 14,000 apprehensions in 2007.[13] As might be expected, the price

[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.

[13] https://www.cbp.gov/newsroom/media-resources/stats/retrievedonJuly31,2020.

of services provided by migrant smugglers (*coyotes*) has also risen sharply. Surprisingly, this spike in costs has not effectively deterred migration (Massey et al., 2014). Figure 1 illustrates the rising costs of migrant smugglers as well as apprehensions at the border, signaling that suppressive measures have not succeeded.[14]

Given the sustained increase in migration from El Salvador despite stricter U.S. immigration policies, a question remains: what drives these persistent flows? 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 from El Salvador (Stanley, 1987; Halliday, 2006; Yang, 2008; Clemens, 2017). Extreme weather conditions are strongly related to internal migration in Central American countries and are also a potential cause of international migration (Baez et al., 2017; WFP, 2017; WB, 2018; Bermeo and Leblang, 2021). El Salvador is not only extremely vulnerable to changing climate conditions[15] but also has sustained more frequent weather shocks in recent years (ECLAC, 2010). Interestingly, newly arrived Salvadorean migrants in the United States increasingly have abandoned rural areas, which are more vulnerable to such shocks (WFP, 2017; Abuelafia et al., 2020). Figure 2 shows a strong correlation between apprehensions of Salvadoreans at the US border and temperature shocks in El Salvador the prior year, measured as two SD above the historic mean.

2.2 Extreme Weather and Temperature Shocks in El Salvador

The frequency of extreme weather events in El Salvador, in particular droughts and high temperatures, has intensified during the last decades, with three extreme droughts in the last 10 years alone. In 2012, a severe and prolonged drought reduced coffee production by 70 percent. Between 2014 and 2015, more than 100,000 farmers suffered losses from another

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

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

drought and the onset of *El Niño*.[16] In 2018, a new drought struck the country before it had recovered from the previous one. This led to a sharp loss of staple crops such as corn and to the declaration of a "red alert" by the government.[17] Droughts and rising temperatures are driving incomes lower but pushing food insecurity and migration higher. The outlook is grim as agricultural production may become unfeasible in some areas (WB, 2018). For example, in the Dry Corridor—a region with severe water shortages, rising temperatures, and persistent droughts—one-third of households are food insecure. Drought shocks and the lack of food are the main motivations for migration from that area (WFP, 2017).

Recurring droughts and extreme temperatures are causing large crop losses (in particular coffee, corn, and beans) and taking a heavy toll on vulnerable rural populations in El Salvador.[18] Most agricultural producers there are small family farms with average land sizes of 1.2 hectares[19] that are dedicated to subsistence farming. As only 1.4 percent of the land is irrigated,[20] agricultural production is highly dependent on the rain cycle (WB, 2018).

Figure 3 illustrates the trend in increasing temperature levels. Importantly, drought frequency is strongly correlated with elevated temperatures (see Figure 4). In our empirical model, the main variable of interest is temperature, but all our specifications control for precipitation. We chose temperature as our main variable of interest because it is a stronger predictor of crop yields than rainfall is (Lobell and Burke, 2008, Burke and Emerick, 2016, Ortiz-Bobea et al., 2019, Ortiz-Bobea et al., 2021, Colmer, 2021). Extreme temperatures are more difficult to manage than low rainfall because the latter is storable or can be replaced by groundwater resources Colmer (2021); average temperature has increased over the years

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

[17] 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.

[18] 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.

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

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

while rainfall is more erratic (Ortiz-Bobea et al., 2021); and rainfall is more likely to have greater measurement error than temperature (Burke and Emerick, 2016). In fact, recent studies find that temperature has a stronger effect on staple crops than precipitation does (Schlenker and Lobell, 2010; Nawrotzki, 2015; Carleton and Hsiang, 2016; Jessoe et al., 2016; Aragón et al., 2021).

3 Data

3.1 Migration

Our empirical analysis uses several data sources. To study migration, we use the Multiple Purpose Household Survey (EHPM from its acronym in Spanish), a yearly cross-sectional survey collected by El Salvador's official statistics agency. The sample in the estimations encompasses 186,910 households for 2009–2018 and collects information on household members' sociodemographic characteristics, housing, employment, agricultural outcomes, land tenure, household income, and migration status, among other elements. The survey is representative at the national level and for 50 municipalities.[21]

We identify the main dependent variable using the migration module, which collects information on household members who live abroad, their year of migration, and their destination country.[22] Our outcome variable is a dummy equal to one when at least one household member migrated abroad one year prior to the survey.[23] Ideally, we should measure migration using data on migrants rather than households with migrants. The latter may underestimate the number of migrants as, in some cases, all household members may migrate together—especially following intense temperature shocks. On the other hand, data collected in the United States regarding migrants from El Salvador may underreport undocumented

[21] We dropped three households with no information on the occupation of the household head.

[22] In our period of interest, between 93 percent and 95 percent of household members living abroad resided in the United States.

[23] We identify recent migration but we cannot identify whether this is a permanent or seasonal migration.

immigrants (Halliday, 2006). To evaluate potential underreporting of entire-household migration, we compare migration trends from the EHPM and the American Community Survey (ACS).[24] Using the ACS, we calculate the percentage of households in the United States with at least one or all members who migrated from El Salvador the previous year. Figure 5 shows similar trends for both surveys for most years except for 2015, when the percentage of entire-household migration reported in the ACS spiked while in the EHPM, households reporting migrant members fell sharply. This suggests 2015 might have been a year when international migration was more common for entire Salvadorean households than for individuals. Reassuringly, our results are robust with and without the 2015 data.

3.2 Labor Markets

Labor outcomes are constructed based on the labor module of the survey for the working-age population 10–65 years old. Labor outcomes include employment, hourly wages, weekly hours, and monthly wages.[25] The module also enables us to identify the occupational sector for each working member of the household. We group the households on: (i) agricultural households growing transitory crops;[26] (ii) agricultural households with any other agricultural production, including livestock; (iii) nonagricultural households; and (iv) unemployed households. We define the household sector based on the main occupation of the household head. We test the robustness of our results by defining a household as agricultural when half of its working members or more work in the agricultural sector.

Tables A1 and A2 report descriptive statistics of the outcome and control variables, respectively. Almost 0.9 percent of households had at least one member who migrated abroad the year before the survey; 17.5 percent of household heads were employed in the

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

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

[26]Transitory crops must be replanted after each harvest. Corn is the most important transitory crop in El Salvador.

agricultural sector; of those, 6.7 percent owned land; and only 3.3 percent of households had an agricultural credit.

3.3 Agricultural Production

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 2013–2018. The ENAMP is a yearly cross-sectional survey of agricultural producers that collects information on crop yield, land size, agricultural inputs (including labor) and self-reported prices. The sample, which includes 19,261 agricultural producers, is representative at the national level and, for grain crops, representative at the provincial level. The survey is administered during the last quarter of the year once the harvest has occurred for the first two seasons, *invierno* and *postrera*. (See Figure A1 in the Appendix for a time line of the different data sources). At that time, respondents are asked to predict the third harvest of the year, *apante*.

We focus on corn production. As noted above, corn is the main staple crop in El Salvador as well as in the rest of Central America (Figure A2 in the Appendix). It is a primary source of caloric intake for rural households and its production is widespread (Nawrotzki, 2015, WB, 2018). In fact, between 83 percent and 90.3 percent of the sample observations produce corn. It is a short-cycle crop for which temperature shock impacts can be traced back in the same period. In addition, other papers have found a significant association between temperature shocks and corn production.[27]

As mentioned, corn production has three harvest seasons: *primera or invierno*, this is the first-harvest season (June and July), *postrera* (August and September), and *apante* (November and December). Figure A3 in the Appendix illustrates the yearly contribution

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

of the three harvest seasons for our period of analysis. Corn production occurs mostly in the first harvest (*primera*). Therefore, our estimates measure the effect of temperature shocks during *primera*, which we refer to as the first harvest season. In addition, we perform robustness tests using the other seasons (*postrera* and *apante*) and the lean season, when we would expect a weak effect or no effect of extreme weather on production.

The outcomes for agricultural production include: (i) output variables: total yield, land productivity (measured as yield per total land plot size and yield per land cultivated in corn), and labor productivity (measured as yield per worker); (ii) input variables: the number of workers (total, hired, and household), a principal component index of other inputs (planting material, agrochemicals, chemical agents, and agroecological elements), and land size (size of land plot and land allocated to corn); and (iii) Total Factor Productivity (TFP), estimated as the residual of regressing the agricultural output on all the inputs listed before. An average agricultural producer has a yield per hectare of 2.3 tons (SVC$ 708.8) and a land plot of 1.5 hectares of which 0.71 hectares are cultivated with corn. The average use of workers is 5.4 workers, 1.7 of who are household workers. Access to irrigation—crucial for managing periods of drought and extreme temperatures—is practically nonexistent (0.4 percent). (See Tables A1 and A2 in the Appendix).

3.4 Temperature

Temperature data come from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature, a data grid of one km resolution that contains eight-day temperature averages for 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 period (*primera*) between 2001 and 2006. Our main variable of interest is the temperature shock during the first harvest season. Temperature shocks measure the number of weeks during this period in which the temperature was two

SD above its historic mean.

On average, there were 1.2 weeks during the first harvest of the year with temperatures two SD above the historic mean. Our empirical strategy exploits the large time and geographic variations of temperature shocks. During 2014 and 2015, the years with the highest temperature spikes, the number of weeks with excessive temperatures was 1.9 and 4.1, respectively. Moreover, temperature shocks varied widely across municipalities: in 2015, some Southeastern municipalities experienced five weeks of such shocks, whereas in the Northwestern region, some municipalities witnessed no such shock (see Figure 6).

3.5 Controls

We control for numerous baseline and time-variant characteristics at the municipality level. Time-variant characteristics are measured in $t-1$ to avoid adding bad controls and include: rainfall shocks during the first harvest season (measured as the number of weeks with rainfall two SD above the historic mean), drought shocks (measured as the number of weeks with rainfall two SD below the historic mean),[28] and crime shocks.[29]

To control for baseline municipality conditions, we interact baseline characteristics and a linear time trend. 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) who are not enrolled in school.[30] Using data from the 2007 Census, we estimate the percentage of the population below 19 years of age, the percentage of the population above 60 years of age, population density, the number

[28] Precipitation data were extracted from the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR), with a resolution of 0.25 degree with monthly periodicity and available from 2003. Historic and standard deviation means are estimated for 2003–2006.

[29] To calculate these shocks, we use yearly data on homicides from the *Policia Nacional Civil*. We calculate the historic mean and standard deviation for homicides per capita 2003–2006 and define crime shocks as the number of weeks during the year in which homicides were two SD above the historic mean.

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

of internal migrants 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 averaged for the municipality.[31]

4 Empirical Strategy

To measure the decision to migrate from El Salvador in response to temperature shocks, our identification strategy exploits temporal and geographic variations in temperature between 2009 and 2018. We hypothesize that the temperature shocks El Salvador has experienced in the last decade have damaged economic outcomes, and that households have responded to these shocks by adjusting production costs and migrating. These responses depend on access to both formal and informal risk-management mechanisms.

We start by estimating the effects of temperature shocks on the probability of international migration using data from the EHPM household survey with the following regression model:

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

where m_{ijt} is a dummy variable equal to one if a member of household i, living in municipality j, in year t migrated from El Salvador in year t, and equal to zero otherwise.[32] The variable T_{jt-1} is the temperature shock in municipality j the year before migration took place, $t-1$. This is measured as the number of weeks during the first harvest season (*primera*) with a temperature shock in $t-1$, where a shock is defined as an average temperature two SD above the historic mean.[33] The coefficient of interest, δ_1, should be interpreted as the effect of an additional week of high temperatures during the harvest season on the probability of

[31] Extracted from ASTER Global Digital Elevation Model NetCDF V003. NASA EOSDIS.
[32] In the empirical regressions, we multiply the dummy variable by 100 to ease the interpretation.
[33] The historic mean is calculated using data from 2000 to 2006.

migration. We test the robustness of temperature shocks using alternative definitions (see section 5.5).

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 be endogenous, we test the robustness of the results without these controls. We also include a vector with time-variant controls at the municipality level, Z'_{jt-1}. To avoid including potentially bad controls in our specification, these variables are measured in $t-1$. Given that temperature might be highly correlated with other climatic variables, this vector includes rainfall shocks and droughts (Auffhammer, 2018).[34] In addition to natural disasters and extreme weather events, high levels of violence have historically been an additional push factor behind migration from El Salvador (Stanley, 1987; Halliday, 2006; Yang, 2008; Clemens, 2017), and recent evidence shows weather shocks may intensify violence (Dell et al., 2014, Carleton and Hsiang, 2016). To control for this, we add a variable of a crime shock measured in $t-1$ and defined as the number of weeks with crime levels two SD above the historic mean. 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 historic level of rainfall and historic mean of temperatures in municipality j. Our specification also includes year fixed effects, ϕ_t, to account for national shocks that would impact migration decisions, such as shocks that could affect prices. Finally, we include interactions between socioeconomic variables measured at baseline (2005 and 2007) and linear time trends (W'_{j2005}), that control for any pre-trend at the municipality level that could bias the results. Our model's validity rely on the assumption that, conditional on the previous controls, there were not unobserved time-varying differences within municipalities correlated with temperature shocks. [35] All the models are estimated using double-clustered

[34]The results are also robust to controlling for level of soil moisture. Ortiz-Bobea et al. (2019) show evidence of the importance of accounting for soil moisture when explaining historic 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.

[35]The vector V'_{j2005} includes measures of poverty, average income per capita, access to drinking water,

standard errors by municipality and year.

4.1 Mechanisms

Temperature shocks can affect migration decisions through different mechanisms. Dell et al. (2012) and Carleton and Hsiang (2016) provide an extensive literature review that describes the effects of temperature on agricultural outcomes, mortality, physical and cognitive capacities, and crime, among others. In this section, we explore the role of agricultural production as one potential mechanism for the effect of temperature shocks on migration. We focus on agricultural production because previous evidence has found a strong correlation between temperature shocks and agricultural production, particularly in countries with rain-fed agriculture and limited access to risk-management mechanisms. For example, Munshi (2003) finds a strong correlation between rainfall and the probability of migration to the United States among individuals who live in agricultural regions in Mexico while Feng et al. (2010) document a significant relationship between climate-driven changes in crop production and net out-migration.

We follow a number of empirical steps to test this theory, beginning with a heterogeneity analysis by occupation of the household head. We expect households whose head is in the agricultural sector—particularly in the production of transitory crops[36]—to be the most affected, and that is indeed what we find.[37] Second, we estimate the direct effect of temperature shocks on agricultural production and the use of agricultural inputs, including labor demand. The results show robust evidence of a negative effect of high temperature on agricultural production, specifically corn.

demographic structure of the population (percentage of the population below 19 years of age and above 60 years), the number of internal migrants and emigrants, school dropout for young adults (16 and 18 years), percentage of people employed in agriculture, population density, and elevation.

[36]Corn is a transitory crop. We estimate the effects only for cereals and the results are robust to this alternative definition.

[37]The occupation of the household head can potentially be endogenous. To explore this concern, in section 5.5, we estimate these heterogeneous effects in alternative ways.

To estimate the direct effect of temperature shocks on agricultural production and the ensuing adjustments producers make to mitigate these impacts, we use data from the ENAMP for 2013–2018.[38] We follow a similar identification strategy as the one in equation (1). Specifically, we estimate the effect of temperature shocks on agricultural outcomes for corn production. We estimate the following regression model:

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

Since we want to estimate the contemporaneous effect of a temperature shock on agricultural outcomes, T_{ijt} represents the temperature shock in the same year of production during the main season (*primera*), measured as the number of weeks with temperatures two SD above the historic mean.[39] Recall that the agricultural survey collects information during the last quarter of the year; therefore, a household interviewed during the survey year t reports their production of the last harvest season in year t. In our model, y_{ijt} represents different variables: total production, yield per hectare for size of land plot and land dedicated to corn production, the value of yield per hectare, TFP, number of workers (total, hired, and household), and other agricultural inputs i in municipality j in year t during the agricultural harvest season.

The controls included in the vectors W'_{j2005} and Z_{jt} are the same controls as in equation (1). Since in this specification we use data from the ENAMP, the household controls are slightly different here and include maximum education at the household level, number of household members, and access to irrigation.

We provide additional evidence of this mechanism by estimating a placebo test with the temperature shock defined as the number of weeks above the historic mean during the

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

[39] For corn, this is the period between June and July, which is ostensibly the rainy season.

entire year or the lean season, instead of the number of weeks with a shock only during the main season. In analyzing the effect of the temperature shock outside the main season, we find no significant effects on agricultural production or migration. This rules out that contemporaneous unobserved events are driving the negative effects on production, and it suggests that agricultural production is the main mechanism through which a temperature shock affects migration.

We also explore how farmers adjust their input use in response to the shock. Two important features influence these adjustments. First, when the extreme temperature shock occurs, most inputs are fixed as decisions have already been taken. Hence, the margin of adjustment is limited. Second, agricultural producers with restricted or no access to financial markets resort to other strategies to offset their income loss and smooth their consumption. One strategy is to lay off hired workers and substitute household workers for them, thus protecting the household's income. The negative impact of the temperature shock may thus transmit to labor markets, affecting workers in the agricultural and nonagricultural sectors (Jayachandran, 2006; Colmer, 2021). The contraction in labor demand of agricultural producers will pressure agricultural wages and push workers to increase working hours or seek employment in the nonagricultural sector. Migration may ease the pressure on labor markets and render the effect on labor outcomes smaller or nonexistent. Therefore, agricultural wages will be highly correlated with weather shocks in communities with incomplete financial markets and low or no migration (Jayachandran, 2006).

We estimate the link between temperature shocks and labor markets in the following model with EHPM data:

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

where l_{ijt} represents the labor outcomes of individual i, living in muncipality j, in year t,

with the same controls used in equation (1). Labor outcomes include whether the person is employed, hourly wage, weekly hours worked, and monthly salary. To determine whether migration and access to financial markets ease pressures on labor markets, we estimate heterogeneous effects for municipalities with emigration and access to financial markets above and below the municipal median.

5 Results

5.1 International Migration

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 2009–2018 for all households (panel A), agricultural households cultivating transitory crops, which includes corn (panel B), other agricultural households (panel C), nonagricultural households (panel D), and unemployed households (panel E). We categorize households based on the occupation of the household head and test the robustness of this classification. Across columns, we test the robustness of our results, including additional controls. Column (1) shows the results when controlling only for time-variant municipality characteristics (rainfall and crime shocks), column (2) adds year fixed effects, column (3) adds municipality fixed effects, and column (4) offers an interaction of pre-trend municipal characteristics interacted with a linear time trend. Column (5) adds time-variant household characteristics. These controls could be endogenous, but the results in columns (4) and (5) show the empirical model is robust to their inclusion. Overall, the results are robust to the inclusion of all the controls. Our preferred specification is the fully controlled model in column (5).

As discussed in the previous section, an effect on agricultural production is one mechanism through which high temperatures can affect the migration decision. If this is a main mechanism, we would expect to see a larger response to these shocks among agricultural

households, especially corn producers. The results in Table 1 point in this direction. They show significant effects of the temperature shock on the probability of migration only for agricultural households working on transitory crops (panel B). Not only are the effects statistically significant for this sample, but the magnitude of coefficient is also four times larger than for all households and 10 times larger than that of other agricultural households.

The results in our preferred specification with the full set of controls (column (5)) for agricultural households who grow corn and other transitory crops (panel B) show that one additional week with a temperature shock increases the probability of international migration by 0.20 percentage points (pp) or 23.2% relative to the mean of international migration in El Salvador - recall that the dependent variable has been multiplied by 100. This means that one additional standard deviation (SD) of the temperature shock increases international migration by 14.3% relative to the mean of internatioanl migration in El Salvador.[40]

Two potential concerns occur with our classification of agricultural households. One concern relates to classifying households based only on the occupation of the household head. In Appendix Table A3, we classify households based on the occupation of all working-age household members. Method I only considers the working-age members as a criterion to classify them in each panel, while Method II also considers if the household head is employed in each sector to classify them. The results on the probability of migration are robust overall to the different classifications. 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, dividing municipalities by whether the share of the population working in agriculture is above or below the median. Appendix Table A4 corroborates that there is a positive effect on the probability of international migration in municipalities with a higher share of individuals in agricultural occupations. For those below the national median, the coefficient estimate is not statistically significant and the magnitude is smaller than for

[40]To calculate this: $\frac{\hat{\delta_1} * temp(SD)}{migration(mean)} = \frac{0.203 * 0.566}{0.876}$

municipalities above the median.

5.2 Mechanisms

The heterogeneity analysis in Table 1 provides suggestive evidence that the effect on agricultural production is an important mechanism through which temperature affects migration decisions. In this section, we show additional evidence that supports this hypothesis. We first estimate the direct effect of temperature shocks on corn production. Table 2 reports 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 first estimate the effects of the temperature shock on agricultural output and different productivity measures. The dependent variables are: the logarithm of total corn production (panel A), the logarithm of corn yield per hectare calculated with the total land plot size (panel B), the logarithm of corn yield per hectare calculated with total land cultivated in corn (panel C), labor productivity (panel D), the logarithm of the value sold per hectare (panel E), and TFP (panel F).

The results show consistently negative effects of the temperature shock on corn production during the main harvest season and on land productivity and TFP. Focusing on the results in column (4), we find that a one SD increase in the temperature shock during the main harvest season of the contemporaneous year decreases total corn production by 1.6 percent (panel A). Given that land and technology are fixed in the short term, land productivity and TFP fall as a consequence of the shock, with land productivity falling between 3.1 percent (panel B) and 2.6 percent (panel C), and TFP dropping by 2.0 percent (panel D) for an additional SD increase in the temperature shock. The sharper decline in land productivity measured with the land plot size vs the one with land cultivated in corn means that households adjust land use to reduce the impact of the shock on total production. Panel E shows no impact on labor productivity: not only is the coefficient estimate statistically

insignificant but the magnitude is also not economically meaningful, which suggests adjustments in the use of agricultural workers. Finally, the results in panel E show a negative and significant effect on the value of land productivity. This suggests that in the short term, the lower supply does not translate into a price increase that could compensate for the fall in production.

Overall, we find that farmers adjust the intensive use of inputs such as land and substitute household workers for hired agricultural workers. This can have important long-term consequences for the well-being of young household members if they spend less time in school and more time doing farm activities. As mentioned above, these results are similar to those of Aragón et al. (2021) in Peru.

5.3 Input Adjustments: Agricultural Workers and Other Inputs

We first investigate how agricultural producers adjust their labor demand when facing a temperature shock. Table 3 reports 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 household 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 household workers. We report only our preferred specification, yet the results are robust to gradually including the different controls. The temperature shock decreases the total number of workers, and this is driven by hired workers. One additional SD reduces the demand for total number of workers by 1 percent and hired workers by 1.6 percent. The coefficient estimate for household workers is positive, which is expected since agricultural producers may substitute household workers for hired workers, but it is not statistically significant. Taking the coefficients at face value, the results suggest an almost perfect substitution of household workers for hired workers. These

results, with the effects found on agricultural production, imply that agricultural income is negatively affected and households adjust to the shock by reducing their demand for hired agricultural workers.

Table 4 reports the coefficient estimate for the use of other production inputs. We construct a principal component index of four types of inputs and estimate the impact for the index and each group separately. The temperature shock has a negative impact on the principal component index, which is mainly driven by chemical agents that are mostly used for postharvest activities. The effect on the other three types of inputs is not statistically significant and the magnitude of the coefficient is small. Consistent with the results from Table 2, the results in column (7) show that corn producers increase the land allocated to corn production by 1 percent when the temperature shock increases by one SD. Together, the results point to a negative impact on corn production and an adjustment at the intensive margin on the use of inputs that are not fixed. Because our data is cross-sectional, we cannot identify adjustments at the extensive margin such as abandonment of agricultural production or sale of the land. Therefore, we identify a lower bound on the impact of temperature shocks on corn production.

We complement this analysis by estimating the effect of temperature shocks on individual labor supply, stratified by whether the individual belongs to an agricultural household (separately identifying the effect for producers of transitory crops and for producers of other agricultural products) or nonagricultural household, where the classification of type of household follows the model from Table 1. Agricultural households are divided further according to whether they are landowners or not. Since landowners demand and supply labor simultaneously, the total effect of the weather shock on agricultural income will depend on their capacity to reduce labor costs by substituting household workers for hired workers. Labor markets, through a reduction in wages, may provide an insurance mechanism to landowners in regions with incomplete financial markets (Jayachandran, 2006). These results give us

more information to better understand whether the migration decision responds to effects caused by adjustments in the labor market.

We start by estimating the effect on the probability of employment in column (1) of Table 5.[41] The results show that while the probability of working does not change for individuals living in agricultural households that own land, it negatively affects the probability of working (either on transitory crops or other agricultural activities) for those individuals from agricultural households without land. This is consistent with the results in Table 3. Landowning households might respond to the shock by replacing hired workers with household workers, thus reducing the likelihood of employment for agricultural workers without land. Column (1) suggests that agricultural workers displaced from transitory crops might seek agricultural employment dedicated to other crops or livestock, yet they do not seem to switch to nonagricultural activities. An increase of one SD in the temperature shock decreases the probability of employment in the agricultural sector for transitory crops by 0.5 pp, and employment in other agricultural activities by 0.3 pp. The magnitude of the effects are about half the size of the effects of a one SD increase in harmful degree days on the local labor markets estimated by Jessoe et al. (2016) for Mexico. Importantly, these negative effects at the extensive margin are driven by individuals without land, who are less likely to adjust to the negative production shock in the short term.

Column (2) shows the effect of the shock at the intensive margin. On average, among workers who stay in the labor force, working hours increase. This effect arises from individuals in landowning households that produce transitory crops, which is consistent with the previous results. According to Jayachandran (2006), the effect on wages depends on the availability of risk-management mechanisms. Without access to financial markets or the ability to save or borrow, wage effects intensify. The effects in column (3) show negative effects on hourly earnings of transitory crop producers. In the next section, we explore the

[41] The survey asks whether the individual worked last week.

heterogeneity of these results by access to risk-management mechanisms.

These findings suggest that declines in corn production are felt in agricultural labor markets. Corn producers reduce their demand for hired workers and use household workers instead. The laid-off agricultural workers migrate or switch to other agricultural activities. The transmission of the temperature shocks into labor markets might be the consequence of incomplete financial markets to manage risk. We next evaluate whether this is the case.

5.4 Heterogeneity by Access to Risk-Management Mechanisms

The transmission of temperature shocks into labor markets depends on the availability of other risk-management mechanisms such as formal credits, informal transfers from family and friends, and crop insurance (Jayachandran, 2006). Since the latter is practically nonexistent in El Salvador, we focus on access to financial markets and remittances, which in El Salvador constitute 24 percent of GDP[42] and play an important role in supporting family members who stay in the country.[43] In order to investigate both risk-management mechanisms, we estimate heterogeneous effects for municipalities above and below the median for: (i) share of migrants in 2007, according to the population census; and (ii) share of households that applied for credits in 2009, according to the EHPM survey. The share of migrants in 2007 is a proxy for remittances (for which we do not have municipal-level information). We use the municipal shares in 2007 and 2009 to assuage endogeneity concerns. However, these results are merely suggestive of the potential causal effect.

We estimate differential effects by access to risk-management mechanisms for labor outcomes and the likelihood of migration. Remittances and credits may help households to compensate for the negative income shock, thereby reducing their need to use more costly

[42] https://data.worldbank.org/indicator/BX.TRF.PWKR.DT.GD.ZS?locations=SV retrieved on February 14, 2021.

[43] Qualitative evidence describes how households in El Salvador depend on remittances from relatives in the United States. See, for example: https://www.nytimes.com/2021/06/07/world/americas/kamala-harris-guatemala.html?smid=url-share.

mechanisms such as distress migration for mitigation. At the same time, remittances and credits may decrease migration costs by funding the relocation process, which may in turn increase the likelihood of migration. The effect of these variables on migration is ultimately an empirical question we pose in the following paragraphs.

Figures 7 (columns (1)–(3)) and 8 explore the effect of the temperature shock in regions with migration shares above (blue line) and below (red line) the municipal median. Columns (1)-(3) in Figure 7 show these differential effects on the probability of migration for agricultural households producing transitory crops, other agricultural households, and nonagricultural households. Looking at these results, at first glance, there seems to be no differential effects on the probability of migration based on access to migrant networks. Although, the point estimates in column (1) are not significantly different from each other; the impact with respect to the baseline is larger in municipalities below the median. In these municipalities, an additional SD of the shock increases migration with respect to the baseline mean by 37.2 percent, whereas in those above the median, the effect is a gain of 19.6 percent (see Table A5).

Similarly, Figure 8 shows that the impact of weather shocks on labor markets stems from municipalities with migration levels below the median. In particular the last three columns show that in municipalities with less access to migrant networks (below the median), farmers sharply adjust their demand for hired agricultural workers. This means worse labor outcomes, in particular hourly wages (column 3), for these workers. In contrast, in municipalities with more access to migrant networks (above the median), labor demand for agricultural workers does not respond to the temperature shock and consequently does not convey to labor markets, arguably because households here rely more on these informal risk-management mechanisms.

The heterogeneous effect with respect to access to formal credit provides further proof of the role of risk-management mechanisms in compensating for the negative income shock.

Columns (4)-(6) in Figure 7 and 9 show the heterogeneity by the share of the population with access to credit at the municipality in 2009. The results in column (4) of Figure 7 show that migratory responses to temperature shocks by agricultural households producing transitory crops are more than three times larger in municipalities with lower access to credit (below the median). An additional SD in the temperature shock increases migration in municipalities with access to financial markets below and above the median by 39.9 percent and 11.4 percent, respectively. In fact, the impact of the temperature shock on migration is driven by agricultural households producing transitory crops without access to credits (see Table A6 in the Appendix). Overall, the results in Figure 9 are noisily estimated, but columns (1)–(3) show a significant effect of the temperature shock on markets with less access to financial credits, as predicted by Jayachandran (2006). These effects are observed only for households that produce transitory crops, which are the most affected by extreme temperatures.

Overall, the results on Figures 7-9 suggest that access to risk-management mechanisms reduces the need for households to rely on distress migration to compensate for the fall in income caused by temperature shocks. Credits or migrant networks may allow agricultural producers to absorb these shocks without resorting to labor markets as a risk-management strategy. Nevertheless, these results are simply suggestive. The next step is to identify whether offering agricultural producers access to financial markets to manage risk *ex ante* through insurance or *ex post* through credits could prevent distress migration.

Our results strongly demonstrate negative effects of temperature shocks on agricultural production and important responses by farmers in the short term. The latter might protect household well-being in that time frame. We find, for example, that extreme temperatures have no effect on total consumption per capita (Table A7). However, the strategies used in the short run may have important consequences in the long run, so more research is necessary to understand those effects.

5.5 Robustness Checks

In this section, we estimate a number of robustness checks to test the validity of our identification strategy. We perform several such tests to examine whether temperature shocks rather than a correlated effect are producing the negative effects on agricultural production, labor markets, and migration.

We first test our definition of the temperature shock. Tables A8, A9, and A10 in the Appendix show results for alternative definitions. First, in Table A8, we define the temperature shock in different periods within the year as an alternative to the harvest season. Column (1) mimics the main results in Table 1—that is, it measures the temperature shock during the main harvest season. In the next columns, we report the results for: (i) the number of weeks with the temperature shock above the historic mean all year round (column (2)); (ii) the *apante* season, which is the last season and predicted in the survey (column (3)); and (iii) the lean season (column (4)). As expected, we find significant effects only when using the shock defined during the main harvest season.

Second, we test robustness using different periods. Recall that to calculate the probability of migration, we use the household survey EHPM for 2009–2018. We estimate the same regression: (i) for 2013–2018, the same period as the agricultural survey; and (ii) excluding 2015, the year with the most intense drought. The coefficient estimates are robust to changing the periods and the results are consistently robust to all the different specifications.[44]

We also test the robustness of the results by measuring the temperature shock four alternative ways. The results for the probability of migration are reported in Table A9 and for agricultural production in Table A10. Columns (1) and (2) define the shock as the number of weeks during winter with a temperature higher than one and 1.5 SDs above the

[44]For all the results, it is important to note that Figure 5 suggests an underestimation of migration rates due to the migration of entire households.

mean, respectively. Columns (3) and (4) define the temperature shock when the temperature was above 29 and 35 degrees Celsius, respectively. Overall, the results are robust to different measures of the shock.

We estimate a placebo test to measure the likelihood of obtaining the estimates we get due to chance. To do this, we randomly assign temperature levels to each municipality/week observation 1,000 times and reestimate the regression models using these alternative measures. We plot the kernel density of the estimated δs from each of these iterations in Figure A4 for the probability of migration, and Figure A5 for agricultural production. We plot our baseline coefficients from Tables 1 and 2 in the red vertical lines. These analyses suggest the estimated effects we find are very unlikely due to chance.

As an additional robustness test, we estimate the effect of the temperature shock on the probability of migration for agricultural and nonagricultural households in rural and urban places.[45] Given the salience of violence in El Salvador, we explore whether the results are robust to controlling for crime. Table A11 in the Appendix shows these results. The results are always robust to controlling for crime; as predicted, the probability of migration increases with extreme temperatures only for agricultural households living in rural areas.

6 Conclusions

We examine the migration responses of rural households to an extreme rise in temperature. Based on household and agricultural producer data, we find that a sharp gain in temperature reduces agricultural productivity and total production. Farmers adjust by cutting demand for hired workers. Labor markets transmit the negative impact of weather shocks to agricultural workers, who react by migrating or moving to the nonagricultural sector.

Our results add to the literature on migration responses to short-term weather shocks

[45] A rural area in El Salvador is all the area in the municipality that is not covered by the population center.

and long-term adaptation to climate change. We show that negative shocks to agricultural production relate to migration decisions. Two reasons for migration may emerge from this relationship. First, rural households often live in regions with poor provision of public goods such as irrigation structures to mitigate the effects of weather shocks. These households also frequently lack access to risk-management mechanisms. As a result, migration offers a strategy to counteract income losses from negative weather shocks (Mueller et al., 2014; Kleemans, 2015). Migration might also enable households to escape untenably impoverished conditions, including those caused by climate change, and to improve their welfare (Dell et al., 2014; Mueller et al., 2014; Kleemans, 2015; Carleton and Hsiang, 2016).

Policies should address both motivations for migration. To prevent distress migration where agricultural production is still feasible, policies should promote access to insurance and financial markets to address the negative income effects of the shock and extend technical assistance to help rural households adjust their agricultural practices to a changing climate (for example, resistant seeds). Humanitarian aid, which is rarely offered in response to extreme weather events (Baez et al., 2017; Mueller et al., 2014), should be available as well. Policies should additionally aim to facilitate migration that can provide a pathway out of poverty. Credit market access or other mechanisms to fund migration costs are some examples of this (Bryan et al., 2014; Kleemans, 2015).

Future research should seek to understand the mechanisms through which extreme weather events prompt migration. Evaluation of the relationship between access to financial and insurance markets, and migration decisions would provide inputs for better policy design. Kleemans (2015) explores how financial mechanisms interact with migration decisions, and Munshi and Rosenzweig (2016) study how informal insurance mechanisms shape migration decisions. Although there is growing evidence on the impact of insurance mechanisms on the welfare and productivity of small rural farmers,[46] there is no proof yet on how these

[46] See, for example, Carter and Lybbert (2012).

mechanisms influence migration responses. Furthermore, improved resilience to negative weather shocks through better agricultural practices, resistant seeds, or public goods such as irrigation may also prevent distress migration. Virtually no literature studies this area, but information about the benefits of such policies could bolster arguments to increase investments in these public goods. Finally, our paper (like most on this subject) studies the effects of weather shocks rather than long-term climatic changes on migration. These short-term results should not be extrapolated to long-term outcomes, since farmers may adapt gradually over time. More research on long-term agricultural responses to climate change will aid in understanding how to help rural households adapt.

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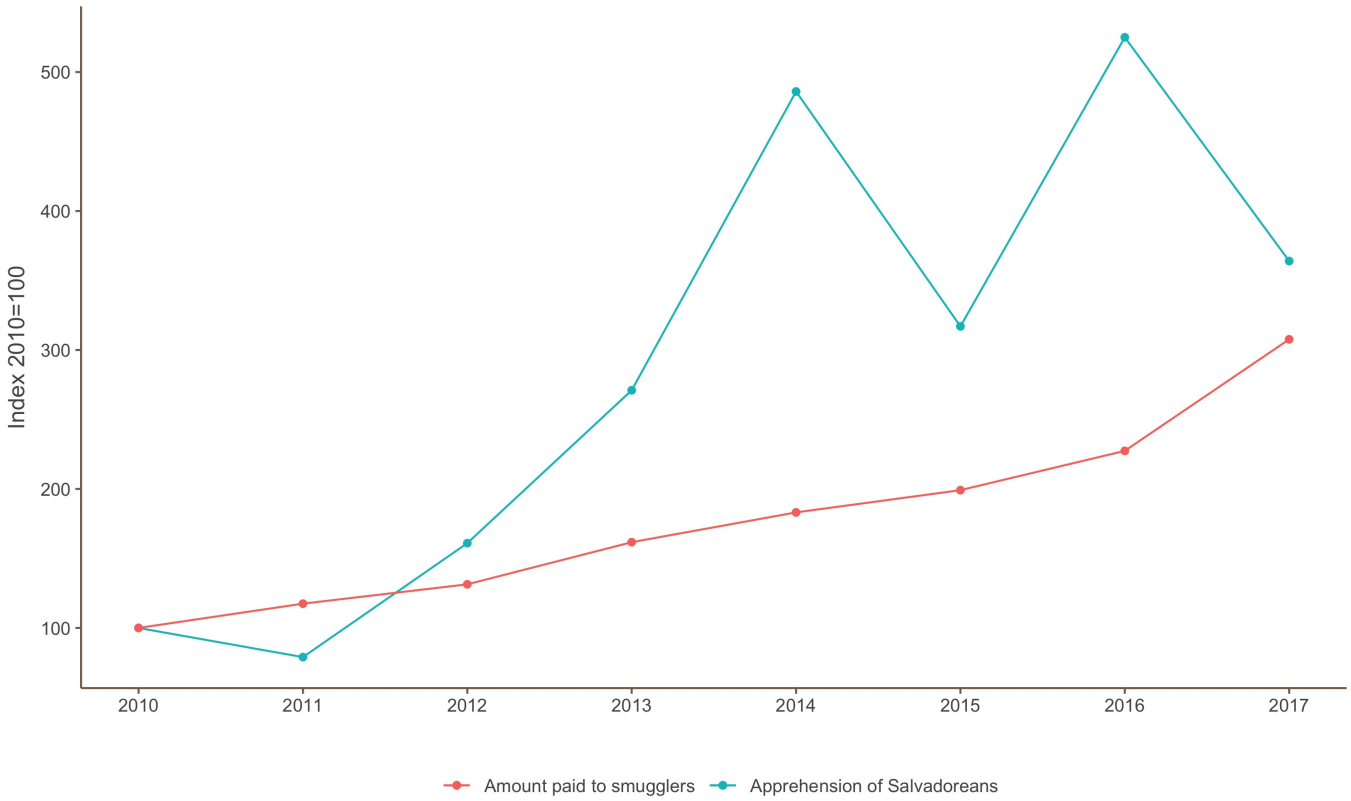
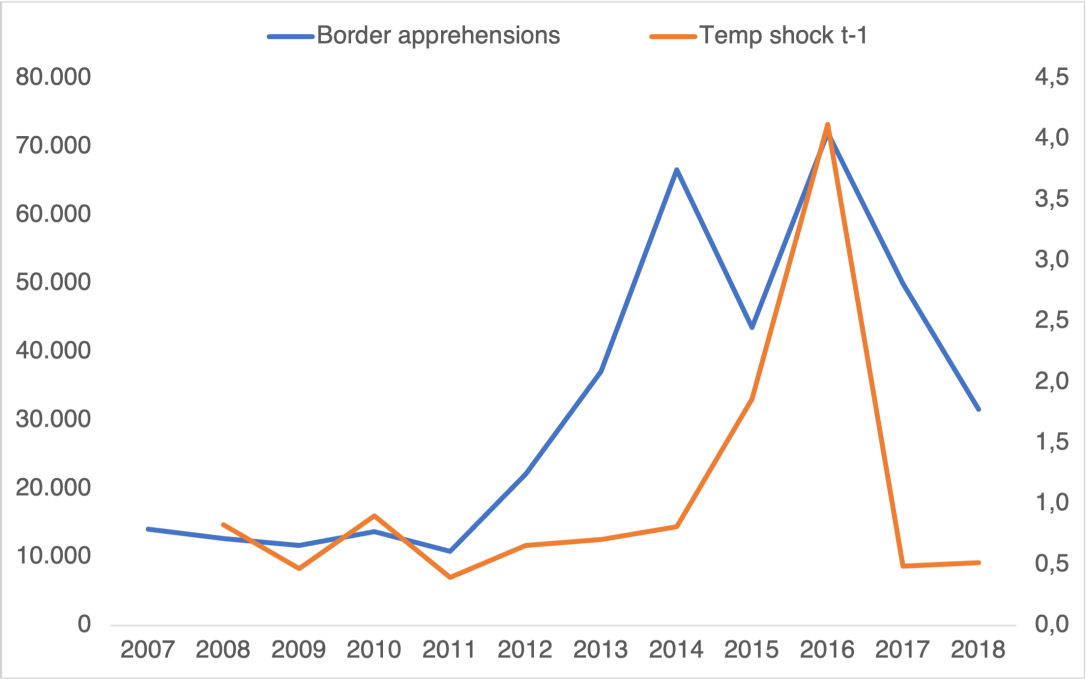
7 Figures

Figure 1: Border Apprehension of Salvadoreans and Cost of Smugglers



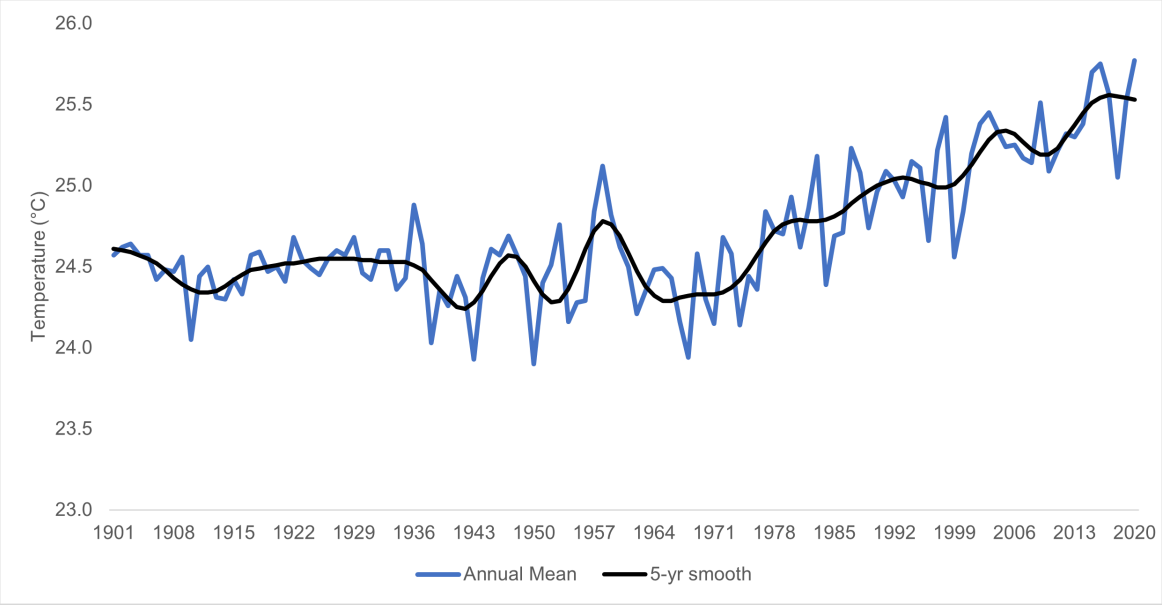
Source: American Community Survey (ACS) and Customs and Border Protection (CBP).

Figure 2: US Border Apprehensions



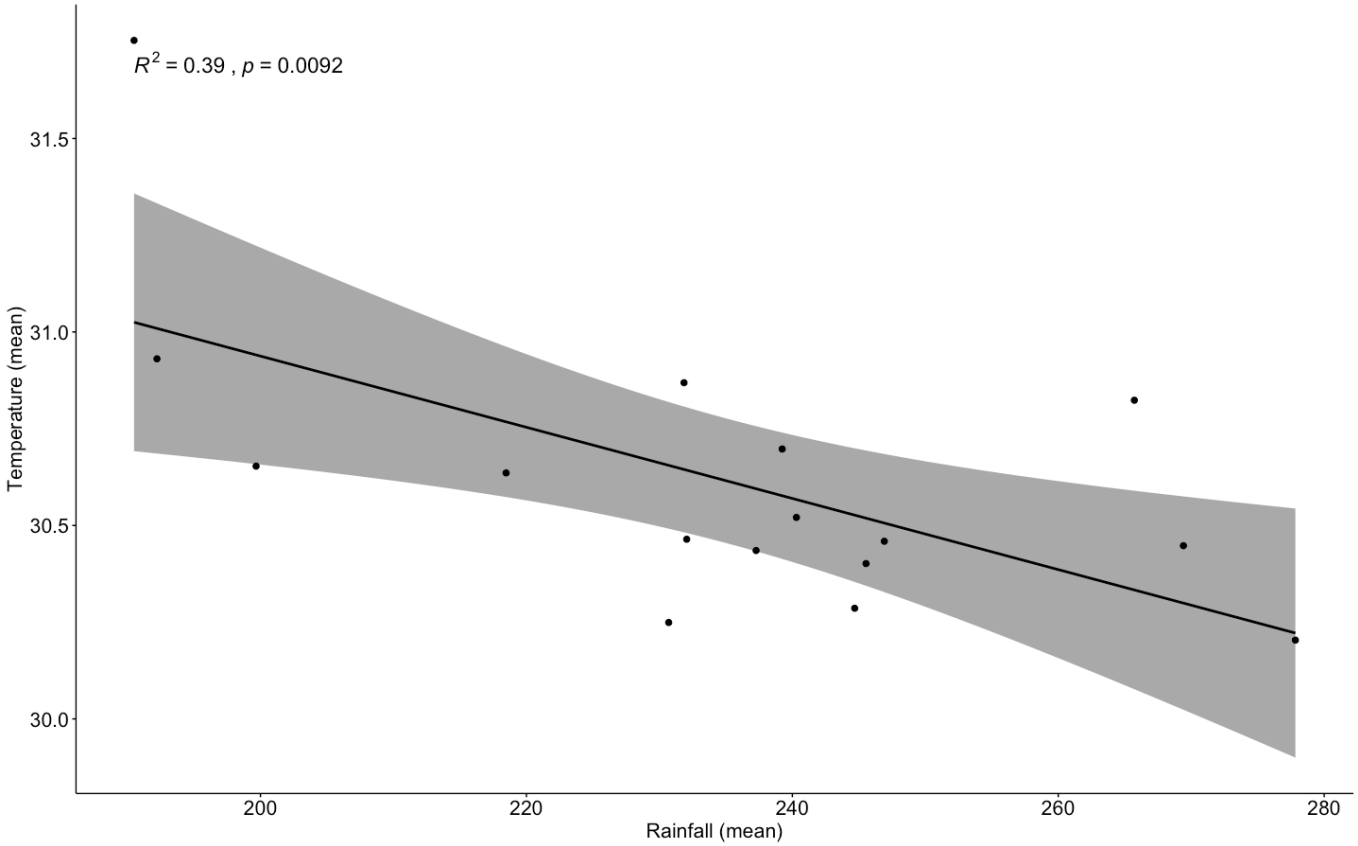
Source: US Customs and Border Protection (CBP) and NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. The blue line represents the average number of weeks in winter with a temperature shock (two SD above the historic mean).

Figure 3: Average Temperature in El Salvador



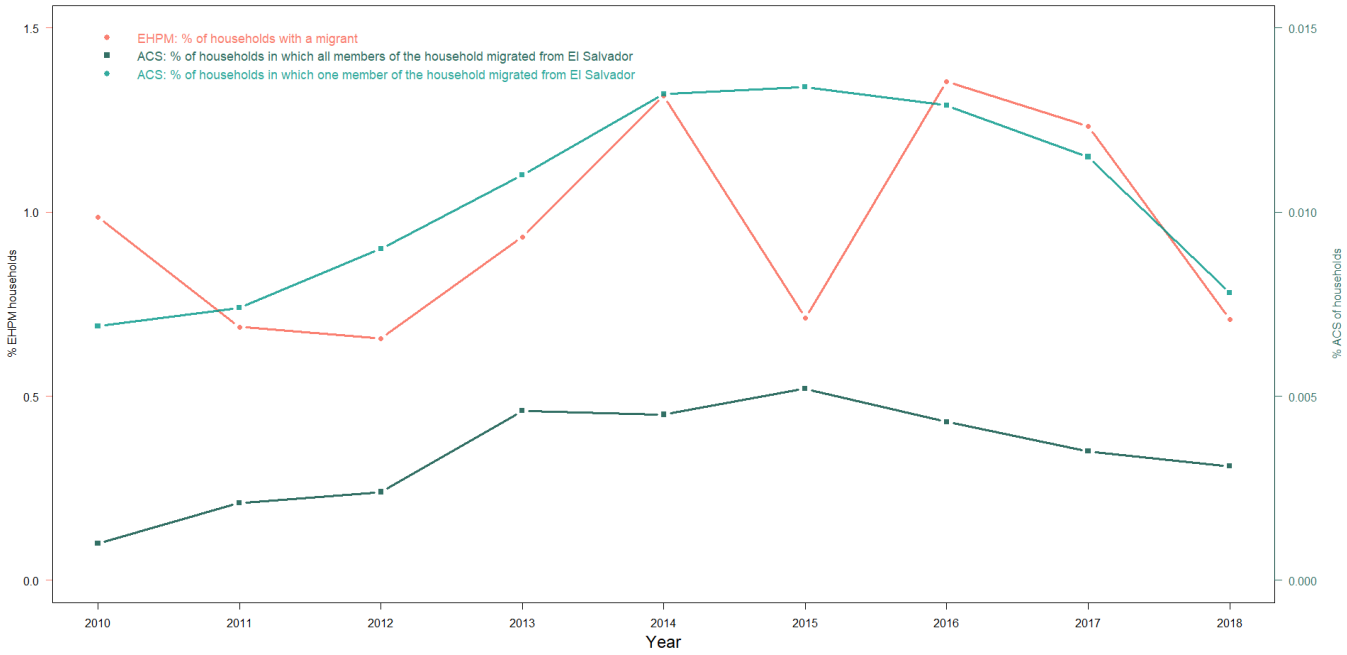
Source: World Bank (2022). Data from Climatic Research Unit (CRU) of the University of East Anglia.

Figure 4: Correlation between Temperature and Rainfall



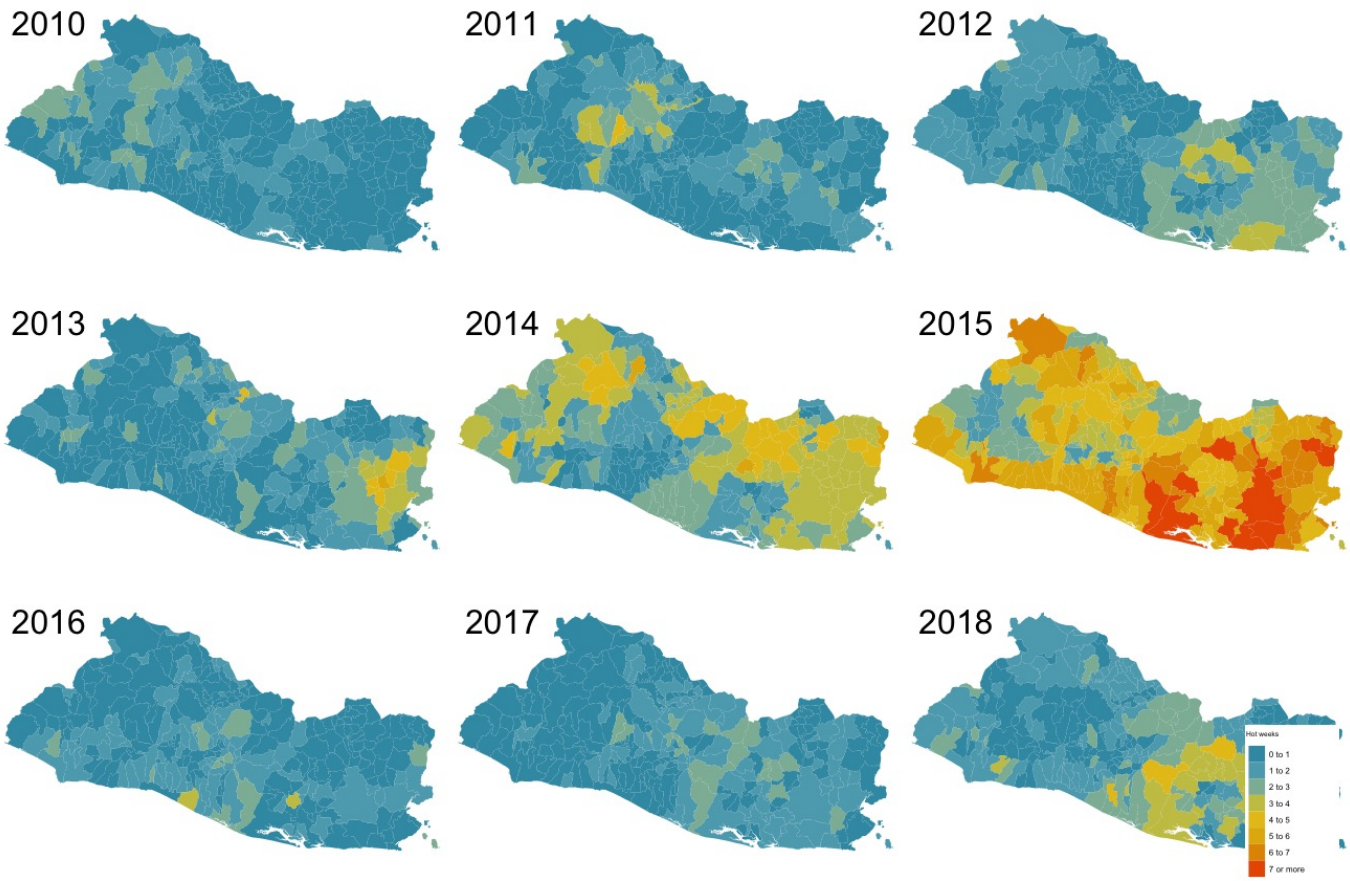
Source: NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks – Climate Data Record (PERSIANN-CDR).

Figure 5: Migration Trends of Salvadoreans – EHPM and ACS



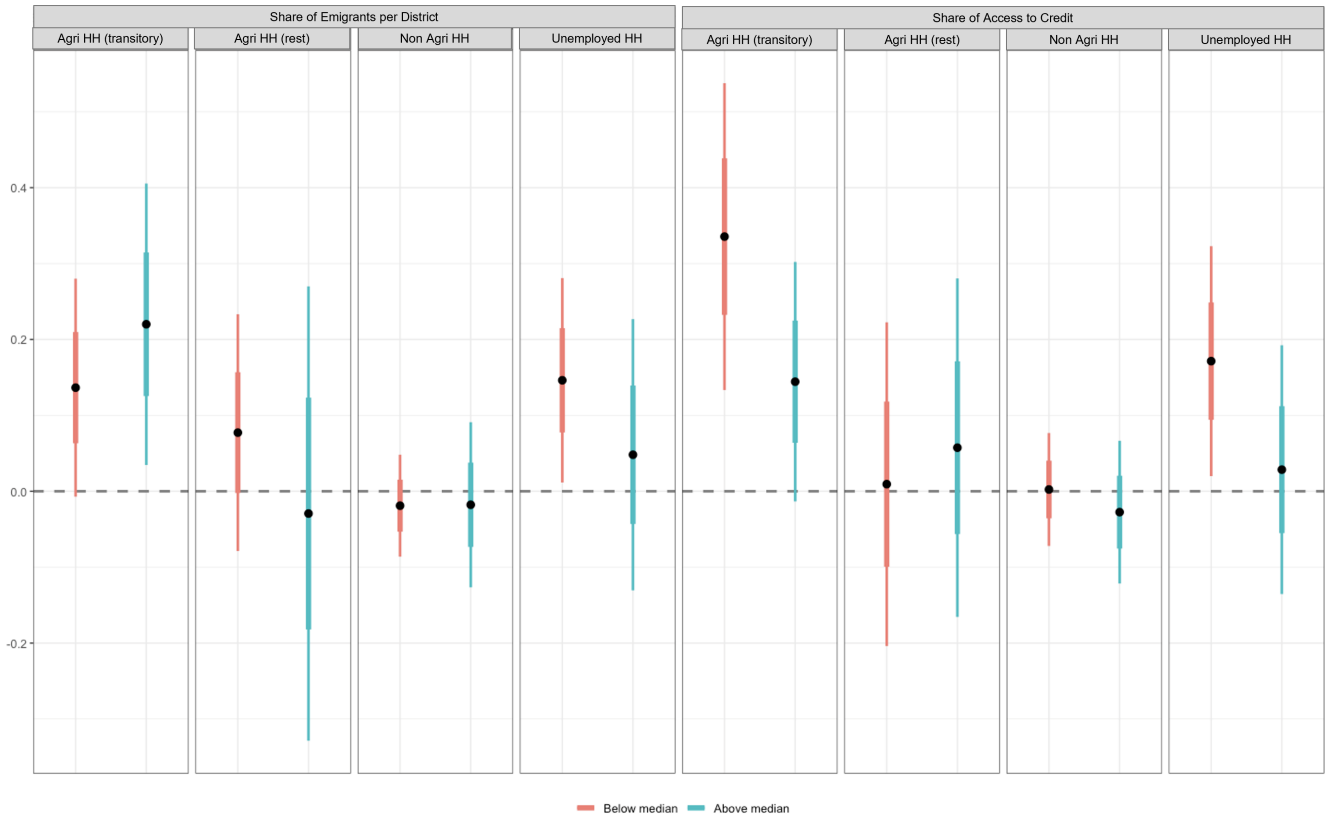
Source: American Community Survey (ACS) and El Salvador's Multiple Purpose Household Survey (EHPM). The lighter green line indicates the percentage of households with a member who was living in El Salvador a year earlier, and the darker green line indicates the percentage of households in which all the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

Figure 6: Temperature Shocks per Municipality



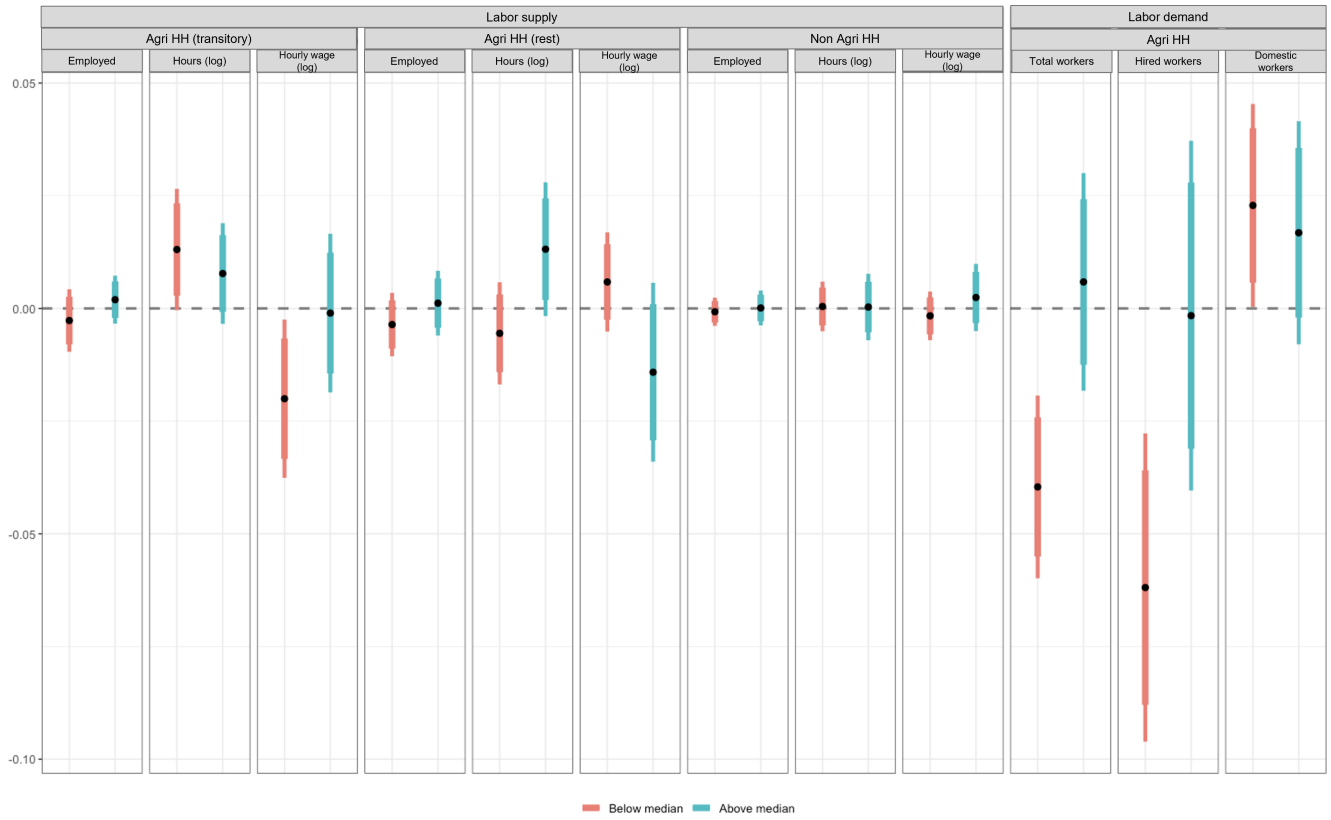
Source: NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. Each map represents the number of weeks in winter with a temperature shock (two SD above the historic mean).

Figure 7: Effect of Temperature Shocks on the Probability of International Migration
Heterogeneity by Access to Risk-Management Mechanisms



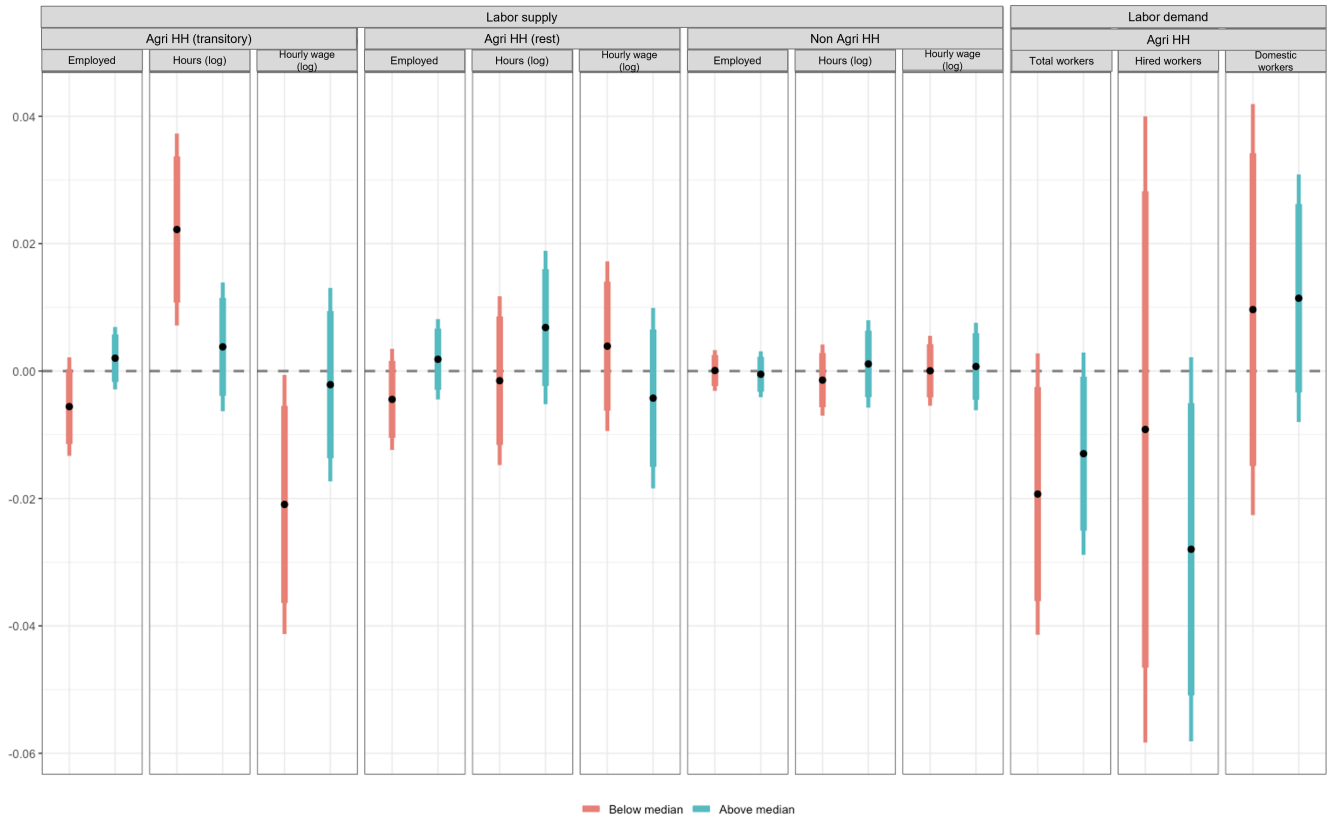
Notes: Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). The first section explores heterogeneity using the share of migrants per municipality in 2007 and the second section uses the share of population with access to credit per municipality in 2009. The red line corresponds to individuals living in municipalities below the median and the blue line corresponds to individuals living in municipalities above the median. The dot represents the coefficient of the temperature shock. The thinner line represents the confidence interval of 95 percent and the thicker line, the confidence interval of 99 percent. Each subsequent panel represents the estimation for the following groups: agricultural households producing transitory crops, other agricultural households, and nonagricultural households. All the estimations include all the set of controls from column 5 of Table 1. Standard errors are clustered by municipality and year.

Figure 8: Effect of Temperature Shocks on Labor Outcomes
Heterogeneity by Share of Migrant Population per Municipality in 2007



Notes: The labor supply results use individual data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018 for people aged between 10 and 65. Sample of individuals surveyed from June to December. The three subsequent panels identified the groups being analyzed: individuals in agricultural households producing transitory crops, individuals in other agricultural households, and individuals in nonagricultural households. For each of these groups, the dependent variables correspond to a dummy if the person is employed, the logarithm of hours worked per week, and the logarithm of hourly wages (from dependent or independent work). The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). All the estimations include all the set of controls from column 5 of Table 1. Standard errors are clustered by municipality and year.
The labor demand results use data from El Salvador's Agricultural Household Survey 2013–2018. The dependent variables correspond to the inverse hyperbolic sine of the number of workers and number of household workers. The independent variables are temperature shock (two SD higher than the historic value during the winter season the previous year) in t. MAll the estimations include all the set of controls from Table 3. Standard errors are clustered by municipality and year.
The red line corresponds to individuals living in municipalities with a share of migrants below the median in 2007 and the blue line corresponds to municipalities above the median. The dot represents the value of the independent variable. The thinner line represents the confidence interval of 95 percent and the thicker line, the confidence interval of 99 percent.

Figure 9: Effect of Temperature Shocks on Labor Outcomes
Heterogeneity by Share of Access to Credit in 2009



Notes: The labor supply results use individual data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018 for people aged between 10 and 65. Sample of individuals surveyed from June to December. The three subsequent panels identified the groups being analyzed: individuals in agricultural households producing transitory crops, individuals in other agricultural households, and individuals in nonagricultural households. For each of these groups, the dependent variables correspond to a dummy if the person is employed, the logarithm of hours worked per week, and the logarithm of hourly wages (from dependent or independent work). The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). All the estimations include all the set of controls from column 5 of Table 1. Standard errors are clustered by municipality and year.
The labor demand results use data from El Salvador's Agricultural Household Survey 2013–2018. The dependent variables correspond to the inverse hyperbolic sine of the number of workers and number of household workers. The independent variables are temperature shock (two SD higher than the historic value during the winter season the previous year) in t. MAll the estimations include all the set of controls from Table 3. Standard errors are clustered by municipality and year.
The red line corresponds to individuals living in municipalities with a share of population with access to credit below the median in 2007 and the blue line corresponds to municipalities above the median. The dot represents the value of the independent variable. The thinner line represents the confidence interval of 95 percent and the thicker line, the confidence interval of 99 percent.

8 Tables

Table 1: Impact of Temperature Shocks in First-Harvest Season on Migration Likelihood

Population Group	(1)	(2)	(3)	(4)	(5)	Mean	Obs
A: All Households							
Temperature shock year t-1	0.043	0.051	0.037	0.046	0.049	0.876	186,910
	(0.047)	(0.062)	(0.058)	(0.061)	(0.065)		
R2	0.002	0.002	0.005	0.005	0.006		
B:Agricultural Households (transitory)							
Temperature shock year t-1	0.099	0.161	0.181	0.195	0.203	0.801	24,332
	(0.072)	(0.088)*	(0.089)**	(0.089)**	(0.093)**		
R2	0.002	0.002	0.007	0.007	0.011		
C:Agricultural Households (other)							
Temperature shock year t-1	0.051	0.092	-0.008	0.013	0.018	0.940	19,141
	(0.038)	(0.061)	(0.074)	(0.082)	(0.086)		
R2	0.004	0.005	0.010	0.011	0.012		
D: Nonagricultural Households							
Temperature shock year t-1	0.024	0.004	-0.013	-0.014	-0.012	0.597	94,165
	(0.038)	(0.044)	(0.047)	(0.046)	(0.048)		
R2	0.001	0.002	0.002	0.002	0.003		
E:Unemployed Households							
Temperature shock year t-1	0.046	0.068	0.085	0.100	0.092	1.423	49,272
	(0.092)	(0.122)	(0.132)	(0.136)	(0.145)		
R2	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's Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). Panel A. All households. Panel B. A household is defined as agricultural (transitory) when the household head is employed in agriculture, producing transitory crops. Panel C. A household is defined as agricultural (other) when the household head is employed in agriculture with any other agricultural production. Panel D. A household is defined as nonagricultural when the household head is employed in the nonagricultural sector. Panel E. A household is defined as unemployed when the household head is unemployed. Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 in First-Harvest Season on Corn Agricultural Outcomes

Agricultural Outcome	(1)	(2)	(3)	(4)	Mean	Obs
A: Log(Total Production)						
Temperature shock year t	-0.070	-0.024	-0.030	-0.028	1.917	19,261
	(0.033)**	(0.014)*	(0.013)**	(0.014)**		
R2	0.060	0.105	0.234	0.237		
B: Log(Production per Ha.)						
Temperature shock year t	-0.092	-0.055	-0.054	-0.054	2.342	19,261
	(0.030)**	(0.028)**	(0.018)**	(0.015)***		
R2	0.061	0.095	0.267	0.270		
C: Log(Production per Ha. cultivated in corn)						
Temperature shock year t	-0.083	-0.047	-0.049	-0.046	2.784	18,618
	(0.029)**	(0.019)**	(0.012)***	(0.009)***		
R2	0.078	0.154	0.444	0.450		
D: Log(TFP production)						
Temperature shock year t	-0.088	-0.034	-0.040	-0.036	0.000	16,438
	(0.029)**	(0.016)**	(0.012)**	(0.011)***		
R2	0.047	0.110	0.287	0.290		
E: Log(Labor productivity)						
Temperature shock year t	-0.055	-0.006	-0.013	-0.009	0.447	18,784
	(0.030)*	(0.018)	(0.016)	(0.014)		
R2	0.019	0.058	0.169	0.173		
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's Agricultural Household Survey (ENAMP). The dependent variable in panel A is the logarithm of the ratio of corn production per hectare in the first harvest; in panel B, it is the logarithm of the total production per hectare in the first harvest; in panel C, it is the logarithm of the total production per hectare dedicated to corn production in the first harvest; in panel D, it is the logarithm of the total production per worker in the first harvest; in panel E, it is the logarithm of the value sold per hectare in the first harvest; and in panel F, it is the logarithm of Total Factor Productivity (TFP) calculated using area cultivated in corn, total of workers, and use of inputs and assets for production. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 in First-Harvest Season on Agricultural Workers

	Total Workers	Hired Workers	Household Workers
	(1)	(2)	(3)
Temperature Shock t	-0.018^{*}	-0.028^{***}	0.015
	(0.010)	(0.010)	(0.015)
Mean workers	5.01	3.3	1.7
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	18,669	18,669	18,669
R^2	0.106	0.112	0.231

Data from 2013–2018 of El Salvador's Agricultural Household Survey (ENAMP). The dependent variables correspond to the inverse hyperbolic sine of the number of workers and number of household workers. The independent variables are temperature shock (two SD higher than the historic value during the winter season the previous year) in t. Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 in First-Harvest Season on Corn Agricultural Inputs

	Input					Land	
Agricultural Outcome	PCA	Planting material	Agrochemicals	Chemical agents	Agroecological	Log(total area)	Log (cultivated area of corn)
Temperature shock year t	-0.020	-0.040	-0.024	-1.305	0.199	0.026	0.017
	(0.010)**	(0.046)	(0.030)	(0.636)**	(0.265)	(0.018)	(0.010)*
R2	0.024	0.013	0.014	0.110	0.047	0.174	0.189
Mean	0.000	99.573	99.858	92.272	1.940	1.490	0.705
Obs	17,573	17,573	17,573	17,573	17,573	19,261	18,623
Crime, Weather, and Household	X	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X	X
Municipal Fixed Effects	X	X	X	X	X	X	X
Municipal Socio*Year	X	X	X	X	X	X	X
Geographic*Year	X	X	X	X	X	X	X

Notes: Data from 2013–2018 of El Salvador's Agricultural Household Survey (ENAMP). The dependent variables correspond to different inputs for production. The first dependent variable is an index using principal components analysis that includes all the inputs considered in the corresponding section. The second variable corresponds to planting material such as seeds and plants. The third variable is agrochemicals such as fertilizers, fungicides, bactericides, pesticides, and insecticides. The fourth variable is chemical agents such as growth regulators, pre- and post-harvest ripening agents, and post-harvest product protection agents. The fifth variable corresponds to agroecological inputs such as compost, fertilizer, bioinsecticides, biopesticides, and biofungicides. The dependent variables in the land section are the logarithm of the total cultivated area and the logarithm of the cultivated area dedicated to corn production. The independent variables are temperature shock (two SD higher than the historic value during the winter season the previous year) in t. Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 5: Impact of Temperature Shocks in First-Harvest Season on Labor Outcomes

Population Group	Employed	Hours (log)	Hourly wage (log($SCP))
Panel A: Individuals in Agri HH (transitory)			
Individuals in all HH	-0.001	0.010	-0.009
	(0.002)	(0.004)**	(0.007)
Obs	91,680	49,363	24,908
Individuals in HH with Lands	0.001	0.010	-0.014
	(0.002)	(0.004)**	(0.007)**
Obs	78,884	42,201	18,252
Individuals in HH without Lands	-0.009	0.005	0.006
	(0.004)**	(0.008)	(0.008)
Obs	12,796	7,162	6,656
Panel B: Individuals in Agri HH (other)			
Individuals in all HH	-0.002	0.003	0.001
	(0.002)	(0.003)	(0.004)
Obs	73,100	40,344	27,498
Individuals in HH with Lands	0.002	0.007	-0.003
	(0.003)	(0.005)	(0.009)
Obs	42,762	22,855	11,107
Individuals in HH without Lands	-0.005	-0.001	0.004
	(0.002)**	(0.004)	(0.005)
Obs	30,338	17,489	16,391
Panel C: Nonagricultural HH			
Individuals in all HH	0.000	-0.001	0.000
	(0.001)	(0.003)	(0.003)
Obs	323,896	185,573	167,507
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

Notes: Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. 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), it is the logarithm of hours worked per week; in column (3), it is the logarithm of hourly wages (from dependent or independent work). Panel A. Individuals in agricultural households producing transitory crops. The first row corresponds to all individuals in these households; the second row, to individuals in households that own land; the third row, to individuals who are not landowners. Panel B. Individuals in agricultural households with any other agricultural production. The first row corresponds to all individuals in these households; the second row, to individuals in households that own land; the third row, to individuals who are not landowners. Panel C. Individuals in nonagricultural households. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historical value in that municipality during the winter season the same year and the previous year). Municipality controls are heavy rain and drought shocks (two SD higher or lower than the historical value during the winter season the same year and the previous year), and crime controls (two SD higher than the historic 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 migrants and emigrants, and percentage of population under 18 and 18–60 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

9 Appendix

Figure A1: Timeline of Data

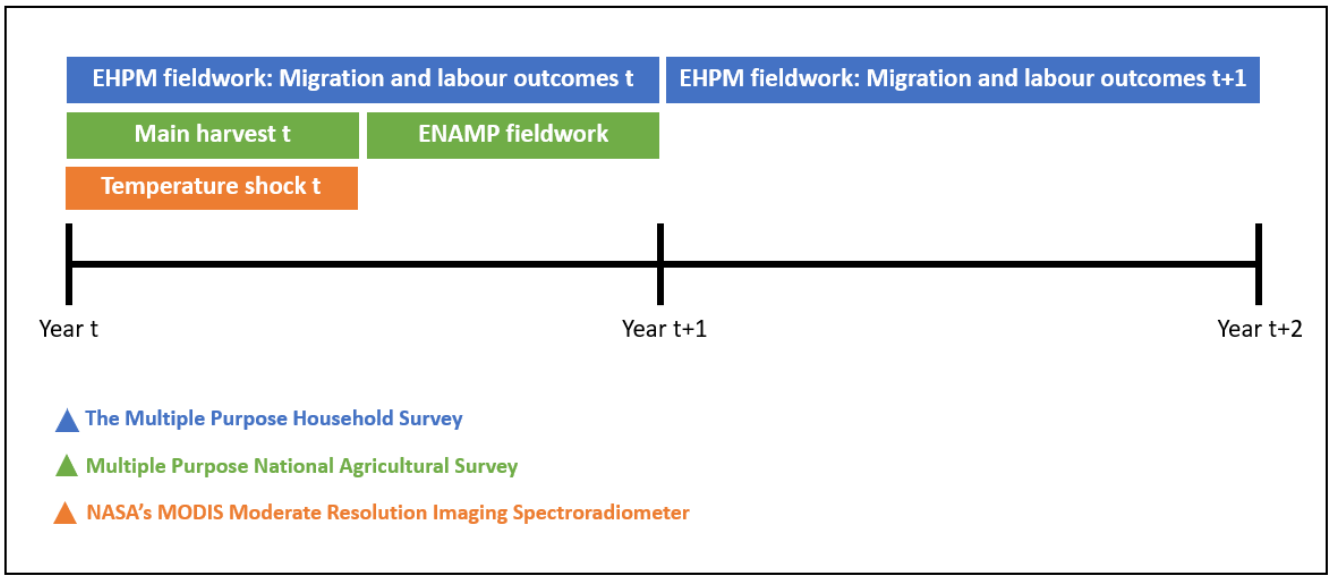
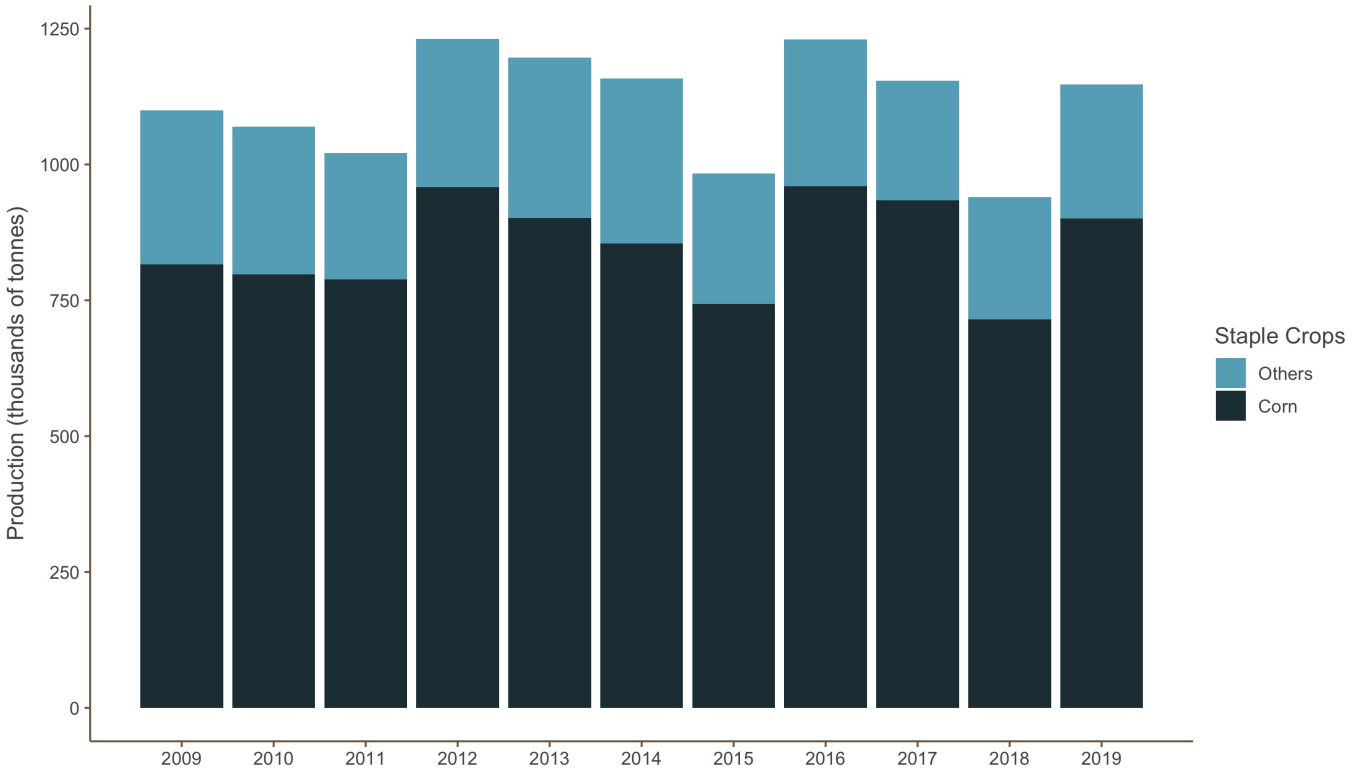
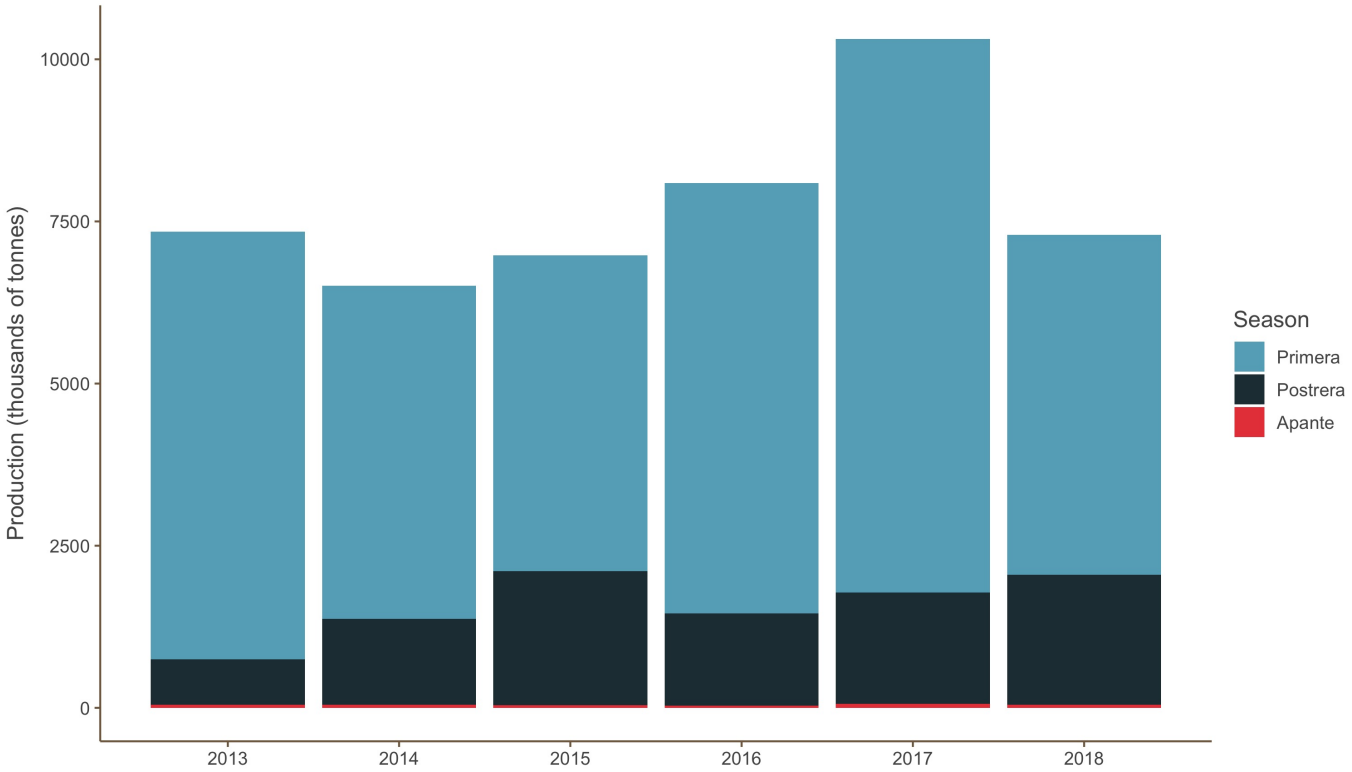


Figure A2: Production of Corn versus Other Staple Crops in El Salvador



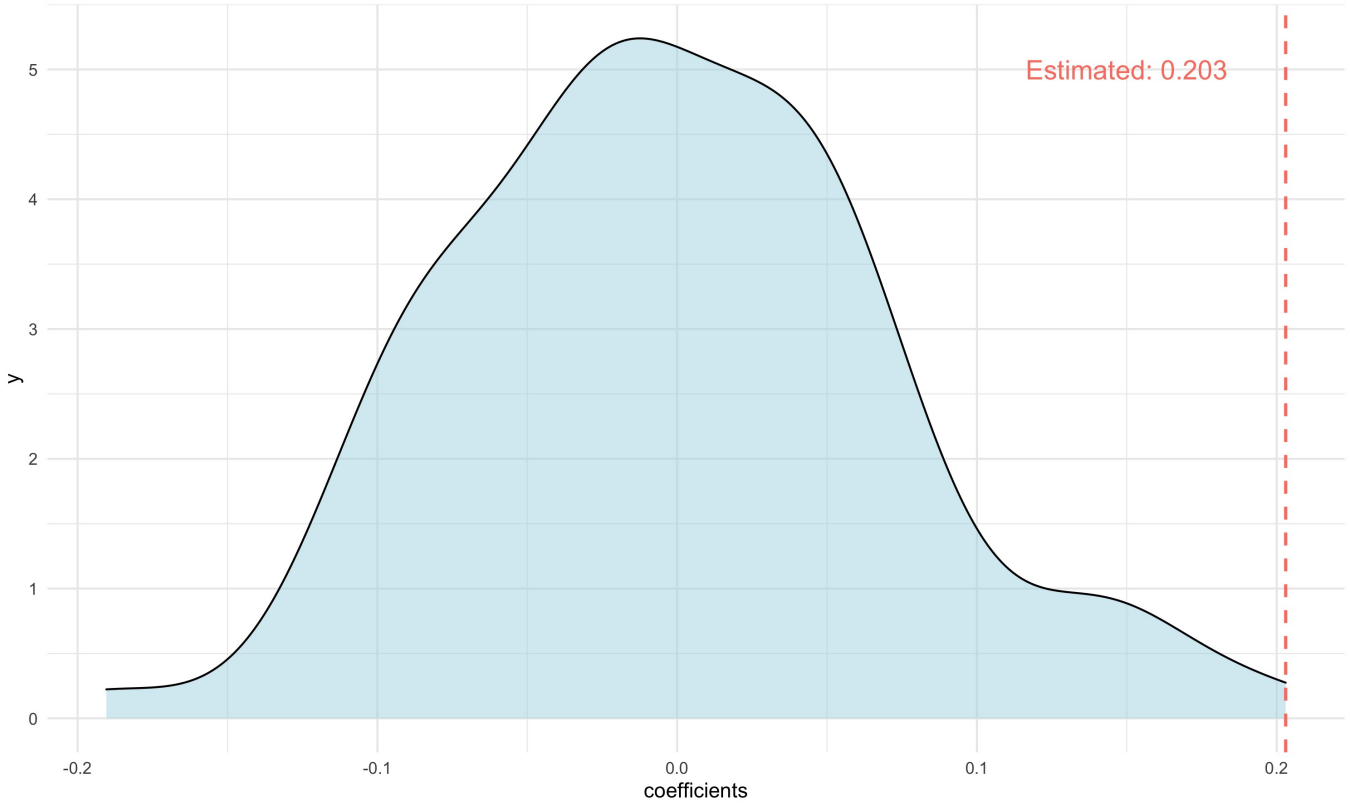
Source: FAOSTAT. Staple crops include corn (maize), rice, sorghum, and beans.

Figure A3: Corn Production across Yearly Seasons in El Salvador



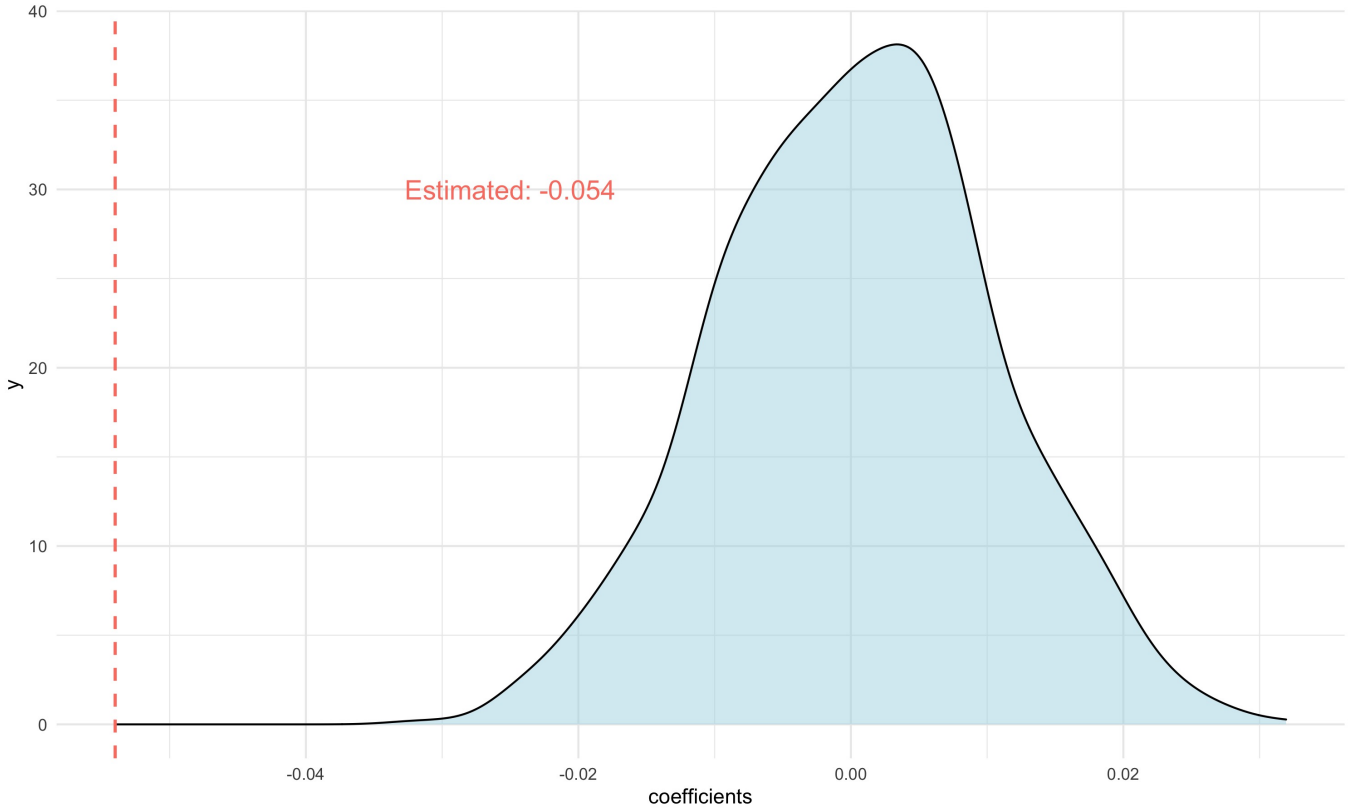
Source: ENAMP 2013–2018.

Figure A4: 1,000 Permutations of Temperature Shocks by Geography: Coefficients on Migration Likelihood



Note: The red dotted line shows the coefficient with the corresponding temperature shocks.

Figure A5: 1,000 Permutations of Temperature Shocks by Geography: Coefficients on Agricultural Productivity



Note: The red dotted line shows the coefficient with the corresponding temperature shocks.

Table A1: Descriptive Statistics: Outcome Variables

Variable	N	Mean	Std. Dev.	Min	Max
Panel A: EHPM					
=1 if at least one migrant member last year	186910	0.876	9.32	0	100
Employed head	186910	0.736	0.441	0	1
Head employed in agriculture	140850	0.175	0.38	0	1
Employed	197796	0.531	0.499	0	1
Weekly hours worked	105085	40.921	16.371	1	84
Hourly wage ($SCV)	87532	0.163	0.179	-0.073	6.882
Panel B: ENAMP					
Corn production (ton.)	19261	1.917	1.892	0.001	58.88
Corn - productivity (ton. per ha)	19261	2.342	1.209	0	19.189
Corn - productivity (ton. per worker)	18784	0.447	0.415	0	9.66
Corn - Value of productivity per ha (SCV$)	19261	709.798	377.003	0.062	5487.429
TFP production	16494	0	0.693	-21.843	1.544
Total workers	18845	5.404	7.325	0	494
Hired workers	18845	3.696	7.379	0	494
Household workers	18845	1.708	1.57	0.000	43.000
PCA index of inputs	17568	0	1	-25.361	0.140
Planting material	17568	0.996	0.065	0.000	1.000
Agrochemicals	17568	0.999	0.038	0.000	1.000
Chemical agents	17568	0.923	0.267	0.000	1.000
Agroecological	17568	0.019	0.138	0	1.000
Land size (Ha)	19261	1.49	4.832	0.077	210.000
Land size cultived in corn (Ha)	18618	0.705	0.695	0.056	45.5

Note: Panel A shows descriptive statistics for El Salvador Multiple Purpose Household Survey (EHPM) from 2009–2018 at the household level. Panel B shows data from 2013–2018 of El Salvador Agricultural Household Survey at the producer level.

Table A2: Descriptive Statistics: Control Variables

Variable	N	Mean	Std. Dev.	Min	Max
Panel A: EHPM					
Male head	186910	0.605	0.489	0.000	1.000
Age of head	186910	47.754	16.405	14.000	98.000
Household size	186910	3.864	1.957	1.000	24.000
Owns land	186910	0.067	0.250	0.000	1.000
Has agricultural credit	186910	0.033	0.178	0.000	1.000
Head employer	140850	0.06	0.238	0.000	1.000
Panel B: ENAMP					
Highest education level in HH	19261	2.465	0.925	0.000	6.000
Has irrigation	19261	0.004	0.067	0.000	1.000
Household size	19261	4.284	2.064	1.000	16.000
Panel C: Municipalities					
Number of weeks temperature 2sd > historic mean	244	1.165	0.566	0.000	4.000
Number of weeks rainfall 2sd > historic mean	244	0.109	0.142	0.000	0.600
Number of weeks rainfall 2sd < historic mean	244	0.327	0.233	0.000	1.000
Number of weeks crime 2sd > historic mean	244	0.32	0.262	0.000	1.000
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 (km2)	244	83.733	88.237	5.400	668.360
Poverty rate (2005)	244	50.632	14.944	10.370	88.50
Extreme poverty (2005)	244	25.751	12.596	4.2	60.4
Income per capita (2005)	244	561.074	266.001	212.600	2763.520
% 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
% Internal migrants	244	19.031	13.552	1.245	108.087
% Emigrants	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 at the household level. Panel B shows data from 2013 – 2018 of El Salvador Agricultural Household Survey at the producer level. Panel C shows municipality-level statistics for the period 2009–2018. The historic mean and standard deviation are calculated for the period between 2001 and 2006.

Table A3: Impact of Temperature Shocks on Migration Likelihood
Heterogeneity by Working-Age Household Member Characteristics

	Method I		Method II	
Population Group	Less 50%	More 50%	Less 50%	More 50%
	(1)	(2)	(3)	(4)
Panel A:Agricultural Households (transitory)				
Temperature shock year t-1	0.033	0.151	0.206	0.207
	(0.072)	(0.112)	(0.140)	(0.093)**
R2	0.008	0.003	0.021	0.006
Obs	157,544	19,925	7,587	15,773
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

Data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM). The dependent variable is 100 if a household member migrated in the surveyed year. Method I and Method II use different classifications to identify households. Method I only considers working-age members as a criterion to classify them in each panel, while Method II also considers if the household head is employed in each sector in order to classify them. Column (1) corresponds to households with less than 50 percent of their working-age members in the corresponding sector. Column (2) corresponds to households with more than 50 percent. Column (3) corresponds to households with less than 50 percent of their working-age members and the household head employed in the corresponding sector. Column (4) corresponds to households with more than 50 percent of their working-age members and the household head working in the corresponding sector. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 A4: Effects of 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 $t-1$	0.074	0.348***
	(0.102)	(0.121)
Mean Migration Likelihood	0.613	1.074
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	14,185	10,148
R^2	0.020	0.027

Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season 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 2005. Column (2) corresponds to households living in municipalities with a share of population working in agriculture above the median municipality, as of 2005. Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 of Temperature Shocks on Migration Likelihood of Agricultural Households Heterogeneity by Share of Emigrants and Share of Population that Apply for Credit at Municipality Level

	Below the Median	Above the Median
	(1)	(2)
Panel A: Share of Emigrants per District		
Temperature shock year $t-1$	0.137*	0.220*
	(0.074)	(0.117)
Mean Migration Likelihood	0.368	1.121
% Effect	37.22%	19.62%
Observations	10,314	14,018
R^2	0.035	0.018
Panel B: Share of Access to credit		
Temperature shock year $t-1$	0.336*	0.144*
	(0.199)	(0.080)
Mean Migration Likelihood	0.603	0.907
% Effect	55.72%	15.87%
Observations	7,958	16,207
R^2	0.021	0.008
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

Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). Panel A explores heterogeneity using the share of migrants per municipality in 2007 and panel B uses the share of population with access to credit per municipality in 2009. 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 (two SD higher than the historic value during the winter season 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 migrants and emigrants, and percentage of population under 18 and 18–60 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: Impact of Temperature Shocks in First-Harvest Season on Migration Likelihood

	Has Credit	
Population Group	Yes	No
Panel A:Agricultural Households (transitory)		
Temperature shock year $t-1$	-0.029	0.219
	(0.325)	(0.092)**
R2	-0.017	0.012
Mean	1.080	0.767
Obs	2,686	21,646
Panel B:Agricultural Households (other)		
Temperature shock year $t-1$	-0.342	0.042
	(0.485)	(0.102)
R2	-0.025	0.014
Mean	1.522	0.902
Obs	1,183	1,183
Panel C:Nonagricultural Households		
Temperature shock year $t-1$	-0.060	-0.011
	(0.162)	(0.050)
R2	-0.070	0.003
Mean	0.658	0.596
Obs	1,215	1,215
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

Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). Column (1) corresponds to households with agricultural credit and column (2), to those without agricultural credit. Panel A. Individuals in agricultural households producing transitory crops. Panel B. Individuals in agricultural households with any other agricultural production. Panel C. Individuals in nonagricultural households. Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season 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 migrants and emigrants, and percentage of population under 18 and 18–60 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: Effect on Food Consumption per Capita (log)

	Agricultural (transitory)	Agricultural (rest)	Nonagricultural
	(1)	(2)	(3)
Temperature Shock $t-1$	−0.009	−0.002	−0.002
	(0.007)	(0.005)	(0.004)
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	24,332	19,141	94,159
R^2	0.354	0.360	0.286

Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is the logarithm of total consumption per capita. Column (1) corresponds to agricultural households producing transitory crops. Column (2) corresponds to agricultural households with any other agricultural production. Column (3) corresponds to nonagricultural households. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 A8: Impact of Temperature Shocks on Migration Likelihood-Different Shocks and Periods

	Changing the months of the shocks				Changing the range of years		
Population Group	Winter Shock	All-year Shock	Apante Shock	Lean Shock	2009-2018	2013-2018	Excluding 2015
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
All Households	0.050	0.030	0.020	-0.042	0.049	0.059	0.065
	(0.065)	(0.031)	(0.060)	(0.061)	(0.065)	(0.085)	(0.077)
R2	0.006	0.006	0.006	0.006	0.006	0.006	0.007
Panel B							
Agricultural Households (transitory)	0.206	0.055	-0.087	-0.029	0.203	0.243	0.238
	(0.094)**	(0.045)	(0.140)	(0.092)	(0.093)**	(0.111)**	(0.099)**
R2	0.011	0.010	0.010	0.010	0.011	0.012	0.011
Panel C							
Agricultural Households (other)	0.014	0.029	0.000	0.067	0.018	0.033	-0.004
	(0.084)	(0.059)	(0.232)	(0.121)	(0.086)	(0.082)	(0.105)
R2	0.012	0.013	0.013	0.012	0.012	0.002	0.013
Panel D							
Nonagricultural Households	-0.013	0.008	0.036	-0.043	-0.012	-0.021	0.024
	(0.049)	(0.018)	(0.059)	(0.050)	(0.048)	(0.071)	(0.044)
R2	0.003	0.003	0.003	0.003	0.003	0.004	0.003
Panel E							
Unemployed Households	0.094	0.145	0.066	-0.026	0.092	0.110	0.076
	(0.145)	(0.073)	(0.132)	(0.109)	(0.145)	(0.192)	(0.181)
R2	0.011	0.011	0.011	0.011	0.011	0.012	0.012
Crime, Weather, and Household	X	X	X	X	X	X	X
Year Fixed Effects	X	X	X	X	X	X	X
Municipal Fixed Effects	X	X	X	X	X	X	X
Municipal Socio*Year	X	X	X	X	X	X	X
Geographic*Year	X	X	X	X	X	X	X

Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. Column (1)'s independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality the previous year). Column (2)'s independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the second-harvest (apante) season the previous year). Column (3)'s independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the first-harvest season the previous year). Column (4)'s independent variable is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during lean season the previous year). The independent variable in columns (5)–(7) is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). Column (5) comprises all years from 2009 and 2018. Column (6) comprises 2013–2018. Column (7) comprises 2009–2018, excluding 2015. Panel A. All households. Panel B. A household is defined as agricultural (transitory) when the household head is employed in agriculture, producing transitory crops. Panel C. A household is defined as agricultural (rest) when the household head is employed in agriculture with any other agricultural production. Panel D. A household is defined as nonagricultural when the household head is employed in the nonagricultural sector. Panel E. A household is defined as unemployed when the household head is unemployed. Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season 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 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 A9: Impact of Temperature Shocks on Migration Likelihood-Different Shocks

Population Group	1 SD	1.5 SD	Higher 29	Higher 35
Panel A				
All Households	0.060	0.048	0.042	0.108
	(0.052)	(0.052)	(0.043)	(0.054)**
R2	0.006	0.006	0.006	0.006
Panel B				
Agricultural Households (transitory)	0.112	0.203	0.102	0.130
	(0.078)	(0.093)**	(0.081)	(0.062)**
R2	0.010	0.011	0.010	0.010
Panel C				
Agricultural Households (other)	0.013	0.040	-0.079	0.291
	(0.056)	(0.072)	(0.059)	(0.094)**
R2	0.012	0.012	0.012	0.012
Panel D				
Nonagricultural Households	0.044	0.005	0.017	0.030
	(0.033)	(0.035)	(0.031)	(0.024)
R2	0.003	0.003	0.003	0.003
Panel E				
Unemployed Households	0.089	0.055	0.110	0.188
	(0.119)	(0.117)	(0.094)	(0.177)
R2	0.011	0.011	0.012	0.012
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

Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. Column (1)'s independent variable is the number of weeks with a temperature shock (one SD higher than that week's historic value in that municipality during the winter season the previous year). Column (2)'s independent variable is the number of weeks with a temperature shock (1.5 SD higher than that week's historic value in that municipality during the winter season the previous year). Column (3)'s independent variable is the number of weeks with a temperature shock (higher than 29 °C in that municipality during the winter season the previous year). Column (4)'s independent variable is the number of weeks with a temperature shock (higher than 35 °C in that municipality during the winter season the previous year). Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the 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 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 migrants and emigrants, and percentage of population under 18 and 18–60 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 A10: Impact of Temperature Shocks in First-Harvest Season on Corn Agricultural Outcomes

Agricultural Outcome	1 SD	1.5 SD	Higher 29	Higher 35	Mean	Obs
A: Log(Total Production)						
Temperature shock year t	-0.027	-0.024	-0.016	-0.022	1.917	19,261
	(0.011)**	(0.012)*	(0.008)**	(0.015)		
R2	0.237	0.237	0.237	0.236		
B: Log(Production per Ha.)						
Temperature shock year t	-0.032	-0.046	-0.019	-0.028	2.342	19,261
	(0.015)**	(0.013)***	(0.014)	(0.013)**		
R2	0.269	0.270	0.268	0.268		
C: Log(Production per Ha. cultivated in corn)						
Temperature shock year t	-0.036	-0.043	-0.016	-0.028	2.342	18,618
	(0.011)***	(0.009)***	(0.011)	(0.013)**		
R2	0.449	0.450	0.447	0.446		
D: Log(TFP production)						
Temperature shock year t	-0.029	-0.032	-0.017	-0.023	2.337	16,438
	(0.013)**	(0.010)**	(0.008)**	(0.015)		
R2	0.290	0.290	0.289	0.289		
E: Log(Labor productivity)						
Temperature shock year t	-0.019	-0.008	-0.023	0.010	2.337	18,784
	(0.015)	(0.012)	(0.014)*	(0.013)		
R2	0.173	0.173	0.173	0.172		
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: Data from El Salvador's Agricultural Household Survey (ENAMP) 2013–2018. Dependent variables and controls as in table 2. Column (1)'s independent variable is the number of weeks with a temperature shock (one SD higher than that week's historic value in that municipality during the winter season the previous year). Column (2)'s independent variable is the number of weeks with a temperature shock (1.5 SD higher than that week's historic value in that municipality during the winter season the previous year). Column (3)'s independent variable is the number of weeks with a temperature shock (higher than 29C in that municipality during the winter season the previous year). Column (4)'s independent variable is the number of weeks with a temperature shock (higher than 35C in that municipality during the winter season the previous year). Municipality controls are crime, heavy rain, and drought shocks (two SD higher than the 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. *p<0.1; **p<0.05; ***p<0.01

Table A11: Impact of Temperature Shocks in First-Harvest Season on Migration Likelihood

	Agri(transitory-rural)		Agri(transitory-urban)		Agri(other-rural)		Agri(other-urban)		Nonagri(rural)		Nonagri(urban)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Temperature shock t-1	0.268	0.256	0.034	0.037	0.048	0.049	-0.117	-0.121	0.024	0.026	-0.030	-0.033
	(0.117)**	(0.116)**	(0.071)	(0.068)	(0.140)	(0.141)	(0.094)	(0.094)	(0.122)	(0.122)	(0.043)	(0.043)
Crime shock t-1		0.444		-0.114		-0.024		0.229		-0.076		0.210
		(0.137)**		(0.208)		(0.239)		(0.226)		(0.179)		(0.075)**
Mean	0.929	0.929	0.494	0.494	1.184	1.184	0.576	0.576	0.742	0.742	0.562	0.562
Obs	17,227	17,227	4,456	4,456	10,723	10,723	6,425	6,425	26,951	26,951	58,186	58,186
R2	0.011	0.011	0.021	0.021	0.008	0.008	0.051	0.051	0.003	0.003	0.004	0.004

Data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable is 100 if a household member migrated in the surveyed year. The independent variable in the first row is the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season the previous year). The independent variable in the second row is the number of weeks with a crime shock (two SD higher than that week's historic value in that municipality the previous year). For each group, two regressions are estimated: the first includes only the temperature shock, and the second includes the temperature and crime shocks. Columns (1)–(2) include agricultural households in the rural area that produce transitory crops. Columns (3)–(4) include agricultural households in the urban area that produce transitory crops. Columns (5)–(6) include agricultural households in the rural area with any other agricultural production. Columns (7)–(8) include agricultural households in the urban area with any other agricultural production. Columns (9)–(10) include nonagricultural households in the rural area. Columns (11)–(12) include nonagricultural households in the urban area. Regressions include all set of controls from column 5 Table 1. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01