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

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Abstract

By 2017, one-quarter of people born in El Salvador were estimated to 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 agricultural landowners respond to the negative shock on production by reducing the labor demand of agricultural workers, who are substituted by household workers. Contrary to what has been found in other settings, we do not find any evidence of reallocation to the non- agricultural sector, which explains in part the significant impact of the temperature shocks on the decision to migrate internationally. Access to risk-coping mechanisms does not alleviate the impact of the shock on agricultural production, but it reduces farmer's need to adjust through labor demand and migration. Our findings highlight that migration is an important response to temperature shocks when local labor markets cannot absorb displaced agricultural workers, or when markets are not fully integrated.

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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 ample evidence shows that extreme temperatures negatively affect crop yield, agricultural productivity, and agricultural income.[1] If these trends persist, the rising economic costs that climate change imposes on subsistence farmers who grow crops highly sensitive to extreme temperatures could negatively impact hundreds of millions of people and affect the global efforts to reduce rural poverty.[2]

The effects of extreme temperatures can be particularly large in regions with rain-fed agriculture, and for small agricultural producers in developing countries, who seldom have access to risk-coping mechanisms. 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. As a consequence, 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), participation in subsistence activities, and migration (Rosenzweig and Wolpin, 1993; Jayachandran, 2006; Hornbeck, 2012; Carter and Lybbert, 2012; Jessoe et al., 2016; Aragón et al., 2021).

Our paper makes a contribution to this literature by measuring the effects of extreme temperatures on agricultural production and by examining the complex ways in which farm-

[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).

ers respond to these shocks in El Salvador. Our results suggest agricultural landowners respond to the shock by adjusting the demand of agricultural workers, who are substituted by household workers, particularly women and young children. Agricultural workers who have no access to land might reallocate to other sectors. However, we find no evidence of reallocation to either other agricultural sectors or to the non-agricultural sector. In a context that lacks access to risk-coping mechanisms, and where the non-agricultural sector cannot absorb the displaced agricultural labor force, migrating internationally becomes an important strategy to adjust to the costs imposed by these weather shocks. Our results support this hypothesis. We find a significant increase on international migration, which is mostly to the U.S., as a response to extreme temperature events in El Salvador. Moreover, we show that the adjustment through labor markets differs by access to both formal and informal mechanisms to address risk (Jayachandran, 2006).

Our conceptual framework follows 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 et al., 2021). Agricultural workers who lose their jobs may move to the non-agricultural sector or migrate to offset income losses. If labor supply for the non-agricultural sector expands, wages in that sector may decrease, with negative consequences ultimately for those workers as well (Colmer, 2021). In contexts where the labor markets are not fully integrated or the non-agricultural sector cannot absorb new workers, migration might be more prevalent (Colmer, 2021). 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.[3] Second, a large number (87 percent) of agricultural producers are subsistence farmers who work on small land plots (on average, 1.2 hectares) and live in contexts with incomplete markets;[4] in 2017, the rural poverty rate was 50 percent.[5] Third, the country is increasingly vulnerable to extreme weather events.[6] 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 analysis uses several data sources. To study migration, we use the Multiple Purpose Household Survey (EHPM from its acronym in Spanish), a nationally representative yearly cross-sectional survey for 2009-2018. Data on agricultural production come from the Multiple Purpose National Agricultural Survey (ENAMP for its acronym in Spanish), a nationally representative cross-section dataset of agricultural producers. Finally, temperature data come from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature, a data grid of one km resolution that contains weekly temperature averages for 2001-2018. We aggregate the grid to the municipal level with a weighted mean using the

[3]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.

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

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

[6]For example, the number of hurricanes in Central America rose to 39 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.

area covered.

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.

We document that temperature shocks decrease production of agricultural seasonal crops, and corn in particular, (also known as maize, El Salvador's main staple crop): an additional one standard deviation (SD) of the temperature shock reduces total agricultural production by 1.8 percent and corn production per hectare between 3.3 and 2.8 percent. Agricultural producers adjust in the short run by reducing labor demand for non-household agricultural workers and substituting household workers for them; this contraction in labor demand depresses agricultural wages and similarly to Aragón et al. (2021) in Peru, we find that agricultural producers respond to these shocks by increasing the area of land use and changing production inputs mainly in post-harvest activities. We find no evidence of reallocation to non-agricultural occupations and important increases in the probability to migrate

to the U.S.: a one SD increase in the temperature shock causes migration to rise by 19.6 percent. In addition, we show suggestive evidence supporting the role of risk-management 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. These results suggest that temperature shocks are a significant push factor for rural Salvadorean households. A caveat of our data is that we cannot distinguish temporal from permanent migration, so this effect includes from types of migration.

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[7] and emigration[8] 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 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.[9] Since developed and developing countries

[7]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).

[8]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).

[9]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).

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, 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).[10] 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[11]— 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.[12] As might be expected, the price 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.[13]

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,

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

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

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

[13] 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.

2021). El Salvador is not only extremely vulnerable to changing climate conditions[14] 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 drought and the onset of *El Niño*.[15] 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.[16] 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

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

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

[16] 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.

Salvador.[17] Most agricultural producers there are small family farms with average land sizes of 1.2 hectares[18] that are dedicated to subsistence farming. As only 1.4 percent of the land is irrigated,[19] 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 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 en-

[17] 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.

[18] 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.

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

compasses 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.[20]

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.[21] Our outcome variable is a dummy equal to one when at least one household member migrated abroad one year prior to the survey.[22] 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 immigrants (Halliday, 2006). To evaluate potential underreporting of entire-household migration, we compare migration trends from the EHPM and the American Community Survey (ACS).[23] 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.

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

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

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

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

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.[24] 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;[25] (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 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

[24] 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.

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

two seasons, *primera* 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.[26] It is a short-cycle crop for which temperature shock impacts can be traced back in the same period.[27] In addition, other papers have found a significant association between temperature shocks and corn production.[28]

As mentioned, corn production has three harvest seasons: *primera*, 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 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

[26] 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. (See Tables A1 and A2 in the Appendix).

[27] Access to irrigation—crucial for managing periods of drought and extreme temperatures—is practically nonexistent (0.4 percent) (Tables A1 and A2.)

[28] 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.

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.

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),[29] and crime shocks.[30]

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.[31] 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 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.[32]

4 Empirical Strategy

To measure the effect of temperature shocks on agricultural production, and responses through labor demand and migration, 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 might depend on access to both formal and informal risk-management mechanisms.

[29]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.

[30]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.

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

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

4.1 Agricultural Production

We start by estimating the effect of extreme temperatures on agricultural production.[33] 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.

To estimate the 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. Specifically, we estimate the effect of temperature shocks on agricultural outcomes for corn and other seasonal crops. We estimate the following regression model:

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

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. We test the robustness of temperature shocks using alternative definitions (see section 5.5). [34] In order to identify the contemporaneous effect of the high temperature, we include $\sum_{k=t-4}^{k=t-1} T_{ijk}$ that is the total number of weeks with extreme temperatures during the previous four years.

[33] 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.

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

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.

Our main specification controls for time-variant household characteristics, X'_{ijt}, such as household head education, number of household members, and access to irrigation for corn. 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).[35] 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

[35]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.

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. [36] All the models are estimated using double-clustered standard errors by municipality and year.

As additional robustness checks we estimate a placebo tests with the temperature shock defined as the number of weeks above the historic mean during the 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. This rules out that contemporaneous unobserved events are driving the negative effects on production.

4.2 Responses to Temperature Shocks

4.2.1 Labor Markets

We continue our analysis by exploring 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 non-agricultural sectors (Jayachandran, 2006; Colmer, 2021). The contraction in labor demand of agricultural producers will pressure agricultural wages and push workers to increase working

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

hours or seek employment in the non-agricultural 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 using the EHPM data:[37]

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

where l_{ijt} represents the labor outcomes of individual i, living in municipality 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. We estimate these effects for individuals working in the agricultural and non-agricultural sectors. However, the occupation of workers might be endogenous. To overcome these challenges, in addition to estimating models at the individual level, we complement this analysis, by estimating effects on labor market outcomes at the municipality level, such as, occupation-specific employment shares, and average hourly wages.

4.2.2 International Migration

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

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

[37] 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.

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.[38] The variable T_{jt-1}, and the controls are the same as the ones specified in equations (1) and (2).

5 Results

5.1 Agricultural Production

We first estimate the effect of temperature shocks on agricultural output and different productivity measures. Table 1 reports the results of estimating equation (1) with the full set of controls using data from the ENAMP for 2013-2018. In Table A3 we add controls across columns to test the robustness of the model, and reassuringly we observe the results are robust to adding the full set of controls. 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), the logarithm of the TFP (panel D) and labor productivity (panel E). Column 1 shows the effect of the contemporaneous temperature shock without controlling for temperature shocks in previous years, and column 2 adds these controls. Both the magnitude of the coefficients and its significance does not change across specifications.

The results show consistently negative effects of the temperature shock on all outcomes, other than labor productivity. Focusing on the results in column (2), we find that an additional year with a temperature shock decreases total corn production by 3.2 percent, or a one standard deviation (SD) increase in the temperature shock during the main harvest season of the contemporaneous year decreases total corn production by 1.8 percent (panel A).[39] Land productivity falls between 3.3 percent (panel B) and 2.8 percent (panel C), and

[38] In the empirical regressions, we multiply the dummy variable by 100 to ease the interpretation.
[39] 0.032*(standard deviation of the temperature shock)=0.032*0.566.

TFP drops by 2.2 percent (panel D) for an additional SD increase in the temperature shock. The sharper decline in land productivity suggest that agricultural workers increase the use of land in the short-term, which is consistent with the results by Aragón et al. (2021) in Peru. 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 there is a reduction in the demand of agricultural workers.

Overall, we find robust evidence of the negative effects extreme temperatures have had on the agricultural production of corn in El Salvador. Some of these results suggest that farmers adjust the intensive use of inputs such as land and workers. We investigate directly this type of adjustments in the next section.

5.2 Input Adjustments: Labor Markets

We first investigate how agricultural producers adjust the use of production inputs. Table 2 reports these estimates. 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 post-harvest 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 1, 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 then investigate how agricultural producers adjust their labor demand when fac-

ing 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 non-household workers, and column (3) on household workers. We only report the results of 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 non-household workers. One additional SD reduces the demand for total number of workers by 1 percent and non-household 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 non-household 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 non-household agricultural workers.

We complement this analysis by estimating the effect of temperature shocks on local labor markets. We estimate equation (2) on the employment rates in the agricultural sector, non-agricultural sector, and on the unemployment rate at the municipality level. Panel A of Table 4 shows that an additional week with a temperature shock decreases the employment rate in the agricultural sector by 1.6% relative to the baseline mean, or a 1 SD increase in the temperature shock decreases employment rate in the agricultural sector by 1% relative to the baseline mean, and the effect is larger for agricultural workers who produce corn. Importantly there is no evidence of reallocation to the non-agricultural sector, instead the results suggest the reduction of the agricultural employment rate is accompanied by an increase in the unemployment rate.[40] Panel B shows the result on the log of average wages. The results

[40]Table A4 shows the results for the non-agricultural sector disaggregated by sector, and the null results

show negative and significant effects on the wages of agricultural workers. This could be driven by adjustments in the wages paid by landowners. 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). 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.

In addition, we estimate the effect of the shock on individual probabilities of employment, and among those working we estimate the effect on working hours and hourly wages. The results at the individual level in Table 5 are consistently with the results at the municipality level. Once again we find a significant and negative effect on the probability of employment in the agricultural sector; but, we find no significant evidence of adjustments at the intensive margin (Table 6). However, the results in Table 6 might mask important heterogeneity. Tables A5 and A6 in the Appendix show that women and children younger than 14 significantly increase their working hours. If there is a substitution between non-household workers and household workers, this suggests that women and young children might be the household members who need to replace the hired labor. This could bee a costly response to the shocks with potentially long-term consequences on the human capital accumulation of young children.

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 could potentially switch to other agricultural activities or to the non-agricultural sector, however, we find no evidence of this reallocation in

persist for all the sectors.

El Salvador. The transmission of the temperature shocks into labor markets might be the consequence of incomplete financial markets to manage risk, and low levels of integration between local labor markets. We provide suggestive evidence about this mechanisms in the next sections.

5.3 International Migration

Without access to risk-coping mechanisms, or to a non-agricultural sector that can absorb agricultural workers, migrating internationally could become an important response to the loss income due to the temperature shocks. We explore this hypothesis by estimating equation (3). The results with the fully controlled models are shown in Table 7.[41] We estimate this model using household-level information from the EHPM 2009–2018 for all households (panel A), all agricultural households (panel B), agricultural households cultivating seasonal crops, which includes corn (panel C), agricultural households cultivating corn (panel D), and non-agricultural households (panel E). We categorize households based on the occupation of the household head, and the occupation of working age individuals in the household. A household is considered agricultural if the household head and at least 50% of the working age individuals work in this sector. A potential concern is that the occupation of the household members might be endogenous. In Appenidx Table A8, we classify households based on alternative specifications. Method 1 is our preferred specification; Method 2 ony considers the occupation of the household head; Method 3 and 4 only considers other working-age members as a criterion to classify them in each panel. The results on the probability of migration are robust overall to the different classifications.

As has been established in the literature, a negative 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

[41] In Table A7 we test the robustness of our results, including a set of controls at a time. Overall, the results are robust to the inclusion of all the controls. Our preferred specification is the fully controlled model.

households, especially corn producers. The results in Table 7 point in this direction. They show significant effects of the temperature shock on the probability of migration only for agricultural households working on seasonal crops, particularly corn (panel D). Not only are the effects statistically significant for this sample, but the magnitude of coefficient is almost 10 times larger than that of all households, and the coefficient for non-agricultural households is non-significant and small in magnitude.

The results in our preferred specification with the full set of controls (column (2)) for agricultural households who grow corn (panel D) show that one additional week with a temperature shock increases the probability of international migration by 0.27 percentage points (pp) - 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 19.6% relative to the mean of internatioanl migration in El Salvador.[42] Although at face value the magnitude of these effects seem large, an important caveat of our measure of migration is that we cannot distinguish permanent from transitory migration.

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[43] and play an important role in supporting family members who stay in the country.[44] In order to investigate both risk-management mechanisms, we estimate heterogeneous effects for municipalities above and below the median of: (i) share

[42] To calculate this: $\frac{\hat{\delta_1} * temp(SD)}{migration(mean)} = \frac{0.273*0.566}{0.788}$

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

[44] 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.

of households that applied for credits in 2009, according to the EHPM survey; (ii) share of migrants in 2007, according to the population census; (iii) share of the population with remittances in 2009 using the EHPM. 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 agricultural production, 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 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.

Table 8 shows the results for different outcomes across panels: agricultural production (panel A), labor outcomes (Panel B), and the likelihood of migration (Panel C). We explore heterogeneity according to whether individuals live in municipalities above or below the mean of share of individuals with access to credit (columns 1 and 2); share of international migrants (columns 3 and 4); and, share of remittances (column 5 and 6). The results in Panel A, suggest that access to risk-coping mechanisms such as formal credits or remittances do not shield farmers from the effects of the temperature shocks. Probably farmers are not using these to protect themselves *ex-ante* through insurance. In this context is important to keep investigating whether farmers decide not to invest in weather resistant seeds, appropriate fertilizer, or irrigation systems, because of liquidity constraints, or lack of information.

Looking at the results in Panels B and C, at first glance, there seems to be no differential effects based on access to credit, migrant networks and remittances on employment rates and migration decisions. Although, the point estimates are not significantly different from each other; the impact with respect to the baseline is consistently larger in municipalities below

the mean of the migrant share and remittances. For example, in these municipalities, an additional SD of the shock decreases the employment rate in the agricultural sector by 3.02% relative to the mean, whereas in those above the mean, the effect is only a 0.7% reduction relative to the baseline mean. The results suggest that in municipalities with less access to migrant networks and remittances (below the mean), farmers sharply adjust their demand for agricultural workers. This means worse labor outcomes for these workers. In contrast, in municipalities with more access to migrant networks (above the mean), labor demand for agricultural workers does not respond as significantly to the temperature shock and consequently does not convey to labor markets, arguably because households here rely more on these informal risk-management mechanisms. This interpretation is consistent with the results in Panel C. In municipalities with a lower share of migrants, a 1 SD increase in the temperature shock increases the probability of migration by 33%, while in municipalities with a larger share of migrants, the migration likelihood increases by 17% relative to the baseline mean. 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. Taking at face value the results in Panel C show a larger effect relative to the baseline mean for households who live in municipalities with less access to formal credits.

Overall, the results in Table 8 suggest that access to risk-management mechanisms might reduce the need for households to rely on distress migration to compensate for the fall in income caused by temperature shocks. Access to remittances 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. A valid concerns is that municipalities below and above these means are different in many ways. It is important to highlight that we add a rich set of controls at the municipality level, in addition to municipality fixed effects. However, unobserved time-variant characteristics of the municipality could be related both with the share of migrants at baseline and the probability to migrate. This is a relationship that needs to be explores in a more rigorous

way in the future, and our results should be interpreted as merely suggestive.

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 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 9, A9, and A10 in the Appendix show results for alternative definitions. First, in Table 9, 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 7—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 (column 5); and (ii) excluding 2015, the year with the most intense drought (column 6). The coefficient estimates are robust to changing the periods and the results are consistently robust to all the different specifications.[45]

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

[45]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.

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 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 7 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 non-agricultural households in rural and urban places.[46] 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 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

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

workers, who cannot reallocate to the non-agricultural sector and respond by migrating internationally.

Our results add to the literature on migration responses to short-term weather shocks 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,[47] there is no proof yet on how these 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.

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

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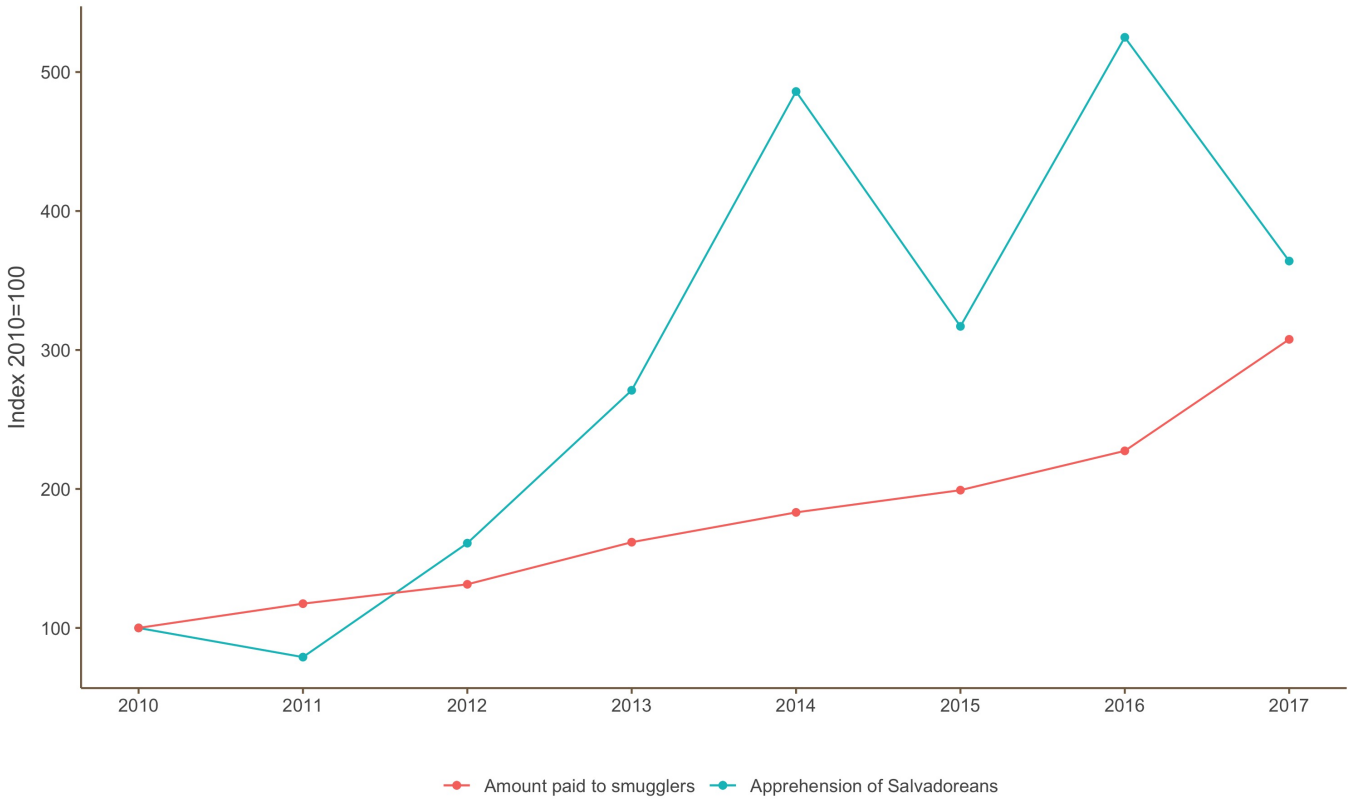
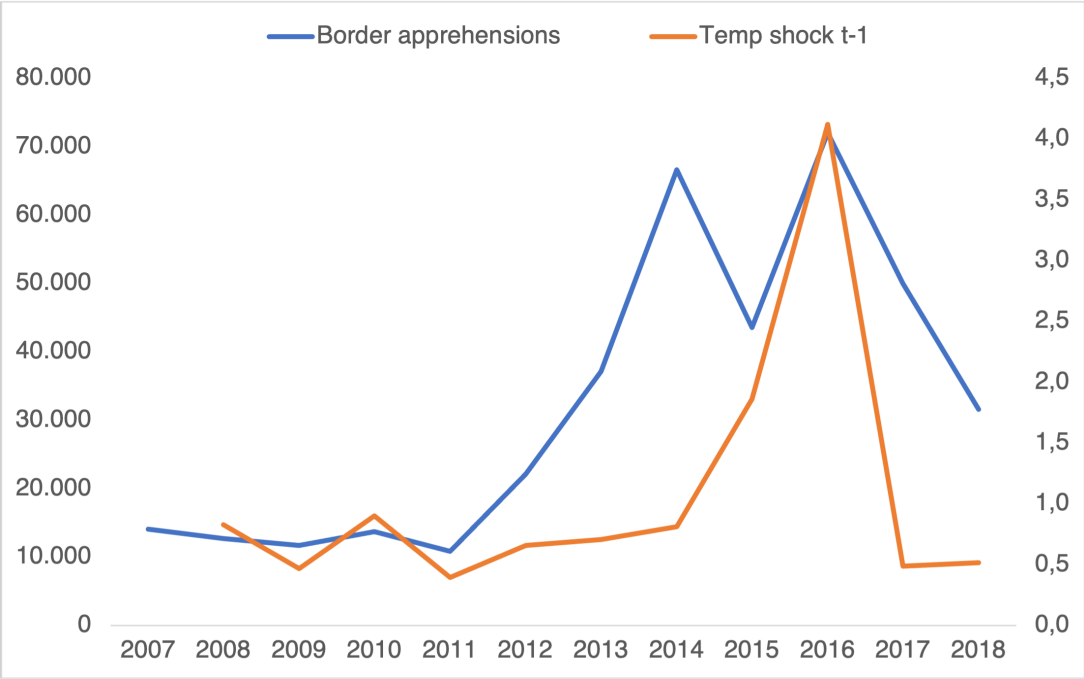
7 Figures

Figure 1: Border Apprehension of Salvadoreans and Cost of Smugglers



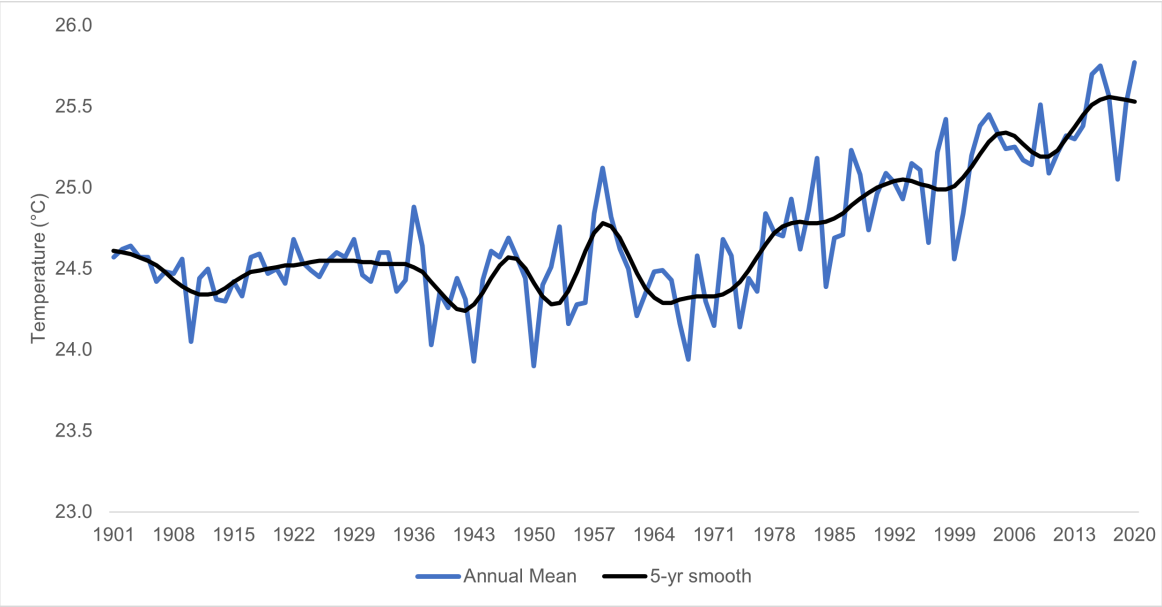
Source: American Community Survey (ACS) and Customs and Border Protection (CBP).

Figure 2: US Border Apprehensions



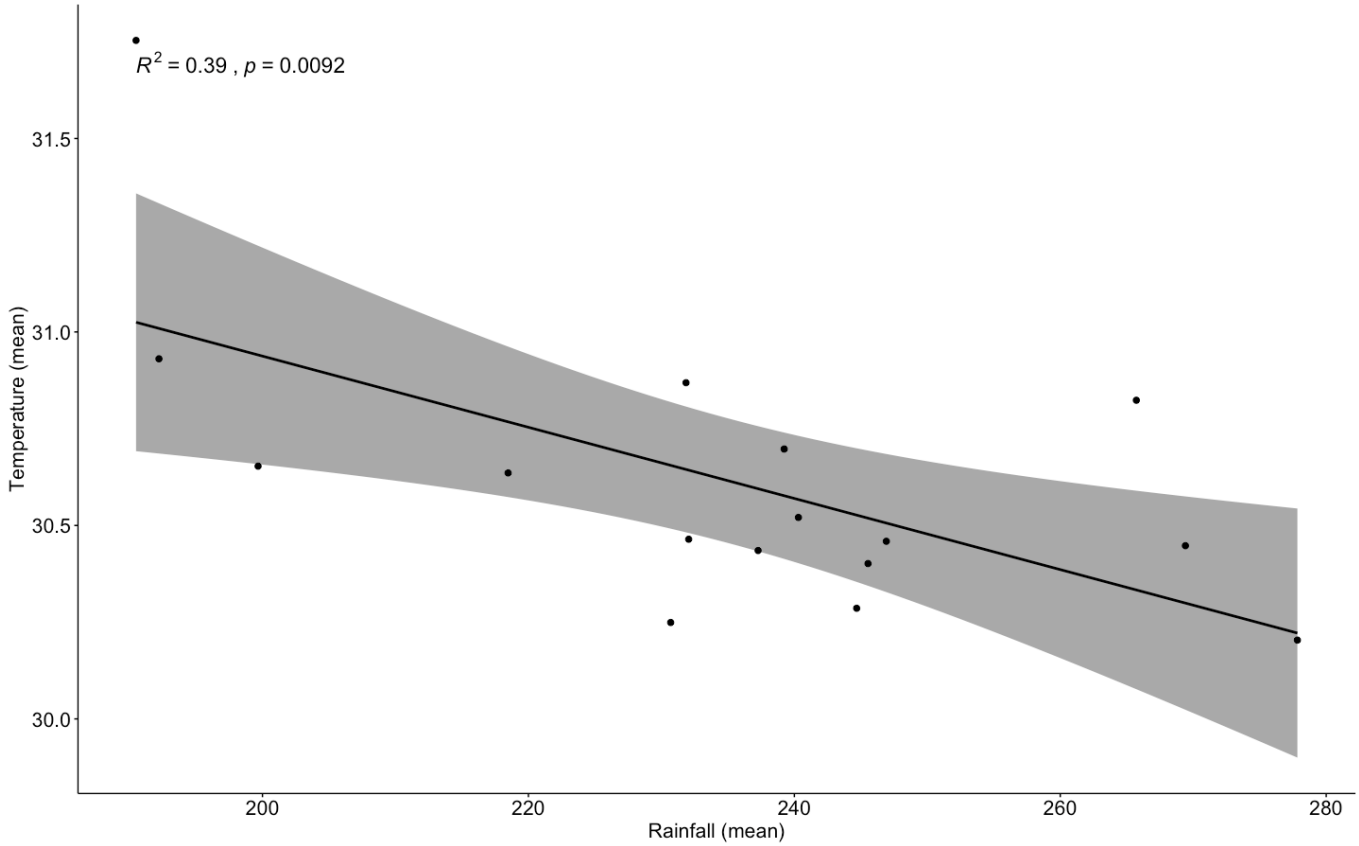
Source: US Customs and Border Protection (CBP) and NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. The blue line represents the average number of weeks in winter with a temperature shock (two SD above the historic mean).

Figure 3: Average Temperature in El Salvador



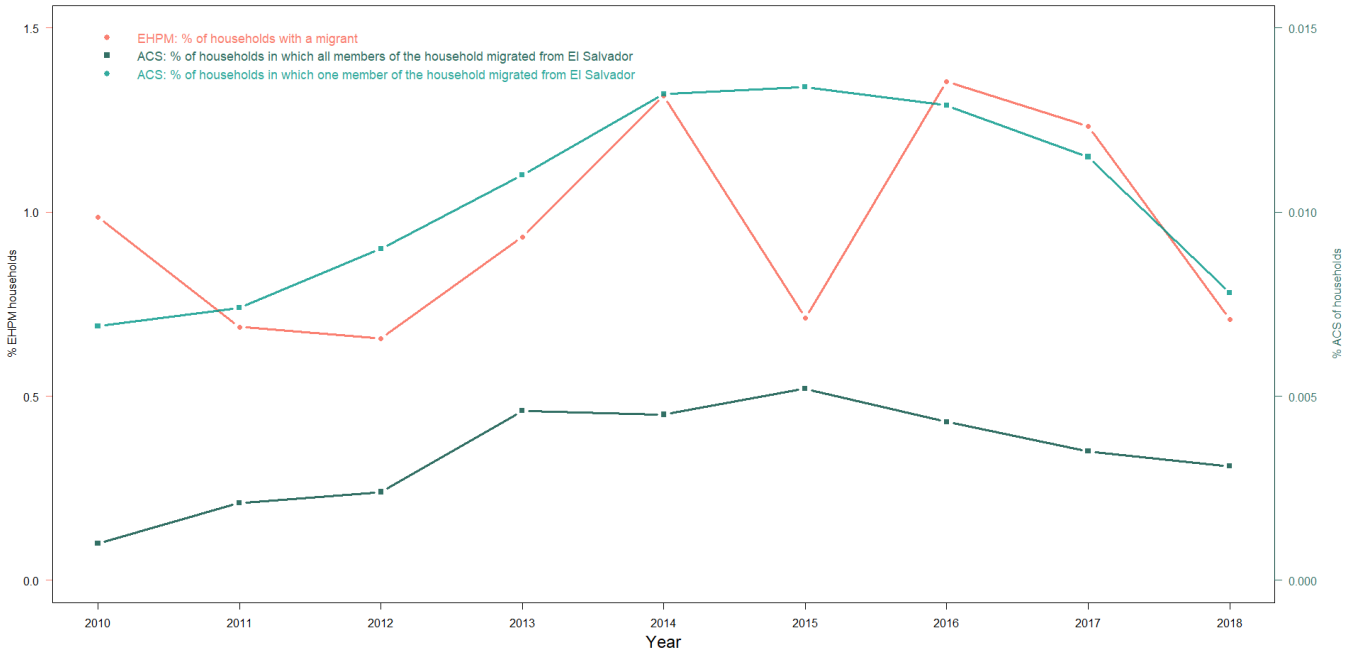
Source: World Bank (2022). Data from Climatic Research Unit (CRU) of the University of East Anglia.

Figure 4: Correlation between Temperature and Rainfall



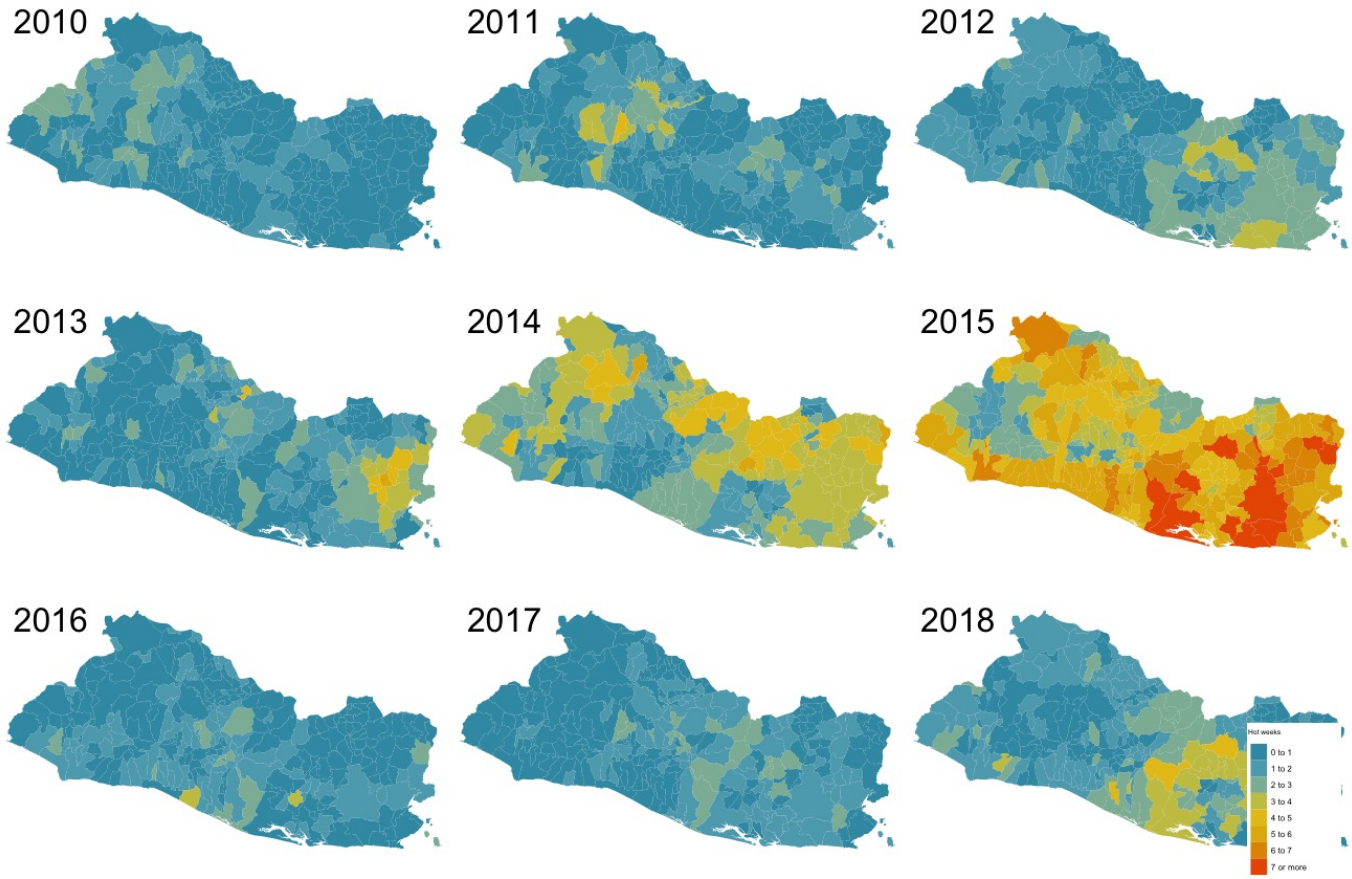
Source: NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks – Climate Data Record (PERSIANN-CDR).

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).

8 Tables

Table 1: Impact of Temperature Shocks on Corn Agricultural Outcomes in First-Harvest Season

Agricultural Outcome	(1)	(2)
A: Log(Total Production)		
Temperature shock t	-0.028	-0.032
	(0.014)**	(0.014)**
Temperature shock t-1 to t-4		-0.011
		(0.035)
Obs	19,261	19,261
R2	0.237	0.238
Mean	1.917	1.917
B: Log(Production per Ha.)		
Temperature shock t	-0.054	-0.058
	(0.015)***	(0.016)***
Temperature shock t-1 to t-4		-0.076
		(0.036)**
Obs	19,261	19,261
R2	0.270	0.271
Mean	2.342	2.342
C: Log(Production per Ha. cultivated in corn)		
Temperature shock t	-0.046	-0.050
	(0.009)***	(0.010)***
Temperature shock t-1 to t-4		-0.052
		(0.029)*
Obs	18,618	18,618
R2	0.450	0.453
Mean	2.784	2.784
F: Log(TFP production)		
Temperature shock t	-0.036	-0.039
	(0.011)***	(0.012)***
Temperature shock t-1 to t-4		-0.020
		(0.033)
Obs	16,438	16,438
R2	0.290	0.291
Mean	0.000	0.000
D: Log(Labor productivity)		
Temperature shock t	-0.009	-0.012
	(0.014)	(0.014)
Temperature shock t-1 to t-4		0.030
		(0.072)
Obs	18,784	18,784
R2	0.173	0.173
Mean	0.447	0.447
Year + Municipality FE	X	X
Rainfall Shock	X	X
Drought Shock	X	X
Crime Shock year t-1	X	X
Municipal characteristics*Year	X	X
Household characteristics	X	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 Total Factor Productivity (TFP) calculated using area cultivated in corn, total of workers, and use of inputs and assets for production; and in panel E, it is the logarithm of the total production per worker in the first harvest. The independent variables are the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. Municipality controls are the number of weeks with a rainfall and drought (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. We also control the number of weeks with a crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Household controls are household head education, number of household members, and access to irrigation for corn. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

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

	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
Year + Municipality FE	X	X	X	X	X	X	X
Rainfall Shock year t-1	X	X	X	X	X	X	X
Drought Shock year t-1	X	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X	X
Household characteristics	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 same year). Municipality controls are the number of weeks with a rainfall, drought and crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Household controls are household head education, number of household members, and access to irrigation for corn. 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	Non Household Workers	Household Workers
	(1)	(2)	(3)
Temperature Shock t	-0.018^{*}	-0.029^{***}	0.015
	(0.011)	(0.011)	(0.015)
Mean workers	5.4	3.7	1.71
Year + Municipality FE	X	X	X
Rainfall Shock year t	X	X	X
Drought Shock year t	X	X	X
Crime Shock year t-1	X	X	X
Municipal characteristics*Year	X	X	X
Household characteristics	X	X	X
Observations	18,845	18,845	18,845
R^2	0.103	0.113	0.231

Data from 2013–2018 of El Salvador'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 the number of weeks with a rainfall, drought and crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Household controls are household head education, number of household members, and access to irrigation for corn. 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 Local Labor Markets

	Agricultural		Agricultural (seasonal)		Agricultural (corn)		Non agro		Unemployed	
Panel A:										
Employment & Unemployment Rate										
Temperature Shock t	-0.003	-0.003	-0.002	-0.002	-0.003	-0.003	0.001	0.000	0.002	0.002
	(0.001)**	(0.001)**	(0.001)	(0.001)	(0.001)**	(0.001)**	(0.000)	(0.000)	(0.001)	(0.001)
Temperature Shock t-1 to t-4		0.001		-0.006		-0.006		0.003		-0.004
		(0.005)		(0.005)		(0.004)		(0.006)		(0.007)
Obs	1,793	1,793	1,793	1,793	1,793	1,793	1,793	1,793	1,793	1,793
Mean	0.181	0.181	0.109	0.109	0.107	0.107	0.337	0.337	0.482	0.482
Panel B:										
Log (average wage)										
Temperature Shock t	-0.027	-0.026	-0.004	-0.005	-0.020	-0.020	0.000	0.000		
	(0.015)*	(0.015)*	(0.024)	(0.023)	(0.026)	(0.025)	(0.001)	(0.001)		
Temperature Shock t-1 to t-4		0.042		0.103		0.069		0.001		
		(0.056)		(0.059)*		(0.068)		(0.002)		
Obs	1,511	1,511	1,324	1,324	1,255	1,255	1,793	1,793		
Mean	0.011	0.011	0.005	0.005	0.004	0.004	0.055	0.055		
Year + Municipality FE	X	X	X	X	X	X	X	X	X	X
Rainfall Shock	X	X	X	X	X	X	X	X	X	X
Drought Shock	X	X	X	X	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X	X	X	X	X

Notes: Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. The dependent variable in Panel A is the share of workers in the corresponding sector according to the working-age population for each municipality and year. The dependent variable in Panel B is the logarithm of the average wage in the corresponding sector for each municipality and year. The independent variables are the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. Municipality controls are the number of weeks with a rainfall and drought (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. We also control the number of weeks with a crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. 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 Individual Probability of Employment

	Employed		Agricultural		Agricultural (seasonal)		Agricultural (corn)		Non agro	
Temperature shock t	0.000	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	0.002	0.002
	(0.001)	(0.001)*	(0.001)	(0.001)	(0.001)*	(0.001)*	(0.001)*	(0.001)**	(0.001)	(0.001)
Temperature shock t-1 to t-4		0.002		0.006		0.005		0.004		-0.006
		(0.002)		(0.003)**		(0.004)		(0.003)		(0.003)**
Obs	658,348	518,012	330,081	261,042	330,081	261,042	330,081	261,042	330,081	261,042
Mean	0.501	0.504	0.242	0.236	0.156	0.154	0.140	0.139	0.758	0.764
Year + Municipality FE	X	X	X	X	X	X	X	X	X	X
Rainfall Shock	X	X	X	X	X	X	X	X	X	X
Drought Shock	X	X	X	X	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X	X	X	X	X
Household characteristics	X	X	X	X	X	X	X	X	X	X

Notes: Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. The dependent variable in the first two columns is a dummy if the person is employed. In the remaining columns, the dependent variable is a dummy if the person is employed in each sector. Controls are the same as in Table 4. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table 6: Impact of Temperature Shocks in First-Harvest Season on Individual Labor Outcomes

	All workers		Workers in Agro		Workers in Agro (seasonal)		Workers in Agro (Corn)		Workers in Non-Agro	
Panel A:										
Log (Hours)										
Temperature Shock t	0.002	0.002	0.006	0.005	0.004	0.006	0.003	0.006	0.000	0.001
	(0.002)	(0.003)	(0.003)**	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
Temperature Shock t-1 to t-4		-0.006		0.003		0.008		0.007		-0.007
		(0.006)		(0.012)		(0.016)		(0.016)		(0.006)
Obs	330,081	261,042	79,732	61,548	51,330	40,256	46,185	36,181	250,349	199,494
Mean	40.721	40.716	34.737	34.564	32.488	32.315	31.960	31.738	42.627	42.614
Panel B:										
Log (Hourly wage (SCP))										
Temperature Shock t	0.002	0.001	0.002	-0.005	0.001	-0.002	-0.008	-0.012	0.000	0.000
	(0.004)	(0.003)	(0.009)	(0.007)	(0.008)	(0.006)	(0.008)	(0.008)	(0.002)	(0.002)
Temperature Shock t-1 to t-4		-0.002		0.008		0.016		0.019		0.000
		(0.005)		(0.019)		(0.033)		(0.029)		(0.005)
Obs	266,489	211,685	34,405	26,774	19,333	15,273	15,133	11,898	232,084	184,911
Mean	0.161	0.162	0.145	0.146	0.156	0.157	0.159	0.161	0.164	0.164
Year + Municipality FE	X	X	X	X	X	X	X	X	X	X
Rainfall Shock	X	X	X	X	X	X	X	X	X	X
Drought Shock	X	X	X	X	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X	X	X	X	X
Household characteristics	X	X	X	X	X	X	X	X	X	X

Notes: Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. The dependent variable in Panel A is the logarithm of the number of hours worked. The dependent variable in Panel B is the logarithm of the hourly wage. Controls are the same as in Table 4. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table 7: Impact of Temperature Shocks in First-Harvest Season on Migration Likelihood

Population Group	(1)	(2)
A: All Households		
Temperature shock t-1	0.049	0.034
	(0.065)	(0.068)
Temperature shock t-2 to t-5		0.048
		(0.147)
Obs	186,910	130,689
R2	0.006	0.007
Mean	0.876	0.940
B: Agricultural Households (all)		
Temperature shock t-1	0.083	0.129
	(0.089)	(0.085)
Temperature shock t-2 to t-5		0.020
		(0.242)
Obs	22,268	14,277
R2	0.006	0.003
Mean	0.799	0.805
C: Agricultural Households (seasonal)		
Temperature shock t-1	0.223	0.264
	(0.108)**	(0.109)**
Temperature shock t-2 to t-5		-0.087
		(0.294)
Obs	14,334	9,370
R2	0.003	-0.001
Mean	0.656	0.726
D: Agricultural Households (corn)		
Temperature shock t-1	0.245	0.273
	(0.124)**	(0.119)**
Temperature shock t-2 to t-5		-0.248
		(0.329)
Obs	12,659	8,251
R2	0.001	-0.003
Mean	0.695	0.788
E: Non Agricultural Households		
Temperature shock t-1	0.014	-0.009
	(0.047)	(0.053)
Temperature shock t-2 to t-5		0.091
		(0.104)
Obs	110,747	78,533
R2	0.004	0.005
Mean	0.654	0.695
Year + Municipality FE	X	X
Rainfall Shock	X	X
Drought Shock	X	X
Crime Shock year t-1	X	X
Municipal characteristics*Year	X	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 variables are the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. Panel A. All households. Panel B. A household is defined as agricultural when the household head and at least 50 percent of the members of working age are employed in agriculture. Panel C. A household is defined as agricultural (seasonal) if it is an agricultural household and at least 50 percent of the members of working age are employed producing seasonal crops. Panel D. A household is defined as agricultural (corn) if it is an agricultural household and at least 50 percent of the members of working age are employed producing corn. Panel E. A household is defined as nonagricultural when the household head or at least 50 percent of the members of working age are employed in the nonagricultural sector. Municipality controls are the number of weeks with a rainfall and drought (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. We also control the number of weeks with a crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Household controls are age and gender of the household head, and number of household members. Standard errors are clustered by municipality and year.
*p<0.1; **p<0.05; ***p<0.01

Table 8

	Access to credit		Migration		Remittances	
Population Group	Below	Above	Below	Above	Below	Above
Panel A: Log(Total Production)						
Temperature shock t	-0.074	-0.093	-0.091	-0.091	-0.084	-0.102
	(0.015)***	(0.012)***	(0.011)***	(0.013)***	(0.005)***	(0.028)***
Obs	6,023	12,513	11,038	7,729	12,604	6,163
R2	0.188	0.180	0.144	0.244	0.166	0.239
Mean	1.616	2.054	1.760	2.142	1.818	2.121
Panel B: Share of workers in agricultural sector (corn)						
Temperature shock t	-0.002	-0.006	-0.007	-0.003	-0.006	-0.004
	(0.001)	(0.001)***	(0.003)**	(0.001)***	(0.001)***	(0.001)**
Obs	853	864	894	899	886	907
R2	0.796	0.745	0.750	0.737	0.790	0.723
Mean	0.144	0.220	0.131	0.233	0.140	0.223
Panel C: Migration Likelihood in Agricultural HH (corn)						
Temperature shock t-1	0.289	0.242	0.178	0.272	0.175	0.305
	(0.316)	(0.093)**	(0.068)**	(0.150)*	(0.059)**	(0.151)**
Obs	3,842	8,742	4,597	8,062	5,476	7,183
R2	0.000	0.004	-0.009	0.005	-0.003	0.004
Mean	0.521	0.778	0.305	0.918	0.365	0.947
Year + Municipality FE	X	X	X	X	X	X
Rainfall Shock	X	X	X	X	X	X
Drought Shock	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X
Household characteristics	X	X	X	X	X	X

Notes: Estimations in panel A use 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. Panel B uses individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. The dependent variable in panel B is the share of workers employed producing corn according to the total number of workers for each municipality and year. Panel C uses data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable in panel C is 100 if a household member migrated in the surveyed year. The sample is constrained to agricultural households (corn). A household is defined as agricultural (corn) if the household head and at least 50 percent of the members of working age are employed in agriculture and employed producing corn. "Access to credit" presents the results for households living in municipalities that had a share of the population with access to credit below and above the median in 2009. "Migration" presents the results for households living in municipalities with a share of migrants above or below the median in 2007. "Remittances" presents the results for households living in municipalities that had a share of the population with remittances above or below the median in 2007. 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 the number of weeks with a rainfall and drought (two SD higher than that week's historic value in that municipality during the winter season the same year). We also control the number of weeks with a crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Household controls in panel A are household head education, number of household members, and access to irrigation for corn. Household controls in panel C are age and gender of the household head, and number of household members. Since the estimations in Panel B are at municipality level, we do not include household controls. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table 9: Impact of Temperature Shocks on Migration Likelihood - Different Shocks

	Preferred specification	Changing the months of the shocks			Changing the range of years	
Population Group	Winter Shock (2009-2018)	All-year Shock	Apante Shock	Lean Shock	2013-2018	Excluding 2015
Panel A						
All Households	0.049	0.030	0.020	-0.042	0.059	0.065
	(0.065)	(0.031)	(0.060)	(0.061)	(0.085)	(0.077)
Obs	186,910	186,910	186,910	186,910	117,415	165,166
R2	0.006	0.006	0.006	0.006	0.006	0.007
Panel B						
Agricultural Households	0.083	-0.002	-0.231	-0.129	0.199	0.099
	(0.089)	(0.040)	(0.122)*	(0.080)	(0.080)**	(0.094)
Obs	22,268	22,268	22,268	22,268	12,043	19,702
R2	0.006	0.006	0.007	0.006	0.000	0.007
Panel C						
Agricultural Households (seasonal)	0.223	0.051	-0.158	-0.108	0.293	0.272
	(0.108)**	(0.036)	(0.186)	(0.079)	(0.126)**	(0.109)**
Obs	14,334	14,334	14,334	14,334	7,903	12,646
R2	0.003	0.002	0.002	0.002	-0.004	0.003
Panel D						
Agricultural Households (corn)	0.245	0.045	-0.177	-0.118	0.315	0.305
	(0.124)**	(0.040)	(0.222)	(0.095)	(0.137)**	(0.126)**
Obs	12,659	12,659	12,659	12,659	6,946	11,156
R2	0.001	0.001	0.000	0.001	-0.005	0.002
Panel E						
Non Agricultural Households	0.014	0.015	0.034	-0.017	-0.003	0.043
	(0.047)	(0.020)	(0.056)	(0.062)	(0.065)	(0.049)
Obs	110,747	110,747	110,747	110,747	69,646	97,560
R2	0.004	0.004	0.004	0.004	0.004	0.005
Year + Municipality FE	X	X	X	X	X	X
Rainfall Shock year t-1	X	X	X	X	X	X
Drought Shock year t-1	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X
Household characteristics	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 2013–2018. Column (6) comprises 2009–2018, excluding 2015. Panel A. All households. Panel B. A household is defined as agricultural when the household head and at least 50 percent of the members of working age are employed in agriculture. Panel C. A household is defined as agricultural (seasonal) if it is an agricultural household and at least 50 percent of the members of working age are employed producing seasonal crops. Panel D. A household is defined as agricultural (corn) if it is an agricultural household and at least 50 percent of the members of working age are employed producing corn. Panel E. A household is defined as nonagricultural when the household head or at least 50 percent of the members of working age are employed in the nonagricultural sector. Municipality controls are the crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season the previous year). Municipal characteristics 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. Household controls are age and gender of the household head, and number of household members. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

9 Appendix

Figure A1: Timeline of Data

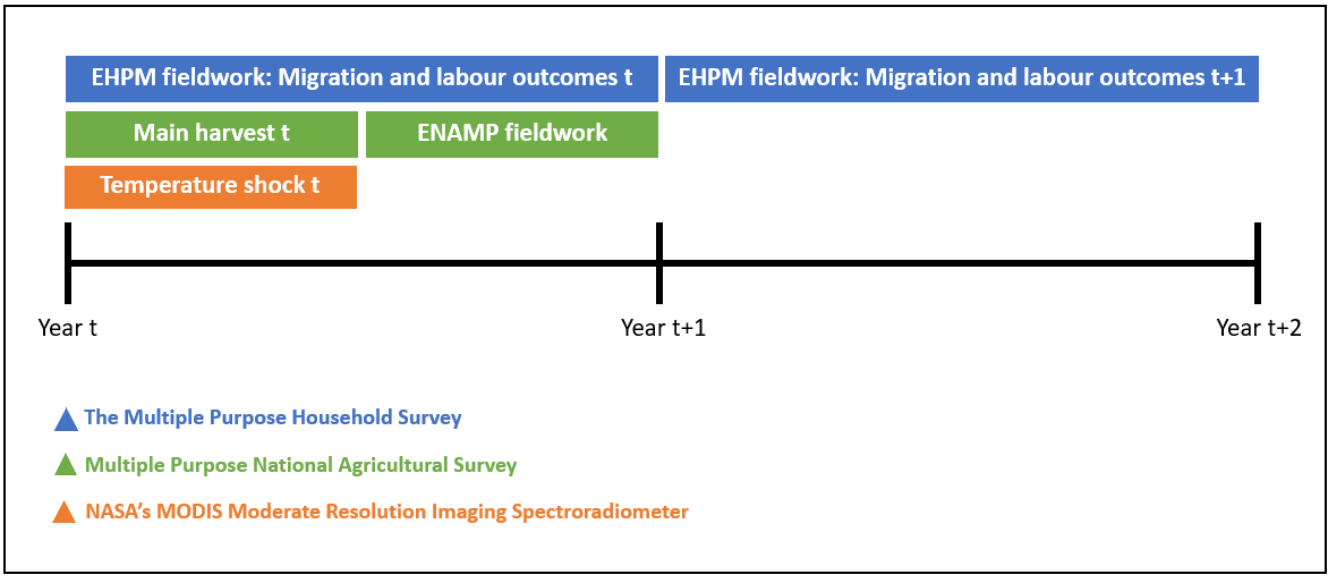
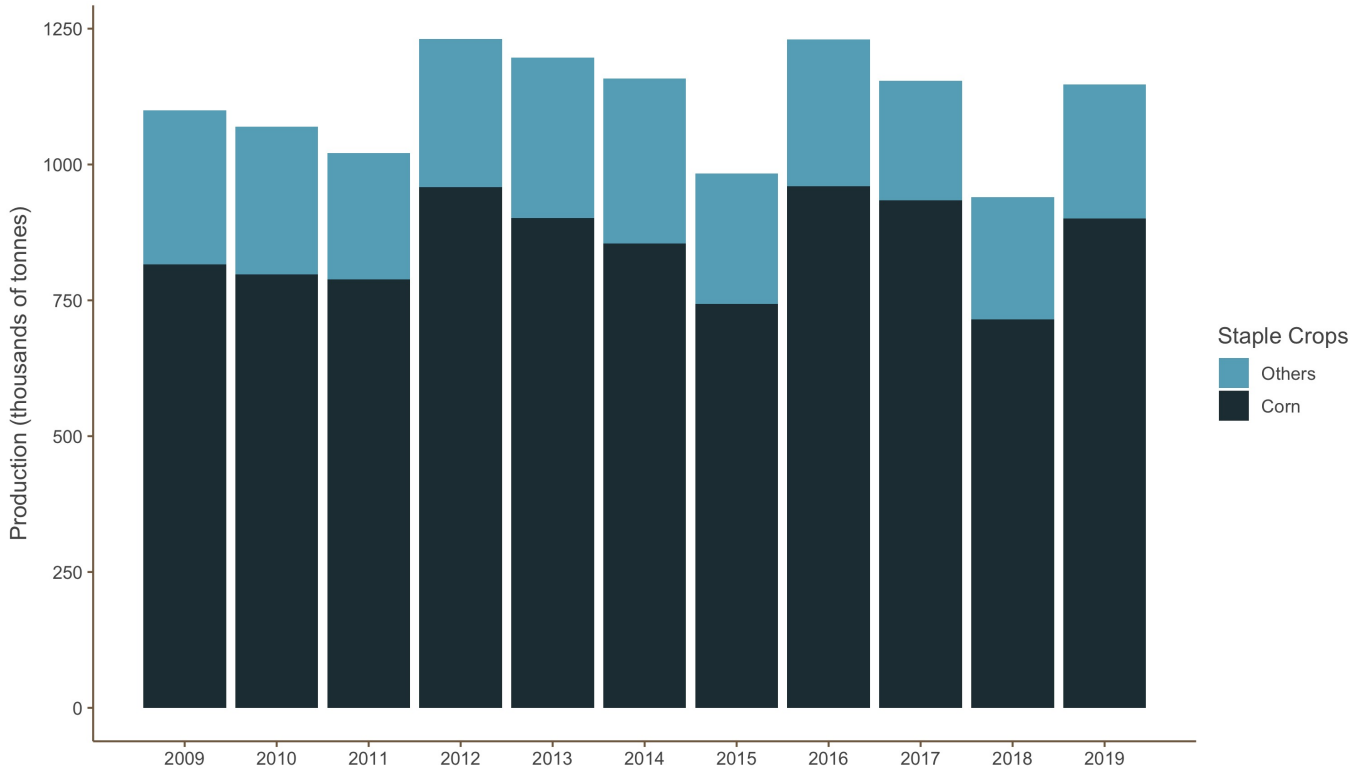
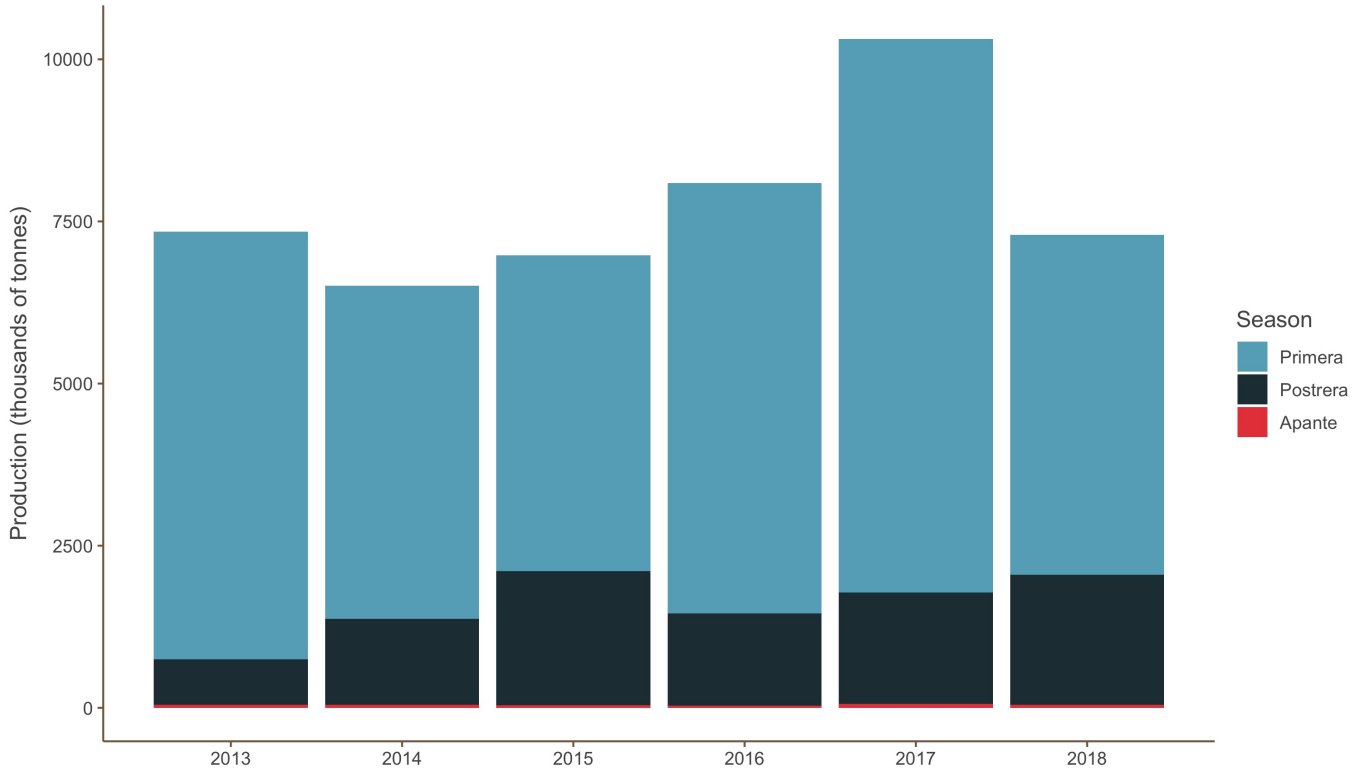


Figure A2: Production of Corn versus Other Staple Crops in El Salvador



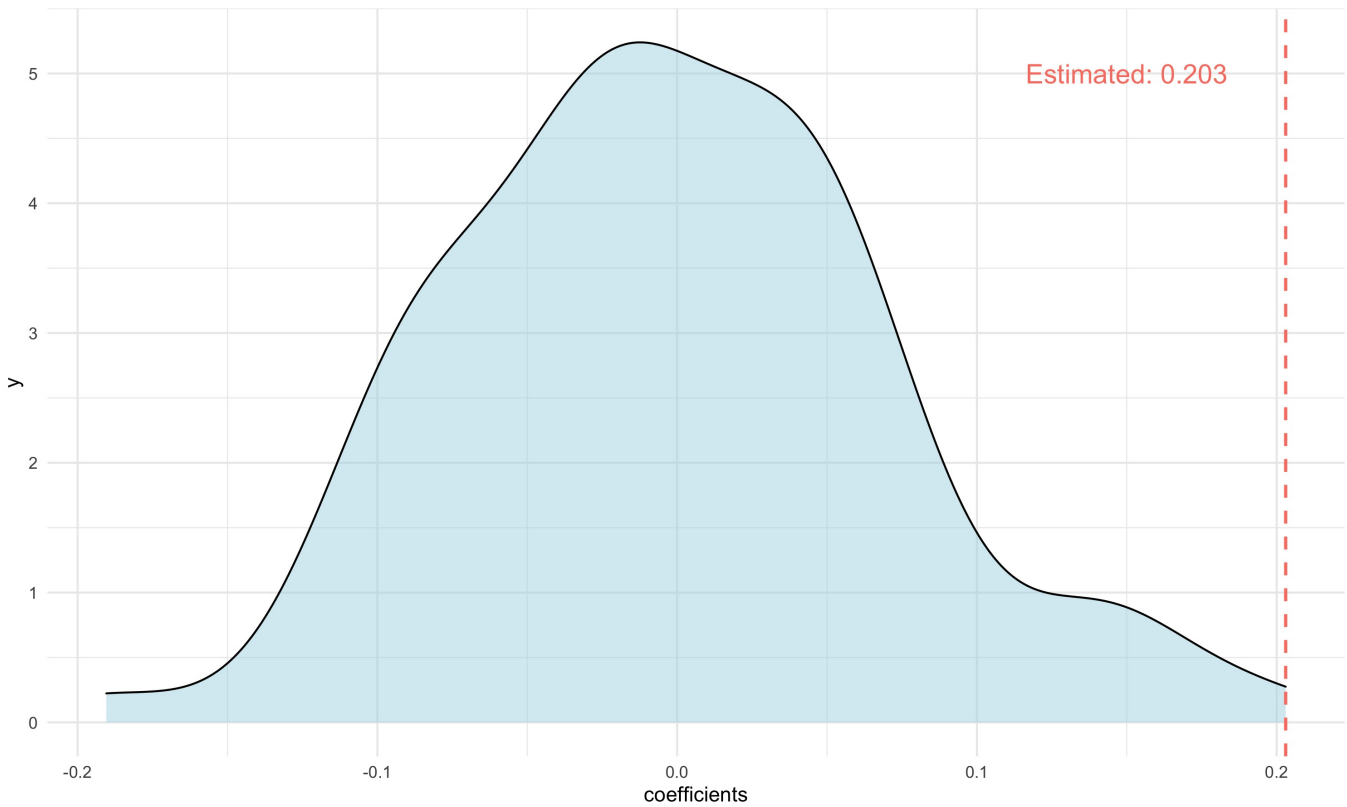
Source: FAOSTAT. Staple crops include corn (maize), rice, sorghum, and beans.

Figure A3: Corn Production across Yearly Seasons in El Salvador



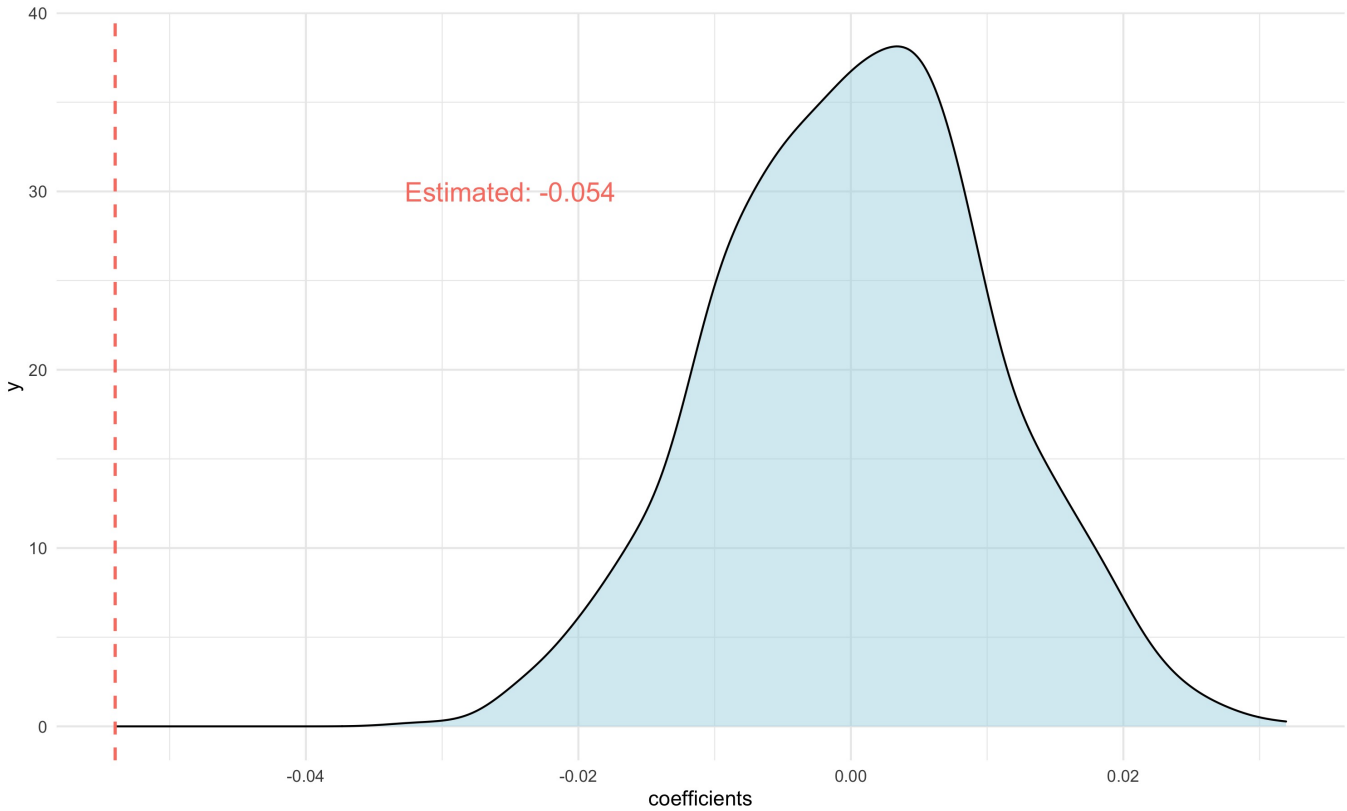
Source: ENAMP 2013–2018.

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 Corn Agricultural Outcomes in First-Harvest Season

Agricultural Outcome	(1)	(2)	(3)	(4)	(5)	(6)	Mean	Obs
A: Log(Total Production)								
Temperature shock year t	-0.060	-0.026	-0.027	-0.028	-0.027	-0.028	1.917	19,261
	(0.025)**	(0.013)**	(0.013)**	(0.013)**	(0.012)**	(0.013)**		
R2	0.012	0.223	0.223	0.223	0.226	0.239		
B: Log(Production per Ha.)								
Temperature shock year t	-0.105	-0.055	-0.055	-0.055	-0.055	-0.054	2.342	19,261
	(0.034)**	(0.018)**	(0.019)**	(0.019)**	(0.016)***	(0.016)***		
R2	0.033	0.265	0.265	0.266	0.267	0.273		
C: Log(Production per Ha. cultivated in corn)								
Temperature shock year t	-0.098	-0.053	-0.049	-0.049	-0.047	-0.047	2.784	18,618
	(0.027)***	(0.012)***	(0.013)***	(0.013)***	(0.010)***	(0.010)***		
R2	0.065	0.450	0.451	0.451	0.455	0.456		
D: Log(TFP production)								
Temperature shock year t	-0.082	-0.036	-0.039	-0.039	-0.036	-0.036	0.000	16,438
	(0.024)***	(0.012)**	(0.013)**	(0.012)**	(0.011)***	(0.011)***		
R2	0.031	0.283	0.284	0.284	0.287	0.292		
E: Log(Labor productivity)								
Temperature shock year t	-0.051	-0.003	-0.012	-0.014	-0.010	-0.010	0.447	18,784
	(0.025)**	(0.016)	(0.018)	(0.017)	(0.014)	(0.014)		
R2	0.008	0.170	0.172	0.172	0.175	0.175		
Year + Municipality FE		X	X	X	X	X		
Rainfall Shock year t-1			X	X	X	X		
Drought Shock year t-1			X	X	X	X		
Crime Shock year t-1				X	X	X		
Municipal characteristics*Year					X	X		
Household characteristics						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 Total Factor Productivity (TFP) calculated using area cultivated in corn, total of workers, and use of inputs and assets for production; and in panel E, it is the logarithm of the total production per worker in the first harvest. 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 the number of weeks with a rainfall, drought and crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Household controls are household head education, number of household members, and access to irrigation for corn. Standard errors are clustered by municipality and year. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A4: Impact of Temperature Shocks in First-Harvest Season on Local Labor Outcomes

	Manufacture		Construction		Finances		Services		Other non agro sector	
Panel A:										
Employment Rate										
Temperature Shock t	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature Shock t-1 to t-4		0.001		0.006		-0.001		-0.007		0.003
		(0.002)		(0.005)		(0.001)		(0.004)*		(0.003)
Obs	1,793	1,793	1,793	1,793	1,793	1,793	1,793	1,793	1,793	1,793
Mean	0.038	0.038	0.177	0.177	0.002	0.002	0.064	0.064	0.062	0.062
Panel B:										
Log (Average Wage)										
Temperature Shock t	0.009	0.007	-0.008	-0.010	0.018	0.008	-0.003	-0.004	-0.017	-0.018
	(0.018)	(0.020)	(0.021)	(0.021)	(0.030)	(0.030)	(0.012)	(0.012)	(0.015)	(0.015)
Temperature Shock t-1 to t-4		-0.104		0.009		-0.088		0.063		0.084
		(0.066)		(0.047)		(0.077)		(0.043)		(0.060)
Obs	1,651	1,651	1,575	1,575	637	637	1,781	1,781	1,704	1,704
Mean	0.009	0.009	0.006	0.006	0.000	0.000	0.033	0.033	0.007	0.007
Year + Municipality FE	X	X	X	X	X	X	X	X	X	X
Rainfall Shock	X	X	X	X	X	X	X	X	X	X
Drought Shock	X	X	X	X	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X	X	X	X	X

Notes: Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. The dependent variable in Panel A is the share of workers in the corresponding sector according to the total number of workers for each municipality and year. The dependent variable in Panel B is the logarithm of the average wage in the corresponding sector for each municipality and year. The independent variables are the number of weeks with a temperature shock (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. Municipality controls are the number of weeks with a rainfall and drought (two SD higher than that week's historic value in that municipality during the winter season) in the same year and the previous two to five years. We also control the number of weeks with a crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Standard errors are clustered by municipality and year. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A5: Impact of Temperature Shocks in First-Harvest Season on Labor Outcomes

	All workers	Workers in Agro	Workers in Agro (seasonal)	Workers in Agro (Corn)	Workers in Non-Agro
Panel A: Hours(log)					
Women					
Temperature Shock t	0.004	0.014	0.010	0.009	0.001
	(0.004)	(0.008)*	(0.016)	(0.024)	(0.004)
Obs	131,074	7,336	3,033	2,347	123,738
Mean	40.042	31.483	27.483	26.102	40.549
Men					
Temperature Shock t	0.001	0.004	0.003	0.003	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Obs	199,007	72,396	48,297	43,838	126,611
Mean	41.168	35.067	32.803	32.274	44.657
Panel B: Hourly wage (log(SCP))					
Women					
Temperature Shock t	-0.002	-0.004	-0.019	0.078	-0.002
	(0.003)	(0.007)	(0.026)	(0.024)**	(0.003)
Obs	114,785	3,249	880	387	111,536
Mean	0.182	0.138	0.158	0.154	0.184
Men					
Temperature Shock t	0.005	0.001	0.001	-0.009	0.003
	(0.005)	(0.009)	(0.007)	(0.007)	(0.002)
Obs	151,704	31,156	18,453	14,746	120,548
Mean	0.146	0.145	0.156	0.159	0.146
Year + Municipality FE	X	X	X	X	X
Rainfall Shock year t-1	X	X	X	X	X
Drought Shock year t-1	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X
Household characteristics	X	X	X	X	X

Notes: Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. The dependent variable in Panel A is the logarithm of the number of hours worked. The dependent variable in Panel B is the logarithm of the hourly wage. Within each panel, we divide the sample by gender. Same controls as in Table 5. 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 Labor Outcomes

	All workers	Workers in Agro	Workers in Agro (seasonal)	Workers in Agro (Corn)	Workers in Non-Agro
Panel A: Hours(log)					
Less than 14 years old					
Temperature Shock t	0.022	0.047	0.034	0.048	-0.011
	(0.013)	(0.014)***	(0.021)	(0.013)***	(0.023)
Obs	6,969	3,751	2,479	3,825	3,218
Mean	22.107	22.497	21.415	22.528	21.652
Between 14 and 18 years old					
Temperature Shock t	0.014	0.013	0.010	0.014	0.017
	(0.010)	(0.011)	(0.011)	(0.010)	(0.015)
Obs	19,174	9,756	6,631	10,025	9,418
Mean	30.411	29.101	27.595	29.200	31.769
Between 18 and 65 years old					
Temperature Shock t	0.001	0.002	0.000	0.001	0.000
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Obs	299,516	64,471	41,157	67,213	235,045
Mean	41.844	36.286	33.910	36.385	43.369
More than 65 years old					
Temperature Shock t	0.011	0.003	0.009	0.006	0.009
	(0.017)	(0.020)	(0.033)	(0.020)	(0.020)
Obs	4,422	1,754	1,063	1,782	2,668
Mean	38.682	35.324	33.788	35.322	40.889
Panel B: Hourly wage (log(SCP))					
Less than 14 years old					
Temperature Shock t	0.005	-0.043	-0.025	-0.029	0.041
	(0.049)	(0.068)	(0.105)	(0.066)	(0.055)
Obs	1,105	440	224	469	665
Mean	0.213	0.204	0.229	0.210	0.218
Between 14 and 18 years old					
Temperature Shock t	-0.001	0.001	0.000	0.002	-0.005
	(0.012)	(0.017)	(0.020)	(0.016)	(0.015)
Obs	8,363	3,160	1,885	3,336	5,203
Mean	0.172	0.169	0.181	0.170	0.174
Between 18 and 65 years old					
Temperature Shock t	0.002	0.003	0.004	0.004	0.000
	(0.003)	(0.008)	(0.007)	(0.008)	(0.002)
Obs	254,042	30,359	17,006	32,905	223,683
Mean	0.161	0.142	0.152	0.144	0.163
More than 65 years old					
Temperature Shock t	-0.015	0.007	-0.052	-0.006	-0.022
	(0.015)	(0.052)	(0.123)	(0.052)	(0.016)
Obs	2,979	446	218	473	2,533
Mean	0.181	0.130	0.138	0.134	0.189
Year + Municipality FE	X	X	X	X	X
Rainfall Shock year t-1	X	X	X	X	X
Drought Shock year t-1	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X
Household characteristics	X	X	X	X	X

Notes: Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. The dependent variable in Panel A is the logarithm of the number of hours worked. The dependent variable in Panel B is the logarithm of the hourly wage. Within each panel, we divide the sample by age group. Same controls as in Table 5. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A7: Impact of Temperature Shocks in First-Harvest Season on Migration Likelihood

Population Group	(1)	(2)	(3)	(4)	(5)	(6)	Mean	Obs
A: All Households								
Temperature shock year t-1	0.107	0.058	0.044	0.037	0.046	0.049	0.876	186,910
	(0.050)**	(0.072)	(0.062)	(0.058)	(0.061)	(0.065)		
R2	0.000	0.005	0.005	0.005	0.005	0.006		
B: Agricultural Households (all)								
Temperature shock year t-1	0.100	0.049	0.044	0.041	0.073	0.083	0.799	22,268
	(0.043)**	(0.081)	(0.085)	(0.086)	(0.084)	(0.089)		
R2	0.000	0.001	0.001	0.001	0.002	0.006		
C: Agricultural Households (seasonal)								
Temperature shock year t-1	0.177	0.209	0.201	0.198	0.216	0.223	0.656	14,334
	(0.041)***	(0.096)**	(0.107)*	(0.108)*	(0.105)**	(0.108)**		
R2	0.001	-0.001	-0.001	-0.001	-0.001	0.003		
D: Agricultural Households (corn)								
Temperature shock year t-1	0.193	0.221	0.218	0.216	0.237	0.245	0.695	12,659
	(0.054)***	(0.110)**	(0.124)*	(0.124)*	(0.121)*	(0.124)**		
R2	0.001	-0.002	-0.002	-0.002	-0.002	0.001		
E: Non Agricultural Households								
Temperature shock year t-1	0.084	0.030	0.012	0.009	0.012	0.014	0.654	110,747
	(0.035)**	(0.054)	(0.045)	(0.043)	(0.045)	(0.047)		
R2	0.000	0.004	0.004	0.004	0.004	0.004		
Year + Municipality FE		X	X	X	X	X		
Rainfall Shock year t-1			X	X	X	X		
Drought Shock year t-1			X	X	X	X		
Crime Shock year t-1				X	X	X		
Municipal characteristics*Year					X	X		
Household characteristics						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 when the household head and at least 50 percent of the members of working age are employed in agriculture. Panel C. A household is defined as agricultural (seasonal) if it is an agricultural household and at least 50 percent of the members of working age are employed producing seasonal crops. Panel D. A household is defined as agricultural (corn) if it is an agricultural household and at least 50 percent of the members of working age are employed producing corn. Panel E. A household is defined as nonagricultural when the household head or at least 50 percent of the members of working age are employed in the nonagricultural sector. Municipality controls are the crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season the previous year).Municipal characteristics 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. Household controls are age and gender of the household head, and number of household members. 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 Heterogeneity by Working-Age Household Member Characteristics

	Method 1: Preferred specification	Method 2: HH works in the agricultural sector		Method 3: At least 50 % of working-age members work in the agricultural sector		Method 4: At least one working-age member works in the agricultural sector	
Population Group		No	Yes	No	Yes	No	Yes
A:Agricultural Households (seasonal)							
Temperature shock year t-1	0.223	-0.001	0.201	0.076	0.158	0.073	0.145
	(0.096)**	(0.045)	(0.090)**	(0.066)	(0.112)	(0.061)	(0.108)
Obs	14,334	116,618	24,232	141,966	20,541	131,717	30,790
R2	0.003	0.004	0.008	0.008	0.003	0.008	0.006
Mean	0.656	0.66	0.801	0.889	0.735	0.867	0.88
Year + Municipality FE	X	X	X	X	X	X	X
Rainfall Shock year t-1	X	X	X	X	X	X	X
Drought Shock year t-1	X	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X	X
Household characteristics	X	X	X	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 1 uses the preferred specification in which the household is defined as agricultural (seasonal) if it is an agricultural household (the household head and at least 50 percent of the members of working age are employed in agriculture) and at least 50 percent of the members of working age are employed producing seasonal crops. Method 2 defines an agricultural household (seasonal) considering if the head of the household is employed producing seasonal crops. Method 3 defines an agricultural household (seasonal) only considering if at least 50 % of the working-age members are employed producing seasonal crops. Method 4 defines an agricultural household (seasonal) considering if at one working-age member is employed producing seasonal crops. 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 the crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season the previous year). Municipal characteristics 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. Household controls are age and gender of the household head, and number of household members. 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	0.062	0.033	0.040	0.131
	(0.059)	(0.053)	(0.050)	(0.045)**
R2	0.007	0.007	0.007	0.007
Panel B				
Agricultural Households	0.189	0.302	0.154	0.222
	(0.080)**	(0.098)**	(0.115)	(0.069)**
R2	0.003	0.004	0.003	0.003
Panel C				
Agricultural Households (seasonal)	0.282	0.422	0.136	0.262
	(0.098)**	(0.140)**	(0.124)	(0.091)**
R2	-0.001	0.000	-0.002	-0.001
Panel D				
Agricultural Households (corn)	0.256	0.418	0.097	0.375
	(0.092)**	(0.146)**	(0.139)	(0.104)***
R2	-0.003	-0.001	-0.003	-0.002
Panel E				
Non Agricultural Households	0.045	0.007	-0.008	0.072
	(0.037)	(0.034)	(0.040)	(0.032)**
R2	0.005	0.005	0.005	0.005
Year + Municipality FE	X	X	X	X
Rainfall Shock year t-1	X	X	X	X
Drought Shock year t-1	X	X	X	X
Crime Shock year t-1	X	X	X	X
Municipal characteristics*Year	X	X	X	X
Household characteristics	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). Panel A. All households. Panel B. A household is defined as agricultural when the household head and at least 50 percent of the members of working age are employed in agriculture. Panel C. A household is defined as agricultural (seasonal) if it is an agricultural household and at least 50 percent of the members of working age are employed producing seasonal crops. Panel D. A household is defined as agricultural (corn) if it is an agricultural household and at least 50 percent of the members of working age are employed producing corn. Panel E. A household is defined as nonagricultural when the household head or at least 50 percent of the members of working age are employed in the nonagricultural sector. Municipality controls are the crime, heavy rain, and drought shocks (two SD higher than the historic value during the winter season the previous year).Municipal characteristics 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. Household controls are age and gender of the household head, and number of household members. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A10: Impact of Temperature Shocks on Corn Agricultural Outcomes in First-Harvest Season

Agricultural Outcome	1 SD	1.5 SD	Higher 29	Higher 35	Mean	Obs
A: Log(Total Production)						
Temperature shock year t	-0.025	-0.021	-0.017	-0.024	1.917	19,261
	(0.012)**	(0.013)	(0.008)**	(0.016)		
R2	0.239	0.238	0.238	0.238		
B: Log(Production per Ha.)						
Temperature shock year t	-0.035	-0.048	-0.018	-0.028	2.342	19,261
	(0.016)**	(0.014)***	(0.014)	(0.014)*		
R2	0.272	0.272	0.271	0.270		
C: Log(Production per Ha. cultivated in corn)						
Temperature shock year t	-0.036	-0.042	-0.017	-0.030	2.342	18,618
	(0.011)**	(0.010)***	(0.011)	(0.015)**		
R2	0.455	0.455	0.452	0.452		
F: Log(TFP production)						
Temperature shock year t	-0.028	-0.031	-0.018	-0.024	2.337	16,438
	(0.013)**	(0.010)**	(0.008)**	(0.015)		
R2	0.292	0.292	0.291	0.291		
D: Log(Labor productivity)						
Temperature shock year t	-0.020	-0.008	-0.024	0.008	2.337	18,784
	(0.016)	(0.014)	(0.015)	(0.013)		
R2	0.175	0.175	0.176	0.175		
Year + Municipality FE	X	X	X	X		
Rainfall Shock year t-1	X	X	X	X		
Drought Shock year t-1	X	X	X	X		
Crime Shock year t-1	X	X	X	X		
Municipal characteristics*Year	X	X	X	X		
Household characteristics	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 the number of weeks with a rainfall, drought and crime shock (two SD higher than that week's historic value in that municipality during the winter season the same year). Municipal characteristics 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. Household controls are household head education, number of household members, and access to irrigation for corn. Standard errors are clustered by municipality and year. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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

	Agri(seasonal-rural)		Agri(seasonal-urban)		Agri(corn-rural)		Agri(corn-urban)		Nonagri(rural)		Nonagri(urban)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Temperature	0.277	0.271	0.012	0.032	0.287	0.283	0.089	0.111	0.090	0.087	-0.038	-0.041
	(0.144)*	(0.145)*	(0.117)	(0.108)	(0.159)*	(0.161)*	(0.103)	(0.102)	(0.113)	(0.110)	(0.042)	(0.042)
Crimen		0.269		-0.558		0.167		-0.492		0.094		0.194
		(0.192)		(0.279)**		(0.179)		(0.235)**		(0.178)		(0.086)**
Mean	0.778	0.778	0.338	0.338	0.824	0.824	0.341	0.341	0.876	0.876	0.565	0.565
Obs	10,535	10,535	2,072	2,072	9,349	9,349	1,762	1,762	35,261	35,261	64,638	64,638
R2	0.004	0.004	-0.045	-0.045	0.002	0.002	-0.052	-0.052	0.005	0.005	0.004	0.004
Year + Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Rainfall Shock year t-1	X	X	X	X	X	X	X	X	X	X	X	X
Drought Shock year t-1	X	X	X	X	X	X	X	X	X	X	X	X
Crime Shock year t-1	X	X	X	X	X	X	X	X	X	X	X	X
Municipal characteristics*Year	X	X	X	X	X	X	X	X	X	X	X	X
Household characteristics	X	X	X	X	X	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. 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 seasonal crops. Columns (3)–(4) include agricultural households in the urban area that produce seasonal 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