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

Ana Maria Ibáñez†
Juliana Quigua‡
Jimena Romero§
Andrea Velásquez¶

July 13, 2023

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. A response from agricultural landowners has been reducing their demand for agricultural workers and substituting household workers in their place. Contrary to findings in other settings, we do not see evidence of reallocation to the non-agricultural sector, which partly explains the positive effects found on international migration. We highlight how international migration is a critical response to temperature shocks when local labor markets cannot absorb displaced workers.

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

*We are grateful to Carolina Arteaga, Michael Clemens, Caroline Fry, Bridget Hoffman, Anna Maria Mayda, Pieter Serneels, and participants at the IDB migration seminar, CGD's Research Seminar Series, Seminario CEDE Universidad de los Andes, ASU Global Institute of Sustainability and Innovation, UC Davis Global Migration Center, UC San Diego School of Global Policy and Strategy, ASHE Research Seminar, Humans Lacea Network, UNU-WIDER, Agricultural and Applied Economic Association, Novafrica Conference on Economic Development, BSE Summer Forum, Simposio sobre cadenas agroalimentarias y cambio climático (Banco de la República y Alianza Bioversity-CIAT), and the First IZA Workshop: Climate Change and Labor Markets, for useful comments and suggestions. All errors are our own.

†Universidad de los Andes and Interamerican Development Bank, email: anaib@iadb.org
‡Interamerican Development Bank, email: julianaqu@iadb.org
§Stockholm University, email: jimena.romero-pinto@su.se
¶University of Colorado Denver, email: andrea.velasquez@ucdenver.edu

1 Introduction

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

The effects of extreme temperatures can be particularly large in regions with rain-fed agriculture and for small agricultural producers in developing countries, who seldom have access to mechanisms that manage risk. 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; Carter and Lybbert, 2012; Hornbeck, 2012; Jessoe et al., 2016; Aragón et al., 2021).

Our paper adds to this literature by measuring the effects of extreme temperatures on agricultural production and by examining the complex ways in which farmers in El Salvador

[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 and Roberts (2009), Schlenker and Lobell (2010), Feng et al. (2010), Dell et al. (2014), Burke and Emerick (2016), Aragón et al. (2021), Colmer (2021), Ortiz-Bobea et al. (2021), and Albert and Bustos (2022); and (ii) use other proxies, including rainfall, for weather shocks: Deschênes and Greenstone (2007), Feng et al. (2010), Schlenker and Lobell (2010), Hornbeck (2012), Hornbeck and Naidu (2014), and Ortiz-Bobea et al. (2019).

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

respond to these shocks. Our results suggest agricultural landowners respond to the shock by lowering their demand for agricultural workers and substituting household members—particularly women and young children—for them. It is plausible that agricultural workers with no access to land might transfer to other sectors. Yet, we find no evidence of labor reallocation to the non-agricultural sector. Without access to risk-management mechanisms and in a setting where the non-agricultural sector cannot absorb displaced farm workers, international migration becomes a key strategy to respond to the costs imposed by these weather shocks. Our results support this hypothesis. We find a significant increase in international migration—mostly to the United States— in response to extreme temperature events in El Salvador. Moreover, we show that the adjustment through labor markets differs by access to 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 substituting household workers who thus increase their hours of farm work (Jayachandran, 2006; Bastos et al., 2013; Jessoe et al., 2016; Aragón et al., 2021). Agricultural workers who lose their jobs may move to the non-agricultural sector or migrate to offset income losses. 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 labor markets are not fully integrated and/or the non-agricultural sector cannot absorb new workers, migration might be more prevalent (Colmer, 2021). We also test whether landownership and access to mechanisms such as credits and remittances lessen distress migration or, on the contrary, facilitate migration by lowering its costs (Massey et al., 1990; Munshi, 2003; Hunter et al., 2013; Nawrotzki, 2015; Mahajan and Yang, 2020; Clemens, 2021).

The setting of El Salvador offers several advantages for this research. First, a large percentage of the population still earns income from agriculture, especially compared to other Latin American countries. Agriculture is the second-largest employer (17.6 percent) after the service sector.[3] Second, a large number (87 percent) of agricultural producers are subsistence farmers who work 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 for its Spanish acronym), 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 Spanish acronym), a nationally representative cross-sectional 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 area covered.

[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 2000–2009 from nine in 1990–1999. https://www.climatelinks.org/sites/default/files/asset/document/2017_USAID%20ATLAS_Climate%20Change%20Risk%20Profile_El%20Salvador.pdf retrieved on July 31, 2020.

Our empirical model exploits both temporal and spatial variations in temperature shocks during corn-growing seasons between 2009 and 2018 in El Salvador. We estimate temperature anomalies with the historic spatial and temporal mean divided by the historic standard deviation. This is a frequent measure employed in rainfall and developed by McKee et al. (1993). Then, we measure extreme temperature shocks as being 2 standard deviations (SD) above the historic mean, which can be interpreted as random draws from a climate distribution.

Our empirical model includes municipality fixed effects to absorb time-invariant geographic characteristics, and it exploits within-municipality variation of this shock (Deschênes and Greenstone, 2007; Feng et al., 2010; Dell et al., 2014; Jagnani et al., 2020). We also include year fixed effects to absorb national-level shocks and interact 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 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. It is meaningful to note that, since we measure the effect of temperature shocks rather than the effect of climate change, our results should be interpreted as short-term effects rather than long-term adjustments by agricultural producers.

We document that temperature shocks decrease production of seasonal crops, especially corn (also known as maize, El Salvador's main staple crop). An increase of one standard deviation (SD) in the temperature shock reduces total agricultural production by 1.9 percent and corn production per hectare by 2.9 percent. Agricultural producers adjust in the short run by reducing labor demand for non-household agricultural workers and substituting household members for them. 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 but we do observe important increases in the probability of migration to the United States. An increase of one SD in the temperature shock during the main harvest season causes migration from corn-based agricultural households to rise by 20.2 percent relative to the baseline mean. It is important to highlight that our analysis captures both permanent and temporary migration, but our available data does not enable us to differentiate between these two categories of migration. These results suggest that temperature shocks are a major push factor for rural Salvadorean households.[7]

In addition, we offer suggestive evidence to support the idea that risk management mitigates the effects of extreme temperatures. Access to remittances might help farmers to cope with the drop in income caused by the negative shock, and we find that households with more access to remittances are less likely to respond to the shock through reductions in their labor demand and through international migration.

We test the robustness of our results via different strategies. First, to assess whether the effect of the shock on migration indeed stemmed from 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 emerges from shocks during the main harvest season. Second, 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 do not occur by chance. Third, we estimate the effects for different definitions of temperature shocks, and the results hold for all our outcomes. Finally, we gauge the robustness of our results by controlling for crime rates. By depressing income, temperature shocks might also be strongly correlated with crime spikes (Dell et al.,

[7]A caveat of our data is that we cannot distinguish temporal from permanent migration, so this effect includes both types.

2014; Carleton and Hsiang, 2016) that have prompted migration from El Salvador and other countries (Stanley, 1987; Clemens, 2021; Bermeo and Leblang, 2021). The magnitude and significance of our coefficient estimates are robust when including these controls.

Our paper contributes to three strands of the literature. First, we provide evidence on how negative temperature shocks affect agricultural production in developing countries, thereby prompting agricultural producers to adjust in a context of incomplete risk markets and weak non-agricultural labor markets (Guiteras, 2009; Auffhammer et al., 2012; Feng et al., 2010; Jessoe et al., 2016; Fishman, 2016; Blakeslee and Fishman, 2018; Aragón et al., 2021; Colmer, 2021). We expect different effects of weather shocks in developed countries, where contrary to developing countries farmers have access to financial and insurance markets and non-agricultural sectors may absorb the laid-off agricultural workers.[8] Since developed and developing countries differ greatly, it might not be valid to extrapolate results from developed countries to developing ones (Dell et al., 2014). Our results highlight the role of the integration of labor markets and formal and informal risk-coping mechanisms in developing countries in explaining the effect of temperature shocks on the decision to migrate internationally (Jayachandran, 2006; Graff Zivin and Neidell, 2014; Jessoe et al., 2016; Colmer, 2021).

Second, we add to the work on migration responses to weather shocks and natural disasters by using microdata that allows us to identify the mechanisms behind these relationships. This literature finds that negative weather shocks—including natural disasters—increase internal migration[9] and emigration[10] mostly for middle-income households, which have lower

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

[9] Examples of papers on internal migration are: Dillon et al. (2011), Gray and Mueller (2012a), 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).

[10] Examples of papers on the influence of weather shocks on emigration are: Halliday (2006), Feng et al. (2010), Gray and Mueller (2012b), 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.

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 but rarely delve into the mechanisms. Some papers explore agriculture as a mechanism but use aggregate data either at the country, state, or county level (see, e.g., Feng et al., 2010; Hornbeck, 2012; Hornbeck and Naidu, 2014; Cai et al., 2016; and Cattaneo and Peri, 2016). Jayachandran (2006), Aragón et al. (2021), and Colmer (2021) which use microdata for agricultural producers, are among noteworthy exceptions. We reinforce this literature with evidence on the role of labor markets as a transmission mechanism for the negative impact of temperature shocks on agricultural workers, some of who react by leaving El Salvador. Labor reallocation is an important margin of adjustment for mitigating temperature shocks, but unlike Colmer (2021) we find that workers are not able to move to the non-agricultural sector. Our results suggest that the non-agricultural sector in El Salvador is not able to absorb excess supply leading people to migrate internationally, which points to distress migration. The economic environment in El Salvador with not well-integrated markets and a small non-agricultural sector, together with low access to formal credit explain the effect of temperature shocks on the decision to migrate internationally. This contribution holds substantial importance as it underscores the significance of understanding the local economic conditions in order to identify the potential mechanisms by which weather shocks impact local labor markets and migration choices.

Third, we show that access to risk-management mechanisms (such as remittances) reduces reliance on reducing labor demand and therefore on distress migration. Our results highlight how incomplete markets in developing countries force rural households to rely on migration—in this case, international migration—to counteract declines in income. It is vital to understand the interactions of these elements in order to design policies to prevent distress migration and facilitate intentional migration from regions where agriculture may no longer be feasible. Migration might lead to better short-term *and* long-term outcomes

(2016), Mahajan and Yang (2020), and Bermeo and Leblang (2021).

if it is voluntary and not for lack of better coping mechanisms. Under certain conditions, however, it can prompt persistent negative effects for both migrants and the households they leave behind. Financial and insurance mechanisms should be tailored to the specific needs of small farmers in order to mitigate the negative impacts of extreme weather events and to prevent distress migration.

Finally, our findings on migration responses to declines in agricultural production and labor demand augment the literature on the consequences of climate change and the strategies households use to address them, including international migration. Even though we focus on short-term effects and do not consider long-term strategies, our results verify some adaptive responses of farmers to increasingly frequent extreme weather events. Climate change caused by global emissions mostly affects households in developing countries that consequently seek refuge, when possible, in developed countries. It is therefore a global responsibility to address the harmful effects of climate change.

The rest of the paper proceeds as follows: section 2 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 Extreme Weather and Temperature Shocks in El Salvador

The frequency of extreme weather events in El Salvador, particularly droughts and high temperatures, has intensified during recent decades with three extreme droughts in the last 10 years alone. In 2012, a severe and prolonged drought reduced coffee production by 70 percent. Between 2014 and 2015, more than 100,000 farmers suffered losses from another drought and the onset of *El Niño*.[11] In 2018, a new drought struck the country before it had

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

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.[12] Droughts and rising temperatures are driving incomes down while pushing food insecurity and migration up. The outlook is grim as agricultural production may become infeasible 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 lack of food are the main motivations for migration from this area (WFP, 2017).

Recurring droughts and extreme temperatures are causing large crop losses (particularly coffee, corn, and beans) and taking a heavy toll on vulnerable rural populations.[13] As noted above, most agricultural producers there are small family farms with average land sizes of 1.2 hectares[14] that are dedicated to subsistence farming. Since only 1.4 percent of the land is irrigated,[15] agricultural production depends largely on the rain cycle (WB, 2018). This is particularly worrying as the Dry Corridor is characterized by high unemployment, limited and seasonal labor demands and low and irregularly paid wages (WFP, 2017), meaning that there is little scope for adjustment in the labor markets following the economic distress caused by weather shocks in the agricultural sector.

Figure 1 illustrates the trend in increasing temperature levels. 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 (Lobell and Burke, 2008; Burke and Emerick, 2016; Ortiz-Bobea et al., 2019; Ortiz-Bobea et al., 2021; Colmer, 2021). Extreme temperatures are more difficult to manage than low rainfall because the latter is storable and can be re-

[12] 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.

[13] 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.

[14] 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.

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

placed 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).

2.2 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, 2021).[16] 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.[17]

The costs of migration from Central America to the United States 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, 2020). 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.[18] As might be expected, the price of services provided by migrant smugglers (*coyotes*) has also risen sharply. Surprisingly, this increase has not effectively deterred migration (Massey et al., 2014). Figure 2 depicts the rising costs of migrant smugglers and apprehensions at the border, illustrating that suppressive measures have not succeeded.[19]

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

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

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

[19] This article provides an example of the decision to migrate in spite of high migration costs: https:

So what causes these persistent flows? Evidence indicates that push factors such as deteriorating economic conditions, negative income shocks, and violence are important determinants of the migration decision (Stanley, 1987; Halliday, 2006; Yang, 2008; Clemens, 2021). Extreme weather conditions are strongly related to internal migration in Central American countries and are also potentially a cause of international migration (Baez et al., 2017; WFP, 2017; WB, 2018; Bermeo and Leblang, 2021). El Salvador is not only extremely vulnerable to changing climate conditions but it has also sustained more frequent weather shocks in recent years (ECLAC, 2010).[20] Interestingly, newly arrived Salvadorean migrants in the United States increasingly come from rural areas, which are more vulnerable to such shocks (WFP, 2017; Abuelafia et al., 2020). Figure 3 shows a strong correlation between apprehensions of Salvadoreans at the U.S. border and temperature shocks in El Salvador the prior year, measured as two SD above the historic mean.

3 Data

3.1 Agricultural Production

Our empirical analysis uses several data sources. Data on agricultural production come from the Multiple Purpose National Agricultural Survey (ENAMP) 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 includes 19,261 agricultural producers and is representative at the national level. For grain crops, it is representative at the provincial level. The survey is administered during the last quarter of the year once the harvest has occurred for the first two seasons, *primera* (the main harvest season) and *postrera*. (See Figure A1 in the Appendix for a timeline of the different data sources). At that time,

//www.nytimes.com/interactive/2020/07/23/magazine/climate-migration.html.

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

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.[21] It is a short-cycle crop for which temperature shock impacts can be traced back in the same period.[22] In addition, other papers have found a significant association between temperature shocks and corn production.[23]

The corn production calendar is as follows: *primera*, the main harvest season (June and July), *postrera* (August and September), and *apante* (November and December). Figure A3 in the Appendix illustrates the yearly contributions of the three harvest seasons for our period of analysis. Corn production occurs mostly in the main harvest season, so our estimates measure the effect of temperature shocks during *primera*. In addition, we perform robustness tests using the other seasons (*postrera* and *apante*) and the lean season, when we would expect a weak effect or no effect of extreme weather on production.

The agricultural production outcomes include: (i) output variables: total yield, land productivity (measured as yield per total land plot size and yield per land cultivated in corn), Total Factor Productivity (TFP), estimated as the residual of regressing the agricultural output on all the inputs listed below in (ii), and labor productivity (measured as yield per worker); and (ii) input variables: the number of workers (total, hired, and household), a principal component index of other inputs (planting material, agrochemicals, chemical agents, and agroecological elements), and land size (size of land plot and land allocated to

[21] An average agricultural producer has a yield per hectare of 2.3 tons (SVC$ 709.8) and a land plot of 1.5 hectares, of which 0.5 hectares are cultivated with corn. (See Tables A1 and A2 in the Appendix).

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

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

corn).

3.2 Labor Markets and Migration

To study labor outcomes and migration, we use the Multiple Purpose Household Survey (EHPM), a yearly cross-sectional survey collected by El Salvador's official statistics agency that includes information on household members' sociodemographic characteristics, housing, employment, agricultural outcomes, land tenure, household income, and migration status, among other elements. The sample in the estimations covers 186,910 households for 2009–2018. The survey is representative at the national level and for 50 municipalities.[24]

Labor outcomes are constructed based on the labor module of the survey for the working-age population aged 10–65 years. Labor outcomes include employment, hourly wages, weekly hours, and monthly wages.[25] The module also enables us to identify an occupational sector for each working member of the household.

Migration outcomes are identified using the migration module, which collects information on household members who live abroad, their year of migration, and their destination country.[26] Our outcome variable is a dummy equal to one when at least one household member migrated abroad one year prior to the survey.[27] Therefore, this analysis is conducted at the household level. We group the households as follows: (i) agricultural households; (ii) agricultural households that grow seasonal crops;[28] (ii) agricultural households that grow corn; (iii) non-agricultural households; and (iv) unemployed households. We define the household sector based on the main occupation of the household head and working-age members. This definition, however, may be endogenous so we test the robustness of our results by defining

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

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

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

[27] We identify recent migration but we cannot identify whether it is permanent or temporary.

[28] Seasonal crops must be replanted after each harvest. Corn is the most important seasonal crop in El Salvador.

a household as agricultural using alternative methods. We discuss these results in section 5.7.

Ideally, we would measure migration using data on migrants rather than households with migrants. The latter may underestimate the number of migrants as, in some cases, all household members may migrate together, especially following intense temperature shocks. On the other hand, data collected in the United States regarding Salvadorean migrants may underreport undocumented ones (Halliday, 2006). To evaluate potential underreporting of entire-household migration, we compare migration trends from the EHPM and the American Community Survey (ACS).[29] 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 4 shows similar trends for both surveys for most years except for 2015. That year, the percentage of entire-household migration reported in the ACS spiked while in the EHPM, households reporting migrant members fell sharply. This suggests 2015 might have been a year when international migration was more common for entire Salvadorean households than for individuals. Reassuringly, our results are robust with and without the 2015 data.

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; 17.2 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 Temperature

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

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

day temperature averages for 2001–2018.[30] We aggregate the grid to the municipal level with a weighted mean using the area covered.

Temperature shocks measure the number of weeks during the main harvest season in which the temperature was 2 SD above its historic mean during that same week.[31] To create our temperature shock we follow the following steps: first, we estimate historic means and standard deviations for temperature for the main harvest period between 2001 and 2006. Second, we standardize the temperature of municipality j, during week w of year y using the historic mean $\mu_{j,w,2001-06}$ and standard deviation $\sigma_{j,w,2001-06}$ of municipality j, during week w, between 2001 and 2006 (McKee et al., 1993; Marchiori et al., 2012):[32]

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

where $Temperature_{j,w,y}$ is the temperature of municipality j and time w (week) during the main harvest season of year y. Third, we define a temperature shock as being 2 SD above the mean.[33]

$$\text{Temperature shock}_{j,w,y} = \mathbb{1}\left[\frac{\text{Temperature}_{j,w,y} - \mu_{j,w,2001-2006}}{\sigma_{j,w,2001-2006}} >= 2\right]$$

Our main dependent variable is the number of weeks with a temperature shock during the main harvest season (8 weeks from July to August).[34] In section 5.7 we show our main results using alternative definitions and thresholds for the temperature shock, for example:

[30] Alternative sources to measure temperature are the daily MODIS and the ERA5. The MODIS at the weekly level is our preferred dataset for two main reasons: first, it is the dataset with the most disaggregated information (one km x one km grids). Second, it has temperature information for all the years and all the municipalities in our Household and Agricultural Surveys. In contrast, the MODIS data available on a daily basis contains missing values due to cloud coverage on each specific day, whereas ERA5 compiles information on a 30 km grid.

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

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

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

[34] This measurement matches the frequency indicator employed in Dallmann and Millock (2017).

harmful degree weeks, number of weeks with temperatures above 29 and 35 degrees Celsius, and thresholds of 1 SD and 1.5 SD to define the shock.

Using our main definition of a temperature shock, on average, there were 1.13 weeks out of 8 weeks during the main harvest season of the year with temperatures 2 SD above the historic mean. During 2014 and 2015 (the years with the biggest 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 had none (Figure 5). The standard deviation of the temperature shock from 2009-2018, is 0.58. When interpreting the results, we will also interpret the effect corresponding to a 1 SD increase in the frequency of the temperature shock.

3.4 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 main harvest season (measured as the number of weeks with rainfall 2 SD above the historic mean), drought shocks (measured as the number of weeks with rainfall 2 SD below the historic mean),[35] soil moisture, and crime shocks.[36]

To control for baseline municipality conditions, we interact baseline characteristics with a linear time trend. We use the following variables from the 2005 Poverty Map of El Salvador: 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

[35] 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.

[36] 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 2 SD above the historic mean.

adults (16 and 18 years of age) who are not enrolled in school.[37] 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 also include linear time trends interacted with the municipality's elevation calculated at the grid level and averaged for the municipality.[38]

4 Empirical Strategy

To measure the effect of temperature shocks on agricultural production plus 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 landownership and access to both formal and informal risk-management mechanisms.

4.1 Agricultural Production

We start by estimating the effect of extreme temperatures on agricultural production.[39] Previous research has shown 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) establish a significant relationship

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

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

[39] 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.

between climate-driven changes in crop production and net out-migration.

To estimate the effect of temperature shocks on agricultural production and assess the 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:

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

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 harvest season,[40] measured as the number of weeks with temperatures 2 SD above the historic mean. We test the robustness of temperature shocks using alternative definitions in section 5.7. In order to identify the contemporaneous short-term effect of high temperatures, and to assure that $\hat{\delta}_1$ is not capturing the effect of temperature shocks from previous seasons, we include $\sum_{k=t-4}^{k=t-1} T_{ijk}$; that is, the total number of weeks with extreme temperatures during the main harvest season of the previous four years.

Recall that the agricultural survey collects information during the last quarter of the year. Therefore, a household interviewed during the survey year t reports its production for the last 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 for producer i in municipality j in year t during the agricultural harvest season.

Our main specification controls for time-variant household characteristics (X'_{ijt}) such

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

as household head's 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).[41] In addition to natural disasters and extreme weather events, high levels of violence have historically been an additional push factor behind migration from El Salvador (Stanley, 1987; Halliday, 2006; Yang, 2008; Clemens, 2021), and recent evidence shows weather shocks may intensify violence (Dell et al., 2014; Carleton and Hsiang, 2016). To control for this, we add a variable of a crime shock measured in $t-1$ and defined as the number of weeks with crime levels 2 SD above the historic mean. We include fixed effects (μ_j) that account for any time-invariant unobserved heterogeneity at the municipality level. Importantly, this includes the historic level of rainfall and historic mean of temperatures in municipality j. Our specification also includes year fixed effects (ϕ_t) to account for national shocks that would impact migration decisions, such as shocks that could affect prices. Finally, we include interactions between socioeconomic variables measured at baseline (2005 and 2007) and linear time trends (W'_{j2005}) that control for any pre-trend at the municipality level that could bias the results.[42] Our model's validity relies on the assumption that, conditional on the previous controls, there were not unobserved time-varying differences within municipalities correlated with temperature shocks. All the models are estimated using double-clustered standard errors by municipality and year, and the results are robust to using Conley standard errors to account for spatial correlation.

[41]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.

[42]The vector W'_{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 old), percentage of people employed in agriculture, population density, and elevation.

As additional robustness checks, we estimate a placebo test 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 responsible for 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 temperature shock. Two important features influence these adjustments. First, when the 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 use other strategies to offset income losses and smooth consumption. One strategy is to lay off hired workers and substitute household workers for them, thus protecting the agricultural producer's household 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 the labor demand of agricultural producers will pressure agricultural wages and push workers to increase working hours or seek employment in the non-agricultural sector.

We estimate the relationship between temperature shocks and labor markets using the EHPM data following the model below:[43]

[43]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.

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

where l_{ijt} represents the labor outcomes of individual i living in municipality j in year t, using the same controls as in equation (1). 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, we also estimate effects on labor market outcomes at the municipality level such as occupation-specific employment shares and average hourly wages.

4.2.2 International Migration

Finally, we estimate the effects of temperature shocks in $t-1$ on the probability of international migration in time t, using data from the EHPM household survey with the following regression model:

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

where m_{ijt} is a dummy variable equal to one if a member of household i living in municipality j in year t migrated from El Salvador in year t, and equal to zero otherwise.[44] The variable T_{jt-1} and the controls are the same as those in equations (1) and (2). It is important to highlight that in this specification the temperature shock is lagged one period because migration is costly and the decision to migrate might not be immediate.

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

5 Results

5.1 Agricultural Production

We start by estimating the effect of temperature shocks on agricultural output and different productivity measures. Because corn cannot absorb additional heat above certain thresholds, we expect to find a negative effect of extreme temperature shocks on corn production (Jessoe et al., 2016). Recall that we follow the agricultural calendar and control for temperature and rainfall shocks during the main harvest season.

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. Reassuringly, 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 those controls. Both the magnitude of the coefficients and their significance do not change across specifications, which is consistent with the fact that our identification strategy captures within-season, short-term temperature effects.

The results show consistently negative effects of the temperature shock on all outcomes other than labor productivity. Focusing on column (2), we find that one temperature shock during the main harvest season decreases total corn production by 3.2 percent, and one standard deviation (SD) increase in the frequency of extreme temperature shock during the main harvest season of the contemporaneous year reduces total corn production by 1.9 percent (panel A).[45] Land productivity falls between 3.4 percent (panel B) and 2.9 percent

[45] 0.032*(standard deviation of the temperature shock)=0.032*0.583.

(panel C), and TFP drops by 2.3 percent (panel D) for an additional SD increase in the temperature shock. The sharper decline in land productivity suggests agricultural workers increase their land use in the short term, which accords with results from Aragón et al. (2021) in Peru.[46] 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 a drop in demand for agricultural workers. All results are robust to using Conley standard errors to account for spatial correlation (Table A4).

Overall, we find robust evidence that extreme temperatures have hurt corn production in El Salvador. Some of these results imply farmers respond by adjusting the intensive use of inputs such as land and workers. We investigate this in the next section.

5.2 Input Adjustments

We now examine how agricultural producers adjust in the short-run the use of production inputs. Since we measure responses in the short-term, the margin of adjustment is limited. We expect to see responses through the use of inputs such as land and fertilizer which can be adjusted if the planting season is not over. Landowners may also respond by reducing their labor demand by hiring fewer agricultural workers and substituting them by household workers (Jayachandran, 2006; Bastos et al., 2013; Jessoe et al., 2016; Aragón et al., 2021).

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

[46] Although the inclusion of the cumulative shocks in previous years does not influence the significance and magnitude of the contemporaneous shock, it is interesting to find a significant effect of the previous shocks on land productivity (panel B). Aragón et al. (2021) explain that if the increase in land use comes at the expense of planting fallow land, this response could have persistent effects in the medium term and long term. While we do not test the effect on the use of fallow land directly, our results are consistent with their hypothesis.

types of inputs is not statistically significant and the magnitude of the coefficient is small. Consistent with the findings in Table 1, the results in column (7) show that corn producers increase the land allocated to corn production by one 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. In particular, the results in column (4) show a significant decrease in chemical agents, which are more responsive to weather shocks because they are mostly used post-harvest.[47] Since our data is cross-sectional, we cannot identify adjustments at the extensive margin such as the abandonment of agricultural production or land sales. Therefore, we identify a lower bound on the impact of temperature shocks on corn production.

5.3 Labor Adjustments

We next study how agricultural producers adjust their labor demand when facing a temperature shock. Table 3 reports results from estimating equation (2) for the number of workers allocated to agricultural production, using data from the ENAMP. Since some households only have either household or hired workers, we have households with zeros in one of these categories. To avoid dropping zeros, we use the 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 report only the results of our preferred specification but they are robust when gradually including the different controls.

The temperature shock decreases the total number of workers, which is driven by non-household workers. One additional week with a temperature shock during the main season reduces the demand for the total number of workers, with a reduction in the inverse-hyperbolic sine of 0.018. In other words, one additional SD in the frequency of extreme temperature shocks reduces the demand for the total number of workers in terms of inverse

[47] Similarly to our paper, Jagnani et al. (2020) estimate the effect of within-season temperature variation on agricultural inputs for corn production in Kenya. They find an increase in the use of pesticides and a reduction in the use of fertilizers.

hyperbolic sine by 0.010 and non-household workers by 0.017. 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. At face value, the results suggest a substitution of household workers for non-household workers. These results, with the effects on agricultural production, imply that income is negatively affected and households adjust to the shock by reducing their demand for non-household workers.

To provide a comprehensive picture of the effect on labor outcomes, we estimate the effect of the temperature shock on individual probabilities of employment using data from the EHPM household survey (panel A, columns (1)–(2), Table 4). The results suggest there is a negative effect on the probability of being employed, but the results are imprecise. In the short term we expect the effects to be driven by individuals working in the agricultural sector, particularly those growing crops that are the most vulnerable to temperature shocks, such as corn. We explore this hypothesis in columns (3) to (8). As expected, the results are negative and significant for agricultural producers of seasonal crops and corn, which is consistent with the effects estimated in Table 3. Columns (5) and (6) show a significant and negative effect on the probability of employment in the agricultural sector, which is driven by workers growing corn (columns (7) and (8)). The results in column (8) show that an increase in the temperature shock by 1 SD decreases the likelihood of being employed in the agricultural sector growing corn by 1.3 percent relative to the mean. The results in columns (9) and (10) show positive but non-statistically significant effects on the probability of working in the non-agricultural sector, which suggests no substitution towards employment in the non-agricultural sector.

We complement this analysis by estimating the effect of temperature shocks on employment rates at the municipality level. We show these results in Table A5. We estimate equation (2) on employment rates in the agricultural sector and the non-agricultural sector, as well as on the unemployment rate at the municipality level using data from the EHPM for

2009-2018.[48] The results in column 2 of Panel A shows that 1 SD increase in the frequency of extreme temperature shocks reduces the employment rate in the agricultural sector by 1.16 percent relative to the baseline mean, and the effect is larger for agricultural workers who produce corn (1.99 percent). Consistent with the estimations at the individual level, and contrary to findings in other settings, there is no evidence of reallocation to the non-agricultural sector (Colmer, 2021). Instead, the results suggest the drop in the agricultural employment rate is accompanied by an increase in the unemployment rate.[49] These results are in line with Mueller et al. (2020) which finds that migration due to weather shocks is inversely related to the demand for workers.

Given that labor is negatively affected at the extensive margin, especially by non-household workers, we proceed to explore if there are any compensations done at the intensive margin. At first glance, there is no overall effect on the number of hours of workers in agriculture or outside of agriculture. Panel A of Table 5 shows the effects of estimating equation 2 on the logarithm of working hours at the individual level, conditional on being active in the labor force. However, when exploring these effects by sex and age, we find that the average effects in Table 5 mask important heterogeneity. Panel A in Tables A6 and A7 show a positive and significant effect on the working hours of women and children younger than 14 years. These findings suggest that if there is a substitution between non-household workers and household workers, women and young children are likely to be the household members who replace the hired labor. This could be a costly response to these shocks with potential long-term consequences for the human capital accumulation of young children. It is important to take into account, however, that these results should be interpreted with caution since the effects are measured for workers in the labor force, and thus might suffer from sample selection.

[48] Employment Rate in Sector j and municipality m=$\frac{\#Workers_{jm}}{WorkingAgePop_m}$

[49] We estimate the effects in the non-agricultural sector by sector, and the null results persist for all the sectors. Results are available upon request.

Finally, we estimate the effect of the temperature shock on wages. Theoretically, we expect the effect on wages to depend on the margin of adjustment of 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 may intensify.

Panel B of Table 5 shows the effects of the temperature shock on individual hourly wages, conditional on being active in the labor force.[50] The results in panel B show no significant effect on contemporaneous wages. The null effects in contemporaneous wages are also found when estimating the effects at the municipality level (Table A5). When disaggregating the effects by sex and age, we find evidence of a positive wage effect for women and young children (Panel B Tables A6 and A7). The absence of any wage impact among males suggests that the rise in unemployment might be countered by a reduction in the availability of labor, potentially due to out-migration plans. Migration may ease the pressure on labor markets and render the effect on labor outcomes smaller or nonexistent. Additionally, the lack of a significant effect on wages on average may mask heterogeneity in access to risk-management mechanisms or stickiness in wages in the short term. Agricultural wages might be more volatile in communities with incomplete financial markets and low or no migration (Jayachandran, 2006). We investigate these hypotheses in section 5.5.

Overall, the findings in this section suggest that declines in corn production are felt in agricultural labor markets. Corn producers reduce their demand for hired workers and use household workers instead. Laid-off agricultural workers can potentially switch to other

[50] As the results for working hours the sample of individuals in the labor force might be selected and we should interpret this results with this caveat in mind.

agricultural activities or to the non-agricultural sector, but we find no evidence of this in El Salvador. Transmission of 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 these mechanisms in the next section.

5.4 International Migration

Without access to risk-management mechanisms or a non-agricultural sector that can absorb displaced workers, international migration could become a key response to the income loss caused by temperature shocks. We explore this hypothesis by estimating equation (3). Results with the fully controlled models are shown in Table 6.[51] We estimate this model using household-level information from 2009–2018 EHPM for all households (panel A), all agricultural households (panel B), agricultural households that cultivate seasonal crops including corn (panel C), agricultural households that cultivate corn (panel D), and non-agricultural households (panel E). We categorize households based on the occupation of the household head and the occupation of working-age members. A household is considered agricultural if the household head and at least 50 percent of the working-age members work in this sector. A potential concern is that the occupation of household members might be endogenous. In Appendix Table A9, we classify households based on alternative specifications. Method (1) is our preferred specification; method (2) only considers the occupation of the household head, and methods (3) and (4) only consider other working-age members as a criterion to classify them in each panel. The results on the probability of migration are robust overall to the different classifications.

A negative effect on agricultural production is one mechanism through which high temperatures can affect migration decisions. If this is the main mechanism in El Salvador,

[51] In Table A8, we test the robustness of our results by including one set of controls at a time. Overall, the results are robust to the inclusion of all controls. Our preferred specification is the fully controlled model. It is also important to recall that our fully controlled model includes rainfall shocks.

we would expect to see a larger response to these shocks among agricultural households, especially corn producers. The results in Table 6 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 the coefficient is almost 10 times larger than that for all households. The coefficient for non-agricultural households is not significant and small in magnitude.

The results in our preferred specification with the full set of controls for agricultural households that grow corn (column (2), panel D) show that one additional week with 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 SD of frequency of temperature shock increases international migration by 20.2 percent relative to the mean of international migration in El Salvador.[52] Although, at face value the magnitude of these effects seems large, it is challenging to directly compared it to other settings given that the effect of temperature shocks on migration is highly dependent on local labor markets (Mueller et al., 2020). Mueller's study indicates that a 1 SD increase in precipitation caused a decline in migration of 10-11% in Kenya and Botswana while causing an increase in migration as large as 24% in Zambia. El Salvador's limited labor market capacity to accommodate unemployment within its small size is coherent with large results on migration, which works as an alternative adaptive measure. Additionally, it is important to remember that we cannot distinguish permanent from temporary migration. Given the patterns of migration in El Salvador and the fact that we measure migration based on the reports of households that stay there, it is reasonable to believe temporary migration represents a substantial percentage of our results.[53]

[52] To calculate this: $\frac{\hat{\delta_1} * temp(SD)}{migration(mean)} = \frac{0.273*0.583}{0.788}$

[53] Around 66% of Salvadorian migrants in the US aim to stay permanently, according to a survey directed to recent immigrants in the US (Abuelafia et al., 2019).

Although we do not have information on migrants, we explore the heterogenous effects of migration based on household characteristics, particularly access to land. Landowners and wage workers are likely to adjust differently to temperature shocks, and we provide evidence to support this hypothesis. On the one hand, landowners face larger opportunity costs of migration (relative to agricultural wage workers) and cope better with negative income shocks due to their increased access to risk-management mechanisms such as credits (Kleemans, 2015; Kubik and Maurel, 2016; Cattaneo and Peri, 2016; Mahajan and Yang, 2020). Both dimensions reduce the likelihood of responding to these shocks through migration (Jayachandran, 2006; Feng et al., 2010; Hornbeck, 2012; Kleemans, 2015; Jessoe et al., 2016; Aragón et al., 2021). On the other hand, access to land makes it easier to finance the up-front costs associated with international migration.

In our data, we divide individuals by: landowners, individuals who claim ownership of the land on which they produce; land tenants, producers who claim to lease the land on which they produce; other type of land tenure, producers who claim to have access to land being settlers, part of a cooperative, sharecroppers or free occupants; and wage workers, who claim not owning land. Table A10 shows the effect of the temperature shock on the probability of migration for these different groups.

There are several takeaways from this table. First, when looking at the means of the outcome for the different panels, landowners show the highest likelihood of international migration. This suggests that in El Salvador access to land might help finance the cost of migration. Second, when looking at the effect of the shock on the probability of migration relative to the mean, landowners and land tenants (Panel B and C) show the smallest effects (37% and 27% relative to the mean, and the effects are not-significantly different from zero) relative to wage workers (Panel E shows a non-significant increase of 44.6% relative to the mean) and to settlers and free occupants (Panel D) whose probability of migration increases by 57% and the effect is significantly different from zero. This might be a group of agricultural producers who is more vulnerable than landowners because they do not have property rights over the land they use, and more vulnerable to wage workers, because they do not receive a wage.

5.5 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 as well as remittances, which in El Salvador constitute 24 percent of GDP[54] and play an important role in supporting family members who stay in the country.[55] In order to investigate both mechanisms, we construct two different measures: (i) share of the population with access to credit in 2009, according to the EHPM; (ii) share of the population with access to remittances in 2007, according to population census.[56] We then classify municipalities in the bottom and the top quartiles of the distribution, in order to estimate the differential impact between agricultural farmers living in municipalities in the bottom quartile versus those living in the top quartile. Empirically we keep only these observations, and we fully interact the models in equations 1-3 with a dummy equal to one if a farmer lives in a municipality in the top quartile:[57]

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

[55] 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.`

[56] By exploring the response to temperature shocks based on access to remittances, we contribute to a growing literature on the effect of remittances in the countries of origin. See: Edwards and Ureta (2003); Mishra (2007); Mobarak et al. (2021); Ambler et al. (2015); Hanson (2010).

[57] Instead of using only this sub-sample we estimated a model with the full sample, fully interacted with the continuous variables measuring access to credit and remittances. The results are robust to those presented in the paper.

$$
\begin{aligned}
log(y_{ijt}) = \alpha + \Gamma_{ij} + \delta_1 T_{ijt} + \delta_2 T_{ijt} \times \Gamma_{ij} + \delta_3 \sum_{k=t-4}^{k=t-1} T_{ijk} + \delta_4 \sum_{k=t-4}^{k=t-1} T_{ijk} \times \Gamma_{ij} + \\
X'_{ijt}\gamma + X'_{ijt}\gamma \times \Gamma_{ij} + \beta_1 Z_{jt} + \beta_1 Z_{jt} \times \Gamma_{ij} + \mu_j + \mu_j \times \Gamma_{ij} + \phi_t + \phi_t \times \Gamma_{ij} + \\
W'_{j2005} * t + W'_{j2005} * t \times \Gamma_{ij} + \epsilon_{ijt}
\end{aligned}
\tag{4}
$$

where Γ_{ij} is the access to the risk coping mechanism: a dummy equal to one if a farmer lives in a municipality in the top quartile on remittances or credit access.

We employ the municipal shares at baseline rather than individual outcomes to assuage endogeneity concerns. Potential concerns still remain because municipalities with more or less access to credit and remittances can be different in unobserved ways that are correlated with the outcomes of interest. We add a rich set of municipality-level controls in addition to municipality fixed effects. However, unobserved time-variant characteristics of the municipality could relate both to the share of remittances or credit access at baseline and the probability of migration. This relationship needs to be explored more rigorously, and our results should be considered merely suggestive.

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 compensate for the negative income shock, thereby reducing their need to use more costly mitigation mechanisms such as distress migration. At the same time, remittances and credits may decrease migration costs by funding the relocation process, which might *increase* the likelihood of migration. The effect of these variables on migration is an empirical question we address in the following paragraphs.

Table 7 shows the fully interacted models with the share of households with credit access in 2009 (column 1); and, the share of the population who received remittances in 2007 (column 2) for the agricultural outcomes measured in the ENAMP. Two main results come to light from these estimations.

First, the results in panels A and B suggest that access to risk-management mechanisms such as formal credits or remittances does not shield farmers from the effects of temperature shocks. Farmers are probably not using these to protect themselves *ex ante* through insurance. This is consistent with a review of the literature discussed in (Huckstep and Clemens, 2023). These results also support the exogeneity assumption of our measure of temperature shocks. In this context, it is important to investigate whether farmers decide not to invest in weather-resistant seeds, appropriate fertilizer, and irrigation systems due to liquidity constraints or lack of information.

Second, more access to remittances is associated with a lower response through a reduction of non-household workers. The results show that the impact of temperature shocks on labor markets is driven by municipalities with lower access to remittances. In these municipalities, households need to resort more to labor markets to cope with the income shocks and the effect of weather shocks thus transmits to labor markets. In contrast, in municipalities with more access to remittances, labor demand for agricultural workers does not respond as significantly to the temperature shock, arguably because these households rely more on informal risk-management mechanisms. Importantly, although the sign of the interaction is the same when looking at access to credit in column 1, the effects are never significantly different from zero. This could be explained by the fact that only 3% of our sample has received a formal credit.

Table 8 shows the same heterogeneity for the individual outcomes measures in the EHPM. The effect of risk-management mechanisms on the decision to migrate is theoretically ambiguous. On the one hand, access to risk-coping mechanisms, decreases the transmission of the shock to the agricultural labor market, and decreases reliance on international migration. On the other hand, access to risk-coping mechanisms finance migration costs, and it increases the likelihood of international migration. The results in Panel D of Table 8 show no significant differential effect of the temperature shock on the decision to migrate by access to formal credit or remittances. This could be explained by the two opposite effects that access to remittances may have on migratory decisions.

Overall, the results in Tables 7 and 8 suggest that access to risk-management mechanisms might reduce household reliance on decreasing labor demand to compensate for the drop in income due to temperature shocks. Access to remittances may allow agricultural producers to absorb these shocks without resorting to labor markets as a risk-management strategy.

5.6 Integration to Other Markets

To study the heterogeneous effects through access to non-agricultural sectors, we use road networks as a proxy for integration into other markets. Road network information was provided by the Transport Division of the Infrastructure and Energy Sector (INE) of the IADB, which uses data from Open Street Maps in 2022 [58]. We use the National road network, which contains 95,410 roads in El Salvador comprising highways, avenues, and streets among 27 different road types.

Access to the non-agricultural sector may alleviate the negative effect on labor markets and reliance on international migration. We estimate the effects on labor markets and migration, leveraging data on the national road network of El Salvador.[59] We classify municipalities based on the distribution of the road network and present results for municipalities in the lowest 25th percentile (the least connected municipalities) and in the top 25th percentile (the most connected municipalities). We use the road network as a proxy for integration

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

[59]Road information was provided by the Transport Division of the Infrastructure and Energy Sector (INE) of the IADB, which uses data from Open Street Maps in 2022. "National road network" includes all the roads in El Salvador, while "main road network" only encompasses roads classified as primary or secondary, which have the infrastructure to accommodate at least 500 vehicles per day, on average.

to other markets. We hypothesize that a more integrated local labor market would facilitate reallocation into the non-agricultural sector, decreasing the effect of the shock on labor outcomes and therefore on distressed migration.

The results support this hypothesis. The effects on the probability of working in the agricultural sector is stronger for individuals living in the least integrated municipalities (bottom quartile in the distribution of roads' network) (Panel A, Table A11). As hypothesized, we should then find a lower response through migration in the most connected municipalities. The negative coefficient of the interaction in Panel D supports this hypothesis, but the effect is noisily estimated. In this context, it is crucial to comprehend integration of local labor markets and sectoral reallocation. These findings highlight the need for further research on these subjects.

5.7 Robustness Checks

We estimate a number of robustness checks to test the validity of our identification strategy. We perform several tests to see whether temperature shocks rather than a correlated effect produce the negative effects on agricultural production, labor markets, and migration.

We first test our definition of the temperature shock. Tables 9 and A12 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—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 (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 EHPM household survey 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 specifications.[60]

We also test for robustness by measuring the temperature shock in four ways. Results for all the main outcomes are in Table A12 in the Appendix. Columns (1) and (2) define the shock as the number of weeks during winter with a temperature higher than 1 and 1.5 SD above the mean, respectively. Columns (3) and (4) define the temperature shock when the temperature was above 29 and 35 degrees Celsius, respectively. Column (5) define the temperature shock as Harmful Degree Weeks (HDW), where every 1-degree Celsius increase in the average temperature above 32 degrees Celsius corresponds to a one-unit increase in HDWs. Overall, the results are robust to these different measures.

We estimate a placebo test to measure the likelihood of obtaining estimates 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 in Figure A5 for agricultural production. We plot our baseline coefficients from Tables 1 and 6 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.[61] Given the salience of violence in El Salvador, we explore whether the results are robust to controlling for crime. Table A13 in the Appendix shows these results. The results

[60]For all results, it is important to note that Figure 4 suggests an underestimation of migration rates due to the migration of entire households.

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

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 study how rural households respond to an extreme rise in temperature. Based on household and agricultural producer data, we find that a sharp gain in temperature reduces agricultural productivity and total production. Farmers adjust by cutting demand for hired workers. Labor markets transmit the negative impact of weather shocks to agricultural workers, who cannot transfer to the non-agricultural sector and respond by migrating internationally.

Our results add to the literature on short-term responses to weather shocks. We show that negative shocks to agricultural production relate to migration decisions for two reasons. 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 way to counteract income losses from negative weather shocks (Mueller et al., 2014; Kleemans, 2015). Migration might also enable households to escape unbearably 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). Like Mueller et al. (2020) and Colmer (2021), we explored the role of labor markets for absorbing the job losses in agriculture. We found that in the case of El Salvador local labor markets do not absorb the displaced labor supply from the agricultural sector, pushing workers towards international migration as a response to the loss of income. Possible factors contributing to this situation include inadequate market integration, as well as unfavorable labor conditions in non-agricultural and urban sectors, impeding the smooth transition to other sectors. Further research on these topics is necessary.

Policies should address both motivations. To prevent distress migration where agricultural production is still feasible, policies should promote access to insurance and financial markets to address the negative income effects and extend technical assistance to help rural households adjust their agricultural practices to a changing climate (e.g., resistant seeds). Humanitarian aid, which is rarely offered in response to extreme weather events (Baez et al., 2017; Mueller et al., 2014), should be available as well. Furthermore, improved resilience to negative weather shocks through better agricultural practices, resistant seeds, and public goods such as irrigation could also prevent distress migration. Information about the benefits of such policies could bolster arguments to increase investments in these public goods.

Policies should additionally aim to facilitate migration that can provide a pathway out of poverty. Credit market access and other mechanisms to fund migration costs are some examples of this (Bryan et al., 2014; Kleemans, 2015). Evaluation of the relationship between access to financial/insurance markets and migration decisions would provide inputs for better policy design. Kleemans (2015) explores how financial mechanisms interact with migration decisions, while 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,[62] we still lack proof of how these mechanisms influence migration responses. Our paper makes important contributions on these regards by showing that access to remittances might alleviate the need to rely on reducing the labor demand of non-household workers. In this context it makes sense to think about policies designed to reduce transaction fees and providing adequate infrastructure of formal channels to send remittances (WB, 2023).

Finally, although our paper studies the effects of short-term responses to weather shocks rather than long-term climatic adaptations, our results suggest short-term responses might have long-term consequences. More research on long-term agricultural responses will aid in

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

understanding how to help rural households adapt to a changing climate.

References

Abuelafia, Emmanuel, Fernando Carrera, and Miryam Hazan, "Migración en Centroamérica," 2020.

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

Albert, Christoph and Paula Bustos, "The Effects of Climate Change on Labor and Capital," 2022.

Ambler, Kate, Diego Aycinena, and Dean Yang, "Channeling Remittances to Education: A Field Experiment among Migrants from El Salvador," *American Economic Journal: Applied Economics*, April 2015, *7* (2), 207–32.

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

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

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

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

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

Bermeo, Sarah and David Leblang, "Honduras Migration: Climate Change, Violence, and Assistance," Technical Report March 2021.

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

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang, "Nonlinear permanent migration response to climatic variations but minimal response to disasters," *Proceedings of the National Academy of Sciences*, 2014, *111* (27), 9780–9785.

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

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

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

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

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

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

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

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

Dallmann, Ingrid and Katrin Millock, "Climate Variability and Inter-State Migration in India," 2017, *63* (4), 560–594.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, July 2012, *4* (3), 66–95.

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

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

Dillon, Andrew, Valerie Mueller, and Sheu Salau, "Migratory Responses to Agricultural Risk in Northern Nigeria," *American Journal of Agricultural Economics*, 2011, *93* (4), 1048–1061.

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

East, Chloe and Andrea Velásquez, "Unintended Consequences of Immigration Enforcement: Household Services and High-Skilled Women's Work," 2020.

ECLAC, "The economics of climate change in Central America: Summary 2010," Technical Report, Economic Commission for Central America and the Caribbean 2010.

Edwards, Alejandra Cox and Manuelita Ureta, "International migration, remittances, and schooling: Evidence from El Salvador," *Journal of Development Economics*, 2003, *72* (2), 429–461.

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

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

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

Gray, Clark and Richard Bilsborrow, "Environmental influences on human migration in rural Ecuador," *Demography*, 2013, *50* (4), 1217–1241.

Gray, Clark and Valerie Mueller, "Drought and Population Mobility in Rural Ethiopia," *World Development*, 2012, *40* (1), 134–145.

Gray, Clark L. and Valerie Mueller, "Natural disasters and population mobility in Bangladesh," *Proceedings of the National Academy of Sciences*, 2012, *109* (16), 6000–6005.

Gröger, André and Yanos Zylberberg, "Internal Labor Migration as a Shock Coping Strategy: Evidence from a Typhoon," *American Economic Journal: Applied Economics*, 2016, *8* (2), 123–53.

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

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

Hanson, Gordon H., "Chapter 66 - International Migration and the Developing World," in Dani Rodrik and Mark Rosenzweig, eds., *Handbooks in Economics*, Vol. 5 of *Handbook of Development Economics*, Elsevier, 2010, pp. 4363–4414.

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

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

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

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

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

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

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

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

Kleemans, Marieke, "Migration Choice under Risk and Liquidity Constraints," 2015.

Kubik, Zaneta and Mathilde Maurel, "Weather Shocks, Agricultural Production and Migration: Evidence from Tanzania," *The Journal of Development Studies*, 2016, *52* (5), 665–680.

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

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

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

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

Massey, Douglas S., Jorge Durand, and Karen A. Pren, "Explaining undocumented migration to the US," *International Migration Review*, 2014, *48* (4), 1028–1061.

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

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

Mishra, Prachi, "Emigration and wages in source countries: Evidence from Mexico," *Journal of Development Economics*, 2007, *82* (1), 180–199.

Mobarak, Ahmed Mushfiq, Iffath Sharif, and Maheshwor Shrestha, "Returns to international migration: Evidence from a Bangladesh-Malaysia visa lottery," 2021.

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

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

Mullins, Jamie T. and Prashant Bharadwaj, "Weather, Climate, and Migration in the United States," NBER Working paper Series 28614, NBER 2021.

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

Munshi, Kaivan and Mark Rosenzweig, "Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap," *American Economic Review*, January 2016, *106* (1), 46–98.

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

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

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

Quiñones, Esteban J., Sabine Liebenehm, and Rasadhika Sharma, "Left home high and dry-reduced migration in response to repeated droughts in Thailand and Vietnam," *Population Environment*, 2021, *4*.

Rendón, José Rodrigo, Virginia Snyder, Ginés Suarez, Nelson Mauricio Estrada Regalado, Jorge Antonio Castaneda Cerón, Carlos Alberto Jacome Montenegro, Juan David Barahona Rebolledo, Juan Benavides, Pablo Roda, Claudia Rave, Mildred Alvarado, Alejandro Lucio, Francisco Perdomo, and Jorge Sánchez, "Plan maestro de infraestructura de El Salvador: Un instrumento de planeación de infraestructura multisectorial a largo plazo que permitirá potenciar el desarrollo económico y social de El Salvador," Technical Report, Interamerican Development Bank 2020.

Roberts, Michael and Wolfram Schlenker, "The evolution of heat tolerance of corn: Implications for climate change," in "in" 2011, pp. 225–251.

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

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

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

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

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

Thiede, Brian, Clark Gray, and Valerie Mueller, "Climate variability and inter-provincial migration in South America, 1970–2011," *Global Environmental Change*, 2016, *41*, 228–240.

WB, *El Salvador: desarrollos económicos recientes en infraestructura : informe estratégico (REDI-SR) : provisión de servicios de infraestructura en El Salvador : combatiendo la pobreza, reanudando el crecimiento*, World Bank, 2006.

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

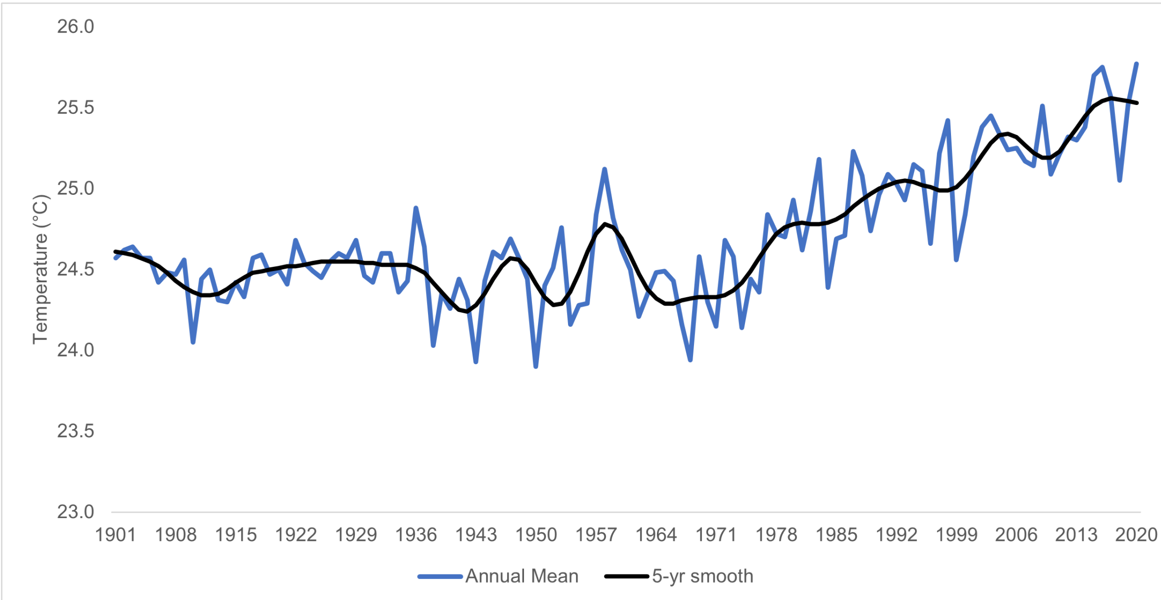
WB, *World Development Report 2023: Migrants, Refugees, and Societies*, The World Bank, 2023.

WFP, "Food Security and emigration. Why people flee and the impact of family members left behind in El Salvador, Guatemala and Honduras," Technical Report, Interamerican Development Bank, International Fund for Agricultural Development, International Organization for Migration, Organization of American States and World Food Programme 2017.

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

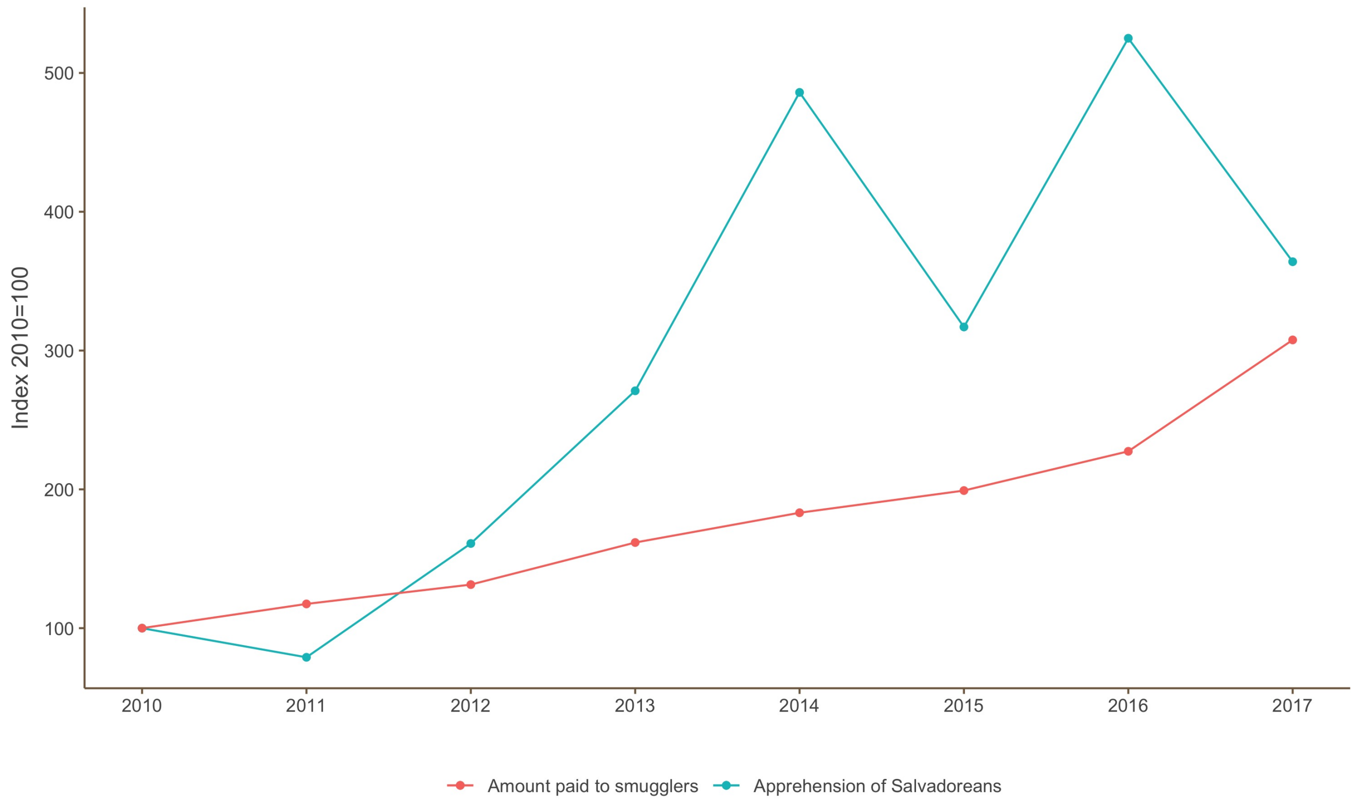
7 Figures

Figure 1: Average Temperature in El Salvador



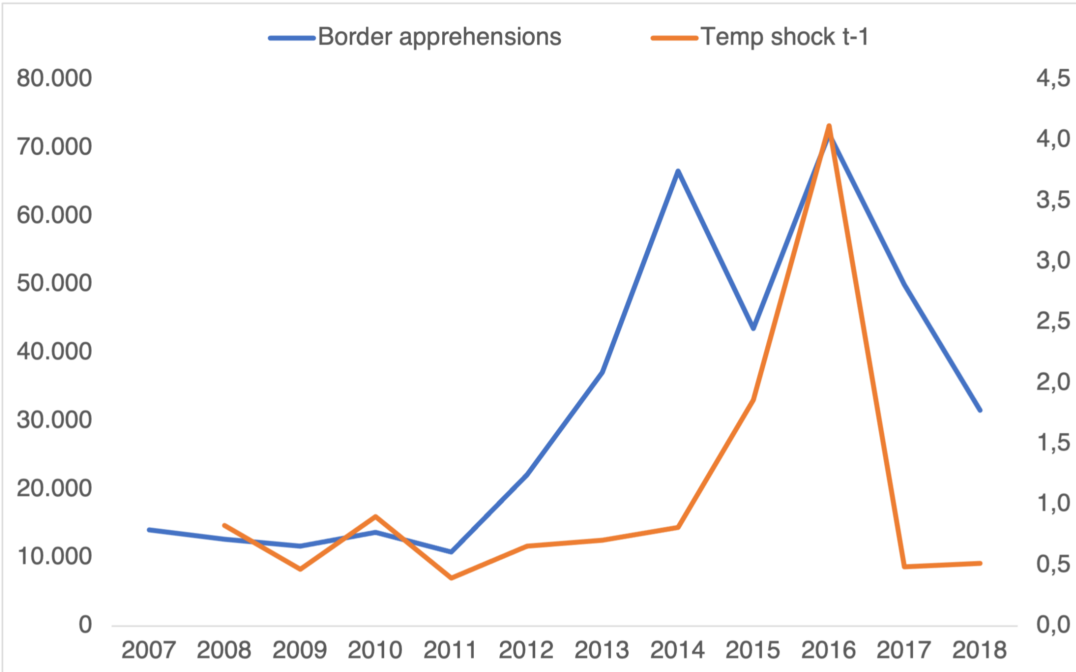
Source: World Bank (2022). Data from Climatic Research Unit (CRU) of the University of East Anglia.

Figure 2: Border Apprehension of Salvadoreans and Cost of Smugglers



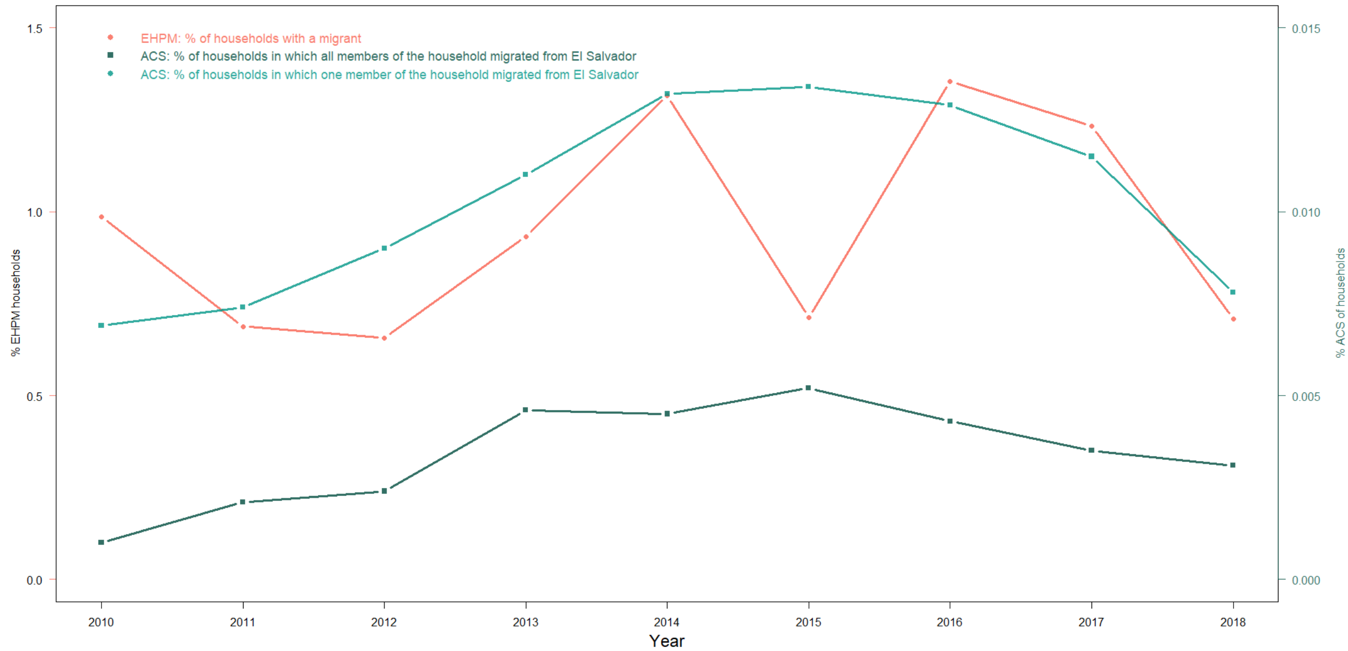
Source: Own elaboration based on American Community Survey (ACS) and Customs and Border Protection (CBP).

Figure 3: US Border Apprehensions



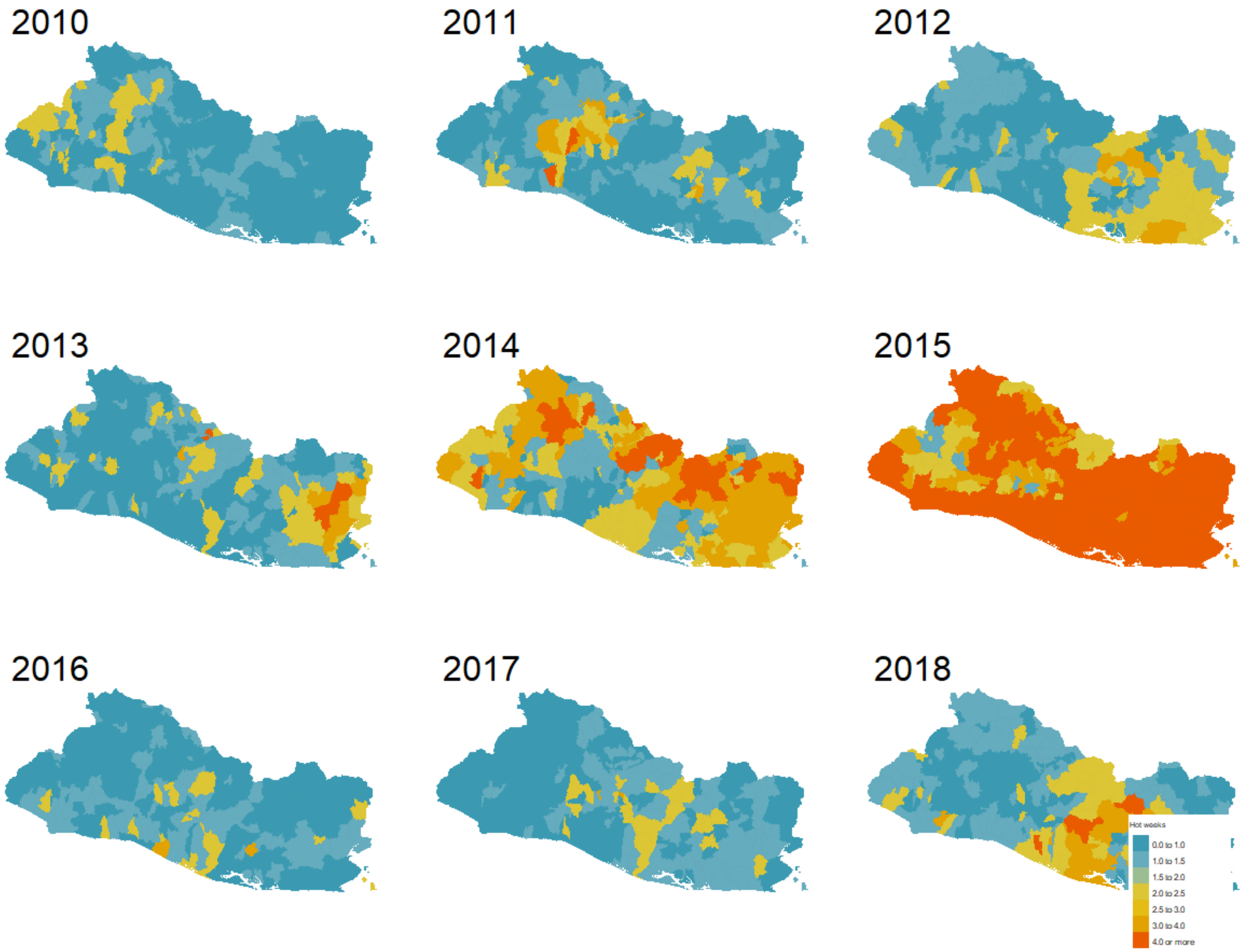
Source: Own elaboration based on US Customs and Border Protection (CBP) and NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. The blue line represents the average number of weeks in winter with a temperature shock (two SD above the historic mean).

Figure 4: Migration Trends of Salvadoreans – EHPM and ACS



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

Figure 5: Temperature Shocks at the Municipality and Year Level



Source: Own elaboration based on NASA – Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature. Each map represents the number of weeks in the first harvest season 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)
Panel 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	0.244	0.245
Mean	1.917	1.917
Panel 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	0.277	0.279
Mean	2.342	2.342
Panel 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	0.456	0.458
Mean	2.784	2.784
Panel D: 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	0.299	0.299
Mean	0.000	0.000
Panel E: 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	0.181	0.182
Mean	0.447	0.447
Crime, Weather and Household	X	X
Year Fixed Effects	X	X
Municipal Fixed Effects	X	X
Municipal Socio*Year	X	X
Geographic*Year	X	X
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 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 rainfall and drought shocks (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 for 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	Agro-chemicals	Chemical agents	Agro-ecological	Log(total area)	Log(corn area)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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)*
Obs	17,573	17,573	17,573	17,573	17,573	19,261	18,623
R2	0.035	0.024	0.024	0.119	0.057	0.182	0.197
Mean	0.000	99.573	99.858	92.272	1.940	1.490	0.705
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-harvest and post-harvest ripening agents, and post-harvest product protection agents. The fifth variable corresponds to agro-ecological 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 variable is temperature shock (two sd higher than the historic value during the winter season the same year). Municipality controls are the number of weeks with rainfall, drought, and crime shocks (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 rainfall, drought, and crime shocks (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 Individual Probability of Employment

	Employed		Agricultural		Agricultural (seasonal)		Agricultural (corn)		Non-Agro	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature shock t	-0.036	-0.138	-0.180	-0.201	-0.205	-0.244	-0.230	-0.305	0.180	0.201
	(0.102)	(0.084)	(0.112)	(0.138)	(0.103)**	(0.126)*	(0.113)**	(0.143)**	(0.112)	(0.138)
Temperature shock t-1 to t-4		0.281		0.638		0.466		0.349		-0.638
		(0.196)		(0.276)**		(0.388)		(0.355)		(0.276)**
Obs	639,412	499,076	328,288	259,249	328,288	259,249	328,288	259,249	328,288	259,249
R2	0.211	0.215	0.284	0.279	0.206	0.207	0.204	0.206	0.284	0.279
Mean	51.342	51.946	24.064	23.459	15.492	15.345	13.935	13.787	75.936	76.541
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
Individual 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 100 if the person is employed. In the remaining columns, the dependent variable is 100 if the person is employed in each sector. The independent variable is the number of weeks with a temperature shock (two sd higher than that week's historic value in that municipality during the winter season) in the same year and the previous one to four years. Municipality controls are the number of weeks with rainfall and drought shocks (two sd higher than that week's historic value in that municipality during the winter season) in the same year and the previous one to four years. We also control for 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. Individuals controls are gender, age and education. 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 Labor Outcomes

	All workers		Workers in Agro		Workers in Agro (seasonal)		Workers in Agro (Corn)		Workers in Non-Agro	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A:										
Hours(log)										
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)**	(0.005)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
Temperature Shock t-1 to t-4		-0.006		0.004		0.010		0.008		-0.007
		(0.006)		(0.012)		(0.016)		(0.016)		(0.006)
Obs	328,288	259,249	79,000	60,816	50,857	39,783	45,746	35,742	249,288	198,433
R2	0.065	0.068	0.088	0.089	0.075	0.080	0.079	0.085	0.059	0.062
Mean	40.742	40.743	34.748	34.575	32.489	32.314	31.962	31.738	42.642	42.634
Panel B:										
Hourly wage (log(SCP))										
Temperature Shock t	0.008	0.003	0.022	0.000	0.024	0.016	0.000	-0.012	-0.001	-0.002
	(0.011)	(0.009)	(0.028)	(0.023)	(0.022)	(0.018)	(0.018)	(0.016)	(0.005)	(0.005)
Temperature Shock t-1 to t-4		-0.034		-0.020		0.034		0.026		-0.022
		(0.016)**		(0.053)		(0.074)		(0.049)		(0.012)*
Obs	265,442	210,609	34,267	26,633	19,253	15,193	15,074	11,839	231,175	183,976
R2	0.129	0.120	0.255	0.282	0.397	0.414	0.480	0.500	0.108	0.098
Mean	9.039	8.923	3.671	3.755	3.770	3.842	3.759	3.823	9.835	9.671
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. 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) in the same year and the previous one to four years. 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 Probability of International Migration

Population Group	(1)	(2)
Panel 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	0.008	0.009
Mean	0.876	0.940
Panel B: Agricultural Households (all)		
Temperature shock t-1	0.085	0.129
	(0.088)	(0.085)
Temperature shock t-2 to t-5		0.020
		(0.242)
Obs	22,268	14,277
R2	0.020	0.021
Mean	0.799	0.805
Panel C: Agricultural Households (seasonal)		
Temperature shock t-1	0.225	0.264
	(0.107)**	(0.109)**
Temperature shock t-2 to t-5		-0.087
		(0.294)
Obs	14,334	9,370
R2	0.022	0.025
Mean	0.656	0.726
Panel 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	0.022	0.027
Mean	0.695	0.788
Panel E: Non Agricultural Households		
Temperature shock t-1	0.015	-0.009
	(0.047)	(0.053)
Temperature shock t-2 to t-5		0.091
		(0.104)
Obs	110,747	78,533
R2	0.007	0.008
Mean	0.654	0.695
Year + Municipality FE	X	X
Rainfall Shock year t-1	X	X
Drought Shock year t-1	X	X
Crime Shock year t-1	X	X
Municipal characteristics*Year	X	X
Household characteristics	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 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) in the previous 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 non-agricultural when the household head or at least 50 percent of the members of working age are employed in the non-agricultural sector. Municipality controls are the number of weeks with rainfall and drought shocks (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 for 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 7: Heterogeneity by Access to Risk-Management Mechanisms: ENAMP Outcomes

Population Group	Access Credit	Remittances (Population %)
Panel A: Log(Total Production)		
Temperature shock t	0.025	-0.024
	(0.045)	(0.021)
Temperature shock t x Q4	-0.037	-0.050
	(0.048)	(0.037)
Obs	7,629	8,249
R2	0.326	0.240
Mean	1.979	1.794
Panel B: Log(Production per Ha. cultivated in corn)		
Temperature shock t	0.000	-0.032
	(0.044)	(0.012)**
Temperature shock t x Q4	-0.023	-0.045
	(0.044)	(0.033)
Obs	7,382	7,995
R2	0.521	0.461
Mean	2.310	2.284
Panel C: PCA - Input		
Temperature shock t	-0.005	0.016
	(0.017)	(0.013)
Temperature shock t x Q4	-0.033	-0.029
	(0.033)	(0.035)
Obs	6,927	7,490
R2	0.048	0.047
Mean	0.035	0.017
Panel D: Total Workers		
Temperature shock t	-0.053	-0.038
	(0.028)*	(0.018)**
Temperature shock t x Q4	0.034	0.092
	(0.027)	(0.044)**
Obs	7,473	8,087
R2	0.129	0.107
Mean	5.637	5.039
Panel E: Non-Household Workers		
Temperature shock t	-0.046	-0.045
	(0.030)	(0.021)**
Temperature shock t x Q4	0.003	0.118
	(0.031)	(0.057)**
Obs	7,473	8,087
R2	0.145	0.112
Mean	3.916	3.253
Panel F: Household Workers		
Temperature shock t	-0.033	-0.003
	(0.033)	(0.018)
Temperature shock t x Q4	0.053	0.026
	(0.031)*	(0.041)
Obs	7,473	8,087
R2	0.252	0.224
Mean	1.721	1.786
Year + Municipality FE	X	X
Rainfall Shock year t-1	X	X
Drought Shock year t-1	X	X
Crime Shock year t-1	X	X
Municipal characteristics*Year	X	X
Household controls	X	X

Notes: Data from 2013–2018 of ENAMP. Dependent variable in panel A is log of ratio of corn prod. per hectare in first harvest; in panel B, it is log total prod. per hectare in first harvest; in panel C, is an index using principal components analysis as in Table 2; in panel D, is the IHS of number total workers, in panel E, is the IHS of number of non-hh workers; in panel F, is the IHS of the number of HH workers. Temperature shock measured as in previous estimations. In column (1) we restrict the sample to municipalities that are in the first or fourth quartile of the distribution of the share of the population with access to credit in 2009. We interact the independent variable with a dummy that indicates if the municipality is in the fourth quartile. In column (2) we restrict the sample to municipalities that are in the first or fourth quartile of the distribution of the share of the population with remittances in 2007. We interact the independent variable with a dummy that indicates if the municipality its in the fourth quartile. Same controls of previous models, and we fully interact the model with dummy that indicates if the municipality is in the fourth quartile of the corresponding distribution. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table 8: Heterogeneity by Access to Risk-Management Mechanisms: EHPM Outcomes

Population Group Group	Access Credit	Remittances (Population %)
Panel A: Likelihood of working in the agricultural sector (corn)		
Temperature shock t	-0.773	-0.286
	(0.179)***	(0.103)**
Temperature shock t x Q4	-0.093	-0.073
	(0.323)	(0.244)
Obs	82,854	117,414
R2	0.232	0.232
Mean	19.405	17.740
Panel B: Hours(log) in the agricultural sector (corn)		
Temperature shock t	-0.005	-0.010
	(0.012)	(0.010)
Temperature shock t x Q4	-0.009	0.026
	(0.011)	(0.011)**
Obs	16,078	20,829
R2	0.095	0.094
Mean	32.286	31.766
Panel C: Hourly wage (log(SCP)) in the agricultural sector (corn)		
Temperature shock t	0.037	0.035
	(0.022)*	(0.026)
Temperature shock t x Q4	-0.038	-0.063
	(0.022)*	(0.024)**
Obs	5,291	6,388
R2	0.315	0.306
Mean	0.156	0.159
Panel D: Migration likelihood in agricultural households (corn)		
Temperature shock t-1	0.239	0.031
	(0.389)	(0.042)
Temperature shock t-1 x Q4	0.016	0.233
	(0.247)	(0.216)
Obs	4,584	5,642
R2	0.033	0.030
Mean	0.589	0.709
Year + Municipality FE	X	X
Rainfall Shock year t-1	X	X
Drought Shock year t-1	X	X
Crime Shock year t-1	X	X
Municipal characteristics*Year	X	X
Individual or household controls	X	X

Notes: Individual data from 2009–2018 of EHPM. In panels A, B and C, the sample is constrained the sample for people 10–65 years old. In Panel A we also restrict the sample to employed individuals; in Panel B and C to individuals working in the agricultural sector producing corn; in panel D 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. The dependent variable in panel A is 100 if the person is employed in the agricultural sector producing corn; in panel B, is the logarithm of the number of hours worked; in panel C, is the logarithm of the hourly wage; in panel D, is 100 if a household member migrated in the surveyed year. For panels A, B and C, 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); for panel D, it 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). In column (1) we restrict the sample to municipalities that are in the first or fourth quartile of the distribution of the share of the population with access to credit in 2009. We interact the independent variable with a dummy that indicates if the municipality is in the fourth quartile. In column (2) we restrict the sample to municipalities that are in the first or fourth quartile of the distribution of the share of the population with remittances in 2007. We interact the independent variable with a dummy that indicates if the municipality is in the fourth quartile. Municipality controls as in previous models. We also interact the controls with the dummy that indicates if the municipality is in the fourth quartile of the corresponding distribution. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

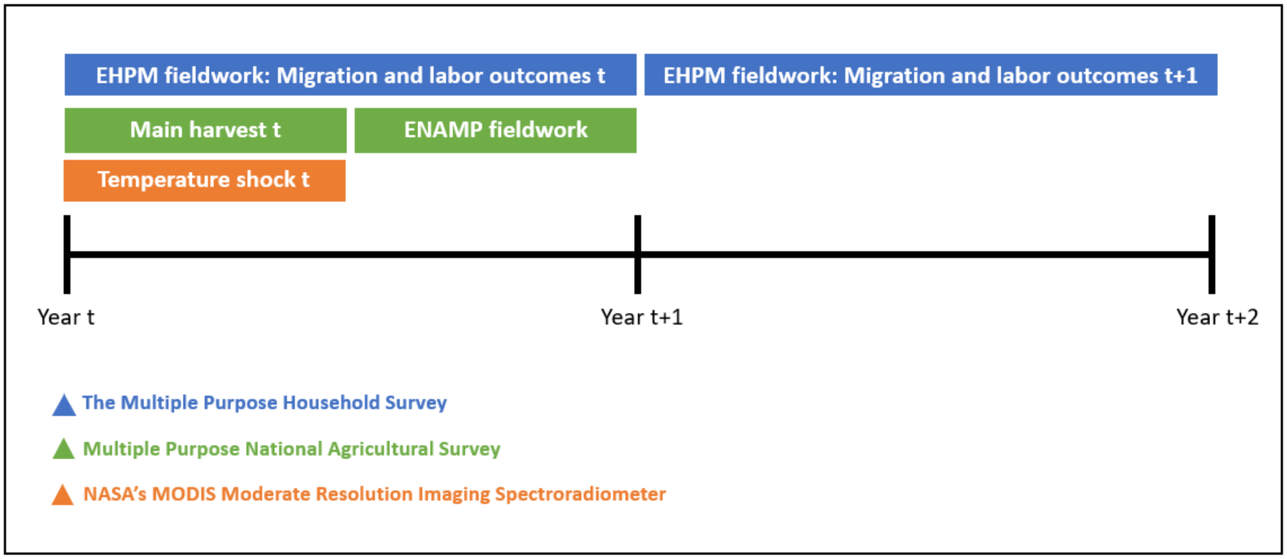
Table 9: Impact of Temperature Shocks on Migration Likelihood – Different Shocks

	Preferred specification	Changing the months of the shocks			Changing the range of years	
Population Group	Main Harvest Season Shock (1)	All-year Shock (2)	Apante Shock (3)	Lean Shock (4)	2013-2018 (5)	Excluding 2015 (6)
Panel A: Share of workers in the agricultural sector (corn)						
Temperature shock year t	-0.277	-0.073	0.108	0.112	-0.380	-0.281
	(0.117)**	(0.068)	(0.161)	(0.218)	(0.135)**	(0.156)*
Obs	2,239	2,239	2,239	2,239	1,361	2,010
R2	0.760	0.759	0.759	0.759	0.795	0.758
Mean	9.066	9.066	9.066	9.066	8.620	9.113
Panel B: Log (average hourly wage (SCP)) in the agricultural sector (corn)						
Temperature shock year t	0.006	-0.009	0.003	-0.031	0.015	0.001
	(0.012)	(0.006)	(0.024)	(0.014)**	(0.012)	(0.015)
Obs	1,573	1,573	1,573	1,573	924	1,407
R2	0.328	0.329	0.327	0.328	0.391	0.346
Mean	0.176	0.176	0.176	0.176	0.166	0.179
Panel C: Migration likelihood in agricultural households (corn)						
Temperature shock year t-1	0.245	0.046	-0.176	-0.106	0.315	0.306
	(0.124)**	(0.039)	(0.223)	(0.099)	(0.137)**	(0.126)**
Obs	12,659	12,659	12,659	12,659	6,946	11,156
R2	0.022	0.022	0.022	0.022	0.029	0.025
Mean	0.695	0.695	0.695	0.695	0.864	0.717
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

Notes: Estimations in panels A and B use 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 employed producing corn 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, correspondingly. 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. For panels A and B: the independent variable in Column (1) is the number of weeks with a temperature shock (two sd higher than that week's historic value in that municipality the same year). The independent variable in Column (2) 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). The independent variable in Column (3) is the number of weeks with a temperature shock (two sd higher than that week's historic value in that municipality during all the previous year). The independent variable in Column (4) is the number of weeks with a temperature shock (two sd higher than that week's historic value in that municipality during the 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. In panel C, we have the same shocks as in the previous year. Municipality controls are the number of weeks with rainfall and drought shocks (two sd higher than that week's historic value in that municipality during the winter season the same year or the previous year, depending on the independent variable). We also control for 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. Since the estimations in panels A and B are at municipality level, we do not include household controls. Household controls in panel C 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

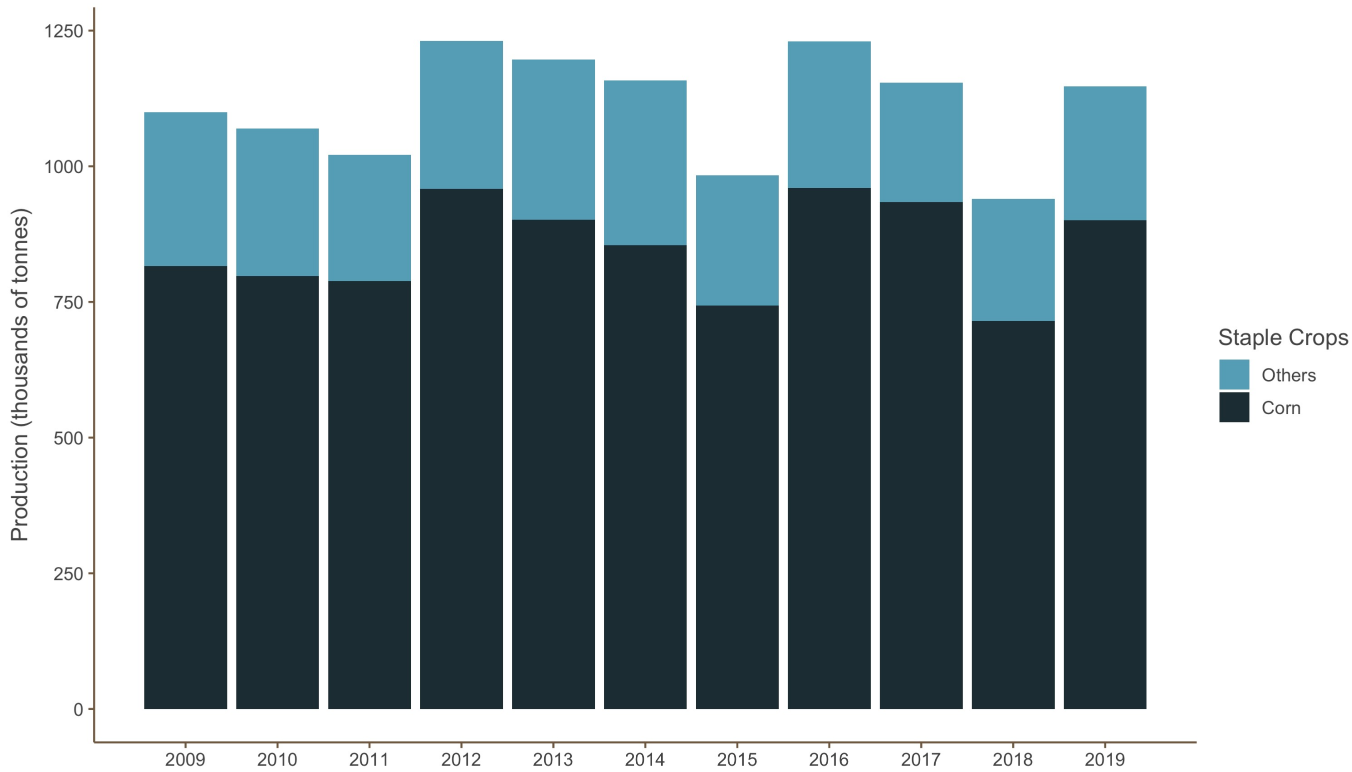
9 Appendix

Figure A1: Timeline of Data



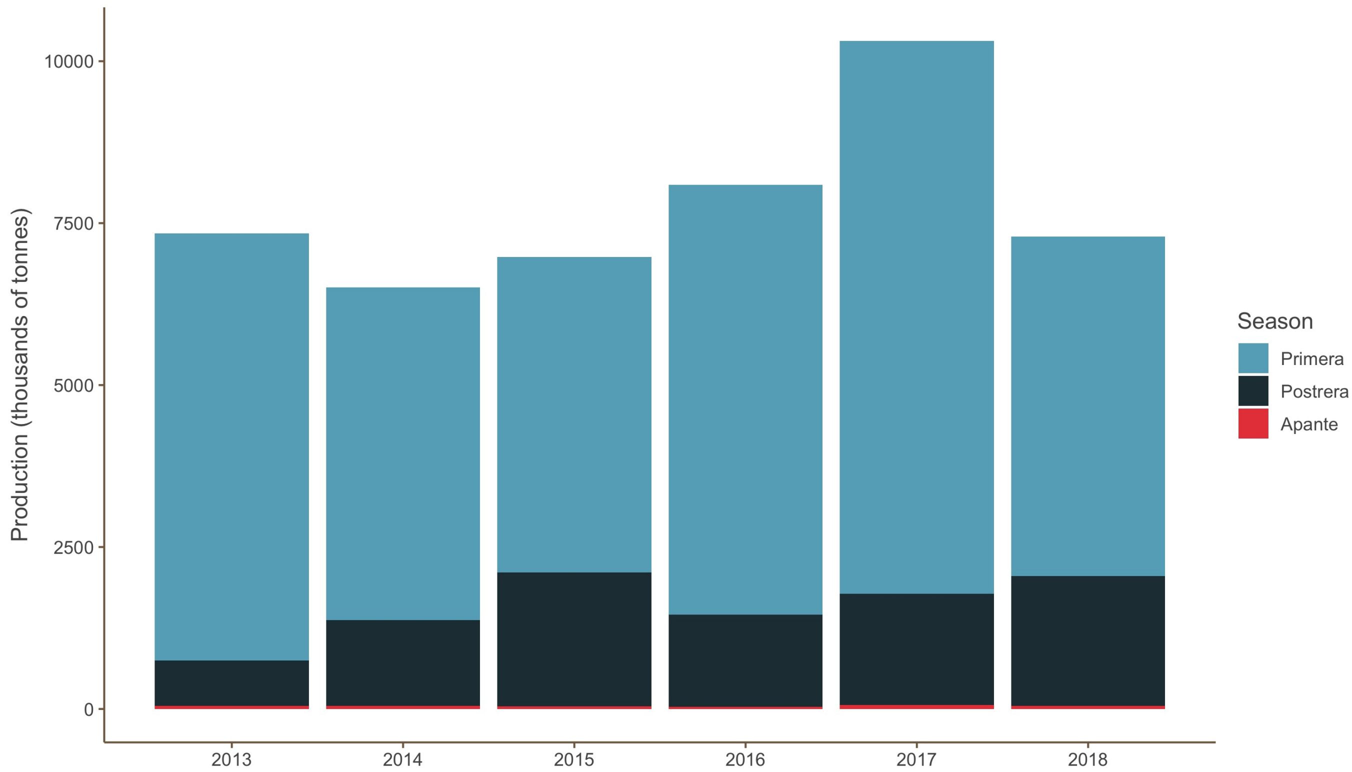
Source: Own elaboration based on El Salvador's Multiple Purpose Household Survey (EHPM), El Salvador's Agricultural Household Survey (ENAMP) and NASA – Moderate Resolution Imaging Spectroradiometer (MODIS).

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



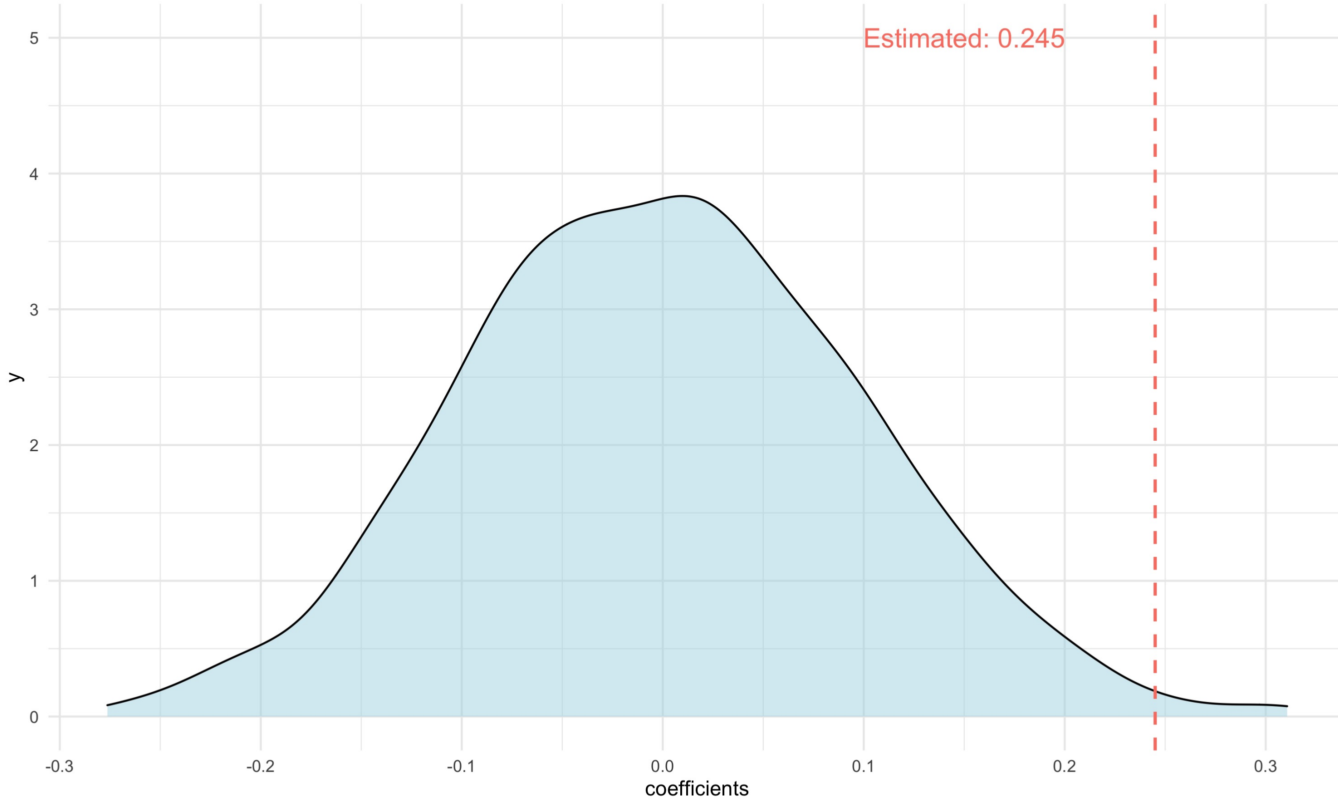
Source: Own elaboration based on FAOSTAT. Staple crops include corn (maize), rice, sorghum, and beans.

Figure A3: Corn Production across Yearly Seasons in El Salvador



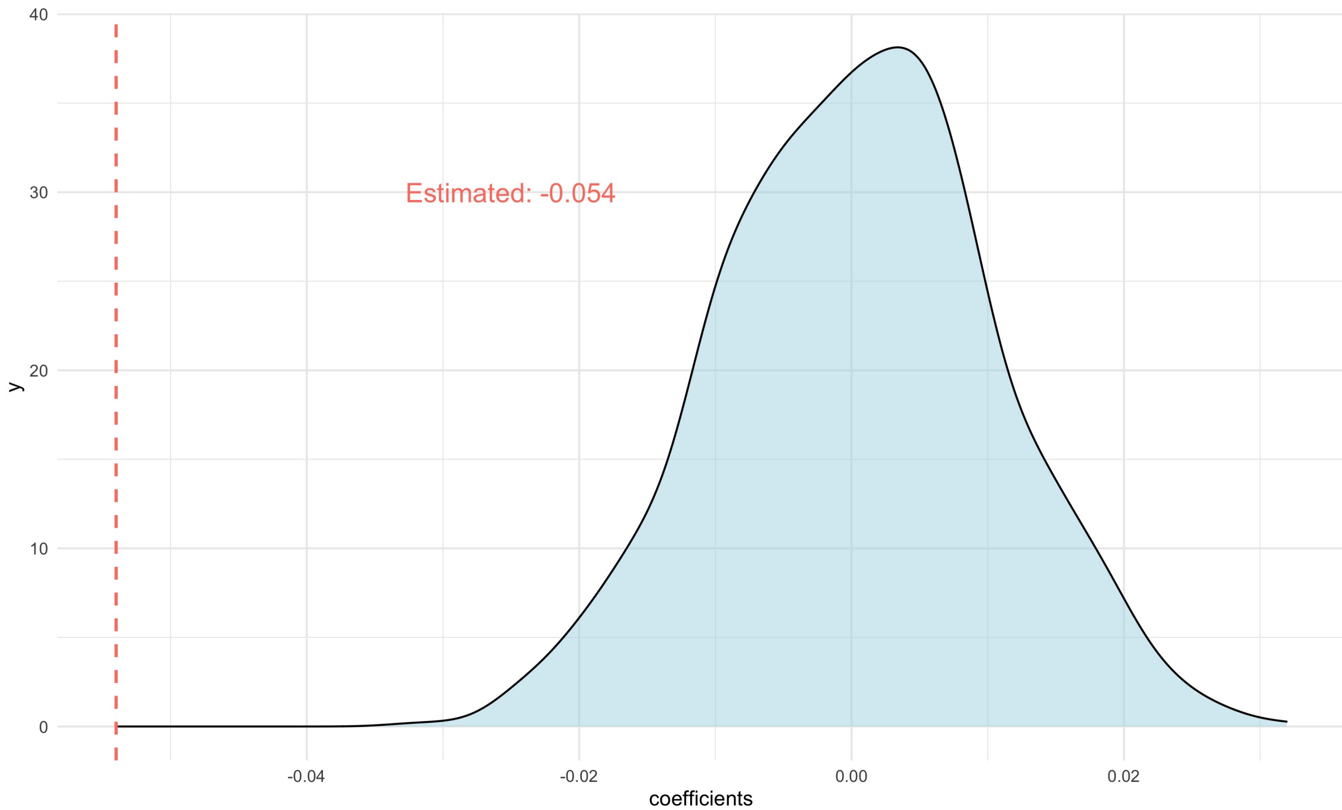
Source: Own elaboration based on ENAMP 2013–2018.

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



Source: Own elaboration based on Individual data from 2009–2018 of El Salvador's Multiple Purpose Household Survey (EHPM) for people 10–65 years old. 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



Source: Own elaboration based on Data from 2013–2018 of El Salvador's Agricultural Household Survey (ENAMP). 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					
$=$100 if at least one migrant member last year	186910	0.876	9.320	0.000	100.000
Employed	639412	51.342	49.982	0.000	100.000
Employed in agricultural sector	639412	12.476	33.045	0.000	100.000
Employed in agricultural sector (seasonal)	639412	8.033	27.18	0.000	100.000
Employed in agricultural sector (corn)	639412	7.224	25.888	0.000	100.000
Employed in the non agricultural sector	639412	38.987	48.772	0.000	100.000
Weekly hours worked - agricultural sector (corn)	328288	40.742	16.417	1.000	84.000
Hourly wage ($SCV) - agricultural sector (corn)	265442	9.039	41.503	0.013	8288.574
Panel B: ENAMP					
Corn production (ton.)	19261	1.917	1.892	0.001	58.880
Corn - productivity (ton. per ha)	19261	2.342	1.209	0.000	19.189
Corn - productivity (ton. per ha cultived in corn)	18618	2.784	1.029	0.006	8.470
TFP production	16494	0.000	0.693	-21.843	1.544
Corn - productivity (ton. per worker)	18784	0.447	0.415	0.000	9.660
Total workers	18845	5.404	7.325	0.000	494.000
Hired workers	18845	3.696	7.379	0.000	494.000
Household workers	18845	1.708	1.570	0.000	43.000
PCA index of inputs	17568	0.000	1.000	-25.361	0.140
Planting material ($=$100 if used)	17568	99.573	6.520	0.000	100.000
Agrochemicals ($=$100 if used)	17568	99.858	3.770	0.000	100.000
Chemical agents ($=$100 if used)	17568	92.270	26.707	0.000	100.000
Agroecological ($=$100 if used)	17568	1.941	13.797	0.000	100.000
Land Size (Ha)	19261	1.490	4.832	0.077	210.000
Land Size cultivated in corn (Ha)	18618	0.493	0.486	0.039	31.850

Note: Panel A shows descriptive statistics for El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018 at the household level. Panel B shows data from 2013–2018 of El Salvador's 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	0.667	0.471	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	0.060	0.238	0.000	1.000
Panel B: ENAMP					
Highest education level	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	1.135	0.583	0.000	4.000
Number of weeks rainfall 2sd > historic mean	244	0.115	0.150	0.000	0.833
Number of weeks rainfall 2sd < historic mean	244	0.317	0.232	0.000	1.000
Number of weeks crime 2sd > historic mean	244	0.310	0.261	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	244	83.733	88.237	5.400	668.360
Poverty rate (2005)	244	50.632	14.944	10.370	88.500
Extreme poverty (2005)	244	25.751	12.596	4.200	60.400
Income per capita (2005)	244	561.074	266.001	212.600	2763.520
% employed in agriculture (2005)	244	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 immigrants	244	19.031	13.552	1.245	108.087
% External immigrants	244	29.947	26.330	3.862	234.916
% Population who received remittances in 2009	244	9.915	8.773	0.881	110.097

Note: Panel A shows descriptive statistics for El Salvador's Multiple Purpose Household Survey (EHPM) from 2009–2018 at the household level. Panel B shows data from 2013 – 2018 of El Salvador's Agricultural Household Survey at the producer level. Panel C shows municipality-level statistics for 2009–2018. The temperature, rainfall and crime shock statistics are calculated using the municipal average. 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	-0.027	-0.028	-0.028	-0.027	-0.028	1.917	19,261
	(0.025)**	(0.013)**	(0.013)**	(0.013)**	(0.014)**	(0.014)**		
R2	0.012	0.228	0.228	0.228	0.232	0.244		
B: Log(Production per Ha.)								
Temperature shock year t	-0.105	-0.055	-0.055	-0.056	-0.055	-0.054	2.342	19,261
	(0.034)**	(0.017)**	(0.018)**	(0.018)**	(0.015)***	(0.015)***		
R2	0.033	0.268	0.268	0.268	0.271	0.277		
C: Log(Production per Ha. cultivated in corn)								
Temperature shock year t	-0.098	-0.053	-0.049	-0.049	-0.046	-0.046	2.784	18,618
	(0.027)***	(0.011)***	(0.012)***	(0.012)***	(0.009)***	(0.009)***		
R2	0.065	0.447	0.448	0.448	0.455	0.456		
D: Log(TFP production)								
Temperature shock year t	-0.082	-0.037	-0.039	-0.040	-0.036	-0.036	0.000	16,438
	(0.024)***	(0.012)**	(0.012)**	(0.012)**	(0.011)***	(0.011)***		
R2	0.031	0.289	0.289	0.289	0.293	0.299		
E: Log(Labor productivity)								
Temperature shock year t	-0.051	-0.002	-0.012	-0.014	-0.009	-0.009	0.447	18,784
	(0.025)**	(0.016)	(0.017)	(0.016)	(0.013)	(0.014)		
R2	0.008	0.174	0.176	0.177	0.180	0.181		
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 rainfall, drought, and crime shocks (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 on Corn Agricultural Outcomes in First-Harvest Season using Conley Standard Errors

Agricultural Outcome	(1)	(2)
A: Log(Total Production)		
Temperature shock t	-0.028	-0.032
	(0.009)**	(0.009)***
Temperature shock t-1 to t-4		-0.004
		(0.020)
Mean	1.917	1.917
B: Log(Production per Ha.)		
Temperature shock t	-0.054	-0.059
	(0.013)***	(0.014)***
Temperature shock t-1 to t-4		-0.068
		(0.033)**
Mean	2.342	2.342
C: Log(Production per Ha. cultivated in corn)		
Temperature shock t	-0.047	-0.051
	(0.012)***	(0.012)***
Temperature shock t-1 to t-4		-0.044
		(0.022)**
Mean	2.784	2.784
F: Log(TFP production)		
Temperature shock t	-0.036	-0.039
	(0.012)**	(0.012)***
Temperature shock t-1 to t-4		-0.039
		(0.019)
Mean	0.000	0.000
D: Log(Labor productivity)		
Temperature shock t	-0.010	-0.013
	(0.015)	(0.016)
Temperature shock t-1 to t-4		0.038
		(0.036)
Mean	0.447	0.447
Crime, Weather and Household	X	X
Year Fixed Effects	X	X
Municipal Fixed Effects	X	X
Municipal Socio*Year	X	X
Geographic*Year	X	X
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 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 rainfall and drought shocks (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 for 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 A5: Impact of Temperature Shocks in First-Harvest Season on Local Labor Markets- Municipal Shares

	Agricultural		Agricultural (seasonal)		Agricultural (corn)		Non-Agro		Unemployed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A:										
Employment and unemployment rate										
Temperature Shock t	-0.323	-0.295	-0.238	-0.253	-0.277	-0.307	0.168	0.044	0.142	0.249
	(0.114)**	(0.101)**	(0.123)*	(0.144)*	(0.117)**	(0.138)**	(0.105)	(0.047)	(0.121)	(0.098)**
Temperature Shock t-1 to t-4		0.123		-0.694		-0.622		0.286		-0.457
		(0.510)		(0.527)		(0.465)		(0.658)		(0.707)
Obs	2,239	1,793	2,239	1,793	2,239	1,793	2,239	1,793	2,239	1,793
R2	0.758	0.776	0.745	0.766	0.760	0.781	0.795	0.806	0.460	0.486
Mean	15.091	14.856	9.842	9.760	9.066	8.973	35.127	35.910	49.917	49.332
Panel B:										
Log (average hourly wage (SCP))										
Temperature Shock t	0.012	-0.004	0.020	0.010	0.000	-0.009	0.001	-0.001		
	(0.020)	(0.019)	(0.027)	(0.024)	(0.022)	(0.023)	(0.008)	(0.009)		
Temperature Shock t-1 to t-4		0.127		0.209		0.214		-0.030		
		(0.055)**		(0.064)**		(0.061)***		(0.031)		
Obs	1,904	1,510	1,657	1,323	1,573	1,254	2,237	1,792		
R2	0.341	0.374	0.389	0.415	0.396	0.419	0.362	0.397		
Mean	4.947	4.915	4.877	4.906	4.859	4.936	9.596	9.570		
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 hourly 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 one to four years. Municipality controls are the number of weeks with rainfall and drought shocks (two sd higher than that week's historic value in that municipality during the winter season) in the same year and the previous one to four years. We also control for 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 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
	(1)	(2)	(3)	(4)	(5)
Panel A: Hours(log)					
Women					
Temperature Shock t	0.004	0.015	0.009	0.007	0.001
	(0.004)	(0.008)*	(0.016)	(0.024)	(0.004)
Obs	130,507	7,305	3,021	2,336	123,202
R2	0.049	0.221	0.138	0.150	0.043
Mean	40.052	31.513	27.509	26.127	40.558
Men					
Temperature Shock t	0.001	0.004	0.004	0.003	0.000
	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)
Obs	197,781	71,695	47,836	43,410	126,086
R2	0.082	0.083	0.070	0.073	0.040
Mean	41.198	35.077	32.804	32.276	44.678
Panel B: Hourly wage (log(SCP))					
Women					
Temperature Shock t	-0.005	0.024	0.036	0.229	-0.007
	(0.006)	(0.019)	(0.051)	(0.094)**	(0.005)
Obs	114,327	3,245	879	387	111,082
R2	0.106	0.223	0.408	0.627	0.102
Mean	9.367	3.529	3.808	3.622	9.537
Men					
Temperature Shock t	0.017	0.018	0.022	-0.005	0.004
	(0.016)	(0.027)	(0.022)	(0.015)	(0.008)
Obs	151,115	31,022	18,374	14,687	120,093
R2	0.158	0.273	0.404	0.484	0.122
Mean	8.791	3.686	3.769	3.763	10.110
Year + Municipality FE	X	X	X	X	X
Rainfall Shock year t	X	X	X	X	X
Drought Shock year t	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. 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) in the same year. Municipality controls are the number of weeks with rainfall and drought shocks (two SD higher than that week's historic value in that municipality during the winter season) in the same year. We also control for 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 A7: Impact of Temperature Shocks in First-Harvest Season on Labor Outcomes

	All workers (1)	Workers in Agro (2)	Workers in Agro (seasonal) (3)	Workers in Agro (Corn) (4)	Workers in Non-Agro (5)
Panel A: Hours(log)					
Less than 14 years old					
Temperature Shock t	0.022	0.046	0.034	0.047	-0.009
	(0.013)*	(0.014)**	(0.021)	(0.014)***	(0.022)
Obs	6,932	3,738	2,473	3,811	3,194
R2	0.096	0.143	0.151	0.138	0.124
Mean	22.142	22.505	21.418	22.539	21.717
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
R2	0.069	0.098	0.111	0.094	0.095
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
R2	0.050	0.071	0.055	0.066	0.050
Mean	41.844	36.286	33.910	36.385	43.369
More than 65 years old					
Temperature Shock t	0.007	-0.010	-0.005	-0.003	0.014
	(0.021)	(0.025)	(0.046)	(0.026)	(0.024)
Obs	2,666	1,035	596	1,050	1,631
R2	0.141	0.354	0.385	0.349	0.160
Mean	39.641	36.361	34.740	36.287	41.723
Panel B: Hourly wage (log(SCP))					
Less than 14 years old					
Temperature Shock t	0.052	-0.057	-0.042	-0.028	0.149
	(0.069)	(0.092)	(0.189)	(0.080)	(0.077)*
Obs	1,126	442	224	471	684
R2	0.387	0.554	0.787	0.538	0.466
Mean	3.418	3.299	4.013	3.581	3.495
Between 14 and 18 years old					
Temperature Shock t	0.026	0.032	0.031	0.038	0.011
	(0.017)	(0.033)	(0.030)	(0.031)	(0.019)
Obs	8,371	3,161	1,886	3,337	5,210
R2	0.228	0.375	0.507	0.362	0.198
Mean	3.951	3.716	4.065	3.762	4.093
Between 18 and 65 years old					
Temperature Shock t	0.006	0.021	0.028	0.021	-0.002
	(0.010)	(0.027)	(0.022)	(0.025)	(0.005)
Obs	254,097	30,364	17,007	32,910	223,733
R2	0.115	0.251	0.392	0.233	0.095
Mean	9.216	3.674	3.736	4.019	9.968
More than 65 years old					
Temperature Shock t	0.014	-0.043	-0.086	-0.073	-0.013
	(NaN)	(0.110)	(0.270)	(0.097)	(0.013)
Obs	1,848	300	136	315	1,548
R2	0.230	0.687	0.931	0.680	0.192
Mean	11.177	3.466	3.600	3.696	12.671
Year + Municipality FE	X	X	X	X	X
Rainfall Shock year t	X	X	X	X	X
Drought Shock year t	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. 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) in the same year. Same controls as in Table A6. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

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

Population Group	(1)	(2)	(3)	(4)	(5)	(6)	Mean	Obs
Panel 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	0.006	0.006	0.006	0.006	0.008		
Panel B: Agricultural Households (all)								
Temperature shock year t-1	0.100	0.049	0.044	0.041	0.073	0.085	0.799	22,268
	(0.043)**	(0.081)	(0.085)	(0.086)	(0.084)	(0.088)		
R2	0.000	0.012	0.012	0.012	0.014	0.020		
Panel C: Agricultural Households (seasonal)								
Temperature shock year t-1	0.177	0.209	0.201	0.198	0.216	0.225	0.656	14,334
	(0.041)***	(0.096)**	(0.107)*	(0.108)*	(0.105)**	(0.107)**		
R2	0.001	0.015	0.016	0.016	0.016	0.022		
Panel 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	0.017	0.017	0.017	0.0178	0.022		
Panel E: Non Agricultural Households								
Temperature shock year t-1	0.084	0.030	0.012	0.009	0.012	0.015	0.654	110,747
	(0.035)**	(0.054)	(0.045)	(0.043)	(0.045)	(0.047)		
R2	0.000	0.006	0.006	0.006	0.006	0.007		
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 includes all households. Panel B: agricultural households. 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: agricultural (seasonal) households. 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: agricultural (corn) households. 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: non-agricultural households. A household is defined as non-agricultural when the household head or at least 50 percent of the members of working age are employed in the non-agricultural sector. Municipality controls are the crime, rainfall, 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 – Heterogeneity by Working-Age Household Member Characteristics

	Method 1: Preferred specification	Method 2: Household head works in agro sector		Method 3: At least 50% of working-age members in agro sector		Method 4: At least one working-age member in agro sector	
Population Group		No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:Agricultural Households (corn)							
Temperature shock year t-1	0.245	-0.003	0.233	0.076	0.172	0.070	0.169
	(0.124)**	(0.044)	(0.105)**	(0.068)	(0.126)	(0.062)	(0.126)
Obs	12,659	119,178	21,672	144,023	18,159	134,714	27,468
R2	0.022	0.007	0.019	0.010	0.015	0.011	0.015
Mean	0.695	0.654	0.854	0.882	0.765	0.854	0.939
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 (corn) 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 corn. Method 2 defines an agricultural household (corn) considering if the head of the household is employed producing corn. Method 3 defines an agricultural household (corn) only considering if at least 50 percent of the working-age members are employed producing corn. Method 4 defines an agricultural household (corn) considering if one working-age member is employed producing corn. 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, rainfall, 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 in First-Harvest Season on Probability of Migration by Access to Land

Population Group	(1)
Panel A: Agricultural Households (corn)	
Temperature shock year t-1	0.245
	(0.124)**
Obs	12,659
R2	0.022
Mean	0.695
Panel B: Landowners	
Temperature shock year t-1	0.463
	(0.403)
Obs	1,887
R2	0.087
Mean	1.219
Panel C: Land tenants	
Temperature shock year t-1	0.186
	(0.117)
Obs	5,771
R2	0.034
Mean	0.676
Panel D: Other type of land tenure	
Temperature shock year t-1	0.423
	(0.237)*
Obs	2,989
R2	0.066
Mean	0.736
Panel E: Wage workers	
Temperature shock year t-1	0.088
	(0.161)
Obs	2,035
R2	0.077
Mean	0.197
Year + Municipality FE	X
Rainfall Shock year t-1	X
Drought Shock year t-1	X
Crime Shock year t-1	X
Municipal characteristics*Year	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 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 previous year. Estimations in Panel A include 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 producing corn. Panel B includes agricultural households (corn) in which at least one member is a landowner. Panel C includes agricultural households (corn) in which at least one member is a land tenant. Panel D includes agricultural households (corn) in which at least one member has another type of land tenure but no member is a landowner or a land tenant. Panel E includes agricultural households (corn) in which no member has access to land. Same controls as in Table A8. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A11: Heterogeneity by Connectivity: EHPM Outcomes

	Roads
Panel A: Likelihood of working in the agricultural sector (corn)	
Temperature shock t	-1.154
	(0.475)**
Temperature shock t x Q4	1.082
	(0.491)**
Obs	217,421
R2	0.201
Mean	10.719
Panel B: Hours(log)	
Temperature shock t	0.006
	(0.010)
Temperature shock t x Q4	0.009
	(0.013)
Obs	23,306
R2	0.087
Mean	31.990
Panel C: Hourly wage (log(SCP))	
Temperature shock t	0.020
	(0.024)
Temperature shock t x Q4	-0.028
	(0.031)
Obs	7,889
R2	0.477
Mean	3.769
Panel D: Migration likelihood in agricultural households (corn)	
Temperature shock t-1	0.280
	(0.233)
Temperature shock t-1 x Q4	-0.106
	(0.279)
Obs	6,384
R2	0.019
Mean	0.548
Year + Municipality FE	X
Rainfall Shock year t-1	X
Drought Shock year t-1	X
Crime Shock year t-1	X
Municipal characteristics*Year	X
Individual or Household controls	X

Notes: Individual data from 2009–2018 of EHPM. In panels A, B and C, the sample is constrained the sample for people 10–65 years old. In Panel A we also restrict the sample to employed individuals; in Panel B and C to individuals working in the agricultural sector producing corn; in panel D 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. The dependent variable in panel A is 100 if the person is employed in the agricultural sector producing corn; in panel B, is the logarithm of the number of hours worked; in panel C, is the logarithm of the hourly wage; in panel D, is 100 if a household member migrated in the surveyed year. For panels A, B and C, 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); for panel D, it 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). We restrict the sample to municipalities that are in the first or fourth quartile of the distribution of the national road network, which contains all the roads in El Salvador. The road information is provided by the Transport Division of the Infrastructure and Energy Sector (INE) of the IADB, which uses data from Open Street Maps in 2022. Municipality controls are the number of weeks with rainfall and drought shocks (two sd higher than that week's historic value in that municipality during the winter season the same year or the previous year, depending on the independent variable). We also control for 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. Individual controls in Panel A, B and C are gender, age and education. Household controls in panel D are the age and gender of the household head, and number of household members. We also interact the controls with the dummy that indicates if the municipality is in the fourth quartile of the corresponding distribution. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A12: Impact of Temperature Shocks on Migration Likelihood – Different Shocks

Population Group	1 SD (1)	1.5 SD (2)	Higher 29 (3)	Higher 35 (4)	HDW (5)	Mean	Obs
Panel A: Log(Total Production)							
Temperature shock year t	-0.029	-0.023	-0.016	-0.022	-0.005	1.917	19,261
	(0.013)**	(0.014)*	(0.008)**	(0.015)	(0.003)		
R2	0.245	0.245	0.244	0.244	0.244		
Panel B: Share of workers in the agricultural sector (corn)							
Temperature shock year t	-0.035	-0.160	-0.157	-0.165	-0.027	9.066	2,239
	(0.119)	(0.107)	(0.109)	(0.119)	(0.020)		
R2	0.759	0.759	0.759	0.759	0.759		
Panel C: Log (average hourly wage (SCP)) in the agricultural sector (corn)							
Temperature shock year t	0.006	-0.004	0.043	-0.052	-0.010	4.859	1,573
	(0.030)	(0.028)	(0.019)**	(0.032)	(0.005)*		
R2	0.396	0.397	0.398	0.397	0.397		
Panel D: Migration Likelihood in agricultural household (corn)							
Temperature shock year t-1	0.153	0.298	0.109	0.280	0.047	0.695	12,659
	(0.088)*	(0.130)**	(0.096)	(0.092)**	(0.020)**		
R2	0.022	0.023	0.022	0.022	0.022		
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: 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. Panels B and C use 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. The dependent variable in panel C is the logarithm of the average wage in the corresponding sector for each municipality and year, correspondingly. Panel D uses data from El Salvador's Multiple Purpose Household Survey (EHPM) 2009–2018. The dependent variable in panel D 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. For Panels A, B, and C: the independent variable in Column (1) 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). The independent variable in Column (2) 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). The independent variable in Column (3) is the number of weeks with a temperature shock (higher than 29 °C in that municipality during the winter season the previous year). The independent variable in Column (4) is the number of weeks with a temperature shock (higher than 35 °C in that municipality during the winter season the previous year). The independent variable in Column (5) is the number of weeks with a temperature shock (harmful-degree weeks in that municipality during the winter season the previous year, where every 1-degree Celsius increase in the average temperature above 32 degrees Celsius corresponds to a one-unit increase in HDWs.). Panel D presents the same shocks but in the previous year. Same controls as in Table 9. Standard errors are clustered by municipality and year. *p<0.1; **p<0.05; ***p<0.01

Table A13: Impact of Temperature Shocks in First-Harvest Season on Migration Likelihood

	Agri(seasonal-rural)		Agri(seasonal-urban)		Agri(corn-rural)		Agri(corn-urban)		Non-agri(rural)		Non-agri(urban)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Temperature	0.278	0.272	0.017	0.036	0.288	0.283	0.092	0.114	0.091	0.088	-0.038	-0.041
	(0.144)*	(0.145)*	(0.113)	(0.105)	(0.159)*	(0.160)*	(0.101)	(0.101)	(0.113)	(0.110)	(0.042)	(0.042)
Crimen		0.264		-0.547		0.163		-0.480		0.094		0.194
		(0.191)		(0.281)*		(0.179)		(0.243)**		(0.178)		(0.086)**
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	0.026	0.026	0.060	0.061	0.027	0.027	0.066	0.067	0.012	0.012	0.008	0.008
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
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 non-agricultural households in the rural area. Columns (11)–(12) include non-agricultural households in the urban area. Regressions include all sets of controls from column (5), Table 1. Standard errors are clustered by municipality and year. *$p<0.1$; **$p<0.05$; ***$p<0.01$