Lessons from the Past: How Experience Reduces the Impact of Weather Shocks on Ugandan Smallholders *

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Abstract

Do people learn from experience how to cope with weather shocks? We use a unique four-wave panel household dataset from Uganda, merged with granular historical weather records, to understand the nexus between experience, weather shocks, and agricultural performance. Our identification strategy exploits cross-sectional variation in the climate experience of immigrant members of the households and the temporal variation in the realization of the weather shocks during the survey years. We show that although temperature shocks can be detrimental to agricultural performance, households with more experience perform relatively better. An additional 10 days of temperature shocks reduce the income of households with little experience by 8 percent, while the effects are negligible for those with higher-than-average experience. Our findings are robust to various robustness checks, including placebo tests on the timing of shocks and falsification tests. Suggestive evidence points towards the adoption of risk-reducing technologies as the driving factor behind the gains of the more experienced households. These findings highlight the relevance of initiatives that promote experiential learning.

JEL Codes: D13, O12, Q12, Q54.

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1 Introduction

Do experiences help in optimizing economic outcomes? The role of experience in shaping socioeconomic outcomes has been well documented (Groppo and Kraehnert, 2016; Santeramo, 2019; Conzo and Salustri, 2019; Malmendier, 2021). The literature also shows that experience leads to learning (Conley and Udry, 2010; Malmendier and Nagel, 2015), and it helps people make better decisions (Foster and Rosenzweig, 1995; Conley and Udry, 2010). But do people learn from experiencing adverse events and make better decisions while facing similar events?

This paper explores this question and provides an answer with respect to the climate experience in the agricultural sector of developing countries. The agricultural sector in developing countries is a perfect setting for seeking answers to our research question, as it is one of the most vulnerable sectors to climate conditions and weather shocks, and therefore, it is ideal for delving into behavioral changes (Schlenker and Roberts, 2008; Gallic and Vermandel, 2020). Climate is one of the agricultural inputs that farmers can learn about (Dell et al., 2014; Iizumi and Ramankutty, 2015). Insofar as climate conditions are rapidly evolving due to climate change, such a learning process is becoming increasingly crucial (Ortiz-Bobea et al., 2021). In particular, the adoption of sustainable agricultural practices is essential for adaptation to increasingly volatile weather (Zilberman et al., 2012). However, adoption remains surprisingly low in the African agricultural sector, despite the continent's heavy dependence on the sector (Suri and Udry, 2022) and the clear need to boost productivity (Jayne and Sanchez, 2021). The climate experience can lead to learning that improves personal expectations about future realizations of increasingly volatile weather, fosters the adoption of sustainable risk-coping agricultural practices, and improves agricultural performance (Magruder, 2018; Jayne and Sanchez, 2021).

We focus on the agricultural sector of Uganda, as it serves as an ideal case study for both conceptual and technical reasons. First, Uganda's economy is still heavily dependent on agriculture, with one-fourth of its GDP generated from the sector, approximately 78 percent of households residing in rural areas and more than one-third of the working population relying on subsistence farming (Magunda, 2020; UBOS, 2019). Second, several observers have noted an increase in the occurrence of weather shocks in Uganda since at least 1981, with steady growth in the last eight years, contributing to a heterogeneous mix of experiences among household members, which we can observe today (World Bank, 2022). Third, this experience is carried over through population migration, even when migration is not related to climate. For example, the conflict between 2002 and 2005 in northern Uganda, near the border, involving the Lord's Resistance Army, led to significant population movements (Rohner et al., 2013), which in turn may have contributed to the varying experiences of climate and weather shock among households in the destination location. Fourth, and perhaps most importantly, we focus on Uganda because of the availability of a rich four-wave panel dataset spanning from 2009-10 to 2019-20. This dataset allows us to reconstruct the previous place of residence of household members before they settled in the location where the first wave of the survey was conducted.

We exploit cross-sectional variation at the household level in climate experience and the temporal variation in the realization of the weather shocks during the survey years to identify the role of climate experience when dealing with weather shocks. As households living in the same region are exposed to the same weather events, we use within-household variations in the migration status to build household-level variations in climate experience. We document that, although temperature shocks are detrimental to most people's agricultural performance, households with more experience perform relatively better. We find suggestive evidence that the adoption of risk-reducing technologies is the driving mechanism behind the gains of more experienced households. Our results are robust to placebo tests on the timing of shocks and falsification tests on the realization of the experience, along with other robustness checks.

This study makes three contributions to the existing literature. First, we contribute to the broad literature that highlights the importance of experience. It is well-documented that experiences shape socioeconomic outcomes (Malmendier, 2021). A subset of this literature focuses on analyzing the impact of experiencing adverse events in the past on present outcomes (Almond, 2006; Dercon and Porter, 2014; Grimard and Laszlo, 2014; Conzo and Salustri, 2019), with some of them focusing on documenting the deleterious impacts of experiencing adverse weather events on different health indicators (Alderman, 2006; Rocha and Soares, 2015; Groppo and Kraehnert, 2016). We contribute to this literature by identifying the causal effect of adverse climate experiences on agricultural performance. The role of experience as a driver of agricultural performance is well-recognized (Foster and Rosenzweig, 1995). The literature also highlights the importance of climate conditions as an agricultural input (Mendelsohn et al., 1994; Lobell et al., 2011; Dell et al., 2014; Iizumi and Ramankutty, 2015). However, to the best of our knowledge, we are the first to causally identify the positive effect of experiencing an adverse climate on agricultural performance. In particular, we show that experiencing adverse weather events improves farmers' reaction to subsequent similar events, boosting their performance.

Our second contribution is to the strand of literature that documents farmers' adaptation to climate change (Seo and Mendelsohn, 2008; Burke and Emerick, 2016; Taraz, 2018; Jagnani et al., 2020; Aragón et al., 2021). In particular, we provide suggestive evidence that experience makes farmers adapt better because they adopt more risk-reducing strategies. This adds to the findings that showcase technology adoption as a driver of improved performance (Foster and Rosenzweig, 2010; Magruder, 2018) by documenting the role of experience as a driver of such adoption. It also connects with the literature that shows that experience leads to better outcomes due to better decision making resulting from associated learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Haggag et al., 2017; Philippe, 2024).

Our final contribution is to the literature that emphasizes the importance of learning from close ties. Learning has long been recognized as a driver of improved performance in the agricultural sector (Magruder, 2018; Takahashi et al., 2019). In particular, the roles of one's own experience and the experience of others have been well documented (Foster and Rosenzweig, 1995; Munshi, 2004; Conley and Udry, 2010; Cai et al., 2020; BenYishay and Mobarak, 2018; Beaman et al., 2021). We extend this literature by showing that learning from adverse events is especially valuable, even when such experience is limited to a subset of household members. This finding underscores the relevance of initiatives that foster experiential learning within close ties.

2 Conceptual Framework

Our conceptual framework builds on Burke and Emerick (2016), examining a farming household that can choose between two agricultural practices: a **traditional practice**, which performs better under historical (or typical) temperatures, and a **temperature-resistant (modern) practice**, which performs relatively better under high temperatures. Following their notations, let us consider the agricultural performance of the farmer i for time t (denoted y_{it}) to be a function of their binary input choice between traditional and modern practices ($x_{it} \in \{0, 1\}$, with 1 denoting modern practice):[1]

$$
\begin{aligned}
y_{it} &= f(x_{it}, z_{it}) \\
&= \beta_0 + \beta_1 z_{it} + \beta_2 z_{it}^2 + x_{it}\Big(\alpha_0 + \alpha_1 z_{it} + \alpha_2 z_{it}^2\Big),
\end{aligned}
\tag{1}
$$

where z_{it} captures the actual temperature for the period t and $z_{it} \sim N(\omega_t, \sigma^2)$. The first derivative of y_{it} with respect to z_{it} is negative, which implies that when a shock occurs, the output declines.

Under the functional form in (1), the modern varieties will be chosen if it is expected to increase production, which happens if and only if:

$$
\mathbb{E}\Big[\alpha_0 + \alpha_1 z_{it} + \alpha_2 z_{it}^2\Big] = \alpha_0 + \alpha_1\, \omega_t + \alpha_2\Big(\omega_t^2 + \sigma^2\Big) \; > \; 0,
\tag{2}
$$

where the parameters α and β in equation (1) are assumed to be known to the farmers but not to the econometrician. Farmers have probably learned the relationship between traditional practices, temperature, and yield by observing past realizations of this functional form, consistent with models of experiential and observational learning in agriculture (Foster and Rosenzweig, 1995; Conley and Udry, 2010). As a result, they may have a well-developed understanding of how traditional practices perform under varying temperature conditions, an understanding that econometricians do not directly observe. In contrast, for modern practices, farmers who have never adopted them may not be fully informed about the distribution of their returns, despite social learning likely playing a role in shaping expectations and adoption behavior, as shown in studies on peer effects in agricultural contexts (Bandiera and Rasul, 2006; Conley and Udry, 2010; Santeramo, 2019). However, even if the α parameters associated with modern practices are unknown to farmers, knowing that beyond a certain temperature threshold, the performance of modern practices exceeds that of traditional ones is *sufficient* for them to make the optimal decision regarding whether or not to adopt modern practices. For the framework presented here, we assume that farmers make optimal choices regarding their adoption decisions, which implies

[1] Burke and Emerick (2016) model this as a choice between traditional and heat-tolerant varieties of seeds. Here, we consider it to be a more general choice of different practices.

the assumption that the sufficient condition described above is satisfied.

As is common in such settings and observed in practice, most agricultural techniques must be adopted *ex-ante*, that is, before the actual realization of the weather conditions, leaving limited scope for *ex-post* adjustments, such as advancing the harvest date or increasing labor input (Aryal et al., 2023). This assumption is both realistic and relatively uncontroversial in rainfed agricultural contexts such as Uganda, where pre-season decisions are necessary due to limited irrigation, lack of infrastructure, and high weather uncertainty (Deressa et al., 2009; Kijima, 2019). Consequently, we assume that farmers must choose their preferred practice based on the expected temperature, rather than the actual temperature and that they are informed about the relative performance of both practices.[2] Using equation (1) and the distribution of z_{it}, we can derive:

$$\begin{aligned} E[y_{it}] &= \beta_0 + \beta_1 E[z_{it}] + \beta_2 E[z_{it}^2] + x_{it}\Big(\alpha_0 + \alpha_1 E[z_{it}] + \alpha_2 E[z_{it}^2]\Big) \\ &= \beta_0 + \beta_1 \omega_t + \beta_2(\sigma^2 + \omega_t^2) + x_{it}\Big(\alpha_0 + \alpha_1 \omega_t + \alpha_2(\sigma^2 + \omega_t^2)\Big) \\ &= (\beta_0 + \beta_2\sigma^2) + \beta_1 \omega_t + \beta_2 \omega_t^2 + x_{it}\Big((\alpha_0 + \alpha_2\sigma^2) + \alpha_1 \omega_t + \alpha_2 \omega_t^2\Big). \end{aligned} \tag{3}$$

This relationship is depicted in the panel 1a of Figure 1, which maps the expected temperature (ω_t) to the expected yield ($E[y_{it}]$). This figure is similar to Figure 2 of Burke and Emerick (2016), which maps the actual temperature to the actual yield. Burke and Emerick (2016) models climate change as a shift in mean temperature from $\omega \to \omega'$, with $\omega < \omega'$. Let $\tilde{\omega}$ represent the temperature threshold at which the performance of the two practices intersect. Then, as per both of our models:

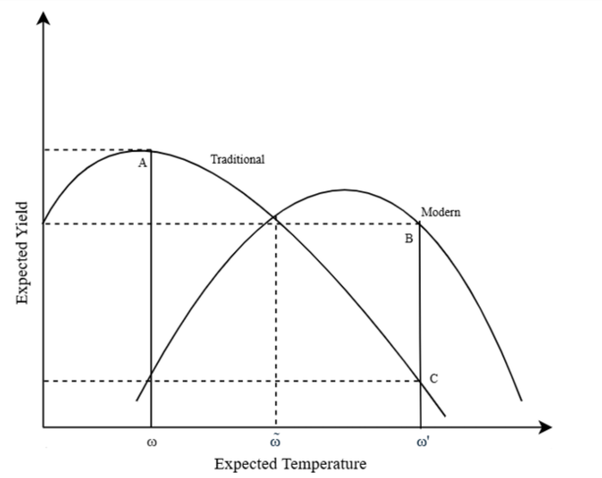
$$f(x_{it} = 0, z_{it} < \tilde{\omega}) > f(x_{it} = 1, z_{it} < \tilde{\omega}) \tag{4}$$

$$f(x_{it} = 0, z_{it} > \tilde{\omega}) < f(x_{it} = 1, z_{it} > \tilde{\omega}). \tag{5}$$

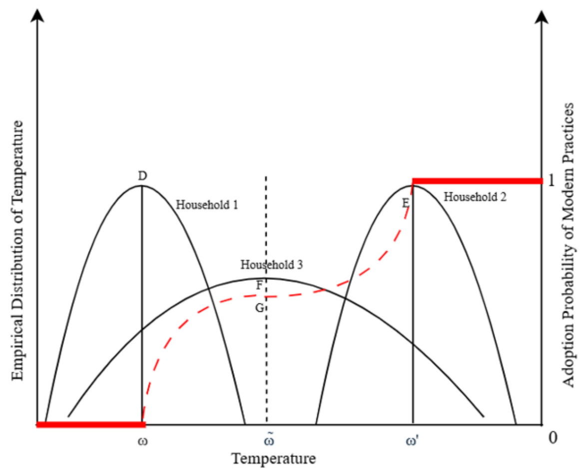
i.e., when the actual temperature exceeds $\tilde{\omega}$, the temperature-resistant practice produces a higher output, but below $\tilde{\omega}$, the yield of the traditional practice is higher. In other words, in the absence of temperature stress, traditional techniques provide better outcomes, possibly due to their better

[2] This is consistent with the framework of Burke and Emerick (2016).

alignment with local conditions or lower input requirements. However, faced with climate change, farmers must adopt modern practices to improve their yields.



(a) Productivity of Different Practices



(b) Heterogeneity in Empirical Distributions

Figure 1: Production and Associated Learning from Experience for a Changing Climate

Burke and Emerick (2016) assumes that farmers learn about the change in climate over time and only adjust their behavior (i.e., adopt modern practices) after acquiring strong information that the climate has changed. Learning is modeled as a belief-updating process (such as in the models of Foster and Rosenzweig (1995), Munshi (2004), and Conley and Udry (2010)) in which, in each period, farmers observe z_{it} and update their belief about the average temperature using a weighted combination of their previous belief and the new realization of the climate they observe. More importantly, the model focuses on learning from farmers' own experience and not the experience of others. Their results show that these adaptations improve with lower temperature variance and more draws of climate realizations.

In this study, we consider a simple extension of the framework described above, in which farmers learn from both their own experiences and the experiences of others within their close social ties (in line with Foster and Rosenzweig (1995)). Although decisions are made at the farm level for each household, they reflect the collective experience of all household members. Each working member gathers information on expected temperature based on past weather realizations, and this information is pooled to inform the decision on whether to adopt a particular agricultural practice.

If all household members share the same weather history, having resided in the same location for most of their lives, then the distribution of past weather experiences will be identical across members and equivalent to the household-level experience. In contrast, if family members come from different regions that have different climatic conditions, their individual experiences will differ. This heterogeneity introduces variation not only in individual expectations, but also in the collective distribution of past temperature realizations. As a result, the aggregated experience at the household level can exhibit a wider or narrower distribution of perceived temperature events, depending on the diversity and variability of past climates encountered by each member. In this sense, for households composed of individuals with heterogeneous weather experiences, the diversity of experience itself can be viewed as an additional channel of social learning. It may accelerate learning, alter the precision with which the household estimates expected temperatures, and either facilitate or hinder their ability to adapt to climate realizations. This mechanism is analogous to receiving more, or more varied, draws from the climate distribution over time, as described in the original model.

Based on this framework, farming households must make adoption decisions using their accumulated experience, expectations about future weather (specifically temperature), and the associated expected yields, as illustrated in panel 1a of Figure 1. To synthesize this complexity of decision making, we introduce panel 1b of Figure 1, which depicts three illustrative cases drawn from the infinite possible distributions of the weather experiences of households. The three households shown at the bottom of the panel represent different experiential profiles. These profiles could result from households with members who have always resided in the same location or from households composed of individuals who have migrated from different areas.

Given these distributions of past temperature experiences, we assume that each household faces a binary decision: whether to adopt or not to adopt the temperature-resistant modern practice.

The decision depends on whether the majority of the experience distribution of the household is above or below a critical temperature threshold, denoted by $\tilde{\omega}$. If most of the probability mass lies to the left of $\tilde{\omega}$, the household is more likely to adopt the traditional practice, anticipating that future temperatures will fall below the threshold, which yields higher expected returns from the traditional method. In contrast, if the distribution is concentrated to the right of $\tilde{\omega}$, the household is more inclined to adopt the modern, temperature-resistant practice, an inference that follows directly from our assumptions. The panel 1b in Figure 1 illustrates this logic through three example households. Household 1, with a history of consistently low temperatures and a median experience of ω, adopts traditional practice. Household 2, having experienced predominantly high temperatures with a median of ω', adopts the temperature-resistant practice. Household 3 has a broader experience distribution with a median of $\bar{\omega}$, close to the threshold $\tilde{\omega}$. In this intermediate case, even small changes in the distribution can determine the adoption choice. If $\bar{\omega}$ is slightly to the right of $\tilde{\omega}$, the household adopts modern practice; if slightly to the left, it opts for the traditional one.[3]

Naturally, adoption is influenced by other factors beyond the experience of temperature. However, in aggregate terms, we expect a positive relationship between the level of experienced temperature and the likelihood of adopting modern practice. This relationship is represented by the red, inverted S-shaped curve in the background of the panel, which reflects the share of adopters as a function of the temperature experience. The curve starts flat (indicating no adoption), gradually increases as households approach the threshold $\tilde{\omega}$, then increases more steeply beyond the threshold, eventually plateauing at high levels of adoption. This inverted S-shape captures the intuition that adoption rates accelerate once the expected temperature crosses a critical point. Although this assumption can be relaxed, we expect that at sufficiently high experience levels, the share of adopters will approach one.

[3]The use of the median is appropriate under the assumption of symmetric distributions, allowing decisions to reflect the dominant experience within the household.

3 Empirical Design

3.1 Empirical Strategy

Climate conditions (i.e., the temporal distribution of weather events) contribute to the shaping of agricultural activities (Mendelsohn et al., 1994; Lobell et al., 2011). For instance, a warm climate allows farmers to cultivate crops (e.g., wheat and olive trees) that cannot be grown in colder climate conditions where other crops are better suited (e.g., potatoes, apple trees, etc.). Therefore, understanding the local climate conditions is the key to success in agricultural activities, particularly with respect to decisions on the adoption of different practices (as discussed in the last section).

In addition to climate conditions, agricultural performance is also shaped by weather events that deviate from the norm (e.g., heat waves and excessive rain) (Gallic and Vermandel, 2020). Such weather events are termed *weather shocks*. Both climate conditions and weather events are location-specific. Usually, households are familiar with the climate conditions of the location where they live and cultivate crops. In addition, if households move between locations, they can potentially become familiar with the climate conditions of locations that are different from the one they live in. Let us call this familiarity with the climate conditions *climate experience*. For the purpose of this study, we are primarily interested in understanding whether *climate experience* helps to better deal with *weather shocks*. To answer this question, ideally, we want to run the household-level regression:

$$\begin{aligned}\text{Performance}_{ilt} = a_0 + a_1\text{Weather Shock}_{lt} + a_2\text{Experience}_{ilt} \\ + a_3\text{Weather Shock}_{lt} \times \text{Experience}_{ilt} + a_4 X_{ilt} + \sigma_{il} + \lambda_t + \epsilon_{ilt}, \qquad (6)\end{aligned}$$

where *Performance*$_{ilt}$ captures the agricultural performance of the household i of location l in period t, *Weather Shock*$_{lt}$ is the location-specific weather shock, and *Experience*$_{ilt}$ captures the *climate experience* of the household. Finally, X_{ilt} is a vector of observable characteristics, σ_{il} and λ_t are the household and year fixed-effects, respectively, and ϵ_{ilt} is the error term.

There are two potential issues in using the above specification. First, people living in the same region experience the same climate conditions. Thus, if we focus on the climate experience gained from their current region, we will not have any household-level variation in $\textit{Experience}_{ilt}$ to identify a_3. To resolve this issue, we exploit the within-household variation in migration decisions. In particular, we differentiate between the experience gained by *movers* (from the region of movement) and *non-movers* (from the current region) within each household. Then, we aggregate this measure at the household level to construct the measure of households' climate experience. This is the measure that we use for our analysis. Second, given that we exploit the variation in the migration decisions of the household members, letting $\textit{Experience}_{ilt}$ vary over time potentially makes the variable endogenous in regression (6) due to endogeneity in migration decisions. To resolve this issue, we use migration decisions at the baseline, making the climate experience variable invariant over time.[4] This implies that the variable at its level cannot be included simultaneously with household fixed effects due to perfect multicollinearity.

To construct the climate experience for the movers, we take their most recent movement and create a variable based on the climate conditions of the region of their migration, up to the year of migration. For non-movers, we create the same variable based on the climate conditions of their current region at the baseline. We calculate the average of these variables at the household level to capture the household's experience (discussed in more detail below). This household-level experience variable is denoted $\textit{Climate Experience}_{il}$ (or, $\textit{Experience}_{il}$ in short) for household i of location l. A high value of this variable represents a higher frequency of having experienced positive deviations in our constructed weather variable at the baseline.[5] The next subsection provides more details on the construction of this variable.

We expect households that experienced a higher frequency of positive deviations in our constructed weather variable at the baseline to handle such deviations better today. To test this, we use the following specification:

$$\begin{aligned} \text{Performance}_{ilt} = \beta_0 + \beta_1 \text{Weather Shock}_{lt} + \beta_2 \text{Weather Shock}_{lt} \times \text{Experience}_{il} \\ + \beta_3 X_{ilt} + \sigma_{il} + \lambda_t + \nu_{ilt}, \end{aligned} \tag{7}$$

[4]In other terms, we assume that climate experience is a stock variable insofar as knowledge of climate conditions decays slowly over time.

[5]As discussed above, this baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s).

where our coefficient of interest (β_2) captures the interaction effect of current weather shock and the past experience with such weather shocks.[6] It is important to note that the presence of both movers and non-movers in a region helps us identify β_2. More specifically, the identification exploits the variation in the experience of movers and non-movers. We expect β_2 to be positive if past experience with certain events helps households deal with similar events in the present.

3.2 Background, Data, and Descriptives

3.2.1 Background and Data

Uganda is a relatively small country in Eastern Africa, bisected by the equator and largely situated on the East African Plateau.[7] The country is a perfect case study for analyzing the impact of climate experience on households' ability to cope with weather shocks because of the reliance and exposure of its agricultural sector to weather. Agriculture in Uganda is predominantly rain-fed, with very limited irrigation.[8] Uganda is also highly vulnerable to rising temperatures, which are likely to have severe impacts, especially when these become extreme.[9] Households residing in different parts of the country have observed very different shocks as, since 1981, the Ugandan territory has observed prolonged droughts and an increased likelihood of floods, leading to water stress, crop losses, landslides, locust invasions, and rising lake water levels (Nsubuga et al., 2014). In this context, households with varying levels of experience are likely to respond differently, depending on their past exposure.

From a structural perspective, understanding the role of experience in a context like Uganda can provide highly relevant insights, given the significant role agriculture still plays in the country's economy. Uganda remains a predominantly agrarian economy, with agriculture still

[6] The variable Experience$_{il}$ is omitted at the level, as the regressions include the household fixed effects.

[7] About one-fifth of the country is covered by water, with its territory encompassing eight major rivers and 165 lakes. The average altitude is 1100 meters above sea level, sloping steadily downward to the Sudanese Plain in the north.

[8] Uganda's agroecological characteristics and geographic position make it a tropical country, contributing to the heterogeneity of its rainfall patterns. The country mainly experiences two rainy seasons across most of its territory: the long rains from March to May and the shorter rains from September to November. The northern region, which accounts for about one-quarter of the country and lies outside the tropical belt, experiences only one rainy season from March to October. Despite abundant water resources, less than 2 percent of the country's irrigation potential has been developed, with only 77,000 hectares of irrigated land recorded (Atamanov et al., 2022).

[9] Since the 1960s, mean surface temperatures have increased by 1.4°C (Mcsweeney et al., 2010), reflecting a clear upward trend (Nsubuga et al., 2014).

accounting for about 24 percent of the total GDP (UBOS, 2022).[10] A large proportion of Uganda's population, about 78 percent, resides in rural areas and relies on farming as the main economic activity (Magunda, 2020). This explains why the agricultural sector employs about 75 percent of the population aged 15 to 24. Agriculture also influences other sectors, with agro-processing dominating the manufacturing sector, accounting for over 60 percent of total output.[11] According to official statistics from 2019, the majority of the population involved in agriculture engages in subsistence farming, accounting for about 39 percent of the working population (UBOS, 2019).[12]

This paper uses a unique data set built by merging several data sources. The first data source is the Uganda National Panel Survey (UNPS), which is a nationally representative survey conducted by the Uganda Bureau of Statistics (UBOS) in collaboration with the World Bank. The survey has origins in the 2005-06 Uganda National Household Survey (UNHS), implemented by the UBS, with the objective of collecting information on the socioeconomic characteristics of households and communities in Uganda. A joint effort between the two institutions has led to the selection of a portion of households to be interviewed with a more sophisticated questionnaire and to be tracked in multiple waves, i.e., 2009-10, 2010-11, 2011-12, 2013-14, 2015-16, 2018-19, 2019-20.

The information collected by the UNPS questionnaire is extensive and involves multi-topic sections, including sociodemographic characteristics, education, agricultural activity, labor and self-employment activity, health status, and subjective perception of shocks. The sociodemographic section provides precise details on the composition of households and the characteristics

[10]Compared to the 1990s when agriculture contributed about 50 percent of Uganda's GDP, there has been a significant decline in the sector's share of domestic production (Magunda, 2020). Recent data indicate that the agricultural sector is experiencing growth, largely driven by a 7.3 percent increase in cash-crop activities and a 3.5 percent increase in food-crop activities. Among the various agricultural activities, crop production plays a dominant role, contributing about 58.4 percent of the total value of agricultural output, followed by livestock at 18.2 percent, with forestry and fishery playing more minor roles (Magunda, 2020).

[11]For these reasons, improvements in poverty from the 1990s to 2013 were primarily driven by agricultural income growth (Cooper, 2018).

[12]Given the country's territorial diversity, crop farming in Uganda is highly varied and supports many options for cultivation. Major food crops include maize, millet, sorghum, rice, cassava, sweet potatoes, and Irish potatoes, as well as legumes like beans, peas, groundnuts, and soybeans. Other crops, such as plantains and coffee, are also cultivated (UBOS, 2019). The diversity of Uganda's agroecological zones means that these crops are grown with varying intensity in different regions, depending on factors such as local ecological conditions, market access, prices, and experience itself. The adoption of climate-resilient technology remains limited but not absent. Recent studies suggest that only 15 percent of farmers use improved seeds, and only 26 percent practice shifting cultivation, while the majority still rely on traditional seeds (Mastenbroek et al., 2021; Maggio et al., 2021).

of their members, including whether they have always lived in the district where they are found at the time of the interview. If this is not the case, the respondent has to report the district of origin of each moving household member and when they migrated. We use this information to build long-term indicators of experience, as discussed in subsections 3.3 and B.1.1. We also use information on the households' current latitude and longitude of residence and a large set of indicators from the UNPS data in our empirical analysis. The LSMS data from Uganda are geographically anonymized by randomly displacing the coordinates of surveyed households by up to 5 kilometers. This ensures that the publicly available data points cannot be traced to their exact real-world locations, but has little influence on the measurement of geospatial remote sensing data, such as those employed in this study, and retains the original information on the administrative levels of the respondents.

The main dependent variable is the natural log of the total value of crop production, calculated as the sum of the nominal value of crop production in the two agricultural seasons reported by households (March-July and August-January).[13] Before taking the log, the value of crop production is transformed into the real value using the Consumer Price Index available from the World Bank Development Indicators.[14]

We control for potential determinants of crop production, such as the size of the household, as a potential substitute for labor (Gautam and Ahmed, 2019; Omotilewa et al., 2021), and the average years of education within the households, which may affect the household's ability to maximize their value of crop production from the available land (Phillips, 1994; Reimers and Klasen, 2013; Oladeebo and Masuku, 2013). We also include an indicator of the size of the land owned or managed by households to account for the inverse farm size-productivity relationship widely discussed in the literature (Benjamin, 1995; Barrett et al., 2010; Desiere and Jolliffe, 2018; Bevis and Barrett, 2020). To account for the technology and wealth available for crop production, we follow the existing literature and build an agricultural wealth index, which is calculated using the first factor of a principal component analysis on the ownership of the following agricultural tools: plows, panga knives, slashers, wheelbarrows, tractors, watering cans, hoes, and livestock (Hackman et al., 2020; Maggio et al., 2021).[15]

[13]More specifically, we use log(total production+1) to avoid taking log of zero.

[14]Link: https://databank.worldbank.org/source/world-development-indicators.

[15]The UNPS data also contain an indicator of the distance from the nearest market in kilometers, which we

We use the geographical location of the households to extract and merge precise geographical information on our main explanatory variables and other controls. The two main explanatory variables, for which more details are provided in subsection 3.3, are built using temperature data, which are sourced from the European Center for Medium-Range Weather Forecasts (ECMWF), which offers detailed information on maximum, minimum, and average temperatures over a 10-day period at a spatial resolution of 0.25 degrees. Our analysis incorporates temperature data from two distinct ECMWF databases: the operational database, which covers the period 1989 to 2010, and the interim database (2011-2014). The primary difference between these datasets lies in the methodology used to process the raw temperature data obtained from the weather stations, which changed over time and is not related to any characteristics of the Ugandan territory or of the households under study.

Additional geospatial controls include the average annual *Nightlight Intensity Index*, gathered from the National Aeronautics and Space Administration (NASA) portal, which makes them available through the Visible Infrared Imaging Radiometer Suite (VIIRS) yearly datasets.[16] The *Nightlight Intensity Index* is a widely recognized proxy for infrastructure development and human activity (Gibson et al., 2021). This index can influence the total value of crop production by capturing residual factors related to input and output market opportunities that may not be fully accounted for by the distance-from-market indicator. We also add an indicator on the average population density per square kilometer (yearly) using data from WorldPop, a dataset that provides information on population density for the whole world with spatial resolution of 1-kilometer^2.[17]

The final dataset of our analysis consists of a balanced panel of 1120 households for the survey waves 2009-10, 2010-11, 2011-12, and 2013-14, with around 90 percent of the sampled households living in the rural areas.[18] Data from 2015-16 onward were excluded from our

include in our specification to account for the availability of better prices, which can affect the total value of crop production. All the continuous explanatory variables are log-linearized, taking the natural log, following the same approach employed for the dependent variable. We treat the zero-valued observations by adding 1 before taking the natural log. Results are consistent when using the inverse-hyperbolic transformation, and they are available upon request.

[16] Link:https://www.earthdata.nasa.gov/learn/backgrounders/nighttime-lights

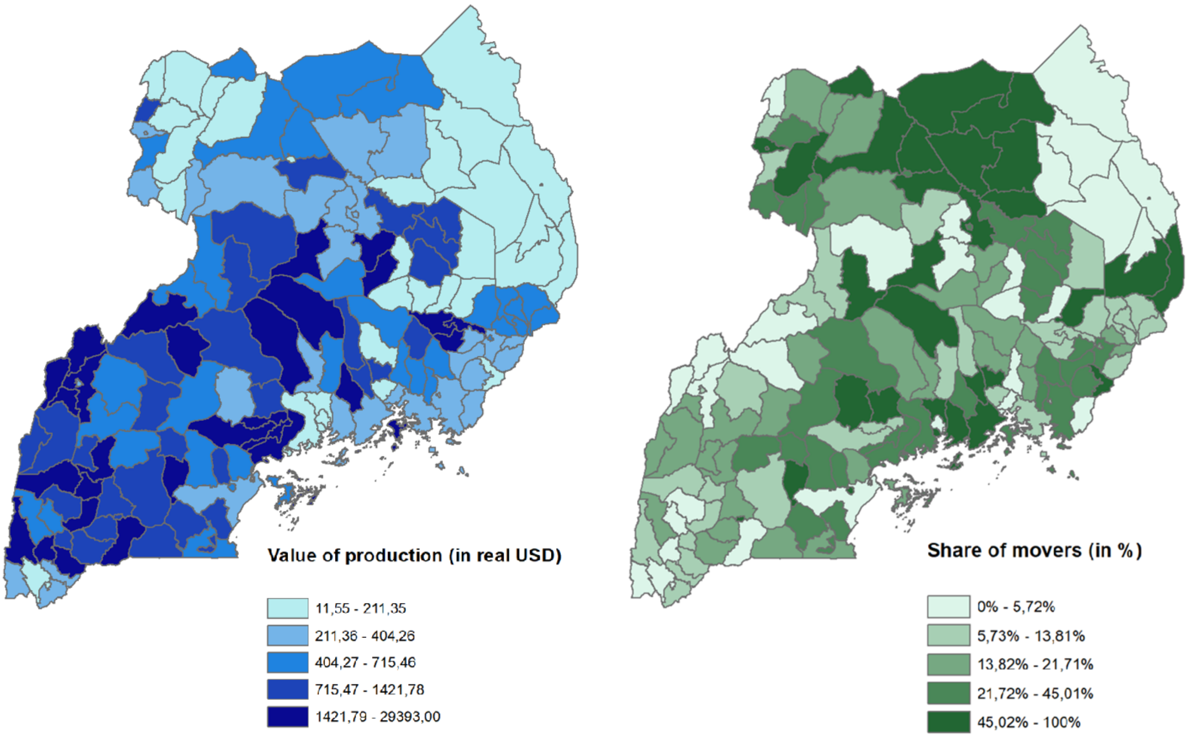
[17] Link: https://www.worldpop.org/.

[18] In the third and fourth waves, some of the control indicators are not available for 14 households. We decided to proceed with the remaining households for the main analysis.

analysis, as the survey was designed with a reshuffling of one-third of the sample each time, leading to a drop in the observations that would not have allowed us to use a balanced panel.

In addition to all of these, we also use Global Agro-Ecological Zones (GAEZ) data provided by the Food and Agriculture Organization (FAO) to conduct some additional analysis reported in the Appendix B.[19] In particular, we extract information on the potential agroecological yield for 71 crops, averaged over the period 1981-2010. We use this information to build a soil compatibility measure between the locations of departure and arrival of the migrants.

3.2.2 Descriptive Statistics



(a) Total value of crop production

(b) Baseline share of movers at the destination

Figure 2: Variation in the value of crop production and baseline share of movers

Notes: The left panel displays the total value of crop production (In real USD) at the district level, while the right panel shows the share of household members who moved to the destination as observed in the LSMS data for 2010. The total value of crop production is calculated by averaging the total value of crop production across all households within each district unit over time, using the latitude and longitude provided in the dataset. The share of movers includes household members who relocated to the current location between 1989 and one year before the survey. For district units without any households, the average is taken from the nearest district unit. All the values are averaged using the survey weights in 2010.

The summary statistics of our dataset show a high level of heterogeneity across the country.

[19]Link to the data:https://gaez.fao.org/.

Figure 2 presents a set of maps showing the quintiles for the total value of crop production (Figure 2a) and the share of household members considered movers (Figure 2b). From these maps, it is evident that the total value of production is slightly higher in the southwest and central belt of Uganda, with the highest values ranging between 1421 and 29393 real USD. In contrast, Figure 2b suggests that households are more likely to include movers when located in the north and northeast areas of the country. As the map suggests, our dataset contains both households without any movers (light-green areas) and households likely to have relocated with all their members (100 percent movers).

Table 1: Summary Statistics for Key Variables over the Survey Years

Variable	2010	2011	2012	2014	Total
Total Value of Production (in real USD)	1832.30	828.40	953.44	840.61	1115.05
	(22437.83)	(2791.62)	(9069.24)	(3535.09)	(12338.06)
Positive Temperature Shock Frequency	9.34	8.94	8.14	8.16	8.65
	(0.84)	(1.65)	(1.74)	(1.16)	(1.49)
Average Maximum Temperature (in °C)	26.01	25.52	26.03	27.73	26.32
	(1.49)	(1.49)	(1.66)	(1.72)	(1.80)
Household Size	5.64	7.55	6.05	5.25	6.11
	(2.79)	(3.45)	(2.78)	(2.80)	(3.09)
Average Years of Education	4.66	3.69	3.55	5.55	4.36
	(2.94)	(2.02)	(2.00)	(2.36)	(2.49)
Land Size (in Hectares)	3.02	2.62	3.40	1.71	2.69
	(8.86)	(4.98)	(1.63)	(2.77)	(5.38)
Agricultural Wealth Index	0.13	0.35	0.06	0.18	0.18
	(0.95)	(1.87)	(1.78)	(1.78)	(1.64)
Distance to the Nearest Market (in KM)	33.17	33.22	33.01	33.01	33.10
	(19.41)	(19.37)	(19.39)	(19.35)	(19.37)
Nightlight Index	0.38	0.77	0.62	0.70	0.62
	(2.09)	(3.03)	(2.49)	(2.89)	(2.65)
Population Density (per 1 KM^2)	300.46	309.25	315.32	333.80	314.65
	(435.52)	(453.25)	(460.03)	(490.01)	(460.03)
Observations	1120	1120	1106	1106	4452

Notes: The table reports the main dependent variable (total value of crop production) and explanatory variables employed in the analysis. For each year, data on temperature are sourced from the European Centre for Medium-Range Weather Forecasts using the latitude and longitude of households' locations. Household size denotes the number of household members at the time of the interview. Average years of education refers to the mean years of completed education by household members. Land size measures the land owned and/or managed by the household. The agricultural wealth index is calculated using the first factor of a principal component analysis on the ownership of the following agricultural tools: plows, panga knives, slashers, wheelbarrows, tractors, watering cans, hoes, and livestock. Distance from the nearest market is measured in kilometers, as reported in the community-level survey. The nightlight index is extracted from VIIRS Day/Night Band data of NASA and is employed to proxy for infrastructure. This variable ranges between 0-63, with higher values indicating higher nightlight intensity. Population density comes from the WorldPop dataset and is measured for each year of the survey at $1km^2$ of spatial resolution.

Table 1 reports the summary statistics of the main dependent and explanatory variables included in our specification by survey years. The numbers suggest a decrease in the total value of crop production between 2010 and 2011, while this remains relatively stable throughout the following years (2012 and 2014). The frequency of positive temperature shocks is also stable, with households in the sample observing an average of 8.65 dekads of shocks over the entire period, with a peak observed in 2010 (9.34 dekads of shocks). The average maximum temperature remains stable at around 26 degrees Celsius during the period under analysis, ranging from 25.52 degrees Celsius (in 2011) to 27.73 degrees Celsius (in 2014). Despite the moderate temperature variation appearing during this short period, this pattern aligns with broader evidence of gradual warming observed in Uganda. Consistent with global trends of climate change, studies have documented a steady increase in temperatures in Uganda, reflecting the country's increasing exposure to the effects of global warming (Mugeere et al., 2021).

In terms of demographics, we observe some changes in both the household size indicator and the average years of education within the household. These two indicators are likely to be correlated, as an increase in household size—due to a newborn or a new member joining the household—is also likely to affect the average years of education within the household. However, this remains consistently lower than 6 years of education per household member. Agricultural wealth does not show substantial variation, except for 2012, where we observe a slight decrease.[20] Interestingly, when we consider geolocalized indicators, households in our sample do not observe substantial changes in the road and market infrastructure around them, as suggested by the low level of volatility over the years in the indicators for the distance to the nearest market and the nightlight index. The distance to the nearest market remains around 33 kilometers during the survey years, while the nightlight index has an average value of about 0.62.[21] Lastly, population density increased from 300 to 333 individuals per square kilometer during the survey years, representing a 10 percent increase for the period 2010-2014, or about 2.66 percent per year, which is in line with the average 3 percent annual growth estimated by the

[20] This variation is partly due to the fact that the first component is calculated independently for each wave on a cross-sectional basis, but this is accounted for in the analysis through the inclusion of time dummies

[21] The average value of the nightlight index is notably lower in 2010 compared to other years. This discrepancy may stem from the fact that 2010 data is not available in the latest VIIRS version (10-21) and was instead extracted using an earlier VIIRS version that preceded version 10. Nevertheless, any computational errors associated with this earlier version should uniformly impact the sample, so we do not consider this as a significant concern.

Ugandan government (Council, 2021).

3.3 Construction of Weather Variables

Defining what constitutes an extreme event and designing an approach to measure it is not always an easy task. Firstly, climate change, together with an increased likelihood of extreme events, is bringing with it a change in the trend of its realizations (i.e., increase in average temperature, decrease in precipitation). We need to separate the long-term trend effect. As explained by Sarewitz and Pielke (2001), the extreme event is rare and unique, with a potentially significant impact. It has two characteristics: discreteness and short duration, and high magnitude of its impact (Smith, 2011). The rarity and uniqueness of the occurrence are necessarily context-specific. In countries where weather is highly heterogeneous, what may be considered extreme in one area of the country can, instead, fall within the bounds of normality in another area (Asfaw and Maggio, 2017). For this reason, measures capturing the occurrence of extreme events and the long-term experience of the event need to be relativized to the historical distribution of a particular weather dimension in the geographical area of study. We operationalize these considerations following an approach similar to other studies on climate change and agriculture (Lobell et al., 2011; Asfaw and Maggio, 2017; Lin and Huybers, 2019; Gallic and Vermandel, 2020; Meierrieks, 2021).

3.3.1 Measuring Weather Shocks

Our approach takes three steps to construct weather variables that capture unanticipated changes in the temperature. We start with the dekadal (i.e., 10-day) data on maximum temperature and restrict our window of analysis to the two Ugandan agricultural seasons, with the first one spanning from March to May and the second one from September to November. For simplicity and to allow the use of all the observations in the dataset, the two agricultural seasons are treated as a single season in our study.[22] Let y_{ltd} denote the temperature observed in dekad d for

[22]For the calculation of the experience and weather shock variables, we exclude data from June to August and from December to February

households residing in location l in season t. Then the first step takes the following form:

$$Z_{ltd} = y_{ltd} - \bar{y}_{lt}, \tag{8}$$

where $\bar{y}_{lt}$ is the average temperature for the season and Z_{ltd} denote the de-meaned counterpart of y_{ltd}. The demeaning process eliminates the expected temperature for the season (assuming that the expected temperature for a season is equal to its mean). If the resulting value is close to zero, it suggests that the dekadal observation has a maximum temperature value aligned with the average seasonal mean. On the other hand, if the value is lower (higher) than zero, it indicates that the dekadal temperature is lower (higher) than the seasonal mean.

In a second step, we account for the fact that each dekadal observation may have a lower or higher value of deviation from the seasonal mean due to seasonality in a location. For example, we may expect the deviation of temperature to be higher in the first dekad of the agricultural rainfall season in a location compared to other dekads of the season, depending on the amount of rainfall typical for the location in that season. Therefore, to account for this seasonality, we calculate the mean value of the dekadal deviation and demean the dekadal deviation Z_{ltd} using this mean. Differently from the previous step, where we were considering the seasonal average, here we consider the long-term average of the dekadal deviation. The long-term average is measured from the first available year of the maximum temperature data, which in our case is 1989. For this calculation, we treat each dekadal observation in a given calendar year separately and link it to the average value of the same dekadal observation measured in other calendar years. Defining as $\tilde{Z}_{ltd}$ the de-seasonalized variable and $\bar{Z}_{ld}$ as the long-term average, this step develops as follows:

$$\tilde{Z}_{ltd} = Z_{ltd} - \bar{Z}_{ld}. \tag{9}$$

Finally, having obtained the demeaned and deseasonalized dekadal maximum temperature observation $\tilde{Z}_{ltd}$, we build our temperature shock variable for households residing in location l

in year t as a count variable measuring the frequency of dekads in which $\tilde{Z}_{ltd} > 0$:

$$\text{Weather Shock}_{lt} = \sum_{d=1}^{N} 1(\tilde{Z}_{ltd} > 0), \tag{10}$$

where N denotes the total number of dekads in an agricultural season t.

3.3.2 Construction of Climate Experience

To construct the climate experience of unanticipated temperature shocks in the past, we take advantage of the richness of information provided by the LSMS data and construct a household-level indicator that leverages the heterogeneous experience each household member has accumulated. From the LSMS data, we extract information on: a) whether the household member has always resided in the same location as the interview; b) if this is not the case, the last location of the household member, before moving to the current location; and c) the year in which the household member moved to the location of the interview. We distinguish between individuals who have never moved, thus always residing in the location of the interview, and individuals who have relocated to the location where the interview took place. For the latter, we then build an indicator of the past experience of weather shocks for the household member by averaging the shock indicator built above from the initial year available in the dataset up to the year of relocation to the current location.

For an individual j residing in location l, having moved there from a location p_j in year k, the climate experience variable takes the following form:[23]

$$\text{Experience}_{jlp_jk} = \frac{\sum_{t=1989}^{k} \text{Weather Shock}_{p_jt}}{(k-1989)+1}, \; 1989 \leq k \leq 2009, \tag{11}$$

which is the average value of the temperature shocks that occurred in the location of origin before the movement. Here, the sum goes from 1989 to the year when the movement occurred (k).

For individuals who never moved, i.e., those who have always resided in the location of the interview, the experience variable corresponds to the average temperature shocks observed in the

[23] We impose $k < 2010$, i.e., that the year of movement has to be anterior to the first year of the survey. Therefore, experience is accumulated before the panel dataset starts and does not vary across time

location of the interview before the beginning of the survey, which takes the following form:[24]

$$\text{Experience}_{jl} = \frac{\sum_{t=1989}^{2009} \text{Weather Shock}_{lt}}{21}, \tag{12}$$

Finally, we construct the household-level measure of climate experience for household i from location l by averaging the measures constructed in (11) and (12):

$$\text{Experience}_{il} = \frac{1}{n_{il}} \sum_{j=1}^{n_{il}} [\text{Mover}_{ijl} \times \text{Experience}_{jlp_jk} + (1 - \text{Mover}_{ijl}) \times \text{Experience}_{jl}], \tag{13}$$

where n_{il} is the total number of members in the household i from location l and Mover_{ijl} is a dummy that takes 1 if the household member j is a mover, 0 otherwise. The resulting household-level Experience_{il} is an average of the individual-level indicators of experience of shock.[25] Since households residing in the same location may be made up of individuals who accumulated experience from different locations, this experience variable varies for households interviewed in the same location, contrary to what happens for the current temperature shocks. Clearly, while the current shocks are time-varying, the experience of shock is assumed to be time-invariant, as the experience and past buildup will only slightly change in the short period of our survey.

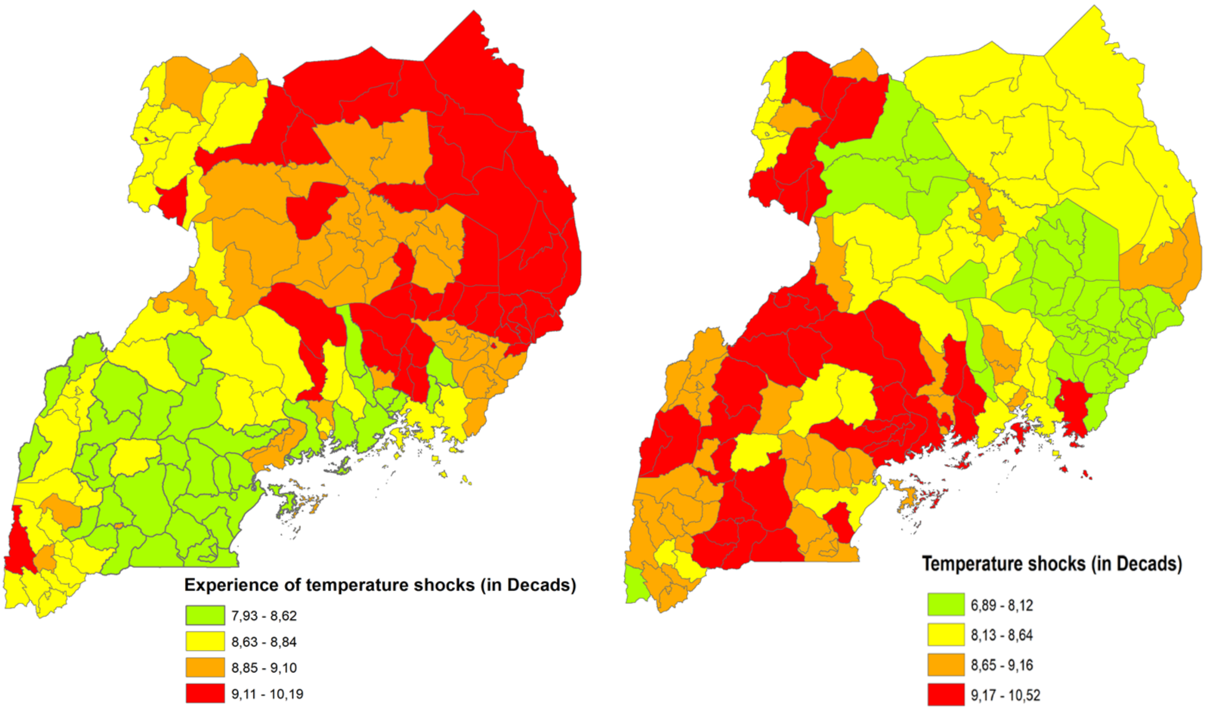
3.3.3 Variation in Weather Shocks and Climate Experience

Figure 3 reports the quintiles for the experience of temperature shocks in the past (Figure 3a) and the temperature shocks that occurred during the survey year (Figure 3b). Figure 3a indicates that households with more experience of weather shocks observed, on average, between 9 and 10 dekads (i.e., around 90-100 days) of positive deviation in $\text{Weather Shock}_{lt}$ in an agricultural year. Furthermore, it seems that people living in the northeast areas of the country have accumulated more experience with weather shocks in the past. This can be attributed to the higher volatility of temperatures in these regions from 1989 to 2010. However, this may also be potentially driven by the high volatility of the temperatures experienced by migrants who moved to these regions.

[24]The sum is averaged dividing by 21 as this is the number of years between 1989 and 2009 (the year of baseline survey).

[25]Although our conceptual framework in Section 2 emphasizes the role played by the median experience of the household members, for our main specification, we use the mean experience of the household members for computational convenience. In Appendix A, we document the robustness of our results to the use of the median experience of the household members.

The latter would suggest endogeneity in the migration decision. To explore this possibility, we conduct two tests.[26]



(a) Experience of temperature shocks

(b) Survey year temperature shocks

Figure 3: Variation in the experience of past shocks and shocks during the survey years

Notes: The left panel displays the experience of past temperature shocks at the district level, while the right panel shows the temperature shocks observed during the time of the panel survey, both measured in the number of dekads (i.e., 10 days). The experience of past temperature shocks is calculated by averaging the exposure to shocks of household members from 1989 up to one year before the survey, measured at their location of origin and averaged across individuals at the district level, following the procedure outlined in Section 3.3. Current temperature shocks are measured at the location where household members were interviewed. Both indicators are built using the latitude and longitude provided in the dataset. For district units without any households, the average is taken from the nearest district unit. All the values are averaged using the survey weights in 2010.

First, we test the predictive power of migration decisions on subsequent weather shocks by regressing weather shocks during the survey years on the household-level number of movers at the baseline (with time-varying controls and year fixed effects). The coefficient of interest of this regression turns out to be small and statistically insignificant, suggesting a lack of correlation between migration decision and weather shocks during our survey years. Second, we run a variation of our regression specification (7), where we replace the climate experience variable with the household-level number of movers at the baseline and find the interaction terms to be statistically insignificant. These results provide evidence that a) migration decisions are not

[26]Detailed results not reported here and available upon request.

endogenous to the occurrence of weather shocks during the survey years, and b) our results are not driven by these migration decisions.

Although we observe a higher frequency of temperature shocks from 1989 to 2010 in the northeast areas of Uganda compared to the rest of the country, this pattern appears to reverse during the survey years. As Figure 3b suggests, more temperature shocks occur in the central and southwest areas of the country during this period. This suggests an increase in weather volatility in areas where households were previously less likely to experience such volatility and a decrease in weather volatility in areas where households were previously more likely to experience such volatility. The latter is also potentially driven by high temperatures becoming more common in the northeast regions of the country. Although descriptive, this evidence provides a solid basis for understanding whether experience allows households to cope better with current shocks, especially since these are increasingly occurring in areas where they were not common in the past. More importantly, these wide range of variations across the country help us in identifying our coefficient of interest in regression specification (7).

4 Main Results

4.1 Does climate experience help in dealing with weather shocks?

Table 2 presents how experience helps deal with weather shocks. Weather shocks have a negative impact on production. The result is consistent across specifications, with coefficients ranging from -1.5 to -1.2, depending on the specification considered. Households with a higher cumulative past experience of positive weather shocks are better able to deal with such shocks in the present. This is consistent across the specifications we use to show the robustness of our findings.

Column (1) focuses on the restricted sample of households that did not have *movers* at the baseline. Thus, the corresponding results exploit the region-level variation in climate experience as the within-region household-level variation for specification (7) is generated by migrant members of the households. The interaction term in this column indicates that households living in regions with higher cumulative past experiences of weather shocks perform better when facing similar weather shocks in the present compared to households living in regions with lower cumulative past experiences of such shocks. However, we cannot exclude that this result derives from unobservable region-level institutions, correlated with the long-term regional climate conditions, which may help explain why households in these regions better cope with weather shocks. This restricts our ability to causally interpret the interaction term, highlighting the need for our identification strategy.

Table 2: Effect of weather shocks on production by climate experience

	(1)	(2)	(3)	(4)	(5)
Weather Shock	-1.245**	-1.439***	-1.486***	-1.239***	-1.222***
	(0.558)	(0.365)	(0.366)	(0.367)	(0.365)
Weather Shock × Experience	0.139**	0.160***	0.166***	0.136***	0.136***
	(0.065)	(0.042)	(0.042)	(0.042)	(0.042)
Mean Baseline Outcome	5.520	5.717	5.717	5.717	5.717
(SD)	(2.004)	(1.792)	(1.792)	(1.792)	(1.792)
Full Sample	No	Yes	Yes	Yes	Yes
Household Controls	Yes	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	Yes	No	No	Yes	Yes
Weather Shock × No. of Movers	Yes	No	No	No	Yes
Observations	2134	4452	4392	4392	4392
Adjusted R^2	0.103	0.071	0.080	0.090	0.091

Notes: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Column (1) results focus on the restricted sample of households that had no movers at the baseline. The rest of the columns report results that use the full sample of households.

Columns (2)-(5) use migrant members of households in our unrestricted sample to generate household-level variation in climate experience within a region. We claim causality for the interaction terms for these columns. This is because our constructed weather shocks (and the cumulative past experience of such shocks) capture unanticipated changes in temperature. Additionally, as we construct the household-level climate experience variable as a combination of past climate experiences from different regions, the variable is independent of unobservable institutions in a region, which helps us to circumvent the causal inference problem we face with column (1). [27]

To improve the precision of our estimates for these columns, we include fixed effects in the regression to control for time-invariant household characteristics and household-invariant survey year characteristics. We also control for some time-varying covariates in columns (3)-(5) and average maximum yearly temperature in columns (4) and (5).[28] After controlling for the factors discussed above, a remaining concern is that the calculation of climate experience depends on the migration status of household members. Thus, if we do not account for the potential differences in the effect of weather shocks by the number of movers, our estimated interaction coefficient of interest may be biased. Thus, in column (5), we also control for this information, and our results do not change. All columns point to a reduction in the adverse impact of weather shocks for households with more experience.

4.2 How to interpret the results in terms of magnitude?

To understand the magnitude of the above results, we use the results in column (5) (which presents the results for our preferred specification) and calculate the marginal effect of an additional unit of shock, i.e., 10 additional days of temperature shock, at different levels of experience. We analyze the entire distribution of the experience variable and report the marginal effects of shocks and their interaction with experience, as shown in Figure 4. The results suggest that an increase of 10 days of temperature shocks during the survey season leads to a decrease in income of approximately 8 percent for households with lower levels of experience. Considering the average total production value in our data, these households would see a reduction of about 90 real USD once the shock occurs. Interestingly, for households with higher levels of experience, the impact of the shock decreases. For example, a household in the 25th percentile of the experience variable would experience a 5 percent decrease in income for the same 10-day increase in temperature shocks. In monetary terms, this would result in a loss of about 55 real USD, which is around

[27]We have also run a specification where, for households with migrants, we account only for the migrants' temperature shock experience, while we keep the average household member experience for households without migrants. The results remain consistent with those shown in Table 2 and are available upon request.

[28]The complete list of control variables is in the table notes.

35 USD lower than the loss observed for households with lower levels of experience. Finally, for households with experience levels above the median, the marginal effect of the temperature shock loses statistical significance and is not different from zero. This means that households in this group are unlikely to experience the 90 real USD loss observed in households with lower levels of experience when a 10-day temperature shock occurs.

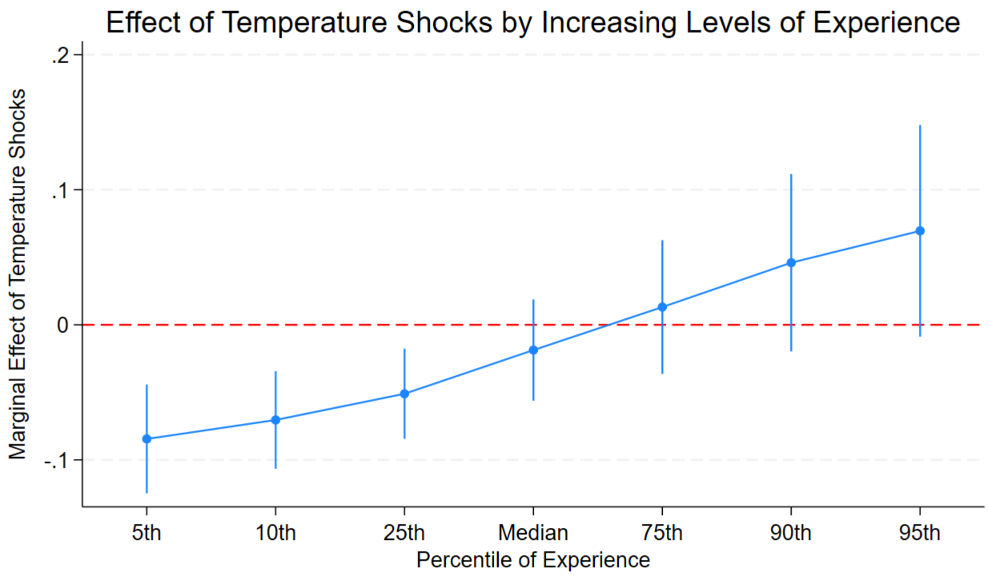


Figure 4: Marginal Effect of Temperature Shocks Across Increasing Levels of Experience

Notes: The dependent variable for the regression is the *Log of (total production +1)*. The estimates, which use estimates from the regression specification (7), represent the marginal effect of an increase in *Weather Shock* (i.e., one unit increase in the frequency of $\tilde{Z}_{ltd}$ defined in (9)) by different percentiles of the *Experience* variable. The figures report 95 percent confidence intervals of robust standard errors clustered at the household level. The regression includes survey year and household fixed effects, household controls, average maximum yearly temperature, and the interaction of *Weather Shock* with the *No. of Movers*. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The *No. of Movers* is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

4.3 Robustness Checks

Although our findings are encouraging, they may be driven by the selection of households with a certain type of experience in regions that experience more or fewer weather shocks. This is unlikely to happen, as, by construction, our weather and climate experience variables focus on shocks that are unanticipated in nature. Nonetheless, we conduct several robustness checks to ensure that our results are not biased. Appendix A documents the detailed results associated with these checks.

The first robustness exercise we present focuses on performing placebo tests using forward shocks instead of current shocks. As forward shocks are yet to be realized in the present, they should not affect current performance differentially less for more experienced households. As documented in Table A.1 of the Appendix A, once we use forward shocks instead of current shocks, the sign and significance of *Weather Shock* $\times$ *Experience* change, and our main results disappear. Thus, our results are not spuriously driven by households with more experience living in regions of less severe weather shocks.

We further test whether we can recreate our key interaction coefficients by randomly shuffling the households' baseline experience with climate. Figure A.1 shows the estimated coefficient of interest β_2 for the regression specification (7) with 100 different randomly shuffled $Experience_{il}$. As the key variations that generate these estimates come from random realizations of $Experience_{il}$ (while keeping the total variations the same as the original variable), the presence of statistically significant coefficients of interest in a particular direction will signal the presence of spurious effects driven by correlated factors. However, our results here suggest that such spurious effects do not bias our main results, as we observe no systematic pattern in the estimated coefficients. Moreover, as we can see from the figure, many of these coefficients are found to be statistically indistinguishable from zero.

The remaining set of robustness checks that we present focuses on understanding the extent to which the construction of different key variables in our analysis drives our results. Table A.2 uses the experience of only adult household members (i.e., those who were 18 years or older during the baseline survey). Although the size of the coefficients changes compared to the case where we consider the experience of all household members, the sign and significance remain the same as our main results. Similarly, Table A.3 focuses on the median experience of the household members, instead of the mean experience of the household members - as in our main analysis, to be more aligned with our conceptual framework in Section 2. The results remain very similar to those reported in Table 2.

In Table A.4 we document the robustness of our results with respect to defining Experience_{il} in terms of $\text{Weather Shock}_{lt}$ as $\sum_{d=1}^{N} 1(\tilde{Z}_{ltd} > 1)$, instead of $\sum_{d=1}^{N} 1(\tilde{Z}_{ltd} > 0)$. Thus, the experience variable here captures the frequency of experiencing more extreme temperature shocks in the past, whereas *Weather Shock* variable is still defined as $\sum_{d=1}^{N} 1(\tilde{Z}_{ltd} > 0)$, capturing the frequency of experiencing positive temperature shocks during the survey years. The results remain similar to those of Table 2, with some decrease in magnitude and significance.[29] Similarly, Tables A.6-A.11 present the robustness of our results using sub-samples with different shares of movers at the household level. The sign and statistical significance of the results do not change across different sub-samples, documenting that our results are not driven by a particular group of households.

Finally, Table A.5 presents the robustness of our results with respect to the restricted sample of observations, after removing outliers for the dependent variable. Our results do not change much compared to the results presented in Table 2, which shows that the results are not driven by outliers.

5 Mechanism for the Main Results

5.1 Specification

Given the substantial impact of climate experience in shaping households' ability to deal with current temperature shocks (as reflected in their agricultural performance), we next explore the underlying mechanism. One potential reason why households with greater experience of past shocks are better able to cope with current temperature shocks is that they have incorporated the risk of these shocks into their production function and, as a result, adopted practices that help them manage the impact. To understand the differential effect of climate experience on decision-making as a response to temperature shocks, we use the following specification:

$$\begin{aligned}\text{Decision}_{ilt} = b_0 + b_1 \text{Weather Shock}_{lt-1} + b_2 \text{Weather Shock}_{lt-1} \times \text{Experience}_{il} \\ + b_3 X_{ilt} + \sigma_{il} + \lambda_t + v_{ilt}, \qquad (14)\end{aligned}$$

[29] This is expected, as these tables capture whether households with a higher frequency of experiencing more extreme temperature shocks perform differently when faced with a higher frequency of experiencing positive temperature shocks during the survey years, which is a slightly different question than the one we answer using Table 2.

where $Decision_{ilt}$ reflects the decision made by the household i from location l in period t, potentially as a response to weather shock in period $(t-1)$. The coefficient of interest (b_2) captures the differential impact of climate experience on dealing with the weather shock in period $(t-1)$, as reflected by the decisions made in period t.

For this analysis, our main focus is on two types of practices: one that helps to cope with temperature shocks and the other that does not. For the category of practices that help households cope with temperature shocks, we expect the adoption to be differentially higher for experienced households at the beginning of the period t, as a response to temperature shocks in the period $(t-1)$. These practices include legume intercropping, improved seed varieties, and irrigation. In general, intercropping, especially with legumes, can increase the stability of crop yields under stressful conditions, such as drought and nutrient deficiency (Chamkhi et al., 2022). Improved seeds refer to varieties developed by research institutes or private companies designed to better withstand heat waves, thereby stabilizing yields (Cairns et al., 2013). Irrigation, meanwhile, is an effective method to reduce water evaporation during heat waves (Yuan et al., 2003). For each of these practices, we build a dummy taking the value 1 if the household adopted the practice in a given season and zero otherwise. Additionally, we construct an indicator for temperature-resilient practices, measuring the proportion of the three practices adopted by each household, resulting in a value ranging from 0 to 1.

For the category of practices that do not help households cope with temperature shocks, we expect the adoption to be differentially lower for experienced households (or similar to non-experienced households) at the beginning of the period t, as a response to temperature shocks in period $(t-1)$. These practices are more directly related to the ability to cope with rainfall shocks and include a) drainage, which increases the runoff of water from the land when excessive rains occur, b) inorganic and organic fertilizers, which increase returns under rainy conditions (Alem et al., 2010), and c) pesticides, which are less effective under drought conditions (Khodaverdi et al., 2016). As before, for each of these practices, we build a dummy taking the value 1 if the household adopted the practice in a given season and zero otherwise. In addition, we construct a second indicator, on rainfall-resistant practices, measuring the proportion of the practices adopted by each household.

5.2 Findings

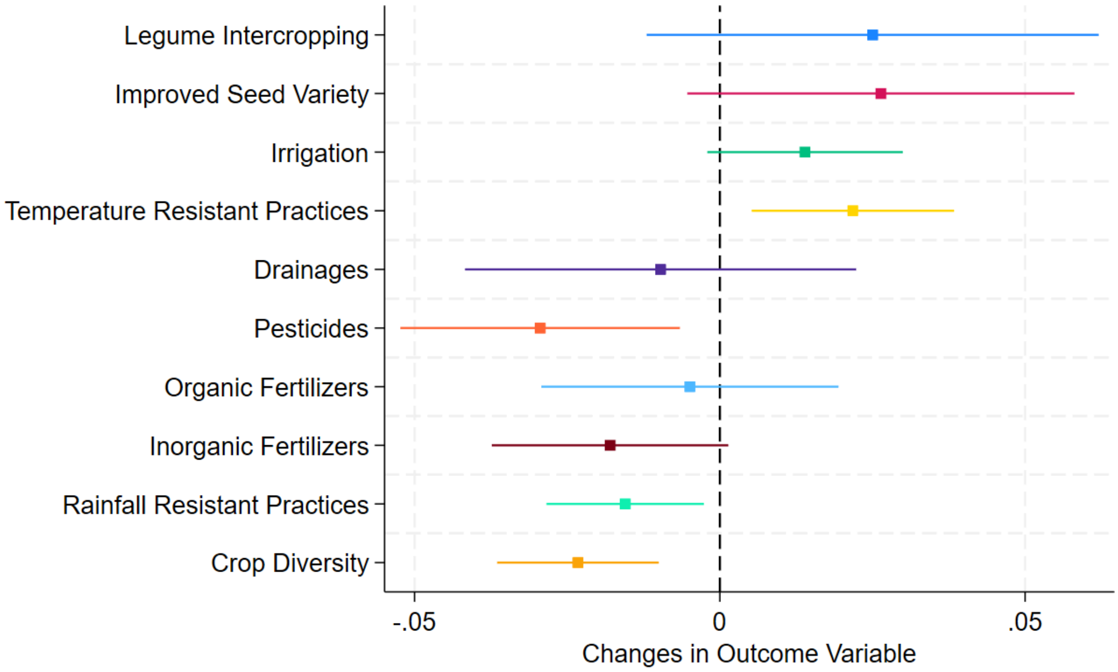


Figure 5: Effect of Experience on the Adoption of Practices

Notes: The reported triple-difference coefficients are from the specification (14), reported here with respect to the corresponding outcome variables. The coefficients are reported with their corresponding 90 percent confidence intervals of robust standard errors clustered at the household level. All regressions include survey year fixed effects, household fixed effects, and household controls. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district.

Figure 5 presents our estimated coefficient of interest (b_2) for different practices, along with their corresponding 90 percent confidence intervals. As expected, the adoption of coping practices that help with temperature shocks is higher for experienced households at the beginning of the period t, as a response to temperature shocks in period $(t-1)$, although the coefficient is not always statistically significant. Specifically, the probability of adopting legume intercropping is around 2.5 percent higher, the probability of using improved seed varieties is about 2.6 percent higher, and the probability of adopting irrigation is 1.4 percent higher. Although the results for these practices are not individually significant, the temperature-resilient practices indicator confirms the positive direction of the effect and is statistically significant, suggesting that the impact of experience is more pronounced when considering the combined adoption of multiple practices rather than any single practice alone. In particular, as a response to temperature shocks in period $(t-1)$, the overall adoption of temperature-resilient practices is 2.2 percent higher for experienced households at the beginning of the period t.

The bottom part of the figure shows the coefficients related to the practices that do not help cope with temperature shocks. For all of these practices, the adoption is lower for experienced households at the beginning of the period t, as a response to temperature shocks in period $(t-1)$. However, none of the estimated coefficients is statistically different from zero, with the exception of the one associated with pesticides. When considering the index of rainfall-resistant practices, our coefficient of interest is negative and significant, indicating that as a response to temperature shocks in period $(t-1)$, the overall adoption of rainfall-resilient practices is 2.3 percent lower for experienced households at the beginning of the period t.

Finally, we also examine whether there is any impact on crop diversification decisions. We do not have a strong ex-ante hypothesis on this. On the one hand, experience can encourage households to increase diversification after a shock; on the other hand, households with greater experience may already be close to an optimal diversification strategy and thus respond differently compared to less experienced households. Our results appear to support the second scenario: the crop diversity index, based on the Gini-Simpson diversification measure, is significantly lower for experienced households at the beginning of the period t, as a response to temperature shocks in the period $(t-1)$.

In summary, our results suggest that temperature shocks in the last period motivate households with the experience of similar shocks in the past to have a differentially higher adoption of practices that better help them cope with such shocks and a differentially lower adoption of practices that do not help them cope with such shocks, compared to the other households. We also provide some suggestive evidence in favor of these households adopting a more optimal diversification strategy as a response to temperature shocks in the last period. This may explain why households that experienced more temperature shocks in the past tend to perform better when similar shocks occur again.

6 Summary and Concluding Remarks

A body of literature has investigated the role of experience in shaping individual choices to optimize outcomes through learning and improved decision-making (Malmendier and Nagel, 2015; Groppo and Kraehnert, 2016; Conzo and Salustri, 2019). However, whether people learn from a past shock and are more able to respond to a new similar shock remains underexplored. One reason for this gap is that the subjective perception of the shock usually plays a significant role when relying on experience. For example, individuals may report or fail to report past shocks due to bias related to how they perceived the shock, its impact on others, or how it was communicated through media or other channels.

In this article, we depart from subjective experience reporting and focus on an objective context: the occurrence of weather shocks in Uganda, a developing country highly exposed to the effects of climate change. We use a nationally representative household panel survey and merge it with an objective measure of experience of weather shocks, measured through the temperature distribution with the household's location, while accounting for the duration each household member has resided there. We investigate whether the occurrence of a new shock, measured during the survey year, has a lower impact on households with a higher average exposure in the past to similar shocks.

Our analysis addresses the need for an approach that accounts for heterogeneity in household experience, even among households residing in the same location. Without considering such heterogeneity, all households within a location would be associated with the same level of experience, creating collinearity between this variable and unobserved institutional or cultural characteristics shaped by past shocks. To overcome this, we use migration decisions within households to generate variation in climate experience among household members and between households.

The results reveal that previous experience positively impacts a household's ability to cope with shocks. Specifically, households with a greater experience of adverse weather events in the past exhibit better outcomes when faced with similar events, as evidenced by their agricultural production. Our estimates suggest that an additional 10 days of temperature shocks during the survey season reduce income by approximately 8 percent (about 90 USD) for households with lower levels of experience. In contrast, households in the 25th percentile of the experience variable face a smaller income decrease of 5 percent (about 55 USD).

This study uncovers a previously unobserved heterogeneity embedded in analyses related to weather shocks, one that is not tied to socioeconomic or demographic characteristics. Although many studies have explored the differential impacts of weather shocks based on gender, wealth, ethnicity, and other factors, this is the first to directly link weather shock outcomes with previous exposure to similar events. Our findings suggest that a household's capacity to withstand shocks is enhanced by its accumulated experience, which acts as a form of intangible wealth, helping mitigate the effects of future shocks.

From a policy perspective, as weather shocks increasingly occur in regions where they were previously rare, the most vulnerable populations, those with little prior experience, will bear the brunt of these shocks. In addition, our findings provide evidence of autonomous adaptation mechanisms developed by individuals through experience. Future research should explore whether such an experience can be effectively communicated and transferred to others, potentially mitigating the impact on less prepared populations. Understanding these dynamics could inform strategies to build resilience and reduce the adverse effects of climate change.

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Online Appendices

Lessons from the Past: How Experience Reduces the Impact of Weather Shocks on Ugandan Smallholders*

Aranya Chakraborty Giuseppe Maggio Fabio G. Santeramo

This online appendix is organized as follows. Appendix A contains the results for the robustness checks discussed in Section 4.3. Appendix B presents the results of additional analysis conducted using a soil incompatibility measure that was constructed using additional data from the GAEZ dataset. Finally, Appendix C documents the robustness of these additional analysis results to alternative specifications.

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A Results for Robustness Checks

Table A.1: Placebo test with respect to forward shock (instead of the current shock)

	(1)	(2)	(3)	(4)	(5)
Forward Weather Shock	1.167	-0.080	0.040	0.080	0.086
	(0.833)	(0.483)	(0.483)	(0.483)	(0.483)
Forward Weather Shock $\times$ Experience	-0.142	0.002	-0.013	-0.017	-0.018
	(0.096)	(0.055)	(0.055)	(0.055)	(0.055)
Full Sample	No	Yes	Yes	Yes	Yes
Household Controls	Yes	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	Yes	No	No	Yes	Yes
Weather Shock $\times$ No. of Movers	Yes	No	No	No	Yes
Observations	1592	3332	3278	3278	3278
Adjusted R^2	0.103	0.056	0.070	0.070	0.070

Notes: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Forward\ Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the following year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Column (1) results focus on the restricted sample of households that had no movers at the baseline. The rest of the columns report results that use the full sample of households.

Table A.2: Robustness for the effect of weather shocks on production by climate experience (using the experience of only the adult household members)

	(1)	(2)	(3)	(4)	(5)
Weather Shock	-1.148**	-0.831***	-0.837***	-0.687***	-0.710***
	(0.557)	(0.241)	(0.244)	(0.243)	(0.243)
Weather Shock $\times$ Experience	0.128**	0.090***	0.091***	0.072***	0.077***
	(0.064)	(0.028)	(0.028)	(0.028)	(0.028)
Mean Baseline Outcome	5.520	5.717	5.717	5.717	5.717
(SD)	(2.004)	(1.792)	(1.792)	(1.792)	(1.792)
Full Sample	No	Yes	Yes	Yes	Yes
Household Controls	Yes	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	Yes	No	No	Yes	Yes
Weather Shock $\times$ No. of Movers	Yes	No	No	No	Yes
Observations	2114	4424	4365	4365	4365
Adjusted R^2	0.103	0.069	0.079	0.089	0.090

Notes: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Column (1) results focus on the restricted sample of households that had no movers at the baseline. The rest of the columns report results that use the full sample of households.

Table A.3: Robustness for the effect of weather shocks on production by climate experience (using the median of experience instead of the mean at the household level)

	(1)	(2)	(3)	(4)	(5)
Weather Shock	-1.245**	-1.492***	-1.546***	-1.307***	-1.250***
	(0.558)	(0.402)	(0.401)	(0.399)	(0.395)
Weather Shock $\times$ Experience	0.139**	0.167***	0.174***	0.144***	0.139***
	(0.065)	(0.046)	(0.046)	(0.046)	(0.046)
Mean Baseline Outcome	5.520	5.717	5.717	5.717	5.717
(SD)	(2.004)	(1.792)	(1.792)	(1.792)	(1.792)
Full Sample	No	Yes	Yes	Yes	Yes
Household Controls	Yes	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	Yes	No	No	Yes	Yes
Weather Shock $\times$ No. of Movers	Yes	No	No	No	Yes
Observations	2134	4452	4392	4392	4392
Adjusted R^2	0.103	0.071	0.080	0.090	0.091

Notes: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the median of cumulative average number of dekads in an agricultural year the household members experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Column (1) results focus on the restricted sample of households that had no movers at the baseline. The rest of the columns report results that use the full sample of households.

Table A.4: Robustness for the effect of weather shocks on production by climate experience (using different climate bins for experience)

	(1)	(2)	(3)	(4)	(5)
Weather Shock	-0.059*	-0.065**	-0.075***	-0.068***	-0.049*
	(0.034)	(0.025)	(0.025)	(0.025)	(0.025)
Weather Shock × Experience	0.019	0.022	0.029**	0.013	0.013
	(0.021)	(0.015)	(0.014)	(0.015)	(0.015)
Mean Baseline Outcome	5.520	5.717	5.717	5.717	5.717
(SD)	(2.004)	(1.792)	(1.792)	(1.792)	(1.792)
Full Sample	No	Yes	Yes	Yes	Yes
Household Controls	Yes	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	Yes	No	No	Yes	Yes
Weather Shock × No. of Movers	Yes	No	No	No	Yes
Observations	2134	4452	4392	4392	4392
Adjusted R^2	0.101	0.068	0.077	0.088	0.089

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced greater than 1 deviation in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Column (1) results focus on the restricted sample of households that had no movers at the baseline. The rest of the columns report results that use the full sample of households.

Table A.5: Robustness for the effect of weather shocks on production by climate experience (for the restricted sample without outliers)

	(1)	(2)	(3)	(4)	(5)
Weather Shock	-1.134**	-1.318***	-1.386***	-1.147***	-1.130***
	(0.545)	(0.364)	(0.363)	(0.365)	(0.363)
Weather Shock × Experience	0.126**	0.146***	0.154***	0.124***	0.125***
	(0.063)	(0.042)	(0.042)	(0.042)	(0.042)
Mean Baseline Outcome	5.520	5.717	5.717	5.717	5.717
(SD)	(2.004)	(1.792)	(1.792)	(1.792)	(1.792)
Full Sample	No	Yes	Yes	Yes	Yes
Household Controls	Yes	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	Yes	No	No	Yes	Yes
Weather Shock × No. of Movers	Yes	No	No	No	Yes
Observations	2054	4296	4241	4241	4241
Adjusted R^2	0.114	0.078	0.087	0.097	0.098

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Column (1) results focus on the restricted sample of households that had no movers at the baseline. The rest of the columns report results that use the full sample of households.

Table A.6: Robustness for the effect of weather shocks on production by climate experience (after dropping households with all movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.543***	-1.593***	-1.318***	-1.335***
	(0.375)	(0.377)	(0.378)	(0.376)
Weather Shock × Experience	0.172***	0.178***	0.144***	0.148***
	(0.043)	(0.043)	(0.044)	(0.043)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4228	4172	4172	4172
Adjusted R^2	0.074	0.083	0.095	0.096

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table A.7: Robustness for the effect of weather shocks on production by climate experience (after dropping households with 75% or more movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.492***	-1.552***	-1.271***	-1.280***
	(0.380)	(0.382)	(0.383)	(0.383)
Weather Shock × Experience	0.167***	0.174***	0.139***	0.142***
	(0.044)	(0.044)	(0.044)	(0.044)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4054	4000	4000	4000
Adjusted R^2	0.070	0.081	0.093	0.093

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table A.8: Robustness for the effect of weather shocks on production by climate experience (with 25% or fewer movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.503***	-1.572***	-1.275***	-1.372***
	(0.423)	(0.425)	(0.430)	(0.439)
Weather Shock × Experience	0.169***	0.176***	0.140***	0.153***
	(0.049)	(0.049)	(0.050)	(0.051)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	3194	3149	3149	3149
Adjusted R^2	0.076	0.088	0.101	0.102

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table A.9: Robustness for the effect of weather shocks on production by climate experience (comparing households between 25-50% movers with those with no movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.453***	-1.546***	-1.230**	-1.284***
	(0.491)	(0.487)	(0.485)	(0.486)
Weather Shock $\times$ Experience	0.164***	0.174***	0.136**	0.143**
	(0.057)	(0.056)	(0.056)	(0.056)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock $\times$ No. of Movers	No	No	No	Yes
Observations	2870	2830	2830	2830
Adjusted R^2	0.069	0.079	0.093	0.093

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table A.10: Robustness for the effect of weather shocks on production by climate experience (comparing households between 50-75% movers with those with no movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.515***	-1.542***	-1.230**	-1.202**
	(0.530)	(0.528)	(0.526)	(0.520)
Weather Shock × Experience	0.173***	0.176***	0.137**	0.135**
	(0.061)	(0.061)	(0.061)	(0.060)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	2366	2333	2333	2333
Adjusted R^2	0.068	0.082	0.098	0.098

Notes: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table A.11: Robustness for the effect of weather shocks on production by climate experience (comparing households between 75-100% movers with those with no movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.330**	-1.416***	-1.154**	-1.113**
	(0.516)	(0.511)	(0.513)	(0.510)
Weather Shock × Experience	0.152**	0.162***	0.129**	0.126**
	(0.060)	(0.059)	(0.059)	(0.059)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	2520	2482	2482	2482
Adjusted R^2	0.074	0.084	0.094	0.095

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and deseasonalized temperature in the current year. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

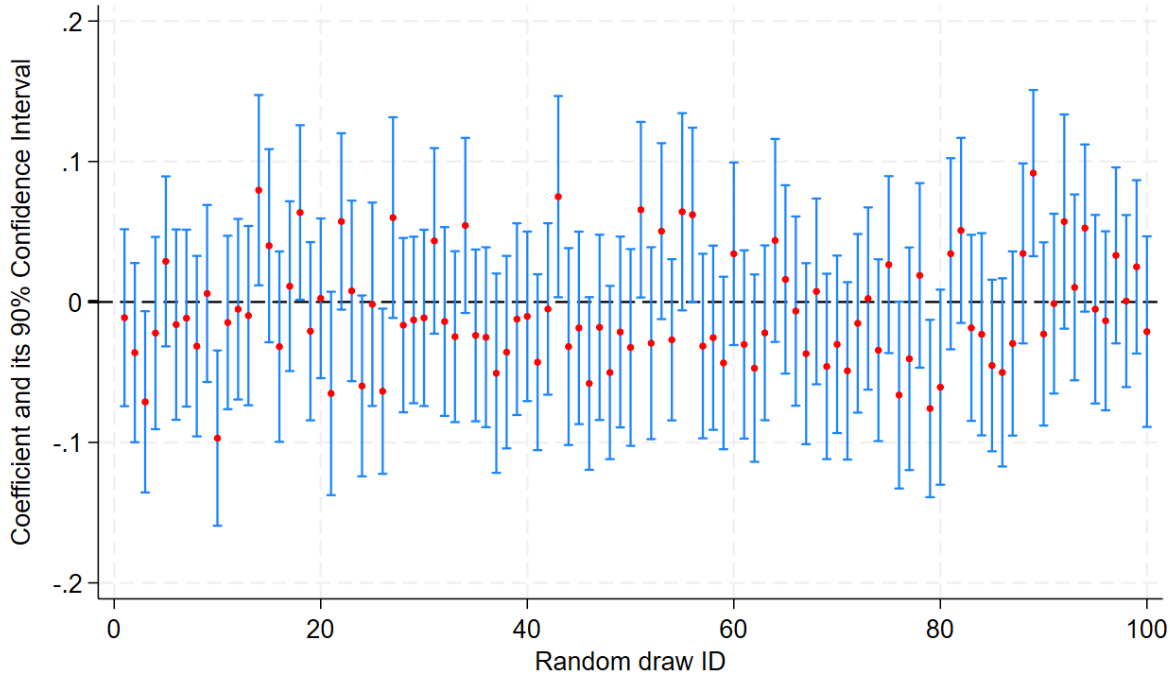

Figure A.1: Effect of the weather shock on agricultural performance by randomly shuffled climate experience

Notes: Each draw represents a random shuffling of the *Experience* variable in the baseline. The figure documents the coefficients for the interaction of *Weather Shock* and *Experience* with shuffled values of *Experience* in regression (7). The dependent variable for all regressions is the *Log of (total production +1)*. All regressions include survey year and household fixed effects, household controls, average maximum temperature (yearly), and the interaction of $Weather\ Shock$ with the $No.\ of\ Movers$, where the $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district.

B Additional Results with Soil (In)Compatibility

B.1 Specification

We further investigate whether the differential effect of climate experience on performance is independent of an experience variable that captures households' familiarity with soil characteristics. Households whose movers migrated from regions where soil quality is similar to that of their current region are likely to be more familiar with the characteristics of the soil, helping them in the production process (in terms of the optimal input mix, given the soil characteristics). We want to examine whether this familiarity differentially affects the interaction effect of current weather shocks and past experience with such shocks. For this purpose, we use the following specification:

$$
\begin{aligned}
&\text{Performance}_{ilt} = \gamma_0 + \gamma_1 \text{Weather Shock}_{lt} \qquad (15)\\
&+ \gamma_2 \text{Weather Shock}_{lt} \times \text{Inverse Compatibility}_{il} + \gamma_3 \text{Weather Shock}_{lt} \times \text{Experience}_{il}\\
&+ \gamma_4 \text{Weather Shock}_{lt} \times \text{Experience}_{il} \times \text{Inverse Compatibility}_{il} + \gamma_5 X_{ilt} + \sigma_{il} + \lambda_t + u_{ilt}.
\end{aligned}
$$

We expect less familiar soil to reduce the advantage of being familiar with the climate that helps deal with current weather shocks. Therefore, our expected sign of γ_4 is negative. Again, the presence of movers and non-movers helps us identify this coefficient. In particular, the key variation is generated by the movers who migrated from a region with climate and soil characteristics different from the baseline climate and soil characteristics of their current region.

B.1.1 Construction of Soil (In)Compatibility Measure

To capture households' familiarity with soil characteristics, we build a measure that represents the soil compatibility between the location of departure and the location of arrival for migrants. The location of departure is the latest location the movers have departed from within the last 10 years, and the location of arrival is their current location at the baseline. As discussed above, the objective behind the construction of this measure is to test the hypothesis that migrants moving to soil highly incompatible with the one they come from are less likely to gain from their climate experience in terms of dealing with current weather shocks, mainly because of their lack of familiarity with the characteristics of the soil.

The measure relies on information about the agro-climatic potential yield for 71 crops, downloaded from the Global Agro-Ecological Zones (GAEZ) of the Food and Agriculture Organization (FAO) for the period 1981-2010.[1] We build this measure as the difference in the average productivity of all the crops reported by GAEZ between the location of departure and the location of arrival. Thus, for an individual j residing in a location l, having moved there from a location p_j,

[1]This also includes different typologies for the same crops, such as biomass highland sorghum and biomass lowland sorghum.

the measure takes the value:

$$\text{Inverse Compatibility}_{jlp_j} = \frac{\sum_{c=1}^{71}(\text{Potential Yield}_{lc} - \text{Potential Yield}_{p_jc})}{71}, \tag{16}$$

where *Potential Yield*$_{lc}$ represents the potential yield for crop c at the current location l and *Potential Yield*$_{p_jc}$ is the potential yield for the same crop at the departure location p_j. Using this, we construct the household-level measure of soil compatibility for the household i from location l, similar to how we construct Experience$_{il}$, i.e.,:

$$\text{Inverse Compatibility}_{il} = \frac{1}{n_{il}}\sum_{j=1}^{n_{il}} \text{Mover}_{ijl} \times \text{Inverse Compatibility}_{jlp_j}, \tag{17}$$

where n_{il} is the total number of members in the household i from location l and Mover$_{ijl}$ is a dummy that takes 1 if the household member j is a mover, 0 otherwise. Similarly to *Experience*$_{il}$, the resulting variable does not vary over time.

B.1.2 Results

Table B.1 documents whether the impact of baseline climate experience in dealing with current weather shock differentially varies by the household members' familiarity with the soil in their current region. The coefficients for the interaction *Weather Shock* $\times$ *Experience* remain quite similar to those of Table 2. As expected, the sign for the differential effect of soil incompatibility on the interaction between *Weather Shock* and *Experience* is negative. However, the coefficient is statistically insignificant, indicating that the impact of baseline experience of temperature shocks in dealing with current temperature shocks is independent of the household members' familiarity with the soil characteristics. Appendix C presents the robustness of these results with respect to the same robustness checks as in Appendix A. The results remain mostly similar across different alternate specifications.

Table B.1: Effect of soil compatibility on the relation between climate experience and production

	(1)	(2)	(3)	(4)
Weather Shock	-1.494***	-1.542***	-1.286***	-1.279***
	(0.367)	(0.368)	(0.370)	(0.368)
Weather Shock × Inverse Compatibility	1.160	1.167	1.026	1.142
	(0.735)	(0.756)	(0.758)	(0.764)
Weather Shock × Experience	0.167***	0.172***	0.141***	0.143***
	(0.042)	(0.042)	(0.043)	(0.042)
Weather Shock × Experience × Inverse Compatibility	-0.137	-0.138	-0.122	-0.135
	(0.086)	(0.088)	(0.089)	(0.089)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4452	4392	4392	4392
Adjusted R^2	0.071	0.080	0.090	0.091

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

C Additional Robustness Check Results

Table C.1: Placebo test with respect to forward shock (instead of the current shock)

	(1)	(2)	(3)	(4)
Forward Weather Shock	-0.024	0.100	0.138	0.144
	(0.494)	(0.493)	(0.495)	(0.495)
Forward Weather Shock × Inverse Compatibility	-0.654	-0.707	-0.711	-0.712
	(0.419)	(0.470)	(0.472)	(0.472)
Forward Weather Shock × Experience	-0.004	-0.019	-0.024	-0.024
	(0.057)	(0.057)	(0.057)	(0.057)
Forward Weather Shock × Experience × Inverse Compatibility	0.075	0.081	0.082	0.082
	(0.049)	(0.055)	(0.055)	(0.055)
Household Controls	No	Yes	No	Yes
Average Maximum Temp. (yearly)	No	Yes	No	Yes
Weather Shock × No. of Movers	No	Yes	No	Yes
Observations	3332	3278	3278	3278
Adjusted R^2	0.056	0.070	0.070	0.070

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Forward\ Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the following year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.2: Robustness for the effect of soil compatibility on the relation between climate experience and production (using the experience of only the adult household members)

	(1)	(2)	(3)	(4)
Weather Shock	-0.902***	-0.909***	-0.753***	-0.784***
	(0.243)	(0.246)	(0.245)	(0.246)
Weather Shock × Inverse Compatibility	0.912***	0.911***	0.846***	0.912***
	(0.316)	(0.319)	(0.315)	(0.322)
Weather Shock × Experience	0.099***	0.099***	0.080***	0.085***
	(0.028)	(0.028)	(0.028)	(0.028)
Weather Shock × Experience × Inverse Compatibility	-0.108***	-0.108***	-0.100***	-0.107***
	(0.037)	(0.037)	(0.037)	(0.038)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4424	4365	4365	4365
Adjusted R^2	0.069	0.080	0.089	0.090

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.3: Robustness for the effect of soil compatibility on the relation between climate experience and production (using the median of experience instead of the mean at the household level)

	(1)	(2)	(3)	(4)
Weather Shock	-1.523***	-1.579***	-1.333***	-1.284***
	(0.404)	(0.403)	(0.401)	(0.397)
Weather Shock × Inverse Compatibility	0.916	0.958	0.813	0.911
	(0.966)	(0.987)	(1.005)	(1.001)
Weather Shock × Experience	0.171***	0.177***	0.147***	0.143***
	(0.047)	(0.046)	(0.046)	(0.046)
Weather Shock × Experience × Inverse Compatibility	-0.108	-0.113	-0.097	-0.108
	(0.113)	(0.116)	(0.118)	(0.117)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4452	4392	4392	4392
Adjusted R^2	0.071	0.080	0.090	0.091

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.4: Robustness for the effect of soil compatibility on the relation between climate experience and production results (using different climate bins for experience)

	(1)	(2)	(3)	(4)
Weather Shock	-0.064**	-0.073***	-0.066***	-0.048*
	(0.025)	(0.025)	(0.025)	(0.025)
Weather Shock × Inverse Compatibility	-0.039	-0.031	-0.028	-0.066
	(0.125)	(0.130)	(0.130)	(0.129)
Weather Shock × Experience	0.022	0.028*	0.012	0.012
	(0.015)	(0.014)	(0.015)	(0.015)
Weather Shock × Experience × Inverse Compatibility	0.035	0.024	0.018	0.071
	(0.157)	(0.164)	(0.164)	(0.162)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4452	4392	4392	4392
Adjusted R^2	0.068	0.077	0.087	0.088

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced greater than 1 deviation in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.5: Robustness for the effect of soil compatibility on the relation between climate experience and production results (for the restricted sample without outliers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.373***	-1.441***	-1.193***	-1.186***
	(0.366)	(0.365)	(0.368)	(0.365)
Weather Shock × Inverse Compatibility	1.120	1.130	0.999	1.100
	(0.740)	(0.764)	(0.768)	(0.771)
Weather Shock × Experience	0.152***	0.160***	0.130***	0.131***
	(0.042)	(0.042)	(0.042)	(0.042)
Weather Shock × Experience × Inverse Compatibility	-0.132	-0.133	-0.118	-0.130
	(0.087)	(0.089)	(0.090)	(0.090)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4296	4241	4241	4241
Adjusted R^2	0.078	0.087	0.097	0.098

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.6: Robustness for the effect of soil compatibility on the relation between climate experience and production results (after dropping households with all movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.609***	-1.658***	-1.373***	-1.399***
	(0.377)	(0.379)	(0.381)	(0.379)
Weather Shock × Inverse Compatibility	1.664**	1.628**	1.419*	1.452
	(0.782)	(0.813)	(0.855)	(0.886)
Weather Shock × Experience	0.179***	0.185***	0.150***	0.156***
	(0.043)	(0.044)	(0.044)	(0.044)
Weather Shock × Experience × Inverse Compatibility	-0.201**	-0.197**	-0.172*	-0.174
	(0.094)	(0.098)	(0.103)	(0.107)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4228	4172	4172	4172
Adjusted R^2	0.074	0.083	0.095	0.096

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.7: Robustness for the effect of soil compatibility on the relation between climate experience and production results (after dropping households with 75% or more movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.553***	-1.613***	-1.321***	-1.335***
	(0.383)	(0.385)	(0.386)	(0.386)
Weather Shock × Inverse Compatibility	1.409*	1.374	1.159	1.186
	(0.835)	(0.876)	(0.928)	(0.944)
Weather Shock × Experience	0.174***	0.181***	0.145***	0.148***
	(0.044)	(0.044)	(0.045)	(0.045)
Weather Shock × Experience × Inverse Compatibility	-0.169*	-0.166	-0.140	-0.142
	(0.101)	(0.106)	(0.112)	(0.114)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	4054	4000	4000	4000
Adjusted R^2	0.070	0.081	0.093	0.093

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.8: Robustness for the effect of soil compatibility on the relation between climate experience and production results (for households with 25% or fewer movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.605***	-1.676***	-1.384***	-1.481***
	(0.425)	(0.425)	(0.431)	(0.441)
Weather Shock × Inverse Compatibility	3.601	3.658	4.343	4.718
	(3.347)	(3.441)	(3.505)	(3.445)
Weather Shock × Experience	0.180***	0.188***	0.153***	0.165***
	(0.049)	(0.049)	(0.050)	(0.051)
Weather Shock × Experience × Inverse Compatibility	-0.411	-0.417	-0.490	-0.529
	(0.366)	(0.377)	(0.383)	(0.377)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	3194	3149	3149	3149
Adjusted R^2	0.076	0.088	0.101	0.102

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.9: Robustness for the effect of soil compatibility on the relation between climate experience and production results (comparing households between 25-50% movers with those with no movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.433***	-1.531***	-1.216**	-1.278***
	(0.497)	(0.493)	(0.491)	(0.493)
Weather Shock × Inverse Compatibility	-2.674	-1.909	-1.855	-0.655
	(4.297)	(4.336)	(4.669)	(4.460)
Weather Shock × Experience	0.162***	0.173***	0.134**	0.143**
	(0.057)	(0.057)	(0.057)	(0.057)
Weather Shock × Experience × Inverse Compatibility	0.292	0.207	0.205	0.075
	(0.486)	(0.490)	(0.527)	(0.504)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	2870	2830	2830	2830
Adjusted R^2	0.069	0.079	0.092	0.093

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.10: Robustness for the effect of soil compatibility on the relation between climate experience and production results (comparing households between 50-75% movers with those with no movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.503***	-1.525***	-1.202**	-1.197**
	(0.531)	(0.529)	(0.528)	(0.525)
Weather Shock × Inverse Compatibility	14.674*	14.385*	14.605*	13.043
	(8.157)	(8.331)	(8.201)	(8.460)
Weather Shock × Experience	0.172***	0.175***	0.135**	0.134**
	(0.061)	(0.061)	(0.061)	(0.061)
Weather Shock × Experience × Inverse Compatibility	-1.773*	-1.739*	-1.766*	-1.577
	(0.985)	(1.006)	(0.991)	(1.022)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	2366	2333	2333	2333
Adjusted R^2	0.069	0.082	0.099	0.099

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

Table C.11: Robustness for the effect of soil compatibility on the relation between climate experience and production results (comparing households between 75-100% movers with those with no movers)

	(1)	(2)	(3)	(4)
Weather Shock	-1.371***	-1.461***	-1.197**	-1.160**
	(0.518)	(0.512)	(0.515)	(0.512)
Weather Shock × Inverse Compatibility	6.278*	7.272*	7.214*	7.298*
	(3.789)	(4.051)	(4.368)	(4.001)
Weather Shock × Experience	0.157***	0.167***	0.134**	0.131**
	(0.060)	(0.059)	(0.060)	(0.059)
Weather Shock × Experience × Inverse Compatibility	-0.733*	-0.849*	-0.842*	-0.852*
	(0.441)	(0.472)	(0.509)	(0.466)
Mean Baseline Outcome	5.717	5.717	5.717	5.717
(SD)	(1.792)	(1.792)	(1.792)	(1.792)
Household Controls	No	Yes	Yes	Yes
Average Maximum Temp. (yearly)	No	No	Yes	Yes
Weather Shock × No. of Movers	No	No	No	Yes
Observations	2520	2482	2482	2482
Adjusted R^2	0.074	0.083	0.094	0.094

Notes: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the Log of (total production +1). $Weather\ Shock$ is captured by the household's current region's frequency (number of dekads out of 18 dekads in an agricultural year) of experiencing positive deviations in de-trended and de-climatized temperature in the current year. $Inverse\ Compatibility$ is the household-level average of the soil compatibility difference measure that captures the differences in soil quality between its members' last location of migration and the current location of residence. $Experience$ is the cumulative average number of dekads in an agricultural year the household experienced positive deviations in de-trended and deseasonalized weather variable up to the baseline (where the baseline is the baseline year at the current region for the non-mover household member(s), but the year of moving at the original region for the mover household member(s)), averaged at the household-level. All regressions include survey year and household fixed effects. Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district. The $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years).

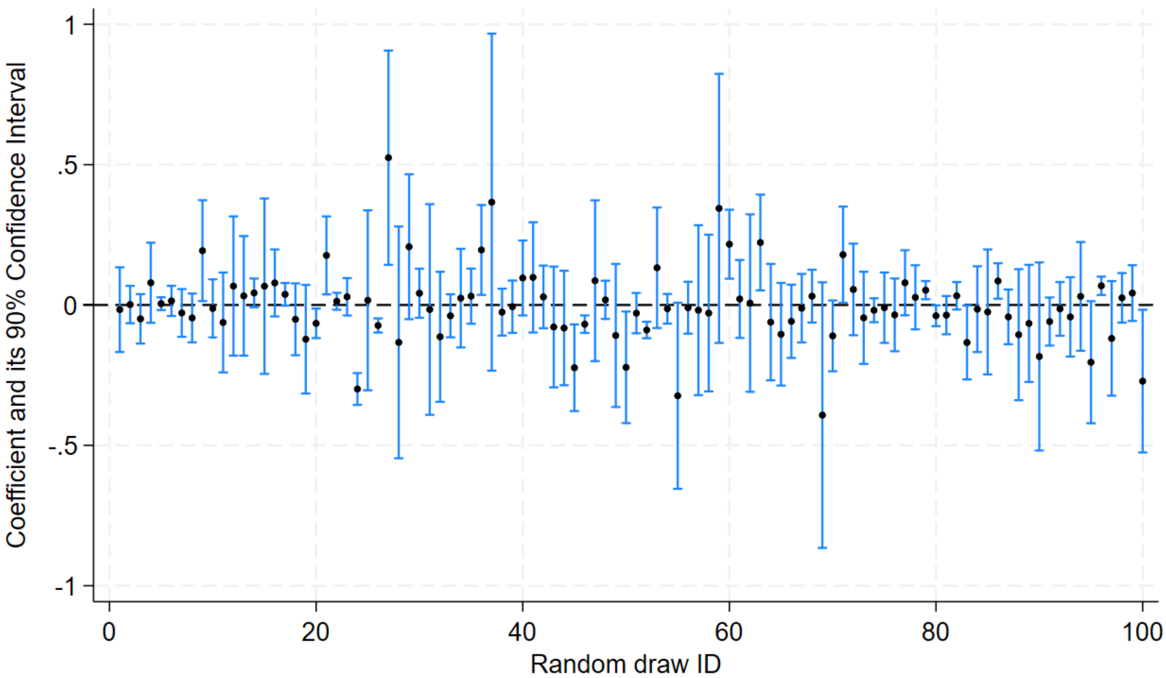

Figure C.1: Differential effect of the weather shock on agricultural performance by randomly shuffled climate experience and Inverse Compatibility

Notes: Each draw represents a random shuffling of the *Experience* and *Inverse Compatibility* in the baseline. The figure documents the coefficients for the interaction of *Weather Shock*, *Experience*, and *Inverse Compatibility* with shuffled values of *Experience* and *Inverse Compatibility* in regression (15). The dependent variable for all regressions is the *Log of (total production +1)*. All regressions include survey year and household fixed effects, household controls, average maximum temperature (yearly), and the interaction of $Weather\ Shock$ with the $No.\ of\ Movers$, where the $No.\ of\ Movers$ is the total number of movers the household had at the baseline (where movers are the ones that lived in at least one other region for 6 months or more in the past 10 years). Household controls include the number of household members, average years of education in the household, total yearly land use in hectares, agricultural wealth index, distance from the household to the nearest market (in kilometers), a measure of nightlights of the district, and population density of the district.