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Abstract

Applying a Panel Fixed Effect model to a large dataset of migration and local weather conditions in 16 sub-Saharan African (SSA) countries, this study estimates the impacts of long-term weather aberrations on within-country migration. To address potential omitted variable bias, this study accounts for weather conditions in alternative places of residence–an aspect which has been overlooked by previous studies. Results establish a causal link between climate change and migration, but this effect is observed primarily in a block of West SSA countries. In this region, climate-related relocation is driven by both long-term changes in weather (specifically rainfall and temperature) and temperature volatility. In this region, climate-related relocation is driven by both long term changes in weather (rainfall and temperature) and temperature volatility. Quantitatively, this study finds that over the last 30 years, an average annual rainfall decline of 120mm increased internal migration by 14 percentage points while a sustained average temperature increase of 0.5°C resulted in an 8 percentage point rise in internal relocation. However, temperature fluctuations are found to lowered the odds of out-migration by 22 percentage points. Additional findings reveal that increasing temperatures force climate migrants to travel to much farther destination areas. However, we do not find evidence that adverse rainfall outcomes increase relocation distance. Additionally, We establish that climate migrants tend to relocate from rural districts to urban centers. Finally, We obtain evidence that climate-related mobility involves relocation of a family units, as suggested by the significance of climate mobility of young children (less than 12 years old). Meanwhile, when the same specifications are applied on East SSA, we find weak evidence of climate-related mobility in this region.

1 Introduction

There exist growing concerns that weather shocks will greatly reduce habitability and economic prospects of some parts of the world, and that this could trigger large scale human displacement. The continued worsening of global climate outcomes in the form of continued rising trends in global surface temperature and increased erratic-ness of rainfall (World Meteorological Organization , WMO) justify these fears. In the developing regions such as Africa where climate vulnerability is high (Wolde et al. (2023), climate change has already heightened the risks of food insecurity and conflicts, necessitating out-migration as one of the adaptation measures ((World Meteorological Organization , WMO)). Current estimations by the Bank (2021) indicate that close to a 100 million Africans could be forced to migrate within their own countries by 2050 due to the effects of changing weather patterns.

Understanding climate-induced mobility is critical because of its potential impacts on both the receiving and the sending communities, as well as the migrants themselves. Resultantly, scholarly efforts have led to a rapid growth in literature on this topic. However, despite these efforts, uncertainty persists regarding the precise relationship between climate change and migration (Bertoli et al. (2022), Wolde et al. (2023), Helbling et al. (2023), Ofori et al. (2023)) – as existing research offers mixed results in terms of direction, extent and significance of impact. This discourages policy efforts to address the challenges related to potential increases in global climate-related migration flows Hoffmann et al. (2020) and to explore migration as a viable adaptation measure to climate change. Conversely, a better understanding of the nature and extent of climate mobility will be important for crafting effective adaptation policies in both the sending and receiving areas (Beltran and Hadzi-Vaskov (2023)).

Meanwhile, as the quest for evidence of climate-driven mobility continues, We identify a few research gaps to address. First, existing research has not considered weather of the potential destination areas, leading to concerns about omitted variable bias. Indeed, climatic conditions in both the place of origin and the destination play a crucial role in explaining migration patterns. Unfavorable weather outcomes at the place of origin act as a push factor, compelling people to seek better prospects elsewhere. Conversely, adverse weather conditions at the potential destination serve as a deterrent, discouraging migration. Similarly, favorable weather conditions in the source area discourage out-migration, while desirable weather conditions in an alternative location constitute a pull factor that attracts individuals seeking improved living conditions (see Lee (1966) and Brettell and Hollifield (2013) for push and pull theory of migration). Additionally, weather conditions tend to be spatially correlated, particularly for shorter distances typically involved in internal relocation relative to international migration. This provides further justification for controlling for weather of potential destination areas.

Second, existing studies on sub-Saharan Africa region have individually covered only a limited geographical extent. According to (Gray and Wise, 2016) and (Wolde et al., 2023), prior to 2016, the bulk of research was country specific. Additionally, while Bertoli et al. (2022) studied a larger sample of the 13 countries, their investigation was confined to West Africa. Overall, the limited geographical coverage coupled with diversity of findings has limited our ability to formulate general claims.

In view of the foregoing, we contribute to existing literature in two ways. First, we take into account weather experiences in alternative locations. Secondly, our measure of migration–which is a dummy of the difference between place of birth and place of current residence–assists in constructing a consistent migration variable across SSA. As a result, We are able to include a relatively large sample of 16 SSA countries in my analysis. Furthermore, given a geographically diverse sample, We classify these country samples into West SSA (9 countries) and East SSA (7 countries), achieving a balanced representation between the western and eastern regions of SSA.

In addressing the causal impact of climate change on within-country relocation, our study formulates and answers several key questions. First, we examine the causal effect of long-term changes in temperature, rainfall, and volatility on migration. Second, we explore heterogeneous effects across different age groups and genders. Additionally, we assess whether climate-induced migration moves people from rural area to urban centers and whether climate-driven migration influences the choice of relocation distance. Lastly, our study investigates whether climate-induced mobility involves the relocation of family units or individuals independently.

The outline of the rest of the study is as follows: Chapter 2 reviews related literature. Chapter 3 discusses data and construction of variables used in the analysis. Chapter 4 lays out the identification strategy. Chapter 5 discusses estimation results. Lastly, Chapter 6 concluded with policy implications, weaknesses of the study and areas for future research.

2 Literature Review

Climate change refers to persistent deviation of temperature and precipitation from historical patterns. This is contrasted to short-term weather shocks, which are sudden and extreme deviations from typical weather lasting for a relatively shorter period. While weather shocks have been a common experience over the stretch of human existence, climate change is a more recent phenomenon primarily driven by anthropogenic global warming (Pörtner et al., 2022). However, the two concepts are related in that climate change has been linked to the frequency and severity of extreme weather events (Hermans and McLeman (2021); Reed and Stringer (2016); Mueller et al. (2020b)).

The response of migration to climate change may differ depending on the magnitude and suddenness of the weather shocks. Kaczan and Orgill-Meyer (2020) and Thiede et al. (2016) distinguish between drastic changes in weather referred to as rapid on-set shocks (such as heavy rain, tropical storms, heat waves) from broad-scale marginal changes in the climate (specifically, in the patterns and levels of rainfall and temperature) referred to slow on-set shocks. Rapid on-set shocks may result in either migration or not depending on whether they spare or destroy capabilities to emigrate. In contrast, slow on-set shocks have also been found to explain migration ((Thiede et al., 2016), (Missirian and Schlenker, 2017)). Similarly, Wolde et al. (2023) identify the so-called direct and indirect environmental changes causing migration. They define direct environmental change drivers as the prompt reason/cause for displacement while indirect drivers as the slowly emerging or accumulated environmental changes putting pressure on already vulnerable communities.

Literature further shows that climate-related migration responses can differ widely across regions and countries even for the same climatic conditions (Bertoli et al. (2022), Thiede et al. (2016)). This suggests that other factors may interact with climate shocks in producing observed migration flows. Indeed, climate change heightens migration risk through its role an additional stressor/threat multiplier. Migration incidence has been shown to be interconnected with the need to escape unfavorable conflict-related conditions and adverse economic/agricultural outcomes, usually to more urbanised destinations (Abel et al. (2019); Missirian and Schlenker (2017); Falco et al. (2019),Marchiori et al. (2012),Wolde et al. (2023).

Several notable studies have been conducted on developing countries.

Thiede et al. (2016) employed logistic regression models on eight South American countries in studying climate-induced mobility across provinces. They measured out-migration as relocation to another province over the past five years prior to census. Regarding weather, they assessed two aspects of climate change namely, intensity of climate anomalies (slow-onset events) and cumulative exposure to climate extremes (sudden-onset events). To enable valid cross-sample comparisons, they normalized weather deviations from their respective historical means using z-scores. They observed that while weather deviations measure intensity of climate change, they do not identify exposure to extreme weather events such as droughts and floods. To measure cumulative exposure to weather extremes, they count the number of monthly observations falling outside a 2-standard deviation threshold in a given observation window. Their finding was that temperature extremes consistently explain migration in the region. Additionally, climate-migrants tend to move into urban. However, since their census data did not indicate the urban status of the place of origin, they were unable to confirm whether climate relocation is from rural to urban. [We will address this issue in my study]. Thirdly, they acknowledge that climate effects on migration vary by country and historical climate conditions.

Similarly, Bertoli et al. (2022) investigated the presence of a universally applicable framework explaining climate-induced mobility in west Africa. Using data on migration intentions and localized weather shocks in a multilevel framework, over 2008-2016 period, they conducted a meta analysis on numerous competing regression specifications. They find that rainfall explains changes in migration intentions, albeit in a few countries only. Overall, they conclude that the significance, sign and magnitude of the effects are neither robust nor consistent across countries, making it challenging to obtain a general link between climate change and migration.

Closely aligned with my study is notable research by Weinreb et al. (2020), who analyzed how changes in weather patterns affected rural-urban migration across 41 sub-Saharan African countries, by age and sex, over the 1980–2015 period. They combine age- and gender-specific estimates of net rural-urban migration with historical weather data from the Climatic Research Unit (CRU). They employ pre-existing rural-urban migration dataset constructed from a variant of the so-called census survival approach, which utilizes population counts by age and sex for the rural and urban sectors at two separate points in order to estimate time-specific net rural-to-urban migration profiles. Their main deviation from prior literature is in weighting local weather by population, which they argue that it more accurately reflects the rural population's experience of climate change. Differences in estimated impacts from weighted and unweighted measures of weather suggest the extent to which unweighted findings are distorted by patterns in relatively underpopulated areas. Their results reveal that rural out-migration of young adults is the most responsive to shifts in weather patterns, with lower rainfall, lower variability in rainfall, and higher temperatures increasing subsequent rural out-migration. Further, they document that the strength of these effects has grown stronger over time for 20–24 year olds, though weaker above age 30. In contrast, increasing temperature variability is associated with a higher rural in-migration of children (0–9) and older adults (55–64). Gender differences in these effects are minimal and concentrated in areas which experienced heavy reductions in rainfall.

Mueller et al. (2020a) studied the response of human migration to climate vulnerability in low and middle-income countries in Africa. Employing census data on migration from 4 million individuals from three middle-income African countries over a 22-year period within country-specific fixed-effect logistic model specifications, they link link these individuals to climate exposures in their origins and estimate climatic effects on migration. While they uncover climate anomaly-related mobility in all sampled countries, namely Botswana, Zambia and Kenya, the direction, magnitude and significance differ by country. For instance, they report a 1-standard deviation increase in temperature inhibits migration in Botswana by 19 percent. Additionally, 1-standard deviation increase in precipitation reduces migration in Botswana (11%) and Kenya (10%), and increases in migration in Zambia (24%). Overall, the authors demonstrate that temperature exerted a minimal influence of migration and precipitation anomalies, though important, varied in direction of impact across the countries. Additionally, they extended their analysis to the examination of the link between climate migration and unemployment. Unclear patterns between weather anomalies, unemployment, and inactivity cast doubt on claims that climate change fosters urbanization in Africa (as advanced by Marchiori et al. (2012), for example)

Employing a diverse set of analytical tools in conducting a meta-analysis of 87 studies on environmental mobility in SSA, Wolde et al. (2023) explore whether and how hydroclimatic variability has affected internal migration flows across 32 SSA. Their results reveal environmental migration is an outcome of a complex interplay between environmental factors and *underlying* non-environmental factors (political, economic, administrative, social, and development processes that lead to the depletion/degradation of natural resources). The impact of non-environmental factors on climate migration is non-negligible, as they subject the population to cumulative environmental changes and erode their resilience.

Nawrotzki and DeWaard (2018) pinpoint two sources of heterogeneity in climatic impacts. First is differential vulnerability of *populations* to climate change. They note that some populations are too materially poor to migrate, referred to as highly vulnerable "trapped" groups. By the same line of argument, we can also argue that some groups are materially well off that they can afford alternative adaptation measures. We refer these groups to as the climate resilient group. Second is the differential vulnerability of *places*. The authors noted that patterns in climate-related migration vary across regions, and sought to explore the distinguishing features of those regions that inhibit climate migration. Combining climate information with aggregated census micro data, they estimate gravity models of inter-district migration flows in Zambia. They document that adverse climate conditions are linked to migration in only in wealthier districts, while in poor districts people tend to remain despite climate-related challenges. Additionally, they indicate that, despite the limitations posed by poverty, having access to migrant networks empowers individuals in the poorest districts to relocate in response climate-related factors. This offers a practical avenue for overcoming mobility limitations.

Similar to the foregoing paper, Nawrotzki et al. (2017) note that adverse climatic conditions may differentially influence human migration patterns between rural and urban areas. They then investigate the relationship between climate shocks and migration between rural and urban areas within Mexico using Mexican censuses and climate data from Terra Populus at municipal level. They measure climate shocks as monthly deviations from a 30-year (1961–1990) long-term climate normal period and specify quadratic and cubic relationships. Their analysis examines four internal migration permutations: rural-urban, rural-rural, urban-urban, and urban-rural. Among other findings, they report that each additional drought month increases the odds of rural-urban migration by 3.6%.

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Although the approach by Weinreb et al. (2020) is similar to my study, important differences emerge. First, their measure of rural-urban migration is at national level, implying that they conducted a macro-level analysis, with country-agegroup-gender as unit of analysis. In contrast, We use out-migration dummy at individual level. My approach and data allows locating precisely the respondents' area of origin and current place of residence. This allows me to identify the more precisely the weather conditions the individual was exposed to. Secondly and related to the first, their weather data is aggregated at national level, which overlooks the within-country variation in weather outcomes. Thirdly, the study assumes linearity in migration response to weather shocks. In contrast, We consider non-linear relationship.

3 Data

3.1 Migration and other census data

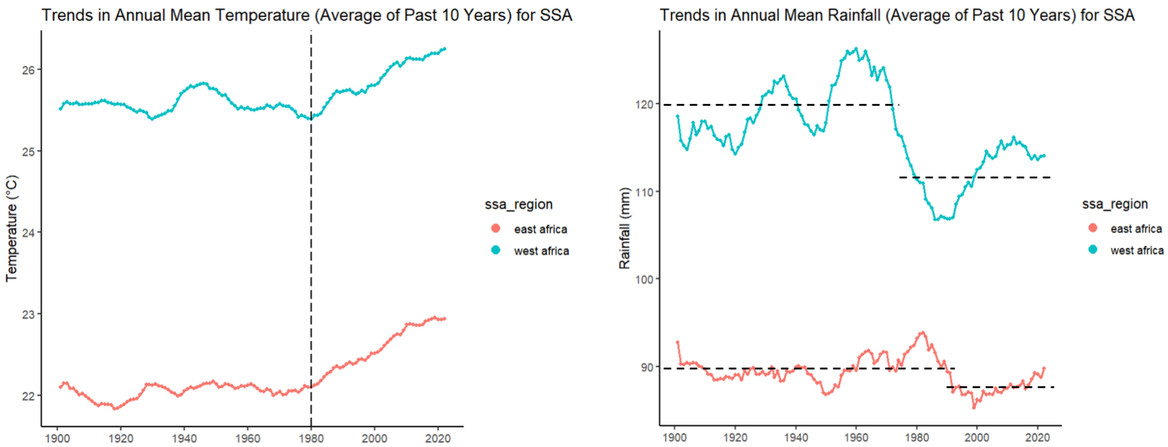
Since our goal is to regress migration incidence on weather changes, we obtained migration measure from national census data of each of the 21 SSA countries supplied by the Integrated Public Use Microdata Series (IPUMS) International (Minnesota Population Center, 2015) Inspired by Blocher et al. (2021) we define migration as relocation from birthplace. Thus, migration incidence was observed by the "mismatch" between an individual's current place of residence and place of birth at a census day, otherwise migration did not occur (birthplace-based migration dummy). This approach was preferred as it resolved the inconsistencies in measurement of migration across countries, which enabled us to pool more countries together. Again, since our sample is large enough, we were able to subsample by age groups and gender, making a more detailed analysis of climate-induced mobility possible. We defined place of origin and destination by the administrative boundary level used for recording birthplace in the census. That is, if a census recorded place of birth at district level, then our measure of migration will be from district to district and if the official record is at regional level, then our measure will also be at regional level.

4 Weather data

We obtained a rich panel of 5-degree by 5-degree gridded monthly mean temperature and mean rainfall data from Climatic Research Unit (CRU) of University of East Anglia. The data, netCDF (CRU version 4.7) file, are have a global cross sectional coverage and 1901-2022 time span. For the purposes of this study, we cut the data to full geographic extents of each of the 16 countries. In addition, since the impact of climate change on migration in SSA is likely to be manifested through impact on agriculture as established by Missirian and Schlenker (2017) and Falco et al. (2019), we restricted weather data only to the crop growing months in each country. The exception for this restriction were those countries which did not have a clearly defined growing season or those whose growing seasons varied substantially across space. For extracting weather data according to location of analysis, we used appropriate administrative boundary maps for each country, which were shapefiles obtained from IPUMS International. Additionally, since the CRU data are monthly frequency data, our calculation of average mean temperature and mean rainfall over a growing season should be read as average monthly temperature and rainfall in a growing season.

Close inspection of weather data for SSA confirms on-going climate change. From Figure 3.1, we observe that beginning around 1980, temperatures assumed a permanent upward shift–hence climate change. Our reading is that SSA became hotter by more than 0.5 C on average over the past 40 years.

Figure 1: Trends in Mean Weather in SSA



Notes: In the above figure, the left hand side chart depicts trends in temperature while the right hand side graph plots the evolution of rainfall in SSA. Both temperature and rainfall are smoothed (that is, they are 10 year moving averages) in order to depict trends more finely. The green and red lines represent West and East SSA, respectively. All 46 SSA countries were used for producing these charts. Source: Climatic Research Unit of UEA; Plots: Kamuikeni & Naito (2024)

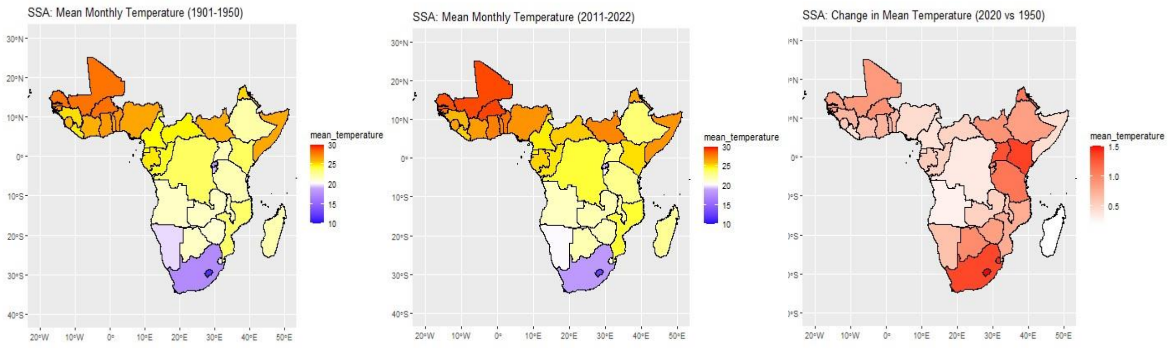
At the same time, while several authoritative sources link climate change to erratic rainfall (World Meteorological Organization , WMO, Pörtner et al., 2022), our analysis of climate data further reveals a general and lasting downward shift in amounts of rainfall received in SSA. From the same figure, we note that the volume of rainfall decreased by about 10 mm a month (about 120 mm a year) on average since 1980s. Similarly, in East SSA, rainfall amounts declined by roughly 2.5 mm a month (about 30 mm a year) beginning 1990s.

Although climate change is discussed in terms of general trends, we observe that all countries in SSA have undergone warming. Furthermore, while temperatures are notably cooler in East SSA compared to West SSA, eastern SSA is warming at a significantly faster rate (as depicted in Figure 3.2, panel A). Specifically, over the past 70 years, Uganda, Kenya, and South Africa have seen a warming of 1.5°C. In contrast, Madagascar has warmed the least.

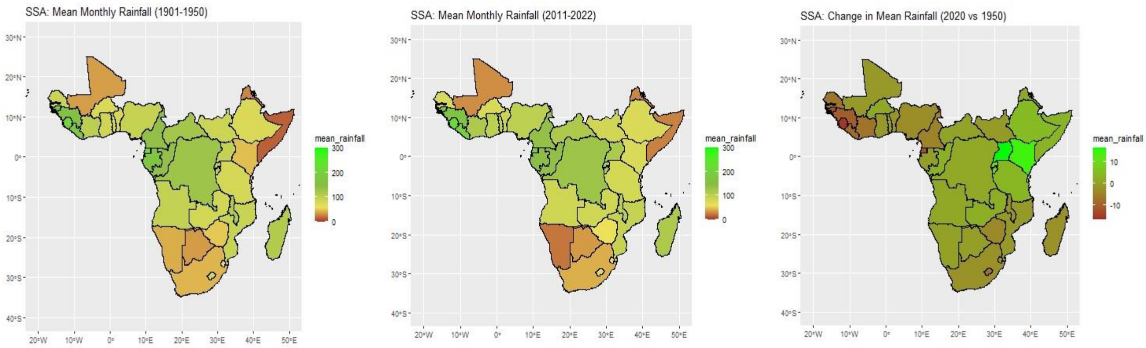
In terms of rainfall, countries have experienced diverse outcomes (Figure 3.2, Panel B). The two countries, Uganda and Kenya, that experienced the largest increases in temperature also saw the greatest increases in the amounts of rainfall received. In contrast, several of the westernmost countries in SSA experienced declines in the amounts of rainfall received. However, for most countries overall, the changes in rainfall amounts were relatively small.

Figure 2: Heat Maps of Weather in SSA

Panel A: Temperature



Panel B: Rainfall

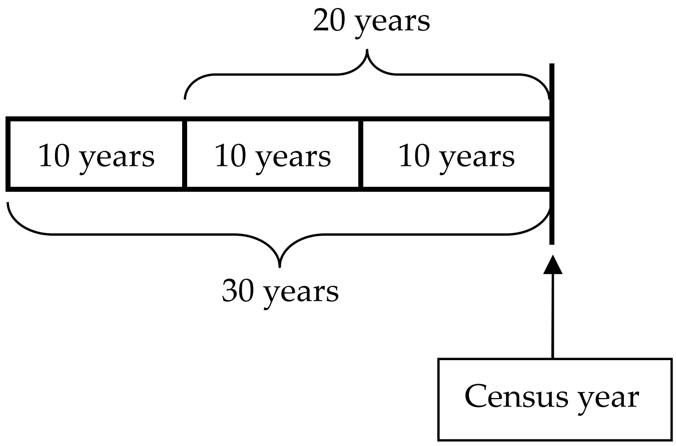


Notes: In each panel of the above figure, the first heat map depicts historical weather averages over 1901-1950 period. The second one shows recent weather averages over 2011-2022. The third heat map is the difference between the first and second heat maps. Thus, in the heading of the third heat map, 2020 represents averages over 2011-2022 and 1950 stands for averages over 1901-1950 period. Source: Climatic Research Unit of UEA; Plots: Kamuikeni & Naito (2024)

5 Combining census and weather data

In integrating weather data with migration data, the challenge is that census-based migration data are collected decennially, while CRU weather data are reported monthly. To address this, we calculated the average monthly weather data over a twenty-year period leading up to each census. Our objective was to create a summary measure of weather exposure during a relevant pre-census period. While our baseline time frame is 20 years before census, we additionally explored alternative time windows (such as 10 and 30 years) preceding each census year as shown in Table 3.2. We reserved these alternative measures for performing robustness checks.

Table 1: Schematic Diagram of Time Spans of Weather Data used in the Analysis



Additionally, it appeared necessary to define the demographic characteristics of a typical weather migrant. In this regard, we hypothesized that these migrants are commonly out-of-school individuals in the age range of 22 to 49 years old. Further, migration patterns may be different across different age groups and gender. In view of this, we constructed two age groups of ages 22-32 and 33-49 and maintained the sex variable. Additionally, we obtained migration record for young children age below 12 years old. Assessing whether the climate mobility patterns of these young children match those of adults would provide evidence on the question of whether climate migrants relocate with their families.

Incidentally, there appears to be an advantage to constructing the age groups as 22-32, 33-49 and 0-11. In developing countries, age misreporting tends to be high, in which individuals approximate their ages. We confirmed this by plotting histograms of ages and noticed spikes on ages 10, 15, 20, 25, 30, 35, 40, 45, so on, suggesting that respondents round off their ages to nearest multiple of 5 (Chart to be shown in Appendix).

Table 2: Definition of Weather Variables

Weather Variable	Description	
	(1)	(2)
1. Recent past mean rainfall	Mean of total monthly rainfall	Calculated over the past 10, 20, 30 years or other periods prior to census depending on the time span of interest. The word "recent" distinguishes it from "historical long term" averages.
2. Recent past mean temperature	Mean of monthly average temperatures	
3. Standard deviation of rainfall	The standard deviation of annualized mean monthly rainfall	Calculated over the past 10, 20, 30 years or other periods prior to census. The deviation from the mean is calculated in two ways: As (1) deviation from recent past (within the data) mean or (2) deviation from historical 1901-1950 average.
4. Standard deviation of temperature	The standard deviation of annualized mean monthly temperature	
5. Coefficient of variation of rainfall	This is the normalization of standard deviation of rainfall by its mean	Useful for accounting for sensitivity of standard deviation to the sizes of the numbers in the data set. (i.e. large number datasets tend to have bigger standard deviation than small number datasets).
6. Coefficient of variation of temperature	This is the normalization of standard deviation of temperature by its mean	

6 Key Weather Variables

From the constructed measures of weather exposure, we define several key explanatory variables that capture exposure to long term climate variability (Table 3.2). [Explain table 3.2]. Similar to Thiede et al. (2016), who standardized their measures of 5-year temperature and rainfall conditions to allow comparability across locations and countries, our study normalises the standard deviation of recent past temperatures and rainfall using mean. The idea is that, standard deviation as a measure of volatility of weather outcomes is sensitive to magnitude of the data points themselves. Thus, a dataset with large numbers will typically give larger standard deviation compared to data sets with small numbers. In perspective, as we observed from Figure 1 that temperature and rainfall levels are significantly higher in west SSA than in East SSA. Thus, failing to account for this feature of the data may invalidate any comparisons between East and West in terms of weather changes. We normalise standard deviation measure by dividing by the sample mean.

7 Limitations of the data

Our migration measure lacks information on the timing of relocation. Although it enables us to expand the country sample by providing a consistent measure across countries, we cannot account for individual-specific characteristics such as schooling due to the absence of migration timing. Understanding when migration occured is crucial for assessing the individual characteristics that existed before the migration.

Scarcity of more recent census and migration data. Most of the census data available are from over 15 years ago. This results in loss of valuable information over a considerable stretch of time.

8 Estimation Strategy

This study examines the relationship between climate change and migration using a Panel Fixed Effects (Panel FE) model. This model is preferable for addressing unobserved time-invariant heterogeneity. As Weinreb et al. (2020) notes, a number of unmeasured factors could influence the relationship between climate variability and migration, including topographical variations across countries, soil quality and tree coverage, traditional systems of agricultural land ownership, and variable standards for defining urban and rural boundaries. Some of these vary significantly over time, while others are fixed or at least relatively stable. They accounted for some of these factors (i.e. the time-stable factors) using within-country fixed effects. Additionally, while weather shocks are fairly exogenous, controlling for fixed effects may enhance the precision of my estimates (CITE). The model is as follows:

$$Y_{\mathrm{itjc}} = \beta_0 + \sum_{h=1}^{m} \beta_h \mathrm{X}_{\mathrm{tjch}} + \sum_{k=m+1}^{n} \beta_k \mathrm{Z}_{\mathrm{tjck}} + \alpha_j + \alpha_t + \alpha_{\mathrm{ct}} + \varepsilon_{\mathrm{tkci}} \quad (1)$$

where Y_{itjc} is a dummy of outmigration, which is equal to 1 if an individual i at census year t in location j of country c lives in a location different from his/her birth location and 0 if he/she still lives in his/her birthplace. It then follows that $E[Y_{itjc}] = prob(Y_{itcj} = 1)$, which is probability of outmigration. X_{tjc} is a measure of weather corresponding to census year t in location j of country c. Z_{tjck} is a vector of confounding factors, particularly weather conditions in alternative places of residence, measured in exactly the same way as in the place of origin. α_j are birthplace fixed effects for accounting for unobserved heterogeneity across birth locations, α_t are time fixed effects for accounting for time varying common shocks to all locations. α_{ct} is an interaction of term for country-specific fixed effect and census year fixed effect. It controls for non-uniform variation of time FE across countries. This is particularly useful for accounting for the fact that different countries conduct censuses at different time points.

To ensure that we capture (long-term) climate change effects, we compare developments between two time periods with an interval ranging between 20 to 40 years depending on available census data for a country. Technically, we achieve this interval by obtaining migration and weather data consistent with the latest and oldest available censuses for each country. Essentially, we utilize two census waves for each country. For countries whose census data was available only as a single wave, such as Ethiopia, we were unable to incorporate them in to our sample because of incompatibility with our Panel FE method.

Migration status is calculated from census data, and corresponding weather data is the average weather outcomes over the last 20 years prior to census. The specification is nonlinear, where mean rainfall and mean temperature together with their squared terms; standard deviations of annual mean rainfall and mean temperature are the key explanatory variables.

The unit of analysis is individual. Thus, from census data, a large dataset is available from which We are able to performing sub-sampling in exploring additional research questions, including heterogeneous impacts across regions, gender, age, as well as the preferred destination type (rural/urban) of rural climate migrants.

Several pieces of literature demonstrate that the channel for climate-driven mobility in regions that are highly dependent on rain-fed agriculture such as SSA is agricultural productivity (Missirian and Schlenker (2017), Falco et al. (2019)). Therefore, in this research, we rely primarily on weather data that are restricted to agricultural season. However, as the onset and closing of growing seasons can vary within the same country and over time, we also perform robustness checks where the growing season restriction is relaxed entirely.

Additionally, our measure of exposure to climate change is to average monthly weather outcomes over the last 20 years before census for *mean weather variable* . Similarly for *standard deviation of weather*, we compute average deviation of weather over the past 20 years prior to census. This means we are linking outmigration incidence to average weather conditions in the last 20 years. Admittedly, the weakness of this approach is that some individuals might have migrated over 20 years ago, and therefore, were unexposed to this average weather. Similarly, other individuals might have relocated more recently that the 20 year average weather may not be quite representative of their climatic experiences. We address this concern in the robustness checks where we construct alternative measures of weather by splitting the 20 year pre-census period into two 10 year periods. Therefore, we estimate additional regressions where weather is observed over the past 10 years prior to census and also over the past 10 years before the 10 years leading up to census.

Lastly, we note that migration may respond not only to temperature and rainfall fluctuations around their recent mean, but also around their historical mean. Thus, we also check this possibility in the robustness checks by measuring standard deviation/coefficent of variation of weather as deviation from historical normal mean.

9 Estimation Results

9.1 Descriptive statistics

Tables 3 and 4 shows the summary of weather and migration experiences of young working age adults aged 22-32 in East and West SSA, respectively. Since our benchmark specification (see Chapter 4) is one where summary measures of weather are calculated over the growing season covering a period of 20 years before census, the weather variables presented in the two tables have been computed in this way.

Birthplace-based out-migration rates for 22-32 age group stood at 28% in East SSA, marginally higher than 27.5% in West SSA and with the same standard deviation of 0.45.

Table 3: Descriptive Statistics of Variables: East SSA

VARIABLES	mean	sd	min	max
Country	646.639	208.089	72.000	894.000
Census year	2003.020	11.063	1969.000	2018.000
Age	26.675	3.138	22.000	32.000
Out-migration	0.279	0.448	0.000	1.000
Recent mean rain (in decimetres)	1.251	0.335	0.353	2.318
Recent mean temperature (°C)	23.302	2.488	14.387	28.897
Rainfall standard deviation	0.231	0.091	0.066	0.578
Temperature standard deviation	0.326	0.072	0.193	0.666
Rainfall coefficient of variation	0.188	0.068	0.063	0.387
Temperature coefficient of variation	0.014	0.003	0.008	0.029
N		*3,949,270*		

Table 4: Descriptive Statistics of Variables: West SSA

VARIABLES	mean	sd	min	max
Country	434.428	246.210	120.000	854.000
Census year	2002.507	11.888	1974.000	2015.000
Age	26.725	3.082	22.000	32.000
Out-migration	0.275	0.447	0.000	1.000
Recent mean rain (in decimetres)	1.468	1.012	0.034	4.592
Recent mean temperature (°C)	27.024	2.169	19.258	32.610
Rainfall standard deviation	0.150	0.081	0.004	0.648
Temperature standard deviation	0.296	0.074	0.145	0.523
Rainfall coefficient of variation	0.125	0.054	0.027	0.385
Temperature coefficient of variation	0.011	0.002	0.005	0.020
N		*2,698,961*		

Additionally, our study is interested in climate-driven mobility of the middle aged economically active group aged 33-49 to quantify any age group-related heterogeneity of climatic impacts, as well in young children aged below 12 to determine familial climate-related mobility patterns. Summary statistics show that out-migration prevalence for age group 33-49 was the same as for 22-32 age group. Meanwhile, children relocated from their birthplace at an average rate of 10.4 % in the East and 10.8% in the West (table not shown). Exposure to weather remains the same.

10 Estimation Results

10.1 West SSA

Table 5 reports coefficient estimates of the impact of climate change on within-country migration in West SSA. Results indicate the existence of climate-induced internal mobility within West SSA countries. We establish the channel of impact to be both changes in mean rainfall and mean temperature, and also fluctuations in temperature. Quantitatively, the marginal effect ($\boldsymbol{\beta}_1 + 2\boldsymbol{\beta}_2 X$) of rainfall when rainfall is at average level of 1.5 dm (see summary statistics), the overall decrease in rainfall is 0.1 dm (see Figure 1) and we use estimates from column 3 is: -0.095 -9.5 percentage points.

Similarly, marginal effect of temperature when temperature is about 27 °C (average over the sample period) and change in temperature is 0.5 °C (see Figure 1) is: 0.125 12.5 percentage points.

However, given that the squared term of temperature is negative, it suggests that increasing temperatures progressively limit migration. The implication is that, as areas become hotter due to climate change, people will be unable to move out. This is a puzzling finding. The standard hypothesis is that ever increasing temperatures are detrimental to agriculture and as yield declines due to adverse climatic conditions, an increasing number of people would be moving out of the affected areas. However, Kaczan and Orgill-Meyer (2020) and Thiede et al. (2016) justify the observation that warming would eventually reduce the probability of out-migration by pointing out that such adverse climatic incomes would weaken the economic well-being of populations, rendering migration unaffordable. This situation has been referred to as the *incapability to migrate* (Kaczan and Orgill-Meyer, 2020) and *migration inhibitor mechanism* (Thiede et al., 2016).

Table 5: Estimates of Climate-Driven Migration: West SSA

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	-0.9957*	-0.9772**	-1.4238***	-1.1074*
	(0.5487)	(0.4945)	(0.4857)	(0.5694)
Recent mean temperature (°C)	2.8245***	2.0635***	3.6211***	3.1345***
	(0.9049)	(0.6836)	(1.1685)	(0.9939)
Recent mean rainfall square	0.0892	0.1201*	0.1578**	0.1099
	(0.0833)	(0.0690)	(0.0725)	(0.0792)
Recent mean temperature square	-0.0477***	-0.0386***	-0.0624***	-0.0528***
	(0.0154)	(0.0117)	(0.0202)	(0.0173)
Rainfall, coefficient of variation	1.0865	0.5773	0.8667	1.3417*
	(0.6928)	(0.6788)	(1.1133)	(0.8103)
Temperature, coefficient of variation	-69.6571**	-28.9760**	-102.5348***	-125.3149***
	(29.1282)	(14.1185)	(37.2313)	(38.2307)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	22-32	22-32	22-32	22-32
Gender	Both	Both	Both	Both
N	2,698,961	2,698,961	2,698,961	2,698,961
R-squared	0.1390	0.1433	0.1409	0.1413

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

Additionally, we find that failure to account for weather of potential destinations would understate the estimated impacts.

We also consider heterogeneous effects across age groups. Applying the specification on age group 33-49 yielded the following result:

Table 6: Estimates of Climate-Driven Migration: West SSA

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	-0.9832*	-0.8156	-1.2201**	-0.9173
	(0.5736)	(0.5114)	(0.5127)	(0.5568)
Recent mean temperature (°C)	2.7176***	1.8541***	3.6101***	3.1404***
	(0.8918)	(0.6625)	(1.1705)	(0.9651)
Recent mean rainfall square	0.0643	0.0837	0.1048	0.0589
	(0.0886)	(0.0735)	(0.0799)	(0.0821)
Recent mean temperature square	-0.0458***	-0.0349***	-0.0615***	-0.0520***
	(0.0152)	(0.0113)	(0.0202)	(0.0168)
Rainfall, coefficient of variation	0.9314	0.5098	0.9138	1.3445
	(0.7396)	(0.7250)	(1.1555)	(0.8604)
Temperature, coefficient of variation	-76.3701**	-35.9721**	-114.2011***	-133.9981***
	(30.6791)	(14.6465)	(38.5203)	(39.5588)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	33-49	33-49	33-49	33-49
Gender	Both	Both	Both	Both
N	2,313,731	2,313,731	2,313,731	2,313,731
R-squared	0.1345	0.1391	0.1366	0.1372

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

From this table (Table 5.4), we see that for model 3, coefficients of rainfall, temperature and volatility in temperature retain their significance and signs.

Similarly, when we estimated for young children, we obtained consistent results the sizes of the estimated coefficients between the regressions for children and adults are comparable (Table 5.5). This outcome confirms that adults respond to climatic shocks by migrating away with their families.

Table 7: Estimates of Climate-Driven Migration: West SSA, Children

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	-0.9872*	-1.0864***	-1.3524***	-1.1605**
	(0.5258)	(0.4114)	(0.4545)	(0.4486)
Recent mean temperature (°C)	1.8074*	0.6792	2.5861**	2.2396**
	(0.9422)	(0.7336)	(1.1026)	(1.0556)
Recent mean rainfall square	0.0935	0.1239**	0.1448**	0.1120*
	(0.0766)	(0.0571)	(0.0633)	(0.0617)
Recent mean temperature square	-0.0299*	-0.0150	-0.0447**	-0.0382**
	(0.0159)	(0.0124)	(0.0189)	(0.0179)
Rainfall, coefficient of variation	0.5735	0.0933	0.3532	0.8631
	(0.6826)	(0.6935)	(1.1914)	(0.8644)
Temperature, coefficient of variation	-79.0193**	-38.7210**	-114.9597***	-143.8472***
	(31.3544)	(15.2341)	(40.3630)	(43.0578)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	0-11	0-11	0-11	0-11
Gender	Both	Both	Both	Both
N	6,138,663	6,138,663	6,138,663	6,138,663
R-squared	0.1931	0.2033	0.1980	0.2000

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

Comparisons between genders revealed uniform responses to climate change.

Table 8: Estimates of Climate-Driven Migration: West SSA, Male

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	-0.8843	-0.8794*	-1.3030***	-0.9126
	(0.5493)	(0.5206)	(0.4982)	(0.6105)
Recent mean temperature (°C)	2.5981***	1.8447**	3.4262***	2.8825***
	(0.9712)	(0.7569)	(1.2384)	(1.0717)
Recent mean rainfall square	0.0843	0.1102	0.1450**	0.0876
	(0.0826)	(0.0730)	(0.0731)	(0.0828)
Recent mean temperature square	-0.0435***	-0.0347***	-0.0588***	-0.0481**
	(0.0166)	(0.0130)	(0.0214)	(0.0188)
Rainfall, coefficient of variation	1.1868*	0.5821	0.7762	1.2868
	(0.7172)	(0.6905)	(1.1218)	(0.8261)
Temperature, coefficient of variation	-66.9664**	-27.5430*	-99.5159***	-121.6757***
	(29.1226)	(14.4736)	(37.1650)	(38.4289)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	22-32	22-32	22-32	22-32
Gender	Male	Male	Male	Male
N	1,227,523	1,227,523	1,227,523	1,227,523
R-squared	0.1424	0.1463	0.1443	0.1446

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Estimates of Climate-Driven Migration: West SSA, Female

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	-1.0636*	-1.0393**	-1.4976***	-1.2327**
	(0.5571)	(0.4809)	(0.4858)	(0.5454)
Recent mean temperature (°C)	2.9978***	2.2275***	3.7908***	3.3534***
	(0.8674)	(0.6480)	(1.1383)	(0.9558)
Recent mean rainfall square	0.0882	0.1241*	0.1632**	0.1219
	(0.0855)	(0.0673)	(0.0740)	(0.0779)
Recent mean temperature square	-0.0509***	-0.0415***	-0.0654***	-0.0567***
	(0.0147)	(0.0111)	(0.0196)	(0.0166)
Rainfall, coefficient of variation	0.9879	0.5600	0.9318	1.3721*
	(0.6785)	(0.6741)	(1.1082)	(0.8030)
Temperature, coefficient of variation	-71.3279**	-29.9906**	-104.4867***	-127.7530***
	(29.1276)	(14.0505)	(37.2902)	(38.0927)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	22-32	22-32	22-32	22-32
Gender	Female	Female	Female	Female
N	1,471,438	1,471,438	1,471,438	1,471,438
R-squared	0.1409	0.1459	0.1430	0.1435

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

11 East SSA

When we applied the exact same specification to East SSA, we could not confirm that climate change affects migration in this region (Table 5.8).

While columns that take into account weather of alternative locations show some evidence that volatility in rainfall reduces likelihood to migrate, the impacts are economically too small (one standard deviation increase in rainfall fluctuations, leads to only 4 percentage point (0.6247 x 0.068SD x 100) decrease in the odds of out-migration.

Similar to West SSA, assessment of the age group differences in climate responses shows no material differences in climate migration behavior between age gropus 22-32 and 33-49 (Tables 5.8 and 5.9). However, young children (0-11 years old) appear to respond by a lesser magnitude to climate variability (Table 5.10). But again, all age group specific results do not show statistical significance in East SSA.

Table 10: Estimates of Climate-Driven Migration: East SSA

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	0.3569	-0.4144	-0.4167	-0.4785*
	(0.3822)	(0.3202)	(0.2767)	(0.2435)
Recent mean temperature (°C)	0.0069	0.0214	-0.0196	0.0350
	(0.0525)	(0.0518)	(0.0568)	(0.1054)
Recent mean rainfall square	-0.1178	0.1304	0.1074	0.1484
	(0.1261)	(0.1074)	(0.0892)	(0.0923)
Recent mean temperature square	0.0000	-0.0004	0.0003	-0.0008
	(0.0012)	(0.0014)	(0.0014)	(0.0024)
Rainfall, coefficient of variation	-0.3240	-0.3888*	-0.6247*	-0.6584**
	(0.2225)	(0.2327)	(0.3202)	(0.3321)
Temperature, coefficient of variation	3.5476	5.5861	10.4752	9.7065
	(6.6057)	(9.1675)	(12.3707)	(9.5620)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	22-32	22-32	22-32	22-32
Gender	Both	Both	Both	Both
N	3,949,270	3,948,565	3,949,270	3,949,270
R-squared	0.0943	0.0951	0.0950	0.0951

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Estimates of Climate-Driven Migration: East SSA, 33-49

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	0.1775	-0.4707	-0.7422**	-0.6788**
	(0.4053)	(0.3787)	(0.2964)	(0.3038)
Recent mean temperature (°C)	0.0414	0.0272	-0.0021	0.0501
	(0.0433)	(0.0472)	(0.0536)	(0.0986)
Recent mean rainfall square	-0.0402	0.1484	0.2312**	0.2120*
	(0.1314)	(0.1248)	(0.0933)	(0.1080)
Recent mean temperature square	-0.0008	-0.0005	-0.0002	-0.0013
	(0.0011)	(0.0013)	(0.0014)	(0.0023)
Rainfall, coefficient of variation	-0.3194	-0.3521	-0.4726*	-0.4805
	(0.2026)	(0.2145)	(0.2831)	(0.3019)
Temperature, coefficient of variation	6.4279	9.8592	10.7830	9.0205
	(6.9328)	(9.4281)	(11.8301)	(8.6500)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	33-49	33-49	33-49	33-49
Gender	Both	Both	Both	Both
N	3,186,135	3,185,443	3,186,135	3,186,135
R-squared	0.0987	0.0994	0.0996	0.0996

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Estimates of Climate-Driven Migration: East SSA

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	0.3970	-0.2898	-0.3185	-0.2577
	(0.2699)	(0.2528)	(0.1997)	(0.1665)
Recent mean temperature (°C)	0.0067	0.0038	0.0272	0.0064
	(0.0360)	(0.0370)	(0.0417)	(0.0694)
Recent mean rainfall square	-0.1022	0.0810	0.0834	0.0911
	(0.0819)	(0.0768)	(0.0582)	(0.0622)
Recent mean temperature square	-0.0002	-0.0004	-0.0009	-0.0004
	(0.0008)	(0.0009)	(0.0010)	(0.0016)
Rainfall, coefficient of variation	0.1332	-0.1723	-0.3418	-0.0776
	(0.2455)	(0.3014)	(0.3121)	(0.4118)
Temperature, coefficient of variation	-1.1695	-5.4512	1.1476	-2.5091
	(7.4794)	(11.0559)	(15.7765)	(12.9074)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	0-11	0-11	0-11	0-11
Gender	Both	Both	Both	Both
N	6,157,092	6,156,196	6,157,092	6,157,092
R-squared	0.0701	0.0713	0.0712	0.0713

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

Gender heterogeneity Assessment of the gender differences in climate responses shows that

Table 13: Estimates of Climate-Driven Migration: East SSA

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	0.3787	-0.5666*	-0.4301	-0.5057*
	(0.4133)	(0.3338)	(0.3430)	(0.2675)
Recent mean temperature (°C)	-0.0178	0.0124	-0.0452	0.0054
	(0.0547)	(0.0528)	(0.0596)	(0.1128)
Recent mean rainfall square	-0.1219	0.1692	0.1021	0.1590*
	(0.1367)	(0.1084)	(0.1021)	(0.0947)
Recent mean temperature square	0.0007	-0.0003	0.0009	-0.0001
	(0.0013)	(0.0014)	(0.0015)	(0.0026)
Rainfall, coefficient of variation	-0.4466*	-0.6750**	-0.8824**	-0.9287**
	(0.2462)	(0.2789)	(0.3673)	(0.3745)
Temperature, coefficient of variation	4.1279	3.8860	13.1129	9.9811
	(6.7598)	(9.7771)	(13.5693)	(12.4087)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	22-32	22-32	22-32	22-32
Gender	Male	Male	Male	Male
N	1,840,428	1,840,077	1,840,428	1,840,428
R-squared	0.1040	0.1050	0.1048	0.1048

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

12 Robustness checks

We conduct a several robustness checks to ascertain the stability of our estimated coefficients. First, we replace our measure of standard deviation of weather from within-sample mean with standard deviation of weather from historical (1901-1950) average. This way, we check whether migration responds to volatility of rainfall and temperature around the historical mean.

The outcome of this test (reported in Appendix A) is similar to the original outcome where standard deviation of weather was measured as dispersion around recent within-sample average. All signs are maintained. East SSA continues to yield insignificant result while West SSA retains evidence of climate-induced mobility. However, the estimated coefficient of standard deviation of temperature declines by about half. This implies that temperature fluctuations around the recent past mean are a stronger driver of climate-related migration than temperature fluctuations around the historical mean.

As mentioned in the Estimation Strategy section, we aim to determine whether calculating weather data over the last 10 years before the census, as opposed to 20 years, has a qualitative impact on our estimates.

Table 14: Estimates of Climate-Driven Migration: East SSA

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	0.3270	-0.2869	-0.4116	-0.4676*
	(0.3676)	(0.3146)	(0.2608)	(0.2703)
Recent mean temperature (°C)	0.0293	0.0293	0.0040	0.0627
	(0.0514)	(0.0524)	(0.0583)	(0.1006)
Recent mean rainfall square	-0.1074	0.1035	0.1192	0.1448
	(0.1188)	(0.1059)	(0.0839)	(0.0975)
Recent mean temperature square	-0.0006	-0.0005	-0.0003	-0.0015
	(0.0012)	(0.0014)	(0.0014)	(0.0023)
Rainfall, coefficient of variation	-0.1825	-0.0970	-0.3345	-0.3808
	(0.2174)	(0.2078)	(0.2960)	(0.3014)
Temperature, coefficient of variation	2.5386	7.0722	8.1010	9.7436
	(6.5344)	(8.4110)	(11.1328)	(7.7189)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	22-32	22-32	22-32	22-32
Gender	Female	Female	Female	Female
N	2,108,842	2,108,488	2,108,842	2,108,842
R-squared	0.0920	0.0927	0.0926	0.0927

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

Table 15: Estimates of Climate-Driven Migration: Weather Measured over the last 10 years before census

For another robustness check, we relax the growing season restriction and allow the summary measures of weather to utilize data point from all calendar months.

Table 16: Estimates of Climate-Driven Migration: No growing season restriction for weather data

Dependent Variable				
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	0.0015	-1.2187**	-1.8498***	-1.5698***
	(0.5757)	(0.5533)	(0.5151)	(0.4803)
Recent mean temperature (°C)	0.0485	-0.0178	-0.0510	0.0483
	(0.0598)	(0.0596)	(0.0529)	(0.0828)
Recent mean rainfall square	0.0489	0.6628**	0.9236***	0.8268***
	(0.3176)	(0.3136)	(0.2835)	(0.2697)
Recent mean temperature square	-0.0012	0.0005	0.0009	-0.0012
	(0.0015)	(0.0015)	(0.0014)	(0.0020)
Rainfall, coefficient of variation	0.0868	-0.0014	-0.0504	-0.1077
	(0.2181)	(0.2396)	(0.2535)	(0.2320)
Temperature, coefficient of variation	3.2718	5.2153	8.1792	16.9749**
	(7.6997)	(9.9480)	(12.1416)	(8.4680)
Control Variables				
Average weather of top destinations	None	Top1	Top3	Top5
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
Age Group	22-32	22-32	22-32	22-32
Gender	Female	Female	Female	Female
N	2,108,842	2,108,488	2,108,842	2,108,842
R-squared	0.0920	0.0930	0.0931	0.0929

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1

13 Discussion

Several studies have investigated the relationship between climate change and human mobility in Africa. Our study contributes to existing literature by addressing a conceptual gap, which was failure to account for weather conditions in potential destinations. Secondly, our measure of migration applies consistently across countries. This allowed us to include many countries into the analysis, which desirable for enhancing generalizability of findings.

Upon observing distinct differences in regression outputs between Eastern and Western SSA countries, we divided our sample into East and West SSA. The substantial sample size provided by IPUMS census data enabled us to create precise estimates for each region. Overall, our findings reveal evidence of climate-related migration in West SSA. Specifically, reduced rainfall and rising temperatures drive people out of affected areas. Surprisingly, we do not detect climate-induced mobility in East SSA.

Although we do not readily explain the insignificant result for East SSA, our study rules out the possibility that inconsistencies between East and West arise from variations in definitions of migrants, measures of migration, study time frame, core explanatory variables, assumptions about the linearity of the relationship between those variables and migration, and model specifications, as suggested by Weinreb et al. (2020). Instead, our findings point to unique differences between East and West, such as variations in adaptation measures. A new investigation could provide further insights into these distinctions.

14 Conclusion

This study set out to examine the existence of climate-driven mobility is sub-Saharan African countries. Overall, we find overwhelming evidence of climate-induced relocation in Western SSA countries. The channel is long term changes in both mean rainfall and mean temperature. Additionally, we uncover evidence that climate-induced mobility involves relocation of family units as opposed to individuals migrating independently. Meanwhile, we are unable to uncover strong evidence from Eastern SSA countries, despite utilizing the same methodology and variable measures as for West SSA. The finding for east SSA necessitates further inquiry. Other researchers (Bertoli et al. (2022); Thiede et al. (2016); Mueller et al. (2020a)) suggest that climate change and weather shocks interact with other existing conditions and practices in intricate ways, which may or may not result in out-migration. Understanding the unique situation of east SSA may help to explain the masked migratory effect of climate change

Our findings have important implications for policy: There is need to understand more clearly the impact of climate-induced migration on the welfare of host and sending communities, as well as the migrants themselves in west SSA. This will be critical for crafting effective policies, particularly those that safeguard the well-being of people in both the sending and receiving communities. Further, climate adaptation policies should focus on cushioning the vulnerable populations. Depending on impacts on the receiving and sending communities, policies facilitating migration (as an adaptation measure) may be instituted.

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A Appendix A

B Appendix B

This is my second appendix.

C Appendix C

This is my third appendix.

Table 17: Robustness Check: Standard Deviation of Weather as Deviation from Historical Mean, East and West SSA

Dependent Variable	Out-migration			
Variables	(1)	(2)	(3)	(4)
Recent mean rainfall (dm)	-0.0013	-0.4078	-1.4335**	-2.2790***
	(0.3600)	(0.3022)	(0.6361)	(0.6138)
Recent mean temperature (°C)	-0.0517	-0.0733	1.1468	2.0900**
	(0.0639)	(0.0813)	(0.8135)	(0.8951)
Recent mean rainfall square	-0.0010	0.1236	0.1969*	0.3257***
	(0.1190)	(0.1012)	(0.1013)	(0.1003)
Recent mean temperature square	0.0013	0.0014	-0.0161	-0.0352**
	(0.0015)	(0.0019)	(0.0146)	(0.0155)
Rainfall, standard deviation from historical mean	0.0761	-0.0870	0.0180	-0.3146
	(0.1424)	(0.1968)	(0.2666)	(0.3519)
Temperature, standard deviation from historical mean	0.2067	0.1975	-1.1257***	-1.5245***
	(0.1386)	(0.2090)	(0.3777)	(0.4053)
Control Variables				
Average weather of top destinations	None	Top3	None	Top3
Location FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country x Time FE	✓	✓	✓	✓
SSA Region	East	East	West	West
Age Group	22-32	22-32	22-32	22-32
Gender	Both	Both	Both	Both
N	3,949,270	3,949,270	2,698,961	2,698,961
R-squared	0.0945	0.0949	0.1414	0.1442

Notes: Clustering robust standard errors in parentheses assuming that the error terms are correlated within each location. *** p<0.01, ** p<0.05, * p<0.1