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Climate-Induced Migration and Unemployment in Middle-Income Africa

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Abstract

One of the major unresolved questions in the study of vulnerability to climate change is how human migration will respond in low and middle-income countries. The present study directly addresses this lacuna by using census data on migration from 4 million individuals from three middle-income African countries over a 22-year period. We link these individuals to climate exposures in their origins and estimate climatic effects on migration using a fixed-effects regression model. We show that climate anomalies affect mobility in all three countries. Specifically, mobility declines by 19% with a 1-standard deviation increase in temperature in Botswana. Equivalent changes in precipitation cause declines in migration in Botswana (11%) and Kenya (10%), and increases in migration in Zambia (24%). The mechanisms underlying these effects appear to differ by country. Negative associations between precipitation anomalies, unemployment, and inactivity suggest migration declines may be due to an increased local demand for workers to offset production risk, while migration increases may be indicative of new opportunities in destinations. These country-specific findings highlight the contextually-specific nature of climate-migration relationships, and do not support claims that climate change is widely contributing to urbanization across Africa.

Keywords

migration; climate anomalies; employment; Africa

1 Introduction

One of the major unresolved questions in the study of vulnerability to climate change is how human migration will respond in low and middle-income countries. Sea level rise is

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expected to result in gradual displacement from low-elevation coastal areas (Wrathall et al., 2019), but temperature increases and precipitation changes across the entire inhabited land surface will also likely influence human mobility in ways that are not yet well described (Hoffmann et al., 2019; Kaczan and Orgill-Meyer 2020). This issue is particularly salient in Sub-Saharan Africa, where a large fraction of the population remains directly or indirectly dependent on rainfed agriculture (Barrett et al., 2017) and where the consequences of climate change are expected to be negative and large (Schlenker and Lobell, 2010). This perceived vulnerability to displacement contributed to earlier predictions of a looming wave of “climate refugees” from low and middle-income countries, predictions that have not been realized (Gemenne, 2011).

To provide new insights to this issue, a growing literature uses demographic and econometric methods to directly measure climatic effects on human migration (Fussell, Hunter and Gray, 2014). The core approach of these studies is to observe a large sample of potential migrants alongside their climate exposures, and then isolate climatic effects on migration using multivariate methods that control for potential socio-demographic and contextual confounders to climate. These methods can then be extended to allow for nonlinearity in climate, differing vulnerability across subpopulations, and adaptation over time (Gray, Hopping and Mueller, 2020). These techniques have now been widely used to investigate climate-induced migration in particular country contexts (Henry, Schoumaker, and Beauchemin 2004; Gray and Mueller, 2012; Mastrorillo et al., 2016; Nawrotzki and DeWaard, 2018) as well as aggregate international migration flows across countries (Cai et al., 2016; Cattaneo and Peri, 2016).

This research confirms that adverse climate conditions tend to increase out-migration as expected, but also reveals many cases in which potential migrants are instead trapped in place, particularly in low-resource settings where migration is costly relative to household resources (Nawrotzki and Bakhtsiyarava 2017). However, when and where trapping occurs (versus displacement) remains unclear, in part because we lack studies that are able to compare internal migration across country contexts. Because the vast majority of global migration occurs within national borders (Bell et al., 2015), and because this is also expected to be true for climate migration into the future (Piguet, Pecoud, Guchteneire, 2011), studies that can examine these processes at continental and global scales are needed in order to understand the size, direction and heterogeneity of climatic effects on human migration (Hendrix, 2017).

The present study directly addresses this lacuna by using census data on migration from 4 million individuals from three African countries (Botswana, Kenya, and Zambia) over a 22-year period. This lengthy study period increases the likelihood of observing events closer to the tail ends of the climate distribution and allows the estimation of an empirical model that can disentangle effects of cyclical trends from the effects of climate anomalies. Furthermore, employment information is collected in each of these countries over the study period, providing sufficient data to explore the extent labor market conditions influence migration responses to climate.

Building on the approach of Thiede, Gray, and Mueller (2016), we link these individuals to climate exposures in their origin and estimate climatic effects on migration using a fixed-effects regression model. This approach directly improves on previous studies which have variously focused on particular country contexts (Henry, Schoumaker, and Beauchemin 2004; Gray and Mueller, 2012; Mastrorillo et al., 2016; Nawrotzki and DeWaard, 2018), examined urbanization as a proxy for migration (thus missing all rural-rural and urban-urban moves; Barrios, Bertinelli, and Strobl, 2006; Marchiori, Maystadt and Schumacher, 2012; Henderson, Storeygard and Deichmann 2017), examined temporary migration only (Mueller et al, 2020b), or used retrospective data over a short time period (Gray and Wise 2016). We show that climate anomalies affect mobility in Botswana, Kenya, and Zambia. Specifically, mobility declines by 19% with a 1-standard deviation increase in temperature in Botswana. Equivalent changes in precipitation cause declines in migration in Botswana (11%) and Kenya (10%), and increases in migration in Zambia (24%). We further show that migratory responses are context-specific, as local employment conditions vary with climate.

2 Literature Review

Previous demographic and econometric studies of climate-induced migration in Africa have largely consisted of sub-national or single-country case studies, drawing primarily on longitudinal or retrospective household survey data. Initiated by Henry, Schoumaker, and Beauchemin (2004) with a study from Burkina Faso, this literature has since grown to include studies from Nigeria (Dillon, Mueller and Sheu, 2011), Ethiopia (Gray and Mueller, 2012), Uganda (Call and Gray, 2020), Tanzania (Hirvonen, 2016), Zambia (Nawrotzki and DeWaard, 2018; Mueller et al., 2020a), and South Africa (Mastrorillo et al., 2016), among other case studies. Using the shared methodological approach described above, these studies have revealed a mix of trapping and displacement processes, sometimes in the same study population. For example, Henry, Schoumaker, and Beauchemin (2004) found that rainfall deficits in Burkina Faso increased long-term migration to rural areas but decreased short-term moves to distant destinations, while Gray and Mueller (2012) revealed that drought in Ethiopia increased men’s labor migration but reduced women’s marriage migration. Globally, studies investigating the effects of temperature on migration have often found displacement effects (Kaczan and Orgill-Meyer 2020), but in the African context displacement and trapping effects appear to be equally common (Dillon, Mueller and Sheu, 2011; Hirvonen, 2016; Mastrorillo et al., 2016; Mueller et al., 2020b; Call and Gray, 2020). These studies have dramatically expanded our understanding of climate-induced migration in Africa, but a major limitation is that no two studies have used the same measurement and analysis approaches, severely limiting our ability to compare across national contexts.

Another set of studies, also drawing on the shared analytical approaches described above, has examined cross-national climatic effects on specific migration flows using macrodata on urbanization and international migration. These studies enable generalization across countries, but are limited to examining a (often small) subset of migration flows at aggregated scales that do not allow exploration of household and individual-level vulnerabilities. At least four studies have examined climatic effects specifically on urbanization in Africa, capturing urban growth associated with rural-urban migration as well as rural-urban reclassification and rural-urban differences in fertility and mortality. Barrios, Bertinelli, and Strobl (2006) linked UN data on urbanization from developing countries at five-year intervals to external data on rainfall, revealing that drought increased urbanization in Africa but not other world regions. Marchiori, Maystadt, and Schumacher (2012) extended this work by using interpolated annual data on urbanization and international out-migration, finding that temperature decreased urbanization and increased international departures but with no effect of rainfall. Cattaneo and Peri (2016) conducted a similar analysis using global-scale decadal data on the same outcomes, and found, in contrast to the previous study, that drought and temperature decreased both urbanization and emigration in Africa. Most recently, Henderson, Storeygard, and Deichmann (2017) showed that urbanization of subnational regions in Africa increased with drought, but only for regions where manufacturing for export was present. Taken together, these studies provide little clarity about the strength and direction of climate-migration relationships in Africa, which in part may reflect the limitations of using aggregate data. In these datasets, individual movements cannot be directly observed but only inferred from changing stocks of international migrants and changing urban fractions, thus missing large categories of migrants such as temporary and rural-rural movers.

To our knowledge only four previous studies have directly examined climatic effects on individual moves in Africa in a cross-nationally comparable way. Gray and Wise (2016) used large-sample, retrospective survey data on internal and international migration from five African countries to show that both temperature effects varied across countries while precipitation effects were weak and inconsistent. Specifically, migration increased with temperature in Uganda, decreased with temperature in Kenya and Burkina Faso, and showed no consistent relationship with temperature in Nigeria and Senegal, and these effects tended to be stronger for internal migration than international. Nawrotzki, Schlak, and Kugler (2016) and Nawrotzki and Bakhtsiyarava (2017) used household-level census data on the departure of international migrants to document that international migration decreased with heat waves in Burkina Faso and increased with heavy precipitation in Senegal, particularly in areas with high rates of malnutrition. Most recently, Mueller et al. (2020b) used longitudinal household survey data on temporary migration from four East African countries to reveal that drought and heat decreased moves by urban residents only, suggesting a trapping process for this population. Taken together, these studies reveal far more evidence of migrant trapping than displacement, consistent with global-scale evidence by Cattaneo and Peri (2016) for poor countries. However these studies also reveal heterogeneity both between and within countries that is largely invisible to both the country-specific and aggregate approaches described above. Below, we extend this micro-level, cross-national approach to investigate the internal migration of 4 million individuals in three African countries, with attention to heterogeneity across both countries and socio-demographic groups.

Our three study countries, Botswana, Kenya and Zambia, share several characteristics that motivate us to examine them side by side. Namely, they are located in Sub-Saharan Africa and classified as middle-income by the World Bank (2020). Additionally, they all experience relatively high levels of internal migration as compared to other countries in the region (Bell et al., 2015; Lucas, 2016) and experienced relatively rapid urbanization, alongside improving population health and well-being, during our study period (United Nations, 2018;

World Bank, 2020). Nonetheless, the three countries are also quite distinct along other dimensions, motivating us to consider them separately, but side by side, in our analysis. Kenya remains the most rural (76% of population in 2010; United Nations, 2018) and agrarian, and thus may be disproportionately vulnerable to climate shocks to agriculture. Zambia remains the most underdeveloped and experienced a child mortality rate of 82 per 1000 in 2010, 41% higher than Kenya and 65% higher than Botswana (World Bank, 2020). Botswana is the most urban (62% percent of population in 2010; United Nations, 2018) and educated (88% of adult with primary education in 2011; World Bank, 2020), but also experiences the most extreme climates, ranging from arid to semi-arid. Consistent with these differences, previous studies, which have yet to consider Botswana, have found strong evidence of climate-induced population trapping in Zambia (Nawrotzki and DeWaard, 2018; Mueller et al., 2020) but mixed evidence in Kenya (Gray and Wise, 2016). Below, we expand these studies through a direct comparison of all three countries.

3 Data

3.1 Migration

We construct the migration outcome based on individual-level census data from three sub-Saharan African countries that is archived by IPUMS (Minnesota Population Center, 2015). IPUMS archives 5-10% randomized samples from various population censuses. From these censuses, we are able to examine the migration and employment behavior of approximately 4 million working-age (18-49 years old) Africans, a sample which is representative of 49 million in Botswana, Kenya, and Zambia over the period of 1989 to 2011.

Table 1 displays how the censuses are distributed over space and time.[1] The censuses either ask the respondents whether they changed their district of residence 1 year prior to the interview or the number of years residing in his/her current location. They further inquire about the respondent's previous district of residence. Where districts were not constant across time, we standardized them by consolidating districts that split based on time-standardized maps developed by IPUMS. Taken together, these data can be used to create a binary migration variable, which takes a value of one if the individual migrated out of the origin district in the last year, and zero otherwise. Migration rates exceed 5% in Botswana and remain below 5% in the other countries in the most recent census years (Figure 1). For Kenya, we can additionally distinguish whether migrants are moving to a rural or urban destination in the new district in all census rounds.[2] In this case, we also create a multinomial migration variable that distinguishes between non-migrants, migrants who moved to rural destinations, and migrants who moved to urban destinations.

[1]Table A.1 delineates the size of the census samples, as well as the number of observations dropped due to the age restriction, coding errors, and missing information on the migration status and origins of migrants. The original study design included five additional countries. Burkina Faso, Cameroon, and Mali were dropped from the analysis, because a significant portion of the migrant sample was missing origin information (e.g., 30% in Burkina Faso, 33% in Cameroon, and 58% in Mali). Mozambique and Uganda were dropped because analysis of the CRU data revealed implausibly high values of year-to-year correlations, consistent with a large fraction of the raw climate values being interpolated.

[2]Rural and urban definitions are determined by the Kenya National Bureau of Statistics.

3.2 Demographics

These censuses also collected information on the gender, age, marital status, and completed education of each household member. We use this information to construct control variables for the regression analysis and to classify the sample into subpopulations. Analysis by subpopulation informs the extent to which specific groups are disproportionately affected by climate. Of particular interest are comparisons of the mobility patterns between men and women, youth (18-34) and non-youth (35-49), and those with and without a primary education.

We also use information on individuals' employment status from the censuses to understand whether a reduction in income opportunities caused by climate anomalies underlies observed migration patterns. The reference period for the employment status variable is 7 days for Kenya and Zambia. Since the reference period differs across years for Botswana, we omit it from the analysis on employment. The categorical responses to the employment status question are converted into a multinomial outcome, which indicates whether the individual was employed, unemployed, or inactive at the time of the survey. A person is considered employed if they have paid employment, with the exception given to those who have agricultural holdings. Inactivity and unemployment both reflect that a person is not working, but individuals defined as having an inactive employment status are typically not searching for work. We provide statistics on the demographics of the population, as well as the proportion of people employed, unemployed, or inactive by country in Table A.2.

3.3 Climate

The migration and demographic data from the censuses were merged with high-resolution gridded climate data from the Climate Research Unit's (CRU) Time Series (Harris et al, 2014). CRU is a monthly global dataset at 0.5 resolution (50km at the equator) that is derived by interpolating data from a network of over 4000 stations, including a large number in Sub-Saharan Africa (UEACRU et al., 2015). CRU data are considered to provide reliable climate information in Africa (Zhang, Kornich, and Holmgren, 2013), as well as offer significant predictors of migration in the region (Gray and Wise, 2016; Nawrotzki, Schlak, and Kugler, 2016; Nawrotzki and Bakhtsiyarava, 2017; Nawrotzki and DeWaard, 2018). Climate variables created from the CRU database are consistently more predictive of social outcomes than the Modern-Era Retrospective Analysis for Research and Applications data (MERRA) (Gray and Wise, 2016) and of similar predictive power to the use of the Climate Hazards Group InfraRed Precipitation and Temperature with Stations data (CHIRPS/ CHIRTS) (Randell, Gray, and Grace, 2020).

Before merging the socioeconomic and climate data sources by origin district, we first extract the precipitation and temperature from CRU as annual spatial means at the district level using spatially harmonized shapefiles from IPUMS designed to be consistent across census years. We then transform these values into annual standardized climate anomalies (z-scores) relative to a constant 1981-2010 reference period. These values capture the magnitude and direction of climate shocks relative to the local historical climate, and have been shown to be stronger determinants of internal migration in Africa than raw climate values (Gray and Wise, 2016; Mueller et al., 2020b). Our preferred specification uses one-year lagged precipitation and temperature anomalies. However, we also perform sensitivity analyses, altering the definition and timing of climate to instead include the raw climate values and contemporaneous anomalies, respectively[3]. We further explore whether nonlinear effects of anomalies on migration exist, by adding quadratic terms to our main specification. We lastly examine whether migration patterns differ by the type of climate event, replacing the lagged climate variables with variables that the capture the numbers of cold, hot, wet, and dry months over the prior 24 months. These variables are derived based on thresholds of 1 standard deviation following Thiede, Gray and Mueller (2016).[4]

Figure 1 displays the values for the one-year lagged climate anomalies that occurred in each census year. Almost all of the districts in our sample experienced a warm spell in recent years, consistent with observed trends under climate change. However, the magnitudes of the anomalies were more pronounced in half of the districts in Botswana, with values exceeding 1 standard deviation from the historical mean. There is more spatial and temporal variation in the precipitation anomaly variables within the three countries. The most recent censuses show wet spells were experienced throughout the three countries. Whereas exposure to drier spells is captured across districts in earlier census rounds. Our analysis takes advantage of the spatial and temporal variation across space in the climate anomaly variables to identify the impacts of climate on migration.

4 Methodology

We estimate the following country-specific logistic regression model to examine how climate anomalies affect mobility:

$$log\left(\frac{\pi_{mi(t)d,t}}{\pi_{ni(t)d,t}}\right) = \alpha + \delta_d + \delta_t + \beta X_{i(t)d,t}\,. \tag{1}$$

The main outcome is the odds of moving out of the district($\pi_{mi(t)d,t}$)relative to the odds of not moving ($\pi_{ni(t)d,t}$) for individual $i(t)$ from origin district d and in census year t. $X_{i(t)d,t}$ signifies the explanatory variables in the model, which include the time-varying climate variables as well as socio-demographic controls such as age categories (15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49), and whether the individual is male, has ever married, and has completed at least a primary education. The addition of district and year fixed effects, captured by δ_d and δ_t in (1), reduces the potential for bias in our parameter estimate of interest β driven by the omission of time-invariant characteristics at the district level (e.g., labor market structure) and time-variant factors (e.g., demographic transition), respectively. All analyses include weights to account for within-census randomized sampling by IPUMS, and standard errors are further adjusted for clustering of the outcome at the origin district level.

Previous studies suggest that climate affects the vulnerability of individuals in complex ways. Youth and women are often retained by a household when exposed to a climatic

[3]We refrain from including contemporaneous and lagged climate variables in the same model, given the high temporal correlation of temperature in Zambia (Table A.3).
[4]For example, the number of cold (hot) months encompasses months in which the temperature z score was less than −1 (more than 1).

shock, possibly due to the concurrent decline in the returns to their labor and/or their marital contracts (Dillon, Mueller, and Sheu, 2011; Gray and Mueller, 2012; Thiede and Gray, 2017). Gray and Mueller (2012) and Mastrorillo et al. (2016) also find that the asset-poor are more inclined to migrate in response to a drought; however, the cost of relocation can also limit one's capacity to adapt (Nawrotzki and DeWaard, 2018). We provide the results from (1) stratifying the sample by youth (18-34) and non-youth (35-49), female and male, and those with and without a primary school education to detect socio-demographic vulnerability to climate-induced migration. Completion of primary school serves as a proxy for wealth in the analysis, as the censuses do not collect asset information about the individuals prior to their migration episodes.

We further expand the above framework in (1) to examine whether migratory responses are urban-bound in Kenya. We consider a new dependent variable, which distinguishes between whether a person stayed in his/her origin district or moved to a rural or urban location in another district. Given the categorical nature of the dependent variable, we estimate a multinomial logistic model to quantify the effect of climate variability exposure on the migration to rural and urban destinations. This approach overcomes limitations posed in previous work, which has used aggregate urbanization data to examine climate-migration relationships in Africa (Poelhekke, 2011; Henderson, Storeygard and Deichmann, 2017).

We lastly examine whether changes in employment coincide with the observed climate migration responses. We estimate the employment-climate responses in Kenya and Zambia by also using a multinomial logistic model. The dependent variable differentiates between a person being employed, inactive, or unemployed. In the analysis, we restrict the sample to non-migrants to reflect how localized changes in climate variables may have influenced the labor market prior to migration. We provide more detail on the interpretation of the coefficients of the model for the purpose of explaining the extent climate serves as a push or pull factor in Section 5.3.

5 Results

5.1 Climate Influences on Migration

Table 2 displays the odds ratios and standard errors from the country-specific logistic regression models. Botswana is the only country where migration changes with temperature. The result for temperature signifies that the odds of mobility decrease by 19% when Botswanians are exposed to a 1 standard deviation (SD) increase in temperature. Yet, the magnitude of this effect and its statistical significance are sensitive to the model specification. Since the value of the standard deviation for temperature is 1°C, we can interpret the magnitude of the temperature effect to be larger when replacing the 1-year lagged climate anomaly with the 1-year lagged climate level (Table A.4). A quadratic model (Table A.5) and a model using contemporaneous anomalies (Table A.6) suggest effects of similar size, however, the parameters are measured imprecisely. Replacing the temperature anomaly with variables capturing the number of cold and hot months in the past 24 months also supports a story of immobility, particularly during cold spells (Table A.7).

We next turn to the results for precipitation, which affects migration in all countries. Increases in rainfall correspond with a reduction in migration in Botswana and Kenya, and an augmentation of migration in Zambia. The findings remain consistent in sign and significance when substituting raw precipitation values for precipitation anomalies (Table A.4), but not when using contemporaneous instead of lagged precipitation (Table A.6) or a quadratic model (Table A.5), with one exception. We find that linear and squared precipitation terms are both positively associated with migration in Zambia. Lagged precipitation, therefore, appears to have a robust effect in Botswana, Kenya, and Zambia. In Botswana and Kenya, a 1 SD increase in precipitation causes a moderate decline in migration of 10-11%, versus an increase in migration as large as 24% in Zambia.[5]

We lastly describe the results for control variables. Migration decreases with age in all countries. In particular, there is a lower likelihood of moving among individuals over the age of 34 relative to the youngest age group (15-19), however, heterogeneity exists with respect to which age groups under 34 are more inclined to migrate. The age effects are consistent with broader migration trends related to age of marriage (Jensen and Thornton, 2003; Hertrich, 2017), educational attainment (Kristensen and Birch-Thomsen, 2013; Elder et al., 2015), and employment (Kristensen and Birch-Thomsen, 2013; Temin et al., 2013).

Gender, marital status, and education are also strongly associated with migration in 2 of the 3 countries. The models reveal men tend to migrate more than women. The percentage difference in the odds of moving for men relative to women ranges between 4% and 13%. Young men and women also appear to be less mobile when they are married. Those who have never been married are between 7% to 21% more likely to move. Similarly, education is positively correlated with migration in most countries. The Kenya model exhibits the greatest effect, where having at least a primary education doubles the odds of moving relative to those lacking an education.

5.2 Vulnerability across the Demographic and Spatial Spectrum

We further explored whether exposure to climate anomalies led to varied migratory responses by gender, age (18-34 versus 35-39), and education (with and without a primary education). Figure 2 exhibits the heterogeneous migratory responses for Botswana, the only country where the measured temperature consequences are statistically significant for the full sample (all country statistics are included in Tables A.8–A.10). The statistics testing the difference in the coefficients across sub-samples confirm that there is a greater tendency for those that lack a primary education to be immobile (Table A.11).[6]

[5]Inferences based on origin-clustered standard errors may be misleading when the number of origins is fewer than 30 (Cameron, Gelbach, and Miller, 2008) or if there is spatial dependency of the climate anomalies at higher levels of aggregation. We therefore perform Wald tests which determine whether the climate parameters are statistically different than zero using wild bootstrap clustered standard errors (Roodman et al., 2019). We find the temperature parameter in the Botswana model becomes statistically significant at a higher critical threshold of 11 percent. The precipitation parameters are statistically significant at the 6, 8, and 1 percent critical values for Botswana, Kenya, and Zambia, respectively. We also repeat the Wald tests using wild bootstrap standard errors clustered at the regional level for Kenya and Zambia, where regional identifiers are provided by IPUMS. The precipitation parameters remain statistically significant for Kenya and Zambia at the 10 and 1 percent critical levels, respectively. Results are available from the authors upon request.

[6]Our inferences are based on z statistics from a fully interacted model. The interacted model allows us to explicitly test whether the differences in the migration effects across sub-samples in Figure 2 are statistically different (Tables A.11–A.13). Each interacted model adds a set of variables that interact the stratifying variable (male, youth, and primary education) with all of the covariates and

Figure 2 also displays the precipitation effects by demographic group. All demographic groups move due to increases in precipitation in Zambia, but the magnitudes statistically differ for men and youth (Table A.12). The reverse effect occurs in the remaining 2 countries: Botswana and Kenya. There are no obvious differences in the mobility patterns of different groups, with the exception of men and the educated in Botswana (Table A.11). Men are less likely affected by precipitation anomalies, while the opposite is true for the educated.

We next evaluate whether rural and urban destinations in Kenya are disproportionately affected by climate-induced migration. Table 3 presents the results from the country-specific multinomial logistic regression. The results for Kenya suggest that urban areas will likely experience higher in-migration rates during droughts, although we cannot reject that the effects on rural and urban moves are the same ($p = 0.48$).

5.3 Mechanisms

In the previous sections we evaluated the impacts of climate anomalies on mobility by country (Section 5.1). We then determined the extent these patterns varied across demographic groups and by destination choice (Section 5.2). In this section, we investigate whether climate effects on labor supply and demand potentially contribute to the observed climate-migration relationships. Specifically, we use a multinomial logistic model to test whether temperature and precipitation anomalies affect unemployment and inactivity (where employment is the reference category). We focus on the non-migrant sample to simplify the interpretation. The objective is to observe whether the direction of the relationships between migration and climate versus employment and climate are similar.

There are at least three mechanisms that might underlie the observed effects of climate on migration and employment. First, if unemployment (or inactivity) and migration concomitantly rise with adverse climates (in these contexts, hot and dry), one possible interpretation of the estimated relationships is that the lack of local job opportunities may push workers to move (Mueller et al., 2020b). Second, if unemployment (or inactivity) and migration both decline with adverse climates, then this could possibly be explained by an increase in local demand for labor due to the elevation of on-farm risk (Rutenberg and Diamond, 1993). Household labor supply may adjust to minimize the damages from an increase in pests or the requirements to preserve crops (Jagnani et al., 2020).

The third scenario is one in which migration and unemployment/inactivity are both inversely related to adverse climates. Such relationships would be indicative of migration responding to pull factors at the destination, which could occur through several channels. First, when negative climate shocks delay production or cause deleterious effects on agricultural yields (Schlenker and Lobell, 2010), the demand for paid labor to perform intensive tasks in the production cycle, such as seeding, weeding, and harvesting, declines (Dimova et al., 2015). Second, there are often strong upstream-downstream linkages in developing countries (Haggblade, Hazell, and Reardon, 2010; Diao, Magalhaes, and Silver, 2019), which renders

fixed effects included in the original model. We focus on the z statistic on the coefficients of the variables that interact climate and the stratifying variable to determine whether the migration responses vary by demographic group.

wage employment in other sectors vulnerable to climate change. As food retail and trade dominate the non-agricultural sector in many African countries, a lack of supply in the main inputs of these activities compromises job creation and sectoral viability. Third, if farmers have less disposable income during a climate shock due to yield losses, the demand for non-essential goods and services is likely to diminish. This exacerbates the demand for non-agricultural labor. The above cases specify the consequences of adverse shocks on employment migration. Similarly, we might expect that local employment in the agricultural and non-agricultural sectors might increase when climate is favorable, reducing the need for households to diversify income through engaging in employment migration.

To understand which mechanism dominates per country, we first turn to the findings in Kenya. In Section 5.1, we identified that precipitation anomalies decrease the likelihood of migration. In Table 4, climate anomalies produce negative effects on inactivity and positive effects on unemployment. Although the effects on inactivity and unemployment are not individually significant (Table 4), the Chi-squared test in the inactivity equation suggests that the effects of climate anomalies are jointly significant (p-value=0.09) and, in particular, that the precipitation parameter significantly differs from that estimated in the unemployment equation (p-value=0.08). The combined effects of precipitation anomalies on migration and inactivity support a narrative, where migration may be deterred by the increased local demand for workers. In the event of excessive rainfall, workers who are typically inactive may serve to supplant other households members while they are tasked with mitigating production risk (Beegle, Dehejia, and Gatti, 2006). For more moderate rainfall events, the local demand for workers may increase to assist with harvesting crops.

We last consider the migration-climate and employment-climate relationships in Zambia. As in the other contexts, climate anomalies tend to reduce both inactivity and unemployment (Table 4). All climate anomaly parameters are statistically significant at the 10 percent critical level, save the precipitation anomaly parameter in the unemployment regression. However, the migration-climate and employment-climate relationships are inversely related, and thus the mechanism underlying observed migration patterns varies from that observed in Kenya. Because inactivity declines and migration rises with increases in precipitation, the associated increases in migration may correspond with pull factors at the destination. Given that the precipitation anomalies are on average slightly positive over the periods in which we have data (Table A.1), our results may be sensitive to the temporal coverage of our study. For example, nominal increases in precipitation are often favorable for agricultural markets and those that rely on raw commodities as inputs, hence, likely promoting the creation of jobs across sectors.

The above relationships are used to provide additional evidence of how labor market conditions may be responsible for differences in the migration-climate relationships across countries. However, these descriptions are clearly not definitive. The climate effects among the non-migrant sample may be implicitly capturing the consequences of climate-induced migration in addition to effects on the local economy, particularly in areas where the degree of spatial correlation between origins and destinations is high. Without accounting for labor market conditions in both origins and destinations, we are unable to decipher whether a lack of employment opportunities at the origin may push migrants to leave, whether an increased demand for workers encourages migrants to stay, or alternatively, whether the paucity of work at destinations reduces aspirations to move. Disentangling the relative merits of these underlying channels is an area worthy of exploration in future research.

6 Discussion

Our analysis demonstrates that temperature had limited migration effects in the broader population in the three African countries under investigation. The one exception we found was in Botswana, where a 1 SD increase in temperature resulted in a 19 percent decrease in migration. The temperature effects appear more pronounced among individuals lacking a primary education. We were unable to detect a mechanism underlying these observed relationships, due to inconsistencies with the reference period for employment on the censuses collected each year. In addition to the cyclical effects of employment on migration, migration decisions are likely driven by other decisions affected by risk, such as shifts in choices regarding schooling or marriage or in exchange labor contracts between households (Rutenberg and Diamond, 1993; Campbell, 2010). How these adaptation strategies affect the well-being of those family members left behind and those choosing to migrate for the various reasons in result of climate variability remains poorly understood.

Our ability to understand how temperature influences this region of the world is greatly limited by the restricted temporal and spatial scope of the available census data. For many of the countries in Africa, we only have one or two years of observational data. This can preclude identification of country-specific temperature effects versus effects quantified by pooling countries over a tropical region (Thiede, Gray, and Mueller, 2016; Mueller et al., 2020b).

Despite these data limitations, we are able to systematically detect the effects of precipitation on migration in all 3 countries. However, the direction of the relationships varies by country. Precipitation anomalies decrease mobility in Botswana and Kenya, while they increase mobility in Zambia. Relating climate anomalies to employment reveals two possible mechanisms for the estimated patterns of migration. In Kenya, precipitation anomalies reduce inactivity and unemployment, consistent with a mostly agrarian population that depends on rainfed agriculture. The local pull factors that arise from atypical precipitation conditions could possibly explain declines in migration. In Zambia, the relationships between migration and precipitation and employment and precipitation are inversely related. Thus, declines in inactivity and unemployment (though imprecisely estimated) coincide with increased migration to suggest that the climate-induced migration may be driven by new job opportunities at the destination. These results are consistent with previous studies which have also documented climate-induced population trapping in Zambia (Nawrotzki and DeWaard, 2018; Mueller et al., 2020a).

These findings add to a small but growing body of literature which has compared climate-migration processes across countries and found them to vary considerably (Thiede, Gray, and Mueller, 2016; Gray and Wise, 2016; Nawrotzki, Schlak, and Kugler , 2016; Nawrotzki and Bakhtsiyarava, 2017). For example, Thiede, Gray, and Mueller (2016) found climatic effects on migration to vary widely in direction and magnitude across South American countries, and Gray and Wise (2016) made similar conclusions about five countries in Africa. This heterogeneity is not consistent with monolithic narratives of displacement under adverse climate conditions (Gemenne, 2011), but is consistent with a large literature documenting the contextually-specific nature of human-environment relationships (Cooper et al, 2019; Randell and Gray, 2019). Future studies should take advantage of the increasing availability of comparable, cross-country data on migration, health and employment to further probe this heterogeneity and uncover what dimensions of the regional and national context are most influential in moderating these processes.

Finally, our study also has implications for the claim that climate change is driving rapid urbanization in Africa (Poelhekke, 2011; Henderson, Storeygard, and Deichmann, 2017). In our study, precipitation shortfalls are associated with increased internal migration in Kenya and Botswana, including specifically to urban areas in Kenya, but less migration in Zambia. Additionally, temperature acts only to decrease migration in Botswana and does not influence migration elsewhere. This mixed evidence is consistent with the existing mixed evidence on climate and urbanization in Africa (Barrios, Bertinelli, and Strobl, 2006; Marchiori, Maystadt, and Schumacher, 2012; Cattaneo and Peri, 2016; Henderson, Storeygard, and Deichmann, 2017). Given this mixed evidence, claims that climate change is driving urbanization in Africa should be avoided, as they do not have a strong evidentiary base.

Acknowledgments

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Appendix for “Climate-Induced Migration and Unemployment in Middle-Income Africa”

Table A.1:

Description of the Analytical Dataset

	Botswana	Kenya	Zambia
Total Sample	600,289	6,323,580	3,105,551
Has age	600,289	6,323,580	3,105,551
Age 18-49	258,626	2,525,639	1,197,275
Has sex and no coding error (zero) for marital status or education	254,665	2,525,639	1,197,275
Know migration status	249,024	2,512,790	1,194,429
Reports being employed, inactive, or unemployed	216,708	2,508,282	1,194,429
Final sample	216,708	2,508,282	1,194,429

Table A.2:

Summary Statistics on Individual Characteristics and Outcomes

	Botswana	Kenya	Zambia
Age: 15-19	0.10	0.11	0.12
Age: 20-24	0.22	0.24	0.24
Age: 25-29	0.20	0.20	0.20
Age: 30-34	0.16	0.15	0.16
Age: 35-39	0.13	0.12	0.12
Age: 40-44	0.10	0.09	0.09
Age: 45-49	0.08	0.08	0.07
Male	0.47	0.48	0.48
Never married	0.55	0.33	0.29
Married	0.42	0.63	0.63
Separated/divorced	0.01	0.03	0.06
Widowed	0.01	0.02	0.03
Less than primary ed. completed	0.23	0.31	0.37
Primary ed. completed	0.53	0.46	0.46
Secondary ed. completed	0.18	0.22	0.15
University completed	0.06	0.01	0.01
Migrant	0.14	0.05	0.06
Employed	0.55	0.76	0.54
Inactive	0.31	0.17	0.40
Unemployed	0.14	0.07	0.05
Temp. level	21.41	21.13	22.28
Temp. anomaly	−0.32	0.57	0.36
Prec. level	42.14	83.26	84.85
Prec. anomaly	0.99	−0.07	0.44
1-year lagged temp. level	21.49	20.94	21.95
1-year lagged temp. anomaly	−0.15	0.11	−0.39
1-year lagged prec. level	39.86	90.28	81.48
1-year lagged prec. anomaly	0.71	0.34	0.17
No. of cold months in prior 24 months	6.26	15.10	10.18
No. of hot months in prior 24 months	9.23	2.03	10.98
No. of wet months in prior 24 months	4.24	5.31	6.87
No. of dry months in prior 24 months	1.30	3.28	2.03
N	216,708	2,508,282	1,194,429

Notes: Sampling weights used. Ed.=education; No.=number. Indicators for unknown marital status and education are omitted for brevity.

Table A.3:

Correlation Matrix of Climate Anomalies

	Temp. t, Prec. t	Temp. t, Temp. t-1	Temp. t, Prec. t-1	Prec. t, Temp. t-1	Prec. t, Prec. t-1	Temp. t-1, Prec. t-1
Botswana	−0.03	0.31	0.15	0.35	0.49	−0.21
Kenya	−0.68	0.09	−0.35	−0.55	0.51	−0.09
Zambia	0.05	0.77	0.48	0.50	−0.30	0.08

Notes: t=survey year; t-1=one-year lag. Unit of analysis is district-year.

Table A.4:

Logistic Regressions of Migration (1-Year Lagged Climate Levels)

	Botswana	Kenya	Zambia
Age: 20-24	1.001 (0.045)	1.319 (0.050)**	1.164 (0.059)**
Age: 25-29	0.791 (0.049)**	1.080 (0.045)+	1.137 (0.069)*
Age: 30-34	0.641 (0.036)**	0.829 (0.029)**	0.984 (0.057)
Age: 35-39	0.541 (0.032)**	0.695 (0.030)**	0.892 (0.043)*
Age: 40-44	0.479 (0.037)**	0.598 (0.031)**	0.828 (0.040)**
Age: 45-49	0.430 (0.027)**	0.522 (0.030)**	0.793 (0.029)**
Male	1.124 (0.036)**	1.117 (0.027)**	1.038 (0.023)+
Never married	1.067 (0.040)+	1.214 (0.062)**	1.109 (0.068)+
At least primary ed. completed	1.684 (0.186)**	1.876 (0.117)**	1.037 (0.199)
1-year lagged temp. level	0.606 (0.181)+	0.862 (0.229)	1.624 (1.063)
1-year lagged prec. level	0.989 (0.006)+	0.996 (0.002)*	1.017 (0.008)*
N	216,708	2,508,282	1,194,429
P-value, Chi-sq. test: Temp.,Prec.=0	0.153	0.044	0.124

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ $p<0.1$

* $p<0.05$;

** $p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status. Chi-sq.=Chi-squared.

Table A.5:

Logistic Regressions of Migration (Add 1-Year Lagged Climate Anomalies Squared)

	Botswana	Kenya	Zambia
Age: 20-24	1.002 (0.046)	1.319 (0.050)**	1.166 (0.058)**
Age: 25-29	0.791 (0.049)**	1.080 (0.045)+	1.139 (0.068)*
Age: 30-34	0.640 (0.036)**	0.829 (0.029)**	0.985 (0.057)
Age: 35-39	0.541 (0.032)**	0.695 (0.030)**	0.891 (0.043)*
Age: 40-44	0.479 (0.037)**	0.598 (0.031)**	0.827 (0.040)**
Age: 45-49	0.430 (0.027)**	0.522 (0.030)**	0.793 (0.029)**
Male	1.125 (0.036)**	1.117 (0.027)**	1.040 (0.023)+
Never married	1.067 (0.040)+	1.214 (0.061)**	1.109 (0.068)+

	Botswana	Kenya	Zambia
At least primary ed. completed	1.686 (0.185)**	1.878 (0.117)**	1.036 (0.198)
1-year lagged temp. anomaly	0.878 (0.113)	0.856 (0.149)	1.830 (0.521)*
1-year lagged temp. anomaly squared	1.035 (0.065)	1.525 (0.471)	0.800 (0.100)$^{+}$
1-year lagged prec. anomaly	0.841 (0.082)$^{+}$	0.861 (0.090)	1.237 (0.133)*
1-year lagged prec. anomaly squared	1.023 (0.037)	1.026 (0.093)	1.107 (0.050)*
N	216,708	2,508,282	1,194,429
P-value, Chi-sq. test: All climate vars.=0	0.170	0.172	0.003

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

$^{+}p<0.1$

$^{*}p<0.05$;

$^{**}p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status. Chi-sq.=Chi-squared.

Table A.6:

Logistic Regressions of Migration (Contemporaneous Climate Anomalies)

	Botswana	Kenya	Zambia
Age: 20-24	1.002 (0.045)	1.319 (0.050)**	1.163 (0.059)**
Age: 25-29	0.791 (0.049)**	1.080 (0.045)$^{+}$	1.134 (0.071)*
Age: 30-34	0.641 (0.036)**	0.830 (0.029)**	0.982 (0.058)
Age: 35-39	0.541 (0.032)**	0.696 (0.030)**	0.890 (0.045)*
Age: 40-44	0.479 (0.037)**	0.599 (0.031)**	0.826 (0.041)**
Age: 45-49	0.430 (0.027)**	0.522 (0.030)**	0.790 (0.030)**
Male	1.124 (0.036)**	1.117 (0.027)**	1.040 (0.024)$^{+}$
Never married	1.068 (0.040)$^{+}$	1.214 (0.061)**	1.109 (0.069)$^{+}$
At least primary ed. completed	1.680 (0.185)**	1.875 (0.117)**	1.036 (0.199)
Temp. anomaly	0.936 (0.095)	0.878 (0.069)$^{+}$	0.587 (0.292)
Prec. anomaly	0.951 (0.049)	1.010 (0.058)	0.902 (0.084)
N	216,708	2,508,282	1,194,429
P-value, Chi-sq. test: Temp., Prec.=0	0.623	0.155	0.048

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

$^{+}p<0.1$

$^{*}p<0.05$;

$^{**}p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status. Chi-sq.=Chi-squared.

Table A.7:

Logistic Regressions of Migration (No. of Cold, Hot, Wet, and Dry Months in Prior 24 Months)

	Botswana	Kenya	Zambia
Age: 20-24	1.003 (0.046)	1.319 (0.050)**	1.164 (0.059)**
Age: 25-29	0.792 (0.050)**	1.080 (0.045)$^{+}$	1.136 (0.070)*

	Botswana	Kenya	Zambia
Age: 30-34	0.641 (0.036) **	0.829 (0.029) **	0.983 (0.058)
Age: 35-39	0.542 (0.033) **	0.695 (0.030) **	0.891 (0.044) *
Age: 40-44	0.480 (0.037) **	0.599 (0.031) **	0.827 (0.041) **
Age: 45-49	0.430 (0.027) **	0.522 (0.030) **	0.792 (0.030) **
Male	1.125 (0.036) **	1.116 (0.027) **	1.039 (0.023) +
Never married	1.066 (0.040) +	1.214 (0.061) **	1.109 (0.069) +
At least primary ed. completed	1.687 (0.186) **	1.875 (0.117) **	1.037 (0.200)
No. of cold months in prior 24 months	0.838 (0.081) +	1.188 (0.301)	0.556 (0.164) *
No. of hot months in prior 24 months	0.991 (0.027)	1.099 (0.039) **	1.221 (0.150)
No. of wet months in prior 24 months	1.008 (0.010)	0.996 (0.010)	0.976 (0.024)
No. of dry months in prior 24 months	1.110 (0.039) **	0.996 (0.015)	1.019 (0.110)
N	216,708	2,508,282	1,194,429
P-value, Chi-sq. test: Temp., Prec.=0	0.000	0.011	0.340

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ p<0.1

* p<0.05;

** p<0.01.

District and year fixed effects included, as well as indicators for missing education and marital status. No.=Number; Chi-sq.=Chi-squared.

Table A.8:

Logistic Regressions of Migration, Botswana

	Pooled	Women	Men	Youth	Non-youth	No primary ed.	Primary ed.
Age: 20-24	1.002 (0.045)	0.930 (0.045)	1.095 (0.058) +	1.009 (0.047)		1.181 (0.116) +	0.992 (0.052)
Age: 25-29	0.791 (0.049) **	0.698 (0.043) **	0.919 (0.066)	0.803 (0.051) **		1.040 (0.108)	0.774 (0.055) **
Age: 30-34	0.641 (0.036) **	0.550 (0.032) **	0.763 (0.054) **	0.653 (0.038) **		0.933 (0.122)	0.611 (0.037) **
Age: 35-39	0.541 (0.032) **	0.422 (0.028) **	0.703 (0.049) **			0.714 (0.085) **	0.528 (0.035) **
Age: 40-44	0.479 (0.037) **	0.369 (0.028) **	0.625 (0.060) **		0.882 (0.024) **	0.614 (0.078) **	0.472 (0.037) **
Age: 45-49	0.430 (0.027) **	0.316 (0.021) **	0.583 (0.046) **		0.795 (0.040) **	0.592 (0.071) **	0.412 (0.033) **
Male	1.125 (0.036) **			1.036 (0.033)	1.478 (0.068) **	1.366 (0.090) **	1.086 (0.029) **
Never married	1.067 (0.040) +	1.114 (0.037) **	1.041 (0.055)	1.096 (0.050) *	1.040 (0.038)	1.101 (0.061) +	1.050 (0.042)
At least primary ed. completed	1.686 (0.185) **	1.765 (0.219) **	1.609 (0.161) **	1.698 (0.176) **	1.600 (0.202) **		
1-year lagged temp. anomaly	0.812 (0.081) *	0.877 (0.091)	0.744 (0.079) **	0.787 (0.077) *	0.900 (0.115)	0.568 (0.119) **	0.825 (0.082) +

	Pooled	Women	Men	Youth	Non-youth	No primary ed.	Primary ed.
1-year lagged prec. anomaly	0.888 (0.037)**	0.924 (0.045)	0.851 (0.038)**	0.890 (0.039)**	0.884 (0.051)*	0.722 (0.060)**	0.896 (0.039)*
N	216,708	113,895	102,813	148,080	68,628	50,619	166,089

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

$^{+}p<0.1$

$^{*}p<0.05$;

$^{**}p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status.

Table A.9:

Logistic Regressions of Migration, Kenya

	Pooled	Women	Men	Youth	Non-youth	No primary ed.	Primary ed.
Age: 20-24	1.319 (0.050)**	1.106 (0.043)**	1.649 (0.060)**	1.326 (0.047)**		1.081 (0.040)*	1.373 (0.054)**
Age: 25-29	1.080 (0.045)+	0.822 (0.031)**	1.511 (0.064)**	1.093 (0.042)*		0.933 (0.053)	1.115 (0.045)**
Age: 30-34	0.829 (0.029)**	0.580 (0.018)**	1.237 (0.049)**	0.841 (0.028)**		0.758 (0.034)**	0.841 (0.031)**
Age: 35-39	0.695 (0.030)**	0.467 (0.021)**	1.062 (0.048)			0.632 (0.037)**	0.700 (0.031)**
Age: 40-44	0.599 (0.031)**	0.373 (0.024)**	0.944 (0.045)		0.858 (0.016)**	0.514 (0.038)**	0.612 (0.031)**
Age: 45-49	0.522 (0.030)**	0.346 (0.021)**	0.792 (0.046)**		0.752 (0.026)**	0.452 (0.030)**	0.523 (0.031)**
Male	1.117 (0.027)**			1.047 (0.027)+	1.513 (0.052)**	1.252 (0.049)**	1.094 (0.025)**
Never married	1.214 (0.062)**	1.267 (0.093)**	1.244 (0.043)**	1.228 (0.064)**	1.366 (0.072)**	1.085 (0.067)	1.227 (0.063)**
At least primary ed. completed	1.877 (0.117)**	1.723 (0.104)**	1.889 (0.125)**	1.921 (0.121)**	1.667 (0.123)**		
1-year lagged temp. anomaly	0.989 (0.080)	0.982 (0.086)	0.994 (0.081)	0.991 (0.082)	0.980 (0.087)	0.922 (0.134)	1.001 (0.069)
1-year lagged prec. anomaly	0.897 (0.040)*	0.909 (0.050)+	0.889 (0.036)**	0.888 (0.042)*	0.934 (0.044)	0.881 (0.061)+	0.906 (0.037)*
N	2,508,282	1,293,391	1,214,891	1,766,563	741,719	739,934	1,768,348

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

$^{+}p<0.1$

$^{*}p<0.05$;

$^{**}p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status.

Table A.10:

Logistic Regressions of Migration, Zambia

	Pooled	Women	Men	Youth	Non-youth	No primary ed.	Primary ed.
Age: 20-24	1.164 (0.059)**	1.076 (0.050)	1.273 (0.073)**	1.162 (0.059)**		1.109 (0.048)*	1.198 (0.066)**
Age: 25-29	1.137 (0.070)*	1.005 (0.042)	1.323 (0.120)**	1.128 (0.069)$^{+}$		1.063 (0.051)	1.196 (0.083)**
Age: 30-34	0.985 (0.057)	0.873 (0.035)**	1.150 (0.105)	0.974 (0.057)		0.931 (0.043)	1.025 (0.073)
Age: 35-39	0.892 (0.043)*	0.787 (0.028)**	1.053 (0.088)			0.874 (0.046)*	0.907 (0.056)
Age: 40-44	0.828 (0.040)**	0.768 (0.029)**	0.938 (0.073)		0.921 (0.015)**	0.784 (0.040)**	0.827 (0.057)**
Age: 45-49	0.794 (0.029)**	0.776 (0.029)**	0.854 (0.054)*		0.882 (0.022)**	0.779 (0.047)**	0.744 (0.042)**
Male	1.038 (0.023)$^{+}$			1.040 (0.026)	1.050 (0.020)*	1.165 (0.029)**	0.993 (0.027)
Never married	1.110 (0.068)$^{+}$	1.066 (0.047)	1.175 (0.103)$^{+}$	1.086 (0.069)	1.388 (0.093)**	0.958 (0.061)	1.166 (0.076)*
At least primary ed. completed	1.038 (0.198)	1.061 (0.211)	1.011 (0.184)	1.092 (0.200)	0.915 (0.189)		
1-year lagged temp. anomaly	1.397 (0.481)	1.452 (0.493)	1.336 (0.467)	1.334 (0.427)	1.627 (0.693)	1.913 (0.805)	1.154 (0.318)
1-year lagged prec. anomaly	1.239 (0.122)*	1.269 (0.129)*	1.207 (0.115)*	1.215 (0.115)*	1.331 (0.148)*	1.283 (0.152)*	1.176 (0.087)*
N	1,194,429	621,540	572,889	857,225	337,204	445,228	749,201

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

$^{+}p<0.1$

$^{*}p<0.05$;

$^{**}p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status.

Table A.11:

Migration Regressions for Botswana with Interaction Variables

	(1)	(2)	(3)
Male	0.862 (0.094)		
Youth		2.573 (0.284)**	
Primary ed. completed			2.397 (0.403)**
1-year lagged temp. anomaly	0.877 (0.091)	0.900 (0.115)	0.574 (0.118)**
1-year lagged prec. anomaly	0.924 (0.045)	0.884 (0.051)*	0.735 (0.061)**
Male × temp. anomaly	0.849 (0.053)**		
Male × prec. anomaly	0.921 (0.034)*		
Youth × temp. anomaly		0.874 (0.058)*	
Youth × prec. anomaly		1.007 (0.050)	

	(1)	(2)	(3)
Primary ed. × temp. anomaly			1.436 (0.254) *
Primary ed. × prec. anomaly			1.219 (0.086) **
N	216,708	216,708	216,708

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ p<0.1

* p<0.05;

** p<0.01.

The models estimated in (1)-(3) includes the covariates, district, and year fixed effects from our preferred model in addition to a set of variables that interact them with a stratifying variable (male, youth, and primary education). We present the coefficients of interest for the purpose of testing meaningful differences in the migration effects presented in Figure 2 in each column of the table.

Table A.12:

Migration Regressions for Zambia with Interaction Variables

	(1)	(2)	(3)
Male	0.705 (0.081) **		
Youth		1.060 (0.161)	
At least primary ed. completed			0.797 (0.168)
1-year lagged prec. anomaly	1.269 (0.129) *	1.331 (0.148) *	1.283 (0.152) *
Male × prec. anomaly	0.951 (0.016) **		
Youth × prec. anomaly		0.913 (0.027) **	
Primary ed. × prec. anomaly			0.916 (0.050)
N	1,194,429	1,194,429	1,194,429

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ p<0.1

* p<0.05;

** p<0.01.

The models estimated in (1)-(3) includes the covariates, district, and year fixed effects from our preferred model in addition to a set of variables that interact them with a stratifying variable (male, youth, and primary education). We present the coefficients of interest for the purpose of testing meaningful differences in the migration effects presented in Figure 2 in each column of the table.

Table A.13:

Migration Regressions for Kenya with Interaction Variables

	(1)	(2)	(3)
Male	0.617 (0.036) **		
Youth		1.639 (0.108) **	
At least primary ed. completed			0.709 (0.059) **
1-year lagged prec. anomaly	0.909 (0.050) +	0.934 (0.044)	0.881 (0.063) +
Male × prec. anomaly	0.978 (0.031)		
Youth × prec. anomaly		0.950 (0.035)	
Primary ed. × prec. anomaly			1.029 (0.054)
N	2,508,282	2,508,282	2,508,282

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ $p<0.1$

* $p<0.05$;

** $p<0.01$.

The models estimated in (1)-(3) includes the covariates, district, and year fixed effects from our preferred model in addition to a set of variables that interact them with a stratifying variable (male, youth, and primary education). We present the coefficients of interest for the purpose of testing meaningful differences in the migration effects presented in Figure 2 in each column of the table.

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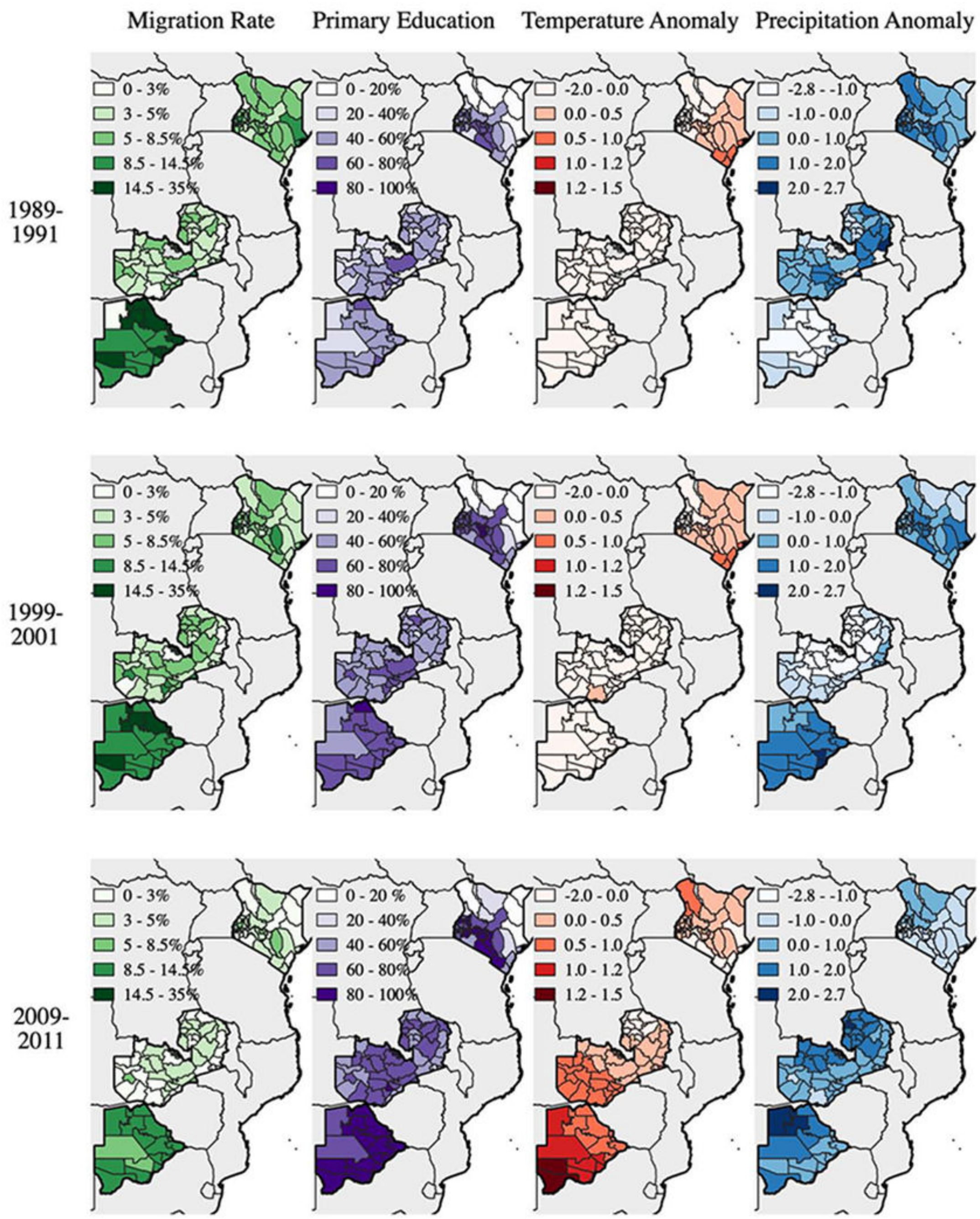

Figure 1:

Social characteristics and climate exposures across time and space.

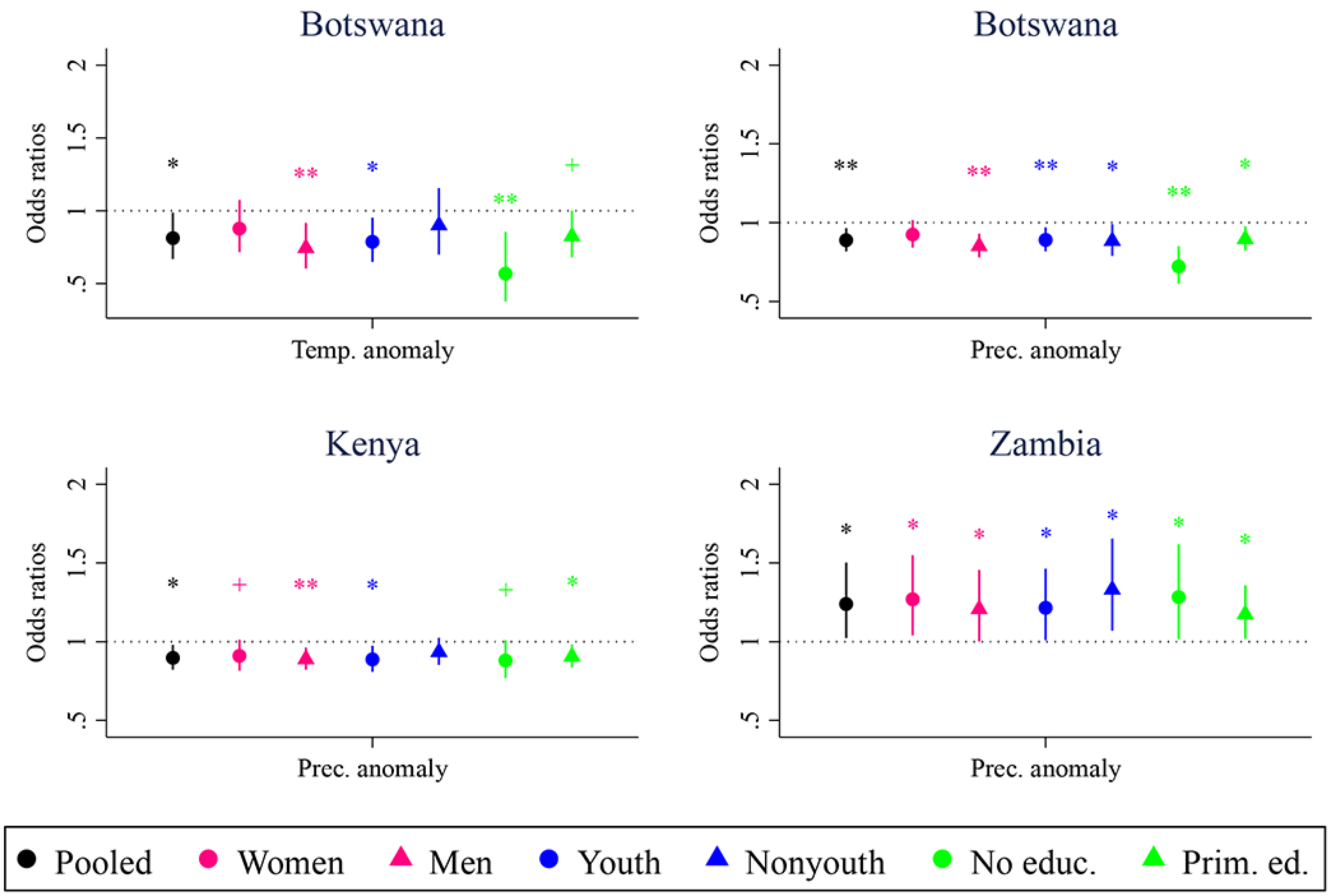

Figure 2: Migration Effects of 1-Year Lagged Climate Anomalies (Odds Ratios, 95% Confidence Intervals, Significance)

** p < .01, * p <0.05, + p<0.1

Table 1:

Census Data and Selected Characteristics of the Study Countries

Country	Years	Spatial units	Migration question	Urban/rural?	Dominant climate
Botswana	1991, 2001, 2011	21	One-year	1991	Warm semi-arid
Kenya	1989, 1999, 2009	35	One-year	1989, 1999, 2009	Tropical savanna
Zambia	1990, 2000, 2010	55	Previous residence	1990, 2000	Humid subtropical

Table 2:

Logistic Regressions of Migration

	Botswana	Kenya	Zambia
Age: 20-24	1.002 (0.045)	1.319 (0.050)**	1.164 (0.059)**
Age: 25-29	0.791 (0.049)**	1.080 (0.045)+	1.137 (0.070)*
Age: 30-34	0.641 (0.036)**	0.829 (0.029)**	0.985 (0.057)
Age: 35-39	0.541 (0.032)**	0.695 (0.030)**	0.892 (0.043)*
Age: 40-44	0.479 (0.037)**	0.599 (0.031)**	0.828 (0.040)**
Age: 45-49	0.430 (0.027)**	0.522 (0.030)**	0.794 (0.029)**
Male	1.125 (0.036)**	1.117 (0.027)**	1.038 (0.023)+
Never married	1.067 (0.040)+	1.214 (0.062)**	1.110 (0.068)+
At least primary ed. completed	1.686 (0.185)**	1.877 (0.117)**	1.038 (0.198)
1-year lagged temp. anomaly	0.812 (0.081)*	0.989 (0.080)	1.397 (0.481)
1-year lagged prec. anomaly	0.888 (0.037)**	0.897 (0.040)*	1.239 (0.122)*
N	216,708	2,508,282	1,194,429
P-value, Chi-sq. test: Temp., Prec.=0	0.019	0.050	0.080

Notes: Odds ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ $p<0.1$

* $p<0.05$;

** $p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status. Chi-sq.=Chi-squared.

Table 3:

Multinomial Logistic Regressions of Migration Outcomes

	Kenya
(A) To Urban	
1-year lagged temp. anomaly	0.992 (0.081)
1-year lagged prec. anomaly	0.876 (0.039) **
P-value, Chi-sq. test: Temp., Prec.=0	0.012
(B) To Rural	
1-year lagged temp. anomaly	1.106 (0.114)
1-year lagged prec. anomaly	0.928 (0.063)
P-value, Chi-sq. test: Temp., Prec.=0	0.379
P-value, Chi-sq. test: Temp(A) =Temp(B)	0.373
P-value, Chi-sq. test: Prec(A)=Prec(B)	0.484
Observations	2,508,282

Notes: Relative risk ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ *p*<0.1

* *p*<0.05;

** *p*<0.01.

District and year fixed effects included, as well as indicators for missing education and marital status. Chi-sq.=Chi-squared.

Table 4:

Multinomial Logistic Regressions of Employment Outcomes (Non-Migrant Sample Only)

	Kenya	Zambia
(A) Inactive		
1-year lagged temp. anomaly	0.758 (0.132)	0.719 (0.143)+
1-year lagged prec. anomaly	0.912 (0.079)	0.885 (0.056)+
P-value, Chi-sq. test: Temp., Prec.=0	0.094	0.124
(B) Unemployed		
1-year lagged temp. anomaly	0.929 (0.106)	0.640 (0.142)*
1-year lagged prec. anomaly	1.099 (0.085)	0.903 (0.060)
P-value, Chi-sq. test: Temp., Prec.=0	0.465	0.120
P-value, Chi-sq. test: Temp(A) =Temp(B)	0.108	0.189
P-value, Chi-sq. test: Prec(A)=Prec(B)	0.079	0.513
Observations	2,383,478	1,121,647

Notes: Relative risk ratios reported. Sampling weights used. Origin-clustered standard errors in parentheses.

+ $p<0.1$

* $p<0.05$;

** $p<0.01$.

District and year fixed effects included, as well as indicators for missing education and marital status. Chi-sq.=Chi-squared.