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Temporary Migration and Climate Variation in Eastern Africa

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Abstract

Africa is likely to experience warming and increased climate variability by the late 21st century. Climate extremes have been linked to adverse economic outcomes. Hence, adaptation is a key component of the United Nations Framework Convention on Climate Change agreements and development assistance. Effective climate adaptation policy requires an understanding of how temperature and rainfall variability affect migration patterns. Yet, how individuals in developing countries manage climate variation is poorly understood, especially in Africa. Combining high-resolution climate data with panel micro-data on migration, labor participation, and demographics, we employ regression analysis to assess temporary migration responses to local temperature and precipitation anomalies in four East African countries. We find that climate impacts are most pronounced in urban areas, with a standard deviation temperature increase and rainfall decrease leading to respective 10 and 12 percent declines in out-migration relative to mean values. Evidence from other labor market outcomes suggests that urban out-migration is not associated with reduced local employment opportunities. Instead, declines in urban out-migration appear to coincide with negative local climate employment impacts. These results challenge the narrative that temporary out-migration serves as a safety valve during climate extremes and that climate change will most strongly affect out-migration rates from rural areas in developing countries.

Keywords

temporary migration; climate; adaptation; Africa; O15; Q54

Africa is likely to experience warming and increased climate variability by the late 21st century (IPCC, 2013; Bathiany et al., 2018).[1] Extreme climate events adversely impact plant growth (Schlenker et al., 2006; Seo et al., 2009; Lobell et al., 2011, 2012; Ortiz-Bobea et al., 2018), as well as productivity in other sectors (Hsiang, 2010; Dell et al., 2012; Burke et al., 2015; Heal and Park, 2016). Adaptation is a key component of the United Nations Framework Convention on Climate Change agreements and development assistance. Yet,

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[1]Climate is defined as “variations in the mean state and other statistics of the climate on all temporal and spatial scales, beyond individual weather events (WMO, 2018).” These variations can be interpreted as deviations from normal climatic conditions based on temporal scales ranging from 12 months to decades (IRI, 2018).

how individuals in developing countries manage climate variation is poorly understood, especially in Africa. We address this knowledge gap by analyzing temporary migration responses to temperature and precipitation variability in four East African countries.

Whether it examines a single country (Feng. et al., 2010; Dillon et al., 2011; Gray and Mueller, 2012a,b; Mueller et al., 2014; Gray and Wise, 2016) or multiple countries (Marchiori et al., 2012; Beine and Parsons, 2015; Cai et al., 2016; Cattaneo and Peri, 2016), the climate-induced migration literature concentrates on links between climate variability and long-term migration, that is, individuals leaving the household for more than a year. While these findings suggest pervasive effects, the broader implications for local adaptive capacity are limited. First, long-term migration – whether internal or external to the country – is rare relative to temporary migration (Banerjee and Duflo, 2011; Bryan et al., 2014). A number of factors contribute to low permanent migration rates, such as a lack of liquidity to pay for travel costs (Stecklov et al., 2005; Angelucci, 2015; Bazzi, 2017), uncertainty regarding employment at the destinations (Munshi, 2003; Beaman, 2012), a strong sense of place at the origin (mooring) (Ingelaere et al., 2018), or fear of land expropriation (De Brauw and Mueller, 2012; Kosec et al., 2018).[2] Second, permanent migration patterns may reflect changes in life cycle status, such as marriage or household formation, rather than employment searches (Rosenzweig and Stark, 1989; Munshi and Rosenzweig, 2016). Given the short duration of absence, temporary migrants retain household membership and therefore are more likely to share income with the rest of the household (Stark and Bloom, 1985; Stark and Lucas, 1988). Temporary migration is thus arguably a more effective form of adaptation for climate-vulnerable households, whereas permanent migration may be considered an option of last resort (Black and Collyer, 2014).

Our study is related to a literature using sub-national and country-level data to measure aggregate effects of climate change on urbanization and international migration. Our use of micro-data on individual migration decisions, however, allows us to avoid conflating other factors that may affect commonly-used internal migration proxies such as urbanization (Barrios et al., 2006; Poelhekke, 2011; Henderson et al., 2017). Implicit in urbanization are changes auxiliary to migration, such as fertility (Eissler et al., 2019) and mortality (Deschenes and Moretti, 2009; Barreca et al., 2016; Carleton, 2017). Furthermore, unlike studies that focus on aggregate international migration flows (Cai et al., 2016; Cattaneo and Peri, 2016) or studies that focus on rural areas alone (Jessoe et al., 2018), we can identify heterogeneities among individuals and across rural and urban labor markets that influence propensity to migrate in reaction to a changing climate. These data help us identify potential mechanisms underlying temporary migration responses.

There is currently a lack of evidence on the channels by which climate affects migration patterns despite the growing number of studies on the subject. The few studies that allude to potential mechanisms typically focus on a single push factor, related to the effect of the climatic shock on agricultural income. The underlying assumption is that subsistence

[2]Moving costs and employment uncertainty at the candidate destinations may also affect decisions to migrate temporarily. However, studies suggest the economic burden is comparatively higher for permanent migrants as they travel longer distances and the requirements to attain a job in the labor market for permanent migrants demands greater upfront investment (Kleemans, 2015; Chen et al., 2019).

households use migration to access additional resources to smooth consumption (Stark and Bloom, 1985; Stark and Lucas, 1988). Several studies find positive statistical associations between migration, household asset depletion (or income losses), and a climatic shock, lending support to the idea that households use migration as a risk management strategy (Feng. et al., 2010; Gray and Mueller, 2012a; Bohra-Mishra et al., 2014; Mueller et al., 2014; Cai et al., 2016; Hirvonen, 2016).

One area that has received little attention, however, is the way that climate shocks affect relative differences in economic opportunities in local labor markets. Diversification into the non-agricultural sector has been the primary means for households to mitigate income risk associated with rainfall shocks (Kochar, 1999; Rose, 2001; Dimova et al., 2015; Mathenge and Tschirley, 2015). If climate affects both agricultural and non-agricultural production (Hsiang, 2010; Burke et al., 2015; Zhang et al., 2018), then observed migratory responses to shocks depends on shifts in local labor demand and potential migrants' ability to secure employment elsewhere.

Our panel micro-data allow us to observe not only whether an individual migrates in a given year, but other economic activities in which he or she engages, as well as socio-economic characteristics such as gender and age. We thus have a unique opportunity to examine the extent to which changes in local employment opportunities due to variations in climate correspond with observed climate migration patterns. In particular, we can evaluate whether the data are consistent with a "push" narrative, i.e., whether the probability of migrating is highest when local employment opportunities are low.

This distinction between push and pull factors motivating temporary migration patterns is important from an adaptation policy perspective. If, for example, periods of high out-migration occur during periods of low local employment opportunities, then migration may be serving as an economic safety valve. If low opportunities exacerbate poverty and social unrest, it could make sense for governments to try reduce migration costs (Bryan et al., 2014). If, however, periods of high out-migration occur during high local opportunities, migrants may be primarily motivated by relatively lucrative outside opportunities. If availability of these outside opportunities, rather than household income, is the binding constraint for the migration decision, then efforts to reduce migration costs to assist the "trapped populations" alluded to by Black et al. (2011) and Black and Collyer (2014), may have little impact.

Perhaps surprisingly, we cannot reject the hypothesis that climate has no effect on rural temporary migration patterns. In contrast, we find that both rainfall and temperature significantly impact temporary out-migration from urban areas of East Africa. Predicted migration rates drop in urban areas by 10 percent with a one standard deviation increase from mean temperature and rise by 12 percent with a one standard deviation decrease in precipitation. Moreover, we observe a similar relationship between climate and migration as between climate and participation in the non-agricultural sector. These results appear inconsistent with a narrative in which extreme climate outcomes push urban workers to migrate. On the contrary, migration rates are highest during moderate climate outcomes when local participation in non-agricultural sectors is also highest.

In Section 1, we describe our main research questions to be tested regarding climate migration and its underlying drivers. Section 2 details construction of the migration, labor, and climate variables from panel household surveys and satellite data for four East African countries. We then specify the migration and labor participation regressions in Section 3, and show how we formalize the research questions into statistical hypothesis tests. Section 4 presents the main empirical results. Section 5 concludes.

1. Research Questions

Our main research objective is to identify whether workers use temporary migration as a form of adaptation to climate variation in rural and urban areas. Conditional on finding a migration response to climate shocks, our secondary research objective is to understand what motivates this behavior. Specifically, we ask whether people migrate because they have fewer work opportunities at home.

1.1. Does climate affect rural and urban migration in East Africa?

To achieve the first objective, we test whether climate variables have no impact on temporary migration decisions, differentiating between rural and urban areas. Although research on climate migration in Africa is sparse, there are a few studies that examine how rural households in Burkina Faso (Henry et al., 2004), Ethiopia (Gray and Mueller, 2012a), Malawi (Lewin et al., 2012), Mali (Grace et al., 2018), South Africa (Mastrorillo et al., 2016) and Zambia (Nawrotzki and DeWaard, 2018) engage in migration to cope with rainfall shocks. The majority of studies find some inclination to move within country in the wake of a drought, but the distances travelled vary across contexts. Two case studies in Malawi (Lewin et al., 2012) and Mali (Grace et al., 2018) are notable exceptions. These studies find respectively a negative and zero association between out-migration and rainfall variability. Temperature has also been identified as a driver of migration in Nigeria (Dillon et al., 2011) and Tanzania (Hirvonen, 2016), especially at levels that exceed thresholds for viable crop production. The findings in Nigeria and Tanzania corroborate expectations that an increasing number of growing degree days causes an increase in rural out-migration rates.

Using nationally representative surveys collected by the World Bank, Gray and Wise (2016) provide one of the first cross-country comparisons of climate-induced rural and urban out-migration. One of their main contributions is to unify the empirical approach and definitions of climate across five African countries (Burkina Faso, Kenya, Nigeria, Senegal, and Uganda). They find no robust relationships between migration and rainfall variability. Fluctuations in temperature systematically affect migration patterns, but the direction of the relationship and statistical significance of the variable varies by country. In Uganda, migration increases with temperature variability, while the opposite occurs in Kenya and Burkina Faso.

Our data allow us to address two shortcomings of previous work. First, many earlier studies either use cross-sectional data, or, when using longitudinal data, exclude individual or household fixed effects. These approaches raise concerns of omitted variable bias since migration decisions may be affected by unobservable characteristics that are also correlated with climate variability. An individual's level of risk aversion, for example, is difficult to measure.[3] It might be the case that more risk averse individuals are both less likely to temporarily migrate and less likely to reside in areas with greater exposure to climate shocks. In such a situation, omission of risk aversion from an empirical model may cause one to mis-estimate the relationship between migration and climatic shocks. In contrast, having migration information for the same individuals over time allows us to control for all time-invariant factors, including geography, culture, and laws, that influence migration decisions.

Second, the literature ignores the potential importance of climate on out-migration in urban, as distinct from rural, areas. The convention has been to focus on rural migration due to the assumed underlying mechanism: climate-induced agricultural productivity shocks. Even if urban workers are primarily employed in non-agricultural activities, however, climate may affect urban migration if shocks affect labor or capital productivity in those sectors (Heal and Park, 2013; Zhang et al., 2018). If firms downsize in response to a climate shock, then urban out-migration may, in turn, increase. Similarly, urban out-migration may decrease if a climate shock is correlated with a decrease in work opportunities in migrant destinations.

1.2. Why do changes in climate cause changes in migration patterns?

It is relatively straightforward to establish whether climate shocks affect temporary migration patterns. Our second set of analyses tries to answer the more challenging question of why climate shocks affect migration. To do so, we take the novel approach of examining how climate affects other local activities in which migrants could potentially engage. If the climate impact on these activities is inverse to its impact on migration, then out-migration may be acting as an adaptation mechanism. That is, workers may migrate to other locations as a means of generating income when other local opportunities are scarce.

Local opportunities to diversify household income away from agriculture, especially in rural areas, may influence the desirability of temporarily migrating when climate shocks reduce agricultural productivity. Prior research suggests that households engage in other local activities to deal with climate-induced income risk (Kochar, 1999; Rose, 2001; Dimova et al., 2015; Mathenge and Tschirley, 2015). The strategy remains a viable coping mechanism as long as the other activity itself is resilient to the climatic shock.

In Africa, the availability of local jobs in alternative sectors may be limited during a climatic shock, rendering out-migration a more desirable coping mechanism. A growing number of studies highlight strong links between the agricultural and non-agricultural sectors, examples being the marketing and trade of food for local consumption and the manufacturing or processing of food (Bezu and Barrett, 2011; McCullough, 2017; Nagler and Naude, 2017). Businesses may slow production when access to agricultural inputs falls, reducing labor demand. Furthermore, there may be lower employment in the service sector if the income effect of an agricultural productivity shock causes a decline in the local demand for services. This income effect might arise from climate-driven yield losses in rural areas (Mueller and

[3]Although in principle one could add a lottery experiment to a household survey (Holt and Laury, 2002), it is typically not done in practice.

Quisumbing, 2011) or lower purchasing power in urban areas due to price hikes from food shortages (Burke and Lobell, 2010).

Our second hypothesis is that the additional out-migration caused by a climatic shock coincides with fewer opportunities in the local non-farm sector. Intuitively, there are two steps to test our second hypothesis. First, we establish whether climate is a relevant determinant for other labor market activities. We then assess whether the migration-climate response curve is inversely related to the curve describing the non-agricultural labor response to climate.

2. Data

We use migration, labor, and demographic information gathered by the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS–ISA). The LSMS–ISA are nationally representative panel household surveys. These data comprise surveys administered in Ethiopia, Malawi, Tanzania, and Uganda spanning six years (2009–2014) as displayed in Table 1. Appendix Figure A.1 illustrates the spatial distribution of survey enumeration areas.

A useful feature of the surveys is that they ask similar questions on the duration of temporary out-migration (but not destination or motive) across several countries, facilitating generalization of inferences across contexts. The number of households surveyed ranges from 3,200 in Uganda and Malawi to 4,000 in Ethiopia and Tanzania.[4] The data allow us to construct variables for individual temporary migration over time, and baseline individual gender, age, and location. The final dataset contains 55,277 person-years.

The surveys ask whether the respondent migrated, but do not collect information regarding a migrant's destination. We define temporary migration as whether an individual present at baseline reported migrating for at least one month in the previous twelve. We create two additional migration outcomes to analyze the degree to which migration duration responds to variations in climate. In particular, we consider alternate definitions of temporary migration to distinguish between individuals who were absent for a period of 1–6 months and 7–12 months.

We generate additional labor participation variables to explore the extent worker participation in other activities might explain observed climate migration responses. Employment modules were available in every country asking for each activity over a 12-month recall period. We create three binary variables based on individual-reported engagement in agricultural wage labor, agricultural self-employed labor, or non-agricultural labor (wage or self-employed) in the last 12 months.[5] A worker can report participation in more than one activity (including temporary migration) in a given year. We generate a fourth

[4]Additional details regarding each survey and round can be found from the Basic Information Documents posted online at: http://surveys.worldbank.org/lsms/integrated-surveys-agriculture-ISA.

[5]Agricultural self-employment participation was recorded in seasonal on-farm labor and livestock modules. Agricultural and non-agricultural wage employment participation was obtained from wage modules. Non-agricultural self-employment data were taken from non-farm enterprise modules. The number of family members documented in the enterprise module varied by country. In Tanzania, all individuals engaged in the enterprise were documented in the first two waves, but a maximum of six workers per enterprise were identified in the last round. For the other countries, surveys reported identities of at most two owners per enterprise.

binary variable to identify individuals who were not employed in the last 12 months, meaning they did not engage in any form of labor, temporary migration, or schooling. These data provide information exclusively on the extensive margin of worker time allocation decisions. They answer the question of whether the respondent engaged in an activity. They provide no information on the intensive margin, i.e., how many hours (other than zero) a worker dedicated to an activity.

We merge these socio-economic data with secondary climate data derived from NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) using the survey interview date and global positioning system (GPS) coordinates of the household's enumeration area. MERRA uses reanalysis to integrate data from NASA's Earth-observing satellites consistent with physical models of the Earth. It produces subdaily data at a resolution of 0.50° latitude × 0.67° longitude covering the modern satellite era (Rienecker, 2011). The climate data are raster, i.e., defined by pixel. We extract climate data from the pixel where the enumeration area of the household lies. To ensure confidentiality, the surveys introduce a small, relative to pixel size, enumeration area location error of 2–5 km.

There is an ongoing discussion of the relative merits of reanalysis versus weather station-based climate data (see, for example Auffhammer et al., 2013). Given the relatively sparse network of weather stations in the region, however, a key advantage of the MERRA data is that the observational network is equally dense around the globe. Evaluations of MERRA data quality have found that annual precipitation has a correlation coefficient of 0.94 with the high-quality weather station dataset for central Tanzania (Koutsouris et al., 2016) and also matches well with the spatial pattern of station-derived precipitation in southern Africa (Zhang et al., 2013). These data have been used to predict migration patterns in Ethiopia, Bangladesh, and Pakistan (Gray and Mueller, 2012a,b; Mueller et al., 2014).

Reanalysis data are inherently limited by the structural assumptions of the underlying climate model (Auffhammer et al., 2013). Reanalysis models are thus unlikely to generate reliable estimates of extreme events. Therefore, rather than consider daily high temperature or low rainfall, we extract monthly means of daily weather variables, and take the mean of these monthly values over a 24-month period ending in the survey month. To account for varying historical climates across study locations and for lagged effects on the outcomes, we use these values to derive z-scores characterizing deviations in climate relative to all other consecutive 24-month periods between 2000 and 2014.

The z-scores are anomalies commonly used to measure climatic variation over time (see, for example, Hansen et al., 2012). Use of z-scores, versus raw or demeaned variables, helps ensure results are applicable across heterogeneous areas. Suppose, for example, that large temperature deviations are far more likely to occur in dry areas. Using demeaned temperature as an explanatory variable would imply that results for extreme temperatures would be driven by (and only applicable to) dry areas. In contrast, by construction, z-scores of a given magnitude should have a similar probability of occurring across all areas. In

Details regarding enterprise staff are restricted to at most five for hired labor in the Ethiopia survey, at most two for any type of worker in the Malawi survey, and at most five of any type of worker in Uganda. Despite evidence on the small size of enterprises (Fox and Sohnesen, 2012), non-agricultural self-employment may be under-reported, especially in Ethiopia and Malawi.

practice, Gray and Wise (2016) have shown z-scores to be stronger predictors of migration outcomes in Africa than raw climate data.

Surveys provide rural and urban classifications. Definitions of these classifications, however, vary by country. To apply a uniform classification, we merge georeferenced population density from the 2010 Gridded Population of the World (GPWv4) using baseline enumeration area GPS coordinates (Center for International Earth Science Information Network, 2016). We use 400 persons per km^2 as the threshold defining urban and rural enumeration areas, a benchmark applied in most censuses (Qadeer, 2010).

Table 2 describes temporary migration rates of the working age (15–65) population by location. Urban and rural migration rates are similar. Overall, 12 percent of the urban sample and 11 percent of the rural sample have migrated for at least 1 month in the previous year. Ethiopia is an exception with a rural migration rate triple the urban rate. This discrepancy highlights a limitation of the urban sample. Ethiopia's baseline survey is representative of only rural areas and small towns with fewer than 10,000 people. It thus excludes mid and large sized towns such as Addis Ababa. In most countries (Uganda being the exception) it is more common to migrate for 1–6 months than for 7–12 months.

Table 2 presents statistics on working-age population labor activities to help explain why individuals may consider migrating temporarily to cope with climate variability. Most individuals are self-employed in agriculture, although the proportion varies greatly between rural areas (85 percent) and urban areas (51 percent). Rural workers rely primarily on self-employed farming, with 8 and 21 percent participation in agricultural wage and non-agricultural employment, respectively. Workers in urban settings appear to be more active in non-agricultural employment (37 percent). Thus, if climate shocks primarily affect agricultural productivity, the lack of non-agricultural options in rural areas may lead one to expect relatively high rural out-migration levels in extreme climate outcomes.

While the combination of MERRA climate data with LSMS–ISA micro-data on temporary migration is well-suited to our purpose, it has limitations in terms of survey frequency. Figure 1 depicts the distribution of climate z-scores by country and survey year. Temperature and rainfall z-scores tend to be inversely correlated, such that climate can be roughly divided into three categories: hot and dry, cool and wet, or moderate "Goldilocks" years. The two surveys for Ethiopia seem to have captured exclusively Goldilocks years with average temperature and rainfall. Uganda has a moderate year and two warm dry years, while Malawi has a moderate year and a hot and particularly dry year. Only Tanzania has a cool wet year, which is accompanied by a warm dry year and a very hot and dry year.

The sparseness of the country-level data presents a challenge for identifying the impact of climate on migration. Ideally, if all countries had several years of data and faced a similar range of climate shocks, one could run separate regressions for each country and test whether parameters had the same values across countries. In light of the data limitations, however, we pool the four countries together in a single regression, imposing common parameter values. This approach enables us to have a more complete set of temperature-rainfall combinations within the sample, improving efficiency and enhancing the ability of the estimates to reflect a range of climate migration impacts. The disadvantage is that we potentially overlook heterogeneous country reactions to climate variability.

3. Empirical Strategy

3.1. Regression Model

We use a linear probability model (LPM) to predict out-migration M_{it} as a function of climate variables $\mathbf{z}_{it}$, individual fixed effects $\boldsymbol{\gamma}_i$, time fixed effects $\boldsymbol{\gamma}_t$, and an individual error term $\boldsymbol{\varepsilon}_{it}$:

$$M_{it} = \sum_{\ell=1}^{2} d_{i\ell}\left[\sum_{m=1}^{2}\left[\beta_{\ell m} z_{imt} + \beta_{\ell mm}[z_{imt}]^2\right] + \beta_{\ell 12} z_{i1t} z_{i2t}\right] + \gamma_i + \gamma_t + \varepsilon_{it} \quad (1)$$
$$\text{for } \ell = \{\text{rural},\ \text{urban}\}, m = \{\text{temperature},\ \text{rainfall}\}\,.$$

The binary indicator M_{it} takes a value of 1 if individual i temporarily migrates during survey period t, zero otherwise. The predicted value of M_{it} has the interpretation of the probability of migrating. The dummy variable vector $\mathbf{d}_i$ denotes our main stratification by urban and rural populations. We specify a second-order approximation to a generic relationship between migration and climate. The squared terms account for possible non-monotonic climate impacts following previous work (Burke et al., 2015). The product of temperature and rainfall allow the marginal impact of one climate variable to vary with the z-score of the other.

Climate shocks $\mathbf{z}$ are represented by the z-scores of the preceding 24-month average value relative to the historical 2000–2014 distribution. In constructing the z score, we rely on the mean and standard deviation of a 15-year historical distribution to provide a frame of reference that is relevant for both older and younger segments of the population. Use of a 24-month average value in the calculation of the z score reflects the fact that there may be lagged climate responses. Similar aggregation of climate variables over multiple years has been validated by previous studies on climate change and migration (e.g., Gray and Mueller, 2012a; Mueller et al., 2014; Henderson et al., 2017).

Individual and time fixed effects reduce the potential for confounding factors, such as innate ability, district or country effects, and business cycle employment trends, to introduce bias. We cluster standard errors by baseline enumeration area to allow for non-independence and serial autocorrelation within these units. We apply inverse probability weights to account for sampling scheme and selective attrition (Fitzgerald et al., 1998). The Appendix contains a detailed discussion of the weighting methodology.

The LPM is preferable to other discrete choice models, such as the probit or logit, because it does not require an additional assumption on the error distribution nor require a transformation of the parameters to aid interpretation of effects (Angrist and Pischke, 2009). The LPM also allows us to control for unobserved time-invariant confounders influencing non-exclusive outcomes without causing sample selection bias. Fixed-effects logit models, for example, drop observations that have no variation in the dependent variable. In contrast, the linear probability model allows us to maintain the full sample.

One limitation of the use of the LPM is that predicted probabilities might fall outside the range of zero and one (Angrist and Pischke, 2009). To avoid erroneous interpretations of effects, we only provide estimates of the predicted probability of migrating for climate values in which we have a relatively high degree of confidence, those within approximately 1.5 standard deviations of the sample mean. For this range of climate values, none of our resulting estimates predict probabilities outside of zero and one within a 95 percent confidence interval (Appendix Table A.1).

3.2. Hypothesis Tests

Our first set of results test separately whether either of the two climate variables affects temporary migration decisions for rural and urban residents. We calculate four F statistics testing the null hypotheses of no impact, i.e.,

$$H_0 : \beta_{\ell m} = 0, \beta_{\ell mm} = 0, \beta_{\ell mn} = 0; \\ \ell = \{\text{rural, urban}\}; m, n = \{\text{temperature, rainfall}\}. \tag{2}$$

To examine whether there is a differential impact of climate on migration for urban and rural areas, we calculate two additional F statistics testing the hypothesis that climate parameters are the same across these two areas:

$$H_0 : \beta_{\text{rural}, m} = \beta_{\text{urban}, m}, \beta_{\text{rural}, mm} = \beta_{\text{urban}, mm}, \beta_{\text{rural}, mn} = \beta_{\text{urban}, mn}; \\ m, n = \{\text{temperature, rainfall}\}. \tag{3}$$

Our second set of results addresses the question of whether climate-induced migration helps compensate for reduced local labor opportunities. This analysis proceeds in two steps. We first estimate the LPM, Eq. (1), replacing migration with participation in the other labor outcomes. We repeat the F tests in Eqs. (2) and (3) for these outcomes to examine whether they are influenced by climate variability.

Next, we examine whether high migration occurs during similar climatic events as low participation in other activities. Since we allow for quadratic impacts, the test is based on inflection points on the respective climate response curves, i.e., where the derivative with respect to climate variable m, $\beta_{\ell m}/2\beta_{\ell mm}$, equals zero.[6] The null hypothesis is that inflection points for migration and the alternative labor activity are equal:

$$H_0 : \frac{\beta_{\ell m}^{Mig}}{2\beta_{\ell mm}^{Mig}} = \frac{\beta_{\ell m}^{Alt}}{2\beta_{\ell mm}^{Alt}}; m = \{\text{temperature, rainfall}\}. \tag{4}$$

Since this statistic is based on a non-linear combination of parameters, we employ the Wald test statistic, which has a χ^2 distribution.

The interpretation of these tests differs based on the curvature of the climate responses of the migration and alternate activity. If both are concave (or convex), rejecting the null

[6]Since we evaluate the curves holding the other climate variable constant at historical means, i.e., where the z score equals zero, the cross term $\beta_{\ell mn} z_n$ is equal to zero.

hypothesis suggests that maximum (or minimum) migration occurs during climate conditions different from maximum (or minimum) participation in the other activity. If one is convex and the other is concave, however, rejecting the null suggests that maximum participation in one activity occurs during periods of minimum participation in the other. Thus the climate push narrative is most consistent with rejecting the null when the curvature is similar and not rejecting the null when the curvature is different.

4. Results

In this section, we test the two sets of hypotheses posed in Section 1. The first sub-section discusses whether there is an effect of climate variability on temporary out-migration in rural and urban East Africa. The second sub-section focuses on providing evidence regarding whether climate-induced migration coincides with a lack of local employment opportunities.

4.1. Do workers leave rural and urban areas in response to climate shocks?

Model 1 of Table 3 presents our main results with respect to the estimated impacts of temperature and rainfall on temporary out-migration. Migration responses to climate variability differ significantly between urban and rural areas with F tests rejecting the hypothesis of identical temperature or rainfall terms across the two areas (p values less than 0.08). Responses are significantly concave to both rainfall and temperature in urban areas. F tests do not reject joint significance of the parameters for either climate variable in urban areas (p values less than 0.08). Rural point estimates suggest a convex climate response, but we cannot reject the hypothesis of no effect for either temperature or rainfall at conventional levels of significance (F test p values of 0.11 and 0.30 for temperature and rainfall).

Figure 2 depicts predicted migration probabilities implied by the estimated parameter values in Model 1 of Table 3, varying temperature and rainfall respectively, while holding other variables constant at observed values. Appendix Table A.1 presents the predicted migration rates for the range of z-scores in which we have relatively high confidence–within approximately 1.5 standard deviations from the sample means pooled over rural and urban areas (0.389 mean for temperature, rounded to 0.5, and −0.138 for rainfall, rounded to zero). Predicted migration rates drop in urban areas by 10 percent with a one standard deviation increase from the urban sample mean temperature (from z-score of 0.5 to 1.5) and by 12 percent with a one standard deviation decrease in the urban sample mean rainfall (from z-score of 0 to −1.0).

Lacking direct information on the motive for migration, in Appendix Table A.2 we stratify the sample on the basis of gender and age to observe whether our results are robust to sub-samples that are most likely to have economic motivations. Since young people and males are most likely to move for employment purposes, there would be reason for concern if the climate migration pattern for these groups were different from those estimated in Table 3. However, similar to the main results, both young and male urban stratifications have a significant concave migration response to both temperature and rainfall. The linear and squared temperature parameters are jointly statistically significant for these two groups (p values less than 0.10).[7] The findings on the effects of temperature on migration are thus consistent with mobility driven by seasonal employment searches rather than family-related reasons.

We next explore whether the duration of the move is consistent with temporary employment searches. We take advantage of information documented in the LSMS–ISA surveys regarding the number of months individuals left the household in the previous year. Specifically, we divide the sample of migrants into two mutually exclusive groups: those who migrated from 1–6 months and those who migrated 7–12 months in the previous year. Our main results, significant concave urban responses to both climate variables, are most consistent with the patterns observed for the shorter-term migrants (Appendix Table A.3) likely to be migrating for temporary or seasonal work.

Thus far, our results suggest that climate variability has a concave impact on urban migration, but does not significantly impact rural migrants. In Models 2–8 of Table 3, we evaluate whether this result is an artifact of our main specification by considering several alternatives regarding level of clustering, sample weights, treatment of individuals who changed permanent locations after the baseline survey or attended school, the urban sample included in the analysis, and definition of the climate variable.

Models 2 and 3 examine robustness of results to two alternative statistical specifications, clustering of standard errors at the district, rather than enumeration area level, and using sample weights alone, excluding attrition weights. The choice of level of clustering reflects a tradeoff between variance and bias in the standard errors, with more smaller EA clusters having less variability at the possible expense of more bias. Model 2 uses larger, but fewer (245 versus 1,211) district clusters. Following Fitzgerald et al. (1998), we use attrition weights to account for the fact that whether an individual responds to subsequent survey rounds is not randomly assigned. There may be concern, however, that the attrition weights are sensitive to the selection of the model used to construct the inverse probability weights (see Appendix). To evaluate whether this choice of weighting scheme is driving our results, Model 3 uses the survey weights provided by the LSMS-ISA. The point estimates and standard errors of most parameters in Models 2 and 3 are similar to the main results, leading us to conclude that bias from either of these sources is unlikely to be driving our results.

Models 4–6 exclude potentially problematic categories of respondents from the sample: “movers”, or those that change location between baseline and subsequent survey rounds; “students”, or those who attended school during any round, and Ethiopia. The inclusion of movers could raise concerns regarding the assignment of baseline location climate variables to individuals who change location. Approximately three percent of the sample left the baseline enumeration area in later rounds, but were assigned climate from their baseline area. By including students in the sample, it is possible that a fraction of migrants may move for educational purposes rather than for work. Ethiopia is a special case since large towns were not included in the sample.

[7]In rural areas, the *F* statistic indicates a significant temperature impact on migration for the young stratification, but the coefficients are not individually significant. Since the functional relationship is convex, there is some evidence that these workers may be leaving as temperatures rise.

In each case, despite dropping almost one fifth of the sample, individual coefficient values and significance are largely similar to the main results. Some *F* tests on joint significance of climate parameters (urban temperature for non-movers and excluding Ethiopia) no longer meet the 10 percent threshold (*p* values of 0.119 and 0.135), however. Similarly, we cannot reject the hypothesis that temperature parameters are jointly different between rural and urban areas excluding students or Ethiopia, or that rainfall parameters are different excluding Ethiopia. The *F* tests excluding movers and students also suggest a potentially significant temperature impact in rural areas, although individual parameter estimates are not significant.

Models 7 and 8 consider competing assumptions about how climate affects migration. Model 7 addresses the concern that individuals respond to contemporaneous (12 month) rather than lagged (24 month) climate anomalies, and Model 8 evaluates whether they are more responsive to changes in raw climate variables (e.g., degrees centigrade) rather than z-scores. Model 7 finds no significant climate impacts, confirming the importance of lagged, rather than contemporaneous, anomalies in driving temporary urban out-migration. In contrast to the main results, Model 8 finds little evidence of migration response to climate, only a significant (concave) impact for rainfall on rural areas. We believe our main results are more credible since in the presence of individual fixed effects, the z score is likely to provide a more meaningful comparison. It implicitly captures how unusual a given climate outcome is relative to the individual's historical experience rather than just the two or three years covered by the survey data.

4.2. Are urban out-migration responses to climate driven by local job scarcity?

Our main results found that temperature and rainfall had a significant impact on urban temporary out-migration. Here we examine why. In particular, our second set of hypotheses explores whether these urban migrants are "pushed" out by a lack of local employment opportunities. To do so, we examine whether predicted climate-induced urban out-migration is highest when predicted climate-induced participation in other urban labor activities is lowest. If so, it would lend support to this push narrative.

Models 1–3 in Table 4 present results for urban areas from regression Eq. (1), respectively replacing migration as the dependent variable with participation in non-agricultural employment, agricultural wage employment, and agricultural self-employment.[8] The dependent variable of Model 4 is a dummy variable taking a value of one if the individual did not participate in any labor activity or school. To facilitate comparison with the literature, Table 4 includes both conventional standard errors and significance and *q*-values corrected for false discovery rates due to multiple outcomes (Anderson, 2008).[9] Predicted probabilities of these outcomes in response to the two climate variables are presented in Appendix Table A.1 and depicted in Figure 3.[10]

[8]Appendix Table A.4 presents complete results for both urban and rural areas.

[9]We calculate *q*-values using the *False Discovery Rate Control* procedure described in Anderson (2008) and the accompanying Stata code posted at are.berkeley.edu/~mlanderson/ARE_Website/Research.html.

[10]Appendix Figure A.2 presents the corresponding information for rural areas.

As shown in Model 1 of Table 4, urban non-agricultural labor participation is significantly concave to temperature and rainfall, peaking for moderate values (*p* values are less than 0.02 for joint significance of both temperature and rainfall).[11] These findings are consistent with other work (Burke et al., 2015), showing that vulnerability to climate extremes is not limited to the agricultural sector.

Although, as indicated in Model 2, climate variables are jointly significant in predicting urban agricultural wage participation, Figure 3 shows the curve is relatively flat compared to migration and non-agricultural employment. Urban agricultural self-employment, Model 3, is not significantly affected by either climate variable. The non-responsiveness of agricultural self employment to climate in urban areas, combined with the fact that agricultural wage employment comprises only three percent of the urban workforce (Table 2), lead us to focus on non-agricultural employment for the remainder of this section.

We examine the null hypothesis that peak migration occurs at the same climate values as peak non-agricultural participation. Failure to reject this hypothesis would undermine the narrative that urban workers are pushed to migrate due to a lack of local employment opportunities. Evaluated at historical mean rainfall, peak migration occurs at a temperature z score of 0.67, while peak non-agricultural participation is at −0.60. The corresponding values for rainfall (evaluated at historical mean temperatures) are 0.18 and 0.43. The *p* values of the χ^2 statistic testing the difference in these values are 0.177 and 0.569. Consequently, we cannot reject the null hypothesis that they are the same.

Lack of a strong push motivation is further corroborated by considering the impact of climate anomalies on the percent of respondents who report no labor or school activity. As illustrated in Figure 3, both temperature and rainfall anomalies have a significant convex impact on labor force non-participation.[12] Due to this convexity there is no “peak” unemployment, so we cannot directly test whether peak migration occurs at maximum unemployment. We can test the null hypothesis that peak migration occurs at minimum non-participation. Failure to reject this hypothesis would further undermine the push narrative. We cannot reject the null hypothesis that minimum non-participation occurs at the same rainfall anomaly as maximum migration (*p*-value 0.870). We do, however reject the null hypothesis that the two values coincide for temperature (*p*-value 0.060). Nonetheless, visual inspection of Figure 3 indicates that predicted levels of respondents reporting no employment are highest at the high end of the temperature range, where both non-agricultural employment and agricultural wage employment are lowest. Labor force non-participation is also highest where migration rates are declining (Figure 2).

Taken together, these results suggest that the climate migration patterns observed in urban areas are not indicative of a relative inability to obtain local employment. Urban residents both migrate and work in the non-agricultural sector during periods of moderate climate. In contrast to the push narrative, it seems that low urban out-migration during climate extremes may exacerbate, rather than ameliorate a lack of local employment opportunities.

[11] Excluding Ethiopia from the sample yields similar parameter values with less precision (Appendix Table A.5, Model 1).
[12] Rainfall is not significant if Ethiopia is excluded (Appendix Table A.5, Model 4)

5. Conclusion

Measurement of climate change implications for migration is receiving increasing attention, especially as the consequences spill over to residents living in vulnerable countries (Strobl and Valfort, 2015; Maystadt et al., 2016; Kleemans and Magruder, 2017) and abroad (Missirian and Schlenker, 2017). Despite the economic importance of temporary or seasonal migration, relatively little is known about the impact of climate on this type of activity, particularly in Africa.

Given well-documented climate impacts on agricultural productivity, it is unsurprising that we find that climate variability significantly affects temporary migration decisions in East Africa. However, our strongest results suggest that extreme temperature and rainfall shocks cause a reduction in urban, rather than rural, temporary out-migration. In particular, our model predicts that a one standard deviation increase in temperature and decrease in rainfall leads to respective 10 and 12 percent reductions in peak urban out-migration rates.

The detailed micro-data in the LSMS surveys allow us to examine whether climate migration relationships are closely tied with local employment opportunities. During climate extremes in urban areas, we do not find that urban temporary out-migration rises when non-agricultural employment falls. In contrast, urban out-migration is highest during relatively moderate climates when labor non-participation rates are low. This evidence does not support a narrative in which urban push factors drive migration decisions, since that hypothesis would expect temporary out-migration to rise (rather than decline) when local job opportunities are scarce.

Although the impact of climate on urban non-agricultural employment may be surprising, it is important to remember that even if climate were to only affect agricultural productivity directly, the non-agricultural sector may be indirectly affected. These indirect impacts may be through a demand effect (reduced income of agricultural producers leads to a reduction in demand for nonagricultural goods) or a supply effect (reduced agricultural output leads to reduced production in non-agricultural sectors that use agricultural inputs).

Interestingly, we were unable to reject the hypothesis that climate has no impact on rural temporary out-migration. Our findings in rural areas are largely consistent with a recent study that found that rainfall did not affect temporary out-migration rates in two Malian villages (Grace et al., 2018). The contrasting findings in the remainder of the literature may be due to a focus on relationships between climate and *permanent* migration. The discrepancy in the two patterns may be a reflection of the type of labor markets that attract people into short-term versus longer term migrant labor and the respective vulnerabilities of those markets to climate shocks. Without knowledge of migrant destinations, however, it is difficult to disentangle why rural workers are less likely to migrate temporarily to cope with climatic shocks.

Another possible explanation for the lack of migratory response to climate in rural areas is lack of employment opportunities in potential destinations. Our results indicate that urban labor force participation is lowest at climate extremes. If climate is correlated between rural areas and potential urban destinations, high urban unemployment may reduce incentives for rural out-migration during extreme events. Due to the limitations of our data, such narratives are simply conjectures that cannot be tested directly. Thus, an important avenue for future work is to collect data on destinations of temporary migrants to determine how climate anomalies experienced at the destination affects demand for migrant labor and hence out-migration rates. This need is particularly acute since other work has found that permanent migration patterns in East Africa tend to be rural-rural and urban-urban (Beegle et al., 2011; Hirvonen, 2016; Mueller and Lee, 2019).

Our results have potential implications for climate adaptation policy in Africa. They suggest that despite the direct impact of climate on agricultural productivity, individuals in urban areas may require social protection due to an inability of local labor markets to absorb urban workers who would normally migrate for work. The lack of strong evidence that climate shocks affect rural out-migration also raises questions about the potential usefulness of policies to reduce migration costs as a means of helping rural communities in East Africa adapt to climate change.

We finally note that our analysis is inherently limited by availability of data by country and year. Ethiopia, for example, lacks information on Addis Ababa, and some joint hypothesis tests move out of statistical significance if the Ethiopian sample is excluded. Similarly, it might be the case that introducing new countries or years of data could affect the conclusions. Thus, generalizing climate migration patterns at a broader geographic scale in Africa remains an important area for further investigation.

Appendix A.

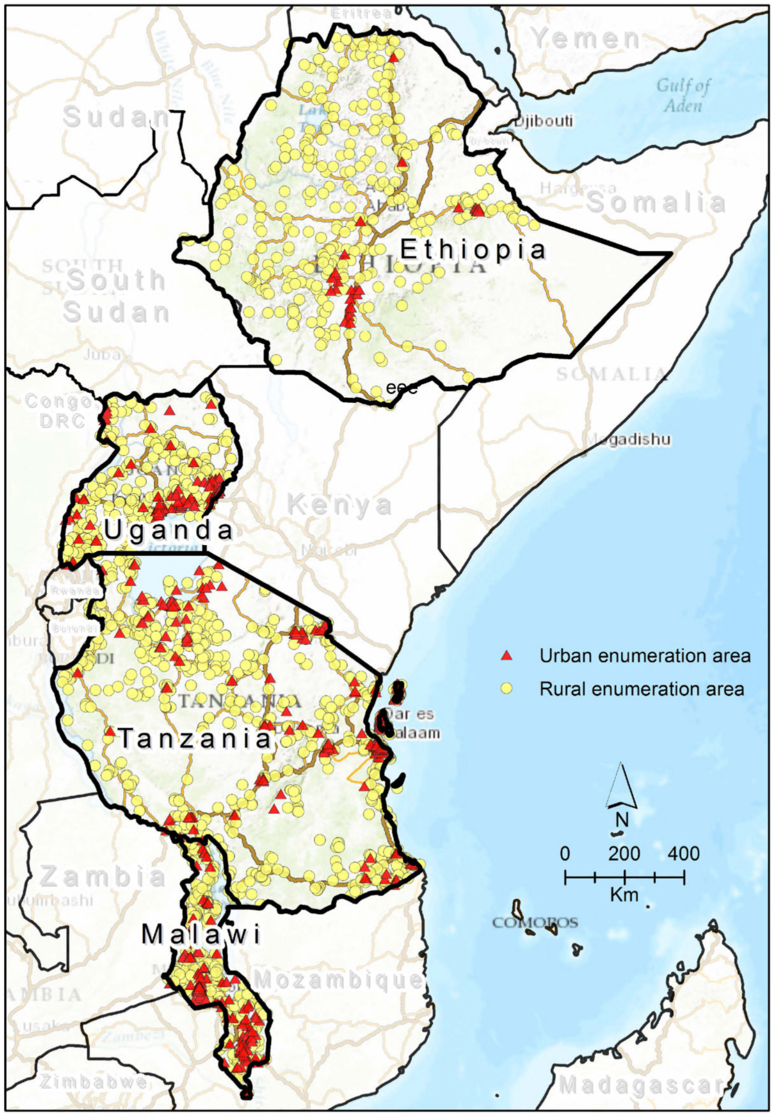

Figure A.1:
Enumeration Areas

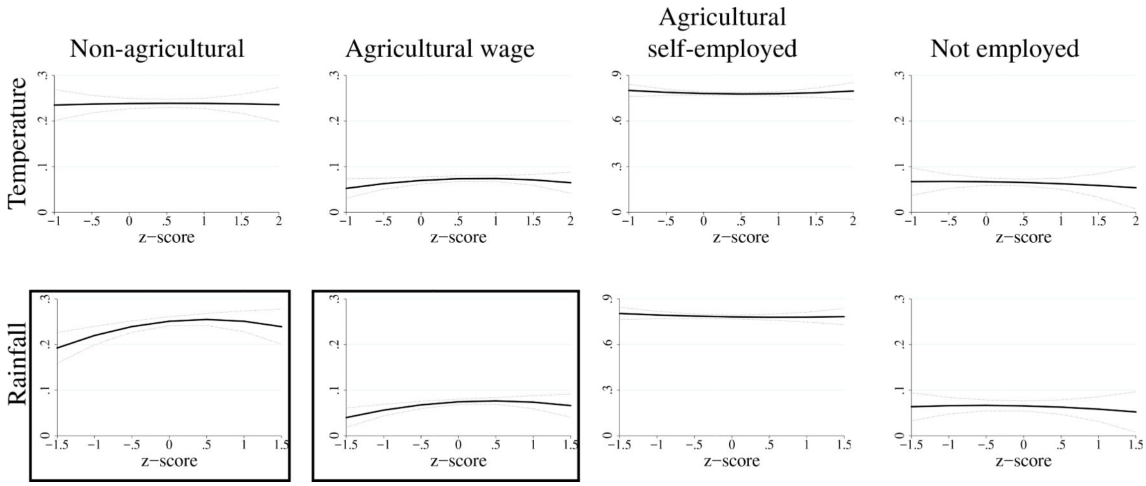

Figure A.2:

Predicted rural labor participation response to climate by activity and location

Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature (or precipitation) fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which an F test shows relevant climate response parameters are jointly significant at $p < 0.10$.

Table A.1:

Predicted participation rates for observed temperature and rainfall

	Dependent variable: Occupational participation dummy									
	Urban					Rural				
		Agriculture					Agriculture			
	Migrate	Wage	Self-employed	Non-agriculture	Not employed	Migrate	Wage	Self-employed	Non-agriculture	Not employed
Temperature z-score										
−1	0.044 [0.00–0.09]	0.239 [0.20–0.28]	0.086 [0.06–0.11]	0.743 [0.68–0.80]	0.097 [0.06–0.14]	0.139 [0.08–0.20]	0.235 [0.20–0.27]	0.052 [0.03–0.07]	0.801 [0.76–0.84]	0.067 [0.04–0.10]
−.5	0.073 [0.05–0.09]	0.240 [0.22–0.26]	0.078 [0.07–0.09]	0.754 [0.72–0.78]	0.085 [0.06–0.11]	0.123 [0.09–0.15]	0.237 [0.22–0.26]	0.063 [0.05–0.07]	0.789 [0.77–0.81]	0.067 [0.05–0.08]
0	0.092 [0.08–0.10]	0.237 [0.23–0.25]	0.071 [0.06–0.08]	0.762 [0.75–0.77]	0.083 [0.07–0.10]	0.115 [0.10–0.13]	0.238 [0.23–0.25]	0.070 [0.06–0.08]	0.781 [0.77–0.79]	0.067 [0.06–0.07]
.5	0.101 [0.09–0.11]	0.230 [0.22–0.24]	0.067 [0.06–0.07]	0.768 [0.76–0.78]	0.090 [0.08–0.10]	0.116 [0.11–0.13]	0.239 [0.23–0.25]	0.073 [0.07–0.08]	0.778 [0.77–0.79]	0.065 [0.06–0.07]
1	0.100 [0.08–0.12]	0.218 [0.20–0.23]	0.063 [0.05–0.07]	0.771 [0.76–0.79]	0.106 [0.09–0.12]	0.126 [0.11–0.14]	0.239 [0.23–0.25]	0.074 [0.07–0.08]	0.780 [0.76–0.79]	0.062 [0.05–0.07]
1.5	0.090 [0.06–0.12]	0.201 [0.18–0.22]	0.061 [0.05–0.08]	0.772 [0.75–0.79]	0.131 [0.11–0.15]	0.144 [0.11–0.17]	0.238 [0.22–0.26]	0.071 [0.06–0.08]	0.786 [0.76–0.82]	0.059 [0.03–0.08]

	Dependent variable: Occupational participation dummy									
	Urban					Rural				
		Agriculture					Agriculture			
	Migrate	Wage	Self-employed	Non-agriculture	Not employed	Migrate	Wage	Self-employed	Non-agriculture	Not employed
2	0.069 [0.02–0.12]	0.180 [0.15–0.21]	0.061 [0.04–0.08]	0.770 [0.74–0.80]	0.166 [0.14–0.20]	0.171 [0.11–0.23]	0.236 [0.20–0.27]	0.065 [0.04–0.09]	0.797 [0.74–0.85]	0.054 [0.01–0.10]
Rainfall z-score										
−1.5	0.067 [0.03–0.10]	0.173 [0.13–0.22]	0.059 [0.04–0.08]	0.746 [0.70–0.79]	0.131 [0.09–0.17]	0.161 [0.11–0.21]	0.193 [0.16–0.23]	0.040 [0.02–0.06]	0.805 [0.76–0.85]	0.064 [0.03–0.09]
−1	0.084 [0.06–0.11]	0.205 [0.18–0.23]	0.071 [0.06–0.08]	0.757 [0.73–0.78]	0.112 [0.09–0.13]	0.143 [0.11–0.18]	0.220 [0.20–0.24]	0.056 [0.04–0.07]	0.795 [0.77–0.82]	0.066 [0.05–0.08]
−.5	0.094 [0.08–0.11]	0.226 [0.21–0.24]	0.077 [0.07–0.09]	0.765 [0.75–0.78]	0.100 [0.09–0.11]	0.130 [0.11–0.15]	0.240 [0.23–0.25]	0.068 [0.06–0.08]	0.788 [0.77–0.80]	0.067 [0.05–0.08]
0	0.095 [0.08–0.11]	0.237 [0.23–0.25]	0.078 [0.07–0.09]	0.769 [0.76–0.78]	0.096 [0.09–0.11]	0.122 [0.11–0.14]	0.251 [0.24–0.26]	0.074 [0.07–0.08]	0.783 [0.77–0.80]	0.066 [0.05–0.08]
.5	0.088 [0.07–0.11]	0.239 [0.22–0.25]	0.073 [0.06–0.08]	0.770 [0.75–0.79]	0.100 [0.09–0.11]	0.120 [0.10–0.14]	0.255 [0.24–0.27]	0.076 [0.07–0.08]	0.781 [0.76–0.80]	0.063 [0.05–0.08]
1	0.072 [0.04–0.10]	0.230 [0.21–0.25]	0.062 [0.05–0.07]	0.767 [0.74–0.79]	0.111 [0.09–0.13]	0.124 [0.09–0.15]	0.251 [0.23–0.27]	0.074 [0.06–0.09]	0.781 [0.75–0.81]	0.058 [0.03–0.09]
1.5	0.048 [0.00–0.09]	0.212 [0.18–0.25]	0.045 [0.03–0.06]	0.760 [0.72–0.80]	0.129 [0.09–0.17]	0.132 [0.08–0.18]	0.239 [0.20–0.28]	0.066 [0.04–0.09]	0.784 [0.73–0.84]	0.052 [0.01–0.10]

Note: Mean predicted values with 95 percent confidence intervals in brackets, using observed values for all variables except temperature or rainfall, respectively. Results presented for z-scores within approximately 1.5 standard deviations of sample mean climate values (0.389 for temperature and −0.138 for rainfall). Sampling and attrition weights applied.

Table A.2:

Climate impacts on migration rates by individual, household, and geographic attributes

	Dependent variable: Migrate							
	Stratification:							
	(1) Gender				(2) Age			
	Urban		Rural		Urban		Rural	
	Male	Female	Male	Female	Old	Young	Old	Young
Temperature	0.034** (0.013)	0.019 (0.012)	−0.000 (0.013)	−0.002 (0.015)	0.001 (0.015)	0.037*** (0.013)	−0.011 (0.014)	0.006 (0.013)
Temperature^2	−0.030** (0.012)	−0.010 (0.010)	0.019 (0.012)	0.016 (0.014)	0.004 (0.009)	−0.030** (0.012)	0.018 (0.016)	0.017 (0.012)
Rainfall	0.006 (0.015)	0.006 (0.013)	−0.018 (0.012)	−0.025* (0.014)	0.015 (0.015)	0.000 (0.015)	−0.014 (0.014)	−0.026** (0.013)
Rainfall^2	−0.020** (0.008)	−0.014** (0.007)	0.009 (0.009)	0.012 (0.008)	−0.017*** (0.006)	−0.016** (0.007)	0.012 (0.011)	0.010 (0.008)
Rain. × Temp.	−0.027* (0.015)	−0.021 (0.014)	0.031 (0.019)	0.035* (0.020)	−0.019 (0.013)	−0.024 (0.015)	0.026 (0.025)	0.038** (0.018)

	Dependent variable: Migrate							
	Stratification:							
	(1) Gender				(2) Age			
	Urban		Rural		Urban		Rural	
	Male	Female	Male	Female	Old	Young	Old	Young
F test: climate parameters = 0 (*p* values)								
Temperature	0.025	0.267	0.116	0.168	0.735	0.018	0.542	0.010
Rainfall	0.046	0.096	0.328	0.152	0.019	0.090	0.469	0.121
F test: climate parameters equal across stratification (*p* values)								
Temperature	0.065		0.813		0.025		0.074	
Rainfall	0.812		0.783		0.790		0.528	
R^2	0.012				0.013			
N	55,277				55,277			

Note: Migration outcome defined by whether an individual moved for at least 1 month in the last year. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. Observations are person-years. Includes individual and year fixed effects. Models (1) and (2) interact independent variables with gender and age dummies. Temperature and rainfall are z-scores of previous 24-months, and both sample and attrition weights applied.

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$.

Table A.3:

Climate impacts on temporary migration rates by duration

	Dependent variable: Temporary migration duration			
	(1) 1–6 months		(2) 7–12 months	
	Urban	Rural	Urban	Rural
Temperature	0.024*** (0.008)	−0.002 (0.013)	0.009 (0.007)	0.000 (0.003)
Temperature^2	−0.016** (0.008)	0.013 (0.013)	−0.007* (0.004)	0.003 (0.003)
Rainfall	0.008 (0.009)	−0.020* (0.012)	0.002 (0.007)	−0.002 (0.004)
Rainfall^2	−0.016*** (0.004)	0.006 (0.008)	−0.004 (0.003)	0.003 (0.003)
Rain. × Temp.	−0.021** (0.008)	0.028 (0.019)	−0.010 (0.007)	0.004 (0.005)
F test: climate parameters = 0 (*p* values)				
Temperature	0.016	0.254	0.281	0.539
Rainfall	0.002	0.339	0.233	0.706
F test: urban = rural climate parameters (*p* values)				
Temperature	0.102		0.117	
Rainfall	0.054		0.278	
R^2	0.009		0.005	

	Dependent variable: Temporary migration duration			
	(1)		(2)	
	1–6 months		7–12 months	
	Urban	**Rural**	**Urban**	**Rural**
N	52,721		51,145	

Note: Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. Observations are person-years. Includes individual and year fixed effects. Temperature and rainfall are z-scores of previous 24-months, and both sample and attrition weights applied. Each model drops observations that migrate for a positive duration outside the indicated category.

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$.

Table A.4:

Climate impacts on labor participation rates by activity

	Dependent variable: Occupational participation dummy							
	(1)		(2)		(3)		(4)	
	Non-agriculture		Agriculture wage		Agriculture self-employed		Not employed	
	Urban	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**
Temperature	−0.011 (0.011) [0.546]	0.000 (0.008) [0.957]	−0.012* (0.006) [0.228]	0.009* (0.005) [0.368]	0.014 (0.017) [0.546]	−0.009 (0.009) [0.561]	0.005 (0.011) [0.663]	−0.003 (0.006) [0.867]
Temperature^2	−0.009* (0.005) [0.189]	−0.001 (0.007) [0.830]	0.003 (0.003) [0.471]	−0.007 (0.004) [0.524]	−0.005 (0.010) [0.607]	0.009 (0.009) [0.613]	0.019*** (0.006) [0.004]	−0.002 (0.007) [0.830]
Rainfall	0.017 (0.013) [0.777]	0.019** (0.009) [0.066]	0.001 (0.007) [0.934]	0.012** (0.006) [0.066]	0.006 (0.012) [0.934]	−0.010 (0.008) [0.292]	−0.003 (0.013) [0.934]	−0.003 (0.006) [0.610]
Rainfall^2	−0.020*** (0.006) [0.004]	−0.016*** (0.006) [0.034]	−0.011*** (0.003) [0.001]	−0.010** (0.004) [0.040]	−0.007 (0.006) [0.247]	0.005 (0.008) [0.588]	0.015** (0.006) [0.025]	−0.003 (0.006) [0.588]
Rain. × Temp.	−0.009 (0.013) [0.880]	−0.008 (0.010) [0.684]	−0.010* (0.006) [0.375]	−0.010* (0.006) [0.318]	−0.002 (0.011) [0.880]	0.010 (0.015) [0.684]	0.005 (0.013) [0.880]	−0.002 (0.012) [0.850]
F test: climate parameters = 0 (*p* values)								
Temperature	0.011	0.767	0.016	0.270	0.777	0.639	0.000	0.890
Rainfall	0.007	0.001	0.000	0.011	0.472	0.594	0.088	0.863
F test: urban = rural climate parameters (*p* values)								
Temperature	0.181		0.009		0.626		0.004	
Rainfall	0.953		0.365		0.304		0.104	
R^2	0.058		0.017		0.005		0.012	
N	55,277		55,277		55,277		55,277	

Note: Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. Observations are person-years. Includes individual and year fixed effects. Temperature and rainfall are z-scores of previous 24-months, and both sample and attrition weights applied. Brackets provide *q*-values (Anderson, 2008).

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$.

Table A.5:

Climate impacts on labor participation rates by activity, excluding Ethiopia

	Dependent variable: Occupational participation dummy							
	(1)		(2)		(3)		(4)	
	Non-agriculture		Agriculture wage		Agriculture self-employed		Not employed	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Temperature	−0.018	−0.009	−0.015**	0.009	0.003	−0.008	0.014	−0.008
	(0.012)	(0.012)	(0.008)	(0.011)	(0.019)	(0.012)	(0.011)	(0.007)
	[0.246]	[0.515]	[0.172]	[0.515]	[0.870]	[0.515]	[0.246]	[0.515]
Temperature^2	−0.008	−0.001	0.002	−0.010	−0.003	−0.004	0.018***	0.011**
	(0.006)	(0.008)	(0.004)	(0.008)	(0.011)	(0.007)	(0.005)	(0.005)
	[0.266]	[0.898]	[0.772]	[0.459]	[0.772]	[0.722]	[0.005]	[0.071]
Rainfall	0.013	0.015	0.004	0.013	−0.001	−0.011	0.001	−0.005
	(0.014)	(0.010)	(0.007)	(0.008)	(0.010)	(0.009)	(0.012)	(0.005)
	[0.935]	[0.276]	[0.935]	[0.276]	[0.935]	[0.276]	[0.935]	[0.338]
Rainfall^2	−0.017***	−0.021***	−0.010***	−0.013**	−0.001	−0.003	0.008	0.010***
	(0.006)	(0.007)	(0.003)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
	[0.014]	[0.007]	[0.002]	[0.031]	[0.840]	[0.525]	[0.172]	[0.017]
Rain. × Temp.	−0.005	−0.014	−0.015***	−0.015	0.002	−0.012	0.002	0.021***
	(0.012)	(0.012)	(0.005)	(0.010)	(0.009)	(0.010)	(0.013)	(0.007)
	[0.862]	[0.240]	[0.030]	[0.240]	[0.862]	[0.240]	[0.862]	[0.010]
F test: climate parameters = 0 (*p* values)								
Temperature	0.001	0.249	0.000	0.507	0.930	0.298	0.000	0.024
Rainfall	0.026	0.002	0.001	0.052	0.969	0.032	0.434	0.017
F test: urban = rural climate parameters (*p* values)								
Temperature	0.187		0.014		0.324		0.002	
Rainfall	0.924		0.564		0.122		0.475	
R^2	0.069		0.018		0.002		0.014	
N	43,005		43,005		43,005		43,005	

Note: Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. Observations are person-years. Includes individual and year fixed effects. Temperature and rainfall are z-scores of previous 24-months, and both sample and attrition weights applied. Brackets provide *q*-values (Anderson, 2008).

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$.

Attrition Weight Methodology

We focus on the sample of baseline households that completed surveys in each subsequent round. A household is omitted from the sample if it moved out of its original residence and was not interviewed or if the household questionnaire was incomplete for some other reason in follow-up rounds. This procedure allows us to stratify the sample into groups of nonattritors and attritors (households and individuals surveyed at baseline who are unidentifiable in later rounds). Approximately, 15 percent of individuals in the 15–65 category at baseline were unable to be tracked over time.

For each country, we estimate probit models to determine which factors influence the probability that baseline individuals stay in the sample in later rounds. The baseline covariates in the regressions include individual gender and age, and the natural logarithms of the number of children, adults, and household land owned. We also include attrition rates of baseline individuals from the EA,[13] indicators for the baseline interview month and year, and indicators of baseline interviewers to reflect the role of field practices on survey quality (Maluccio, 2004; Thomas et al., 2012).

Table A.6 displays probit regression results. Youth are less likely to appear in Uganda and more likely to appear in Ethiopia. Households with more children and more land may be over-represented in Tanzania and Malawi. The EA attrition rate (Ethiopia and Malawi only) and the interviewer indicators are strongly correlated with remaining in the sample. This latter is determined by χ^2 tests of joint parameter significance presented at the bottom of Table A.6, which indicates we can reject that the EA attrition rate and interview variable coefficients jointly are equal to zero at the 10 percent level.

We estimated restricted versions of models in Table A.6, excluding the EA attrition rate and interview indicators (our excluded instruments) to account for selective attrition (Fitzgerald et al., 1998).[14] The ratio of predicted values from restricted and unrestricted probit regressions is used to create the inverse probability weights applied to all descriptive statistics and regressions.

Table A.6:

Determinants of remaining in sample

	Ethiopia	Malawi	Tanzania	Uganda
Female	−0.063 (0.046)	0.008 (0.086)	−0.062 (0.039)	−0.004 (0.036)
Age 20–29	0.368*** (0.082)	−0.121 (0.110)	0.055 (0.066)	−0.112* (0.060)
Age 30–39	0.719*** (0.118)	−0.004 (0.135)	0.133* (0.072)	0.258*** (0.057)
Age 40–49	0.864*** (0.121)	0.193 (0.167)	0.333*** (0.080)	0.427*** (0.062)
Age 50–59	0.790*** (0.136)	−0.116 (0.248)	0.245*** (0.094)	0.649*** (0.074)
Age 60–65	0.762*** (0.195)	0.182 (0.299)	0.235 (0.166)	0.695*** (0.117)
ln(1 + Household members age 2–15)	0.088 (0.054)	−0.075 (0.093)	0.160*** (0.045)	0.077 (0.056)
ln(1+ Household members above age 15)	−0.461*** (0.154)	−0.361** (0.146)	−0.182** (0.084)	−0.586*** (0.093)
ln(1 + Land area owned)	−0.017 (0.074)	0.329** (0.128)	0.062* (0.033)	0.043 (0.040)
ln(1 + EA attrition rate)	−2.300** (1.122)	2.611* (1.347)	0.399 (0.433)	0.006 (0.770)

[13]Individuals excluded from calculation of own attrition rate. Attrition rates based on round 2 (and 3 if available).
[14]We are unable to include climate variables in the attrition model since they are highly correlated with the excluded instruments (the interviewer indicators and the village attrition rate), which are defined at a similar geographic level.

	Ethiopia	Malawi	Tanzania	Uganda
χ^2	5.845	206.988	78.503	123.271
p value	0.054	0.000	0.016	0.000
Observations	7,266	4,377	8,800	6,372

Note: Observations are baseline individuals. Children, adults, and land owned measured at household level. Attrition rate is individuals who left the sample from a given enumeration area divided by total individuals from the enumeration area at baseline; calculation excludes surveyed individual. Indicators for the interviewer presiding over the survey and interview month and year are included. χ^2 statistic tests joint significance of interview indicators and attrition rate. A value of 1 was added to all variables before taking logs.

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$.

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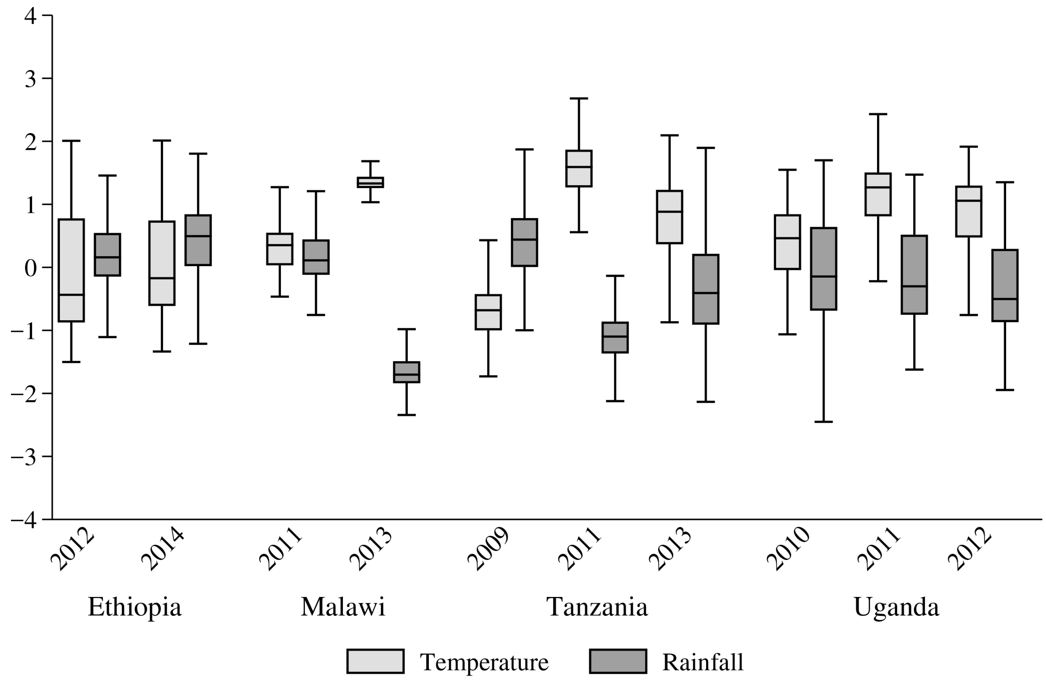

Figure 1:

Distribution of climate z-scores by country and year

Note: Lines in boxes depict 25th percentile, median, and 75th percentile. Whiskers depict farthest observations that are within 1.5 times the range of the 25th and 75th percentiles (Tukey, 1977). Sample and attrition weights applied.

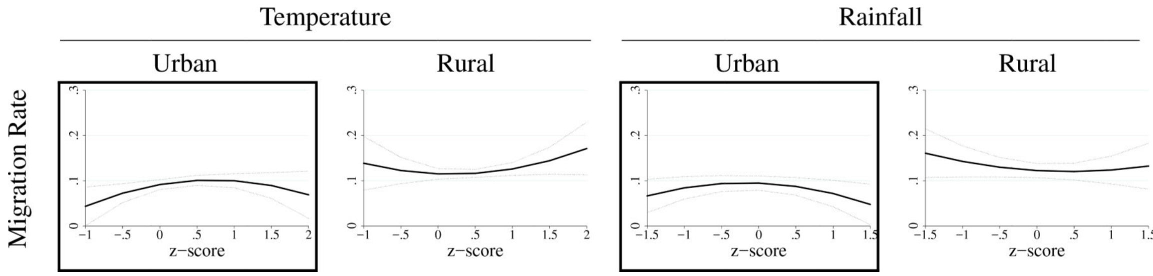

Figure 2:

Predicted temporary (1–12 month) migration response to climate by location

Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature (or precipitation) fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which an *F* test shows relevant climate response parameters are jointly significant at $p < 0.10$.

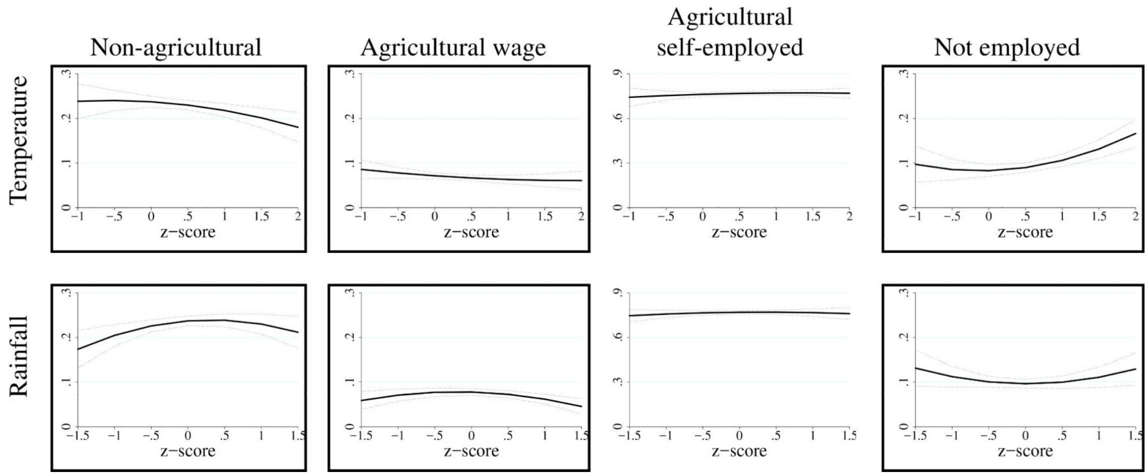

Figure 3:
Predicted urban labor participation response to climate by activity and location

Note: Solid lines are mean predicted participation rates in each activity holding all variables except temperature (or precipitation) fixed at mean values. Dotted lines represent 95 percent confidence intervals. Boxes indicate outcomes for which an F test shows relevant climate response parameters are jointly significant at $p < 0.10$.

Table 1:

Available LSMS-ISA Rounds by Country

	2009	2010	2011	2012	2013	2014
Ethiopia				X		X
Malawi			X		X	
Tanzania	X		X		X	
Uganda		X	X	X		

Note: LSMS-ISA: Living Standards Measurement Study-Integrated Surveys on Agriculture.

Table 2:

Descriptive Statistics of Working Age Population

	Ethiopia		Malawi		Tanzania		Uganda		Pooled	
	Urban	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**
Migration rates										
more than 1 month	0.03	0.09	0.09	0.07	0.16	0.12	0.13	0.12	0.12	0.11
1–6 months	0.03	0.08	0.06	0.05	0.09	0.07	0.04	0.04	0.06	0.07
7–12 months	0.00	0.01	0.03	0.02	0.06	0.05	0.09	0.08	0.05	0.04
Other occupational participation rates										
Agricultural self-employed	0.90	0.88	0.52	0.85	0.31	0.82	0.53	0.82	0.51	0.85
Agricultural wage	0.01	0.01	0.01	0.03	0.03	0.14	0.05	0.13	0.03	0.08
Non-agricultural employment	0.23	0.15	0.41	0.21	0.42	0.22	0.41	0.32	0.37	0.21
School	0.13	0.10	0.15	0.12	0.17	0.13	0.26	0.22	0.18	0.13
Not employed	0.05	0.07	0.16	0.05	0.21	0.05	0.07	0.04	0.14	0.06
Climate										
Temperature z-score	0.29 (0.73)	−0.12 (0.87)	0.88 (0.59)	0.82 (0.59)	0.44 (1.17)	0.58 (1.04)	0.83 (0.68)	0.75 (0.65)	0.52 (0.97)	0.35 (0.99)
Rainfall z-score	0.22 (0.67)	0.21 (0.67)	−0.74 (0.90)	−0.76 (1.00)	−0.02 (0.94)	−0.39 (0.84)	−0.26 (0.75)	−0.14 (0.80)	−0.07 (0.88)	−0.15 (0.84)
Other										
Age 15–34	0.62	0.59	0.68	0.65	0.68	0.65	0.58	0.58	0.65	0.62
Female	0.50	0.51	0.50	0.52	0.53	0.51	0.51	0.53	0.52	0.52
Observations	1,338	10,934	2,536	5,828	7,587	15,186	3,780	8,088	15,241	40,036

Note: Means (proportions for binary variables) with standard deviations in parentheses. Occupational variables refer to whether the individual engaged in the activity in the previous 12 months except school, which refers to current school year. Observations are person-years aged 15–65. Sample and attrition weights applied.

Table 3:

Effect of climate variation on migration rates

	(1) Main		(2) District clusters		(3) Sample weights		(4) No movers		(5) No students		(6) No Ethiopia		(7) 12 month		(8) Raw climate	
			Alternate Specifications													
	Urban	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**
Temperature	0.027** (0.010)	−0.001 (0.013)	0.027** (0.012)	−0.001 (0.013)	0.026** (0.010)	−0.001 (0.013)	0.025** (0.011)	−0.005 (0.013)	0.026*** (0.010)	0.004 (0.015)	0.019* (0.011)	−0.000 (0.010)	0.012 (0.008)	0.005 (0.009)	−0.021 (0.274)	0.014 (0.255)
Temperature^2	−0.020** (0.010)	0.017 (0.012)	−0.020* (0.011)	0.017 (0.011)	−0.019** (0.010)	0.017 (0.012)	−0.021** (0.010)	0.018 (0.012)	−0.012 (0.009)	0.016 (0.014)	−0.020** (0.010)	0.001 (0.006)	−0.006 (0.007)	0.007 (0.009)	−0.000 (0.005)	0.000 (0.005)
Rainfall	0.006 (0.011)	−0.021* (0.012)	0.006 (0.011)	−0.021* (0.011)	0.006 (0.011)	−0.021* (0.012)	0.007 (0.011)	−0.023* (0.012)	0.010 (0.011)	−0.018 (0.014)	0.009 (0.011)	−0.010 (0.007)	−0.018* (0.009)	−0.001 (0.009)	−0.335 (0.312)	0.061 (0.209)
Rainfall^2	−0.017*** (0.006)	0.011 (0.008)	−0.017*** (0.005)	0.011 (0.007)	−0.016*** (0.006)	0.010 (0.008)	−0.016*** (0.006)	0.013 (0.008)	−0.016*** (0.005)	0.015* (0.009)	−0.014** (0.006)	0.002 (0.005)	0.003 (0.006)	0.011 (0.009)	0.001 (0.007)	−0.015** (0.007)
Rain. × Temp.	−0.024** (0.011)	0.033* (0.019)	−0.024* (0.014)	0.033** (0.016)	−0.023** (0.011)	0.033* (0.018)	−0.023** (0.012)	0.038** (0.019)	−0.017 (0.010)	0.036* (0.022)	−0.027** (0.012)	0.003 (0.009)	0.014 (0.011)	0.016 (0.017)	0.014 (0.012)	0.002 (0.008)
F test: climate parameters = 0 (*p* values)																
Temperature	0.072	0.113	0.167	0.070	0.080	0.114	0.119	0.084	0.071	0.049	0.135	0.974	0.153	0.597	0.382	0.590
Rainfall	0.026	0.301	0.019	0.190	0.038	0.295	0.034	0.211	0.028	0.367	0.054	0.445	0.292	0.625	0.252	0.038
F test: urban = rural climate parameters (*p* values)																
Temperature	0.071		0.080		0.075		0.049		0.164		0.219		0.405		0.516	
Rainfall	0.029		0.018		0.036		0.020		0.017		0.125		0.298		0.359	
R^2	0.012		0.012		0.012		0.012		0.007		0.013		0.010		0.013	
N	55,277		55,277		55,277		53,573		42,894		43,005		55,277		55,277	

Note: Migration outcome defined by whether an individual moved for at least 1 month in the last year. Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. Observations are person-years. Includes individual and year fixed effects. Unless otherwise noted: temperature and rainfall are z-scores of previous 24-months, and both sample and attrition weights applied.

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$.

Table 4:

Climate impacts on urban labor participation rates by activity

	Dependent variable: Occupational participation dummy			
	(1)	**(2)**	**(3)**	**(4)**
	Non-agriculture	**Agriculture wage**	**Agriculture self-employed**	**Not employed**
Temperature	−0.011 (0.011) [0.546]	−0.012* (0.006) [0.228]	0.014 (0.017) [0.546]	0.005 (0.011) [0.663]
Temperature^2	−0.009* (0.005) [0.189]	0.003 (0.003) [0.471]	−0.005 (0.010) [0.607]	0.019*** (0.006) [0.004]
Rainfall	0.017 (0.013) [0.777]	0.001 (0.007) [0.934]	0.006 (0.012) [0.934]	−0.003 (0.013) [0.934]
Rainfall^2	−0.020*** (0.006) [0.004]	−0.011*** (0.003) [0.001]	−0.007 (0.006) [0.247]	0.015** (0.006) [0.025]
Rain. × Temp.	−0.009 (0.013) [0.880]	−0.010* (0.006) [0.375]	−0.002 (0.011) [0.880]	0.005 (0.013) [0.880]
F test: climate parameters = 0 (*p* values)				
Temperature	0.011	0.016	0.777	0.000
Rainfall	0.007	0.000	0.472	0.088
R^2	0.058	0.017	0.005	0.012
N	55,277	55,277	55,277	55,277

Note: Parameter estimates with standard errors in parentheses clustered by baseline enumeration area. Observations are person-years. Includes individual and year fixed effects. Temperature and rainfall are z-scores of previous 24-months, and both sample and attrition weights applied. Brackets provide *q*-values (Anderson, 2008).

*$p < 0.1$

**$p < 0.05$

***$p < 0.01$.