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Country-Specific Effects of Climate Variability on Human Migration

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Abstract

Involuntary human migration is among the social outcomes of greatest concern in the current era of global climate change. Responding to this concern, a growing number of studies have investigated the consequences of short to medium-term climate variability for human migration using demographic and econometric approaches. These studies have provided important insights, but at the same time have been significantly limited by lack of expertise in the use of climate data, access to cross-national data on migration, and attention to model specification. To address these limitations, we link data on internal and international migration over a 6-year period from 9,812 origin households in Kenya, Uganda, Nigeria, Burkina Faso and Senegal to high-resolution gridded climate data from both station and satellite sources. Analyses of these data using several plausible specifications reveal that climate variability has country-specific effects on migration: Migration tends to increase with temperature anomalies in Uganda, tends to decrease with temperature anomalies in Kenya and Burkina Faso, and shows no consistent relationship with temperature in Nigeria and Senegal. Consistent with previous studies, precipitation shows weak and inconsistent relationships with migration across countries. These results challenge generalizing narratives that foresee a consistent migratory response to climate change across the globe.

Keywords

human migration; climate; environmental migrant; Africa

1 Introduction

For decades, many human-environment scholars predicted that climate change would result in large-scale human displacements, creating a Malthusian wave of “climate refugees” (Houghton et al. 1992; Myers 2002). Concern in particular focused on rural populations in the developing world and in Sub-Saharan Africa, reflecting their high dependence on agriculture and lack of resources for adaptation (Müller et al. 2011). However only in the past few years has a significant body of scientific evidence begun to accumulate that rigorously evaluates these claims. These studies have linked climate data to georeferenced data on human migration, most commonly from specialized household surveys, and then

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tested climate-migration hypotheses using multivariate approaches that account for potential confounders (Bohra-Mishra et al. 2014; Gray and Mueller 2012a; Gray and Mueller 2012b; Hunter et al. 2013; Mueller et al. 2014). These studies have confirmed predictions that climate extremes can increase human migration, but otherwise the story they reveal often does not fit the conventional narrative of climate-induced displacement (Hunter et al. 2015; Obokata et al. 2014). Specifically, the effects of climate variability on migration are often larger for short-distance or temporary moves (Gray and Mueller 2012b), the effects of precipitation (which have received disproportionate attention) are often weak relative to temperature (Bohra-Mishra et al. 2014; Mueller et al. 2014), and reverse effects can occur in which climate extremes trap vulnerable populations in place (Black et al. 2011; Gray and Mueller 2012a).

Theoretical developments within migration studies and human-environment research also support a revised view of climate-induced migration. Demographers have emphasized the high social and economic costs of migration in the developing world and the selectivity of this process, often for wealthier and educated individuals, as well as the large economic benefits for migrants and sending households (Bowles 1970; Massey et al. 1993; Sjaastad 1962). This view suggests that, rather than distress migration following climate shocks, we could observe a dynamic in which better-off households send migrants as a form of investment when environmental conditions are favorable. Similarly, worse-off households might be prevented from sending migrants following shocks to their income and assets, thus representing “trapped populations” (Black et al. 2011). Meanwhile, geographers and others have emphasized the contextually-specific nature of human-environment relationships (Blaikie and Brookfield 1987), a view supported by empirical studies documenting variation in climate-agriculture and climate-conflict relationships across Sub-Saharan Africa (O’Loughlin et al. 2012; Seo et al. 2009). Human-environment researchers have also highlighted the many local adaptation strategies available to households other than migration (Deressa et al. 2009), suggesting that migration need not be the first response to environmental stress.

Thus, abundant theoretical support and limited empirical support exist to challenge generalizing narratives that envision a monolithic and unidirectional migratory response to climatic variation. To date, our ability to more broadly test for these patterns has been limited by the absence of comparable high-quality, cross-national datasets on migration. Previous studies have been constrained to the national and subnational scale by existing survey data, or to the use of national-scale data that ignores within-country heterogeneity (Marchiori et al. 2012). Previous studies have also typically made use of a single climate data source and many have focused on precipitation, ignoring evidence that climate anomalies are often poorly correlated across alternative data sources (Auffhammer et al. 2013) and that temperature often has large effects on migration relative to precipitation (Bohra-Mishra et al. 2014; Mueller et al. 2014).

To address these limitations, we make use of comparable, large-sample migration surveys conducted in Kenya, Uganda, Nigeria, Burkina Faso and Senegal in 2009–10, along with two high-resolution gridded climate datasets derived from station and satellite data. These five countries are particularly appropriate for studying climate-induced migration because they encompass a diverse range of climates and have been previously identified as potentially vulnerable to climate-induced displacement, reflecting their relative poverty and agricultural dependence. To estimate climatic effects on migration, we build a household-year dataset for 9,812 households over a 6 year period (2009-2004), link households to climate anomalies based on their district-level unit of residence, and estimate country-specific negative binomial regression models of the number of migrants sent per household-year, as described in detail below. In addition to providing a direct cross-country comparison, this approach improves on previous demographic and econometric studies of climate-induced migration by addressing uncertainties that arise from the use of a single climate dataset and the use of a single model specification. While we are not able to observe human migration over the decadal time scales that characterize long-term climate change, we use climate anomalies and a large spatial extent to observe a wide range of climate conditions, and thus hopefully provide insight into the potential impacts of future climate change.

2 Methods

Survey data are derived from the World Bank's African Migration and Remittances Surveys (AMRS), which collected standardized retrospective data on international and internal migration for ~2,000 households per country. Retrospective household-level data have a long history of successful use for investigating the determinants of migration in the developing world (Massey and Espinosa 1997; Smith and Thomas 2003). In the case of AMRS, households reported the destination of all departed household members and return migrants, as well as the timing and motivation of each move. To limit errors due to retrospection and whole-household mobility, we use data on migrants who departed in the year of data collection and in the five years prior (2004–09). In Uganda, Nigeria and Senegal the household sample is nationally representative. In Burkina Faso and Kenya, 10 provinces[1] and 17 districts respectively were included as the most important sources of migrants identified by census data (Table 1; Supplement F2). In all countries, disproportionate sampling was then used within the sample areas to oversample enumeration areas that were more important sources of migration as measured by census data, and two-phase sampling was used within enumeration areas to select households, oversampling those that had sent migrants (Gray & Bilsborrow 2013; Plaza et al. 2011). We use survey weights in all analyses to account for this sampling design. Interviews took place in late 2009 in Kenya, Burkina Faso and Senegal and early 2010 in Uganda; a small number of moves which took place in Uganda in 2010 are consolidated with those of 2009.

We use AMRS to create a household-year dataset on 9,812 households over a 6 year period (2009-2004) with information on migration and control variables (Table 1). Migration is measured as the number of migrants ages ten or older sent by the household in year *t*, a count which is subsequently decomposed by migrant destination, gender and reported motivation. Included control variables are standard for the literature on the determinants of

1To address the small number of spatial units in Burkina Faso we conducted a simulation in which one unit was removed at a time from Specification A. In these 10 simulations, the raw temperature coefficient remained highly significant in all cases and increased or decreased by a maximum of 11%. The precipitation coefficient remained non-significant in all cases.

migration (Massey and Espinosa 1997) and include household composition and characteristics of the household head at the beginning of 2004 (Table 2). These values were estimated by adding household members born before 2004 to migrants who departed during the study period and adjusting ages appropriately. Potential control variables which were likely to have been measured with error for 2004 were excluded. Given that very few households had heads under age 20 at the time of the survey, 272 households with heads under age 25 at the time of the survey were excluded from the analysis as unlikely to have been in existence in 2004. Data on one or more control variables are missing for 313 households. These values are interpolated to the country median and this interpolation was accounted for through the inclusion of missing indicators in the regression analysis. Table 2 also documents considerable heterogeneity across the five study countries, ranging from Kenya with the highest level of education, smallest household size, lowest rate of previous migration, lowest proportion rural, and lowest proportion working in the primary sector, to Burkina Faso at the opposite end of the spectrum.

Households in AMRS are linked to climate by their district-level administrative unit of residence, for a total of 140 such units. For comparison purposes, we chose two high-quality datasets that are available at high spatial resolution and extracted them as spatial means for these units: (1) the Climatic Research Unit's (CRU) time-series 3.21 containing high-resolution monthly precipitation and temperature; and (2) monthly mean land surface temperature and total surface precipitation from the NASA Modern Era-Retrospective Analysis for Research and Applications (MERRA). CRU is a monthly global dataset at 0.5° resolution (~50km at the equator) created by interpolating data from weather stations (UEACRU et al. 2013). Derived from a network of over 4000 stations, including a large number in Sub-Saharan Africa, CRU data are considered to provide reliable climate information in Africa (e.g., Zhang et al. 2013). MERRA is a reanalysis product, produced through the integration of observed data, including satellite data, with numerical models. The MERRA data are available sub-daily at 0.5° × 0.67° lat-long resolution (Rienecker et al. 2011).

From these climate data sources, we extract the following values as spatial means at the district-year scale: the total annual precipitation, the month in which 50% annual precipitation was reached, and the mean annual temperature. Temperature and precipitation anomalies were also defined relative to a 1981–2010 base period. District-level units were defined as districts in Kenya and Uganda, provinces in Burkina Faso and departments in Senegal. Temperature anomalies have been shown to have robust negative effects on agricultural output across Sub-Saharan Africa, while precipitation usually but not always has positive effects (Seo et al. 2009). Because previous studies have shown that climate can have lagged effects on migration for at least two years (Bohra-Mishra et al. 2014), we average annual climate values across year t and t-1 as well as test for longer lags (Table 3). Substantial differences in climate anomalies extracted from CRU and MERRA (Table 3) reinforce the importance of using data from multiple climate sources (Auffhammer et al. 2013).

Negative binomial regression is then used to model the number of migrants per household-year as a function of climate variables and controls. This modelling approach has been widely used across the quantitative social sciences to model count outcomes (Cameron and Trivedi 2013), including migration (Taylor et al. 2003). Our core specification of climate includes linear measures of annual precipitation and temperature anomalies derived from CRU and averaged over years *t* and *t*-1 (Table 3). We also test additional plausible specifications of climate as described below. Predictors include climate variables, a set of socio-demographic controls, district-level fixed effects, a quadratic time trend (to account for potential retrospective reporting biases), and, for a small fraction of households, indicators for missing values on one or more control variables. Standard errors are corrected for clustering at the district-level unit. Socio-demographic control variables include the number of migrants sent before 2004, rural versus urban location, and various demographic characteristics of the household and household head estimated for 2004 (Table 2). The inclusion of district-level fixed effects allows each district to have a baseline rate of migration and accounts for all time-invariant district-level factors as long as these effects are linear. To account for potential errors of retrospection we allow for a quadratic time trend by including both linear and squared terms for the year (VanWey 2005). With inclusion of the time trend, the effects of climate variables are statistically identified by local deviations of climate from the national-scale trend.

3 Results

Results of the main specifications are shown in Table 4, where the coefficients can be interpreted as the multiplicative effect of a one-unit increase in the predictor on the number of migrants sent per household. The complete results including control variables are shown in the Supplement (T2–6). As described above, our core model (specification A) includes annual precipitation and temperature anomalies averaged over years *t* and *t*-1. To test the robustness of these results, the subsequent specifications alter the climate measures, the climate data source and the temporal lag. Specification B replaces climate anomalies with raw values of temperature and precipitation, specification C adds a measure of the precipitation timing to these raw values (defined as the number of months before one half of total annual precipitation was reached), specification D uses MERRA data in place of CRU, specification E extends the lag to cover years *t* though *t*-3, and specification F removes controls for the time trend.

Consistent with previous studies focusing on single countries, this approach reveals important effects of temperature on migration but inconsistent effects of precipitation. However, novel to this literature, by using a consistent methodological approach we show that the direction of temperature effects varies across countries. With each unit increase of the two-year temperature anomaly in specification A, the number of migrants sent per household increases 123% in Uganda ($p = 0.008$), decreases 42% in Kenya ($p = 0.003$), decreases 71% in Burkina Faso ($p < 0.001$), and does not significantly change in Nigeria ($p = 0.35$) or Senegal ($p = 0.75$). The direction and significance of these effects are largely robust across alternative specifications B–F, with two key exceptions. In Specifications D–F, the positive effect of temperature in Uganda becomes marginally significant or non-significant, and the previously non-significant negative effect of temperature in Nigeria becomes statistically significant. In Kenya, Nigeria and Burkina Faso, the effect of precipitation also becomes statistically significant in particular specifications, likely reflecting differences in measurement between CRU and MERRA (Specification D), the accumulation of effects over a four-year period (Specification E), and a lack of robustness to removing the time trend (Specification F). Overall these results indicate the effect of climate on migration is somewhat sensitive to the model specification, an issue which has been largely ignored in previous studies using one or a few specifications. At the same time, the importance of climate is clear across all approaches, and for all specifications the effects of temperature are predominantly negative.

To further test the robustness of these results to alterative assumptions, we allow the effects of precipitation and temperature to be nonlinear using two approaches, maintaining the use of CRU anomalies averaged over two years as described above. First, we estimate models[2] that allow the effects of precipitation and temperature to be nonlinear via restricted cubic splines (Buis 2009). Consistent with the linear specification, the nonlinear effects of temperature are jointly significant in Kenya ($p < 0.001$), Uganda ($p < 0.001$), Nigeria ($p < 0.001$) and Burkina Faso ($p < 0.001$) (Figure 1), but non-significant in Senegal ($p = 0.21$). The nonlinear effects of precipitation are significant only for Uganda ($p = 0.034$) and Nigeria ($p < 0.001$) (Supplement F2). Migration increases most notably with the highest observed temperatures in Uganda versus with the lowest observed temperatures in Nigeria and Burkina Faso, and at both ends of the temperature spectrum in Kenya.

Second, we allow the precipitation and temperature effects to continue to be nonlinear via a quadratic specification while also allowing the linear precipitation and temperature terms to interact[3]. As observed for the prior nonlinear specification, these effects are jointly significant for Kenya ($p < 0.001$), Uganda ($p = 0.003$), Nigeria ($p < 0.001$) and Burkina Faso ($p < 0.001$), but non-significant for Senegal ($p = 0.54$). In Table 5, we present these results in the form of the predicted number of migrants per household-year for nine combinations of precipitation and temperature anomalies, ranging from dry to wet and cool to hot (see Table 2). The climate conditions producing the highest levels of migration are cool and rainy in Kenya, warm and rainy in Uganda and Nigeria, and cool and dry in Burkina Faso, though with large standard errors in all cases. As a whole, the results of these nonlinear specifications support the finding that the nature of temperature effects differs strongly across countries.

Finally, recognizing that human migration encompasses many different types of population movements, we allow the effects of climate to differ across types of migrants and households. First, we sequentially disaggregate the migration outcome by type of destination, gender of the migrant, and reported motivation of the migrant (Table 6). This analysis reveals that the effects of climate are most important for internal, male labor migrants in Kenya; internal, female non-labor migrants in Uganda; and are jointly significant for all migration flows in Nigeria and Burkina Faso. Across countries the greatest distinction appears to be between internal and international migration: climatic effects on internal migration are jointly significant or marginally significant in four countries versus two

2These models are estimated as Poisson rather than negative binomial because the POSTRCSPLINE package in Stata is available only for the former (Buis 2009).

3Thus relative to Specification A this model has three additional terms: temperature squared, precipitation squared and temperature times precipitation.

countries for international migration. Additionally, we tested for two-way interactions between climate and education, employment in the primary sector, rural location, and location in a low-precipitation district, but, consistent with previous studies (Gray and Mueller 2012a; Gray and Mueller 2012b; Mueller et al. 2014), we find that these interactions are largely non-significant (Supplement T1).

4 Discussion

Taken together, these results support further revision of the standard conceptual model of climate-induced migration, which assumes that climate change will increasingly result in long-distance, permanent flows of migrants from the developing world. Instead, our results support previous findings that temperature variability is more important for internal than international moves, and that variations in precipitation have inconsistent effects. Additionally, we provide novel cross-national evidence that temperature effects can act in opposite directions on migration, even between neighboring countries. Specifically, in Kenya we show that cool temperatures, particularly when combined with high precipitation, drive internal labor-related moves by men. This finding is consistent with views of migration as a household investment strategy (Bowles 1970; Sjaastad 1962; Stark and Bloom 1985), and suggests that households take advantage of beneficial agricultural conditions to invest in internal moves by men. In Uganda, where rates of migration are lower and poverty is higher, we find that internal non-labor-related moves by women consistently increase with temperature. This suggests a Malthusian dynamic in which households send female non-labor migrants, likely for marriage, in response to poor agricultural conditions.

Across the continent in Burkina Faso, temperature has a consistently negative effect on all migration streams including international migration, much of which is to neighboring countries in this case (Plaza et al. 2011). International migration from Burkina Faso also declines with precipitation, likely reflecting negative effects of precipitation on agricultural output in this context (Seo et al. 2009). These findings again suggest an investment or trapped populations dynamic, which appears to be operating in the very different contexts of Kenya and Burkina Faso. In Senegal, where the sample is mostly urban, we do not detect any effects of climate on migration. This finding and the high rates of previous migration for this sample suggest that Senegalese migrants are mostly insulated from these shocks. Finally, in Nigeria the results are not robust across model specifications, indicating that additional research is needed.

Geographers and others have long-recognized that human-environment relationships tend to be contextually specific, and these results strongly support that view for the case of climate and migration in Sub-Saharan Africa. Future climate change is likely to have negative consequences for many populations in the developing world (IPCC 2014), but it is becoming increasingly clear that generalizing narratives that encompass all of Africa or the developing world are likely to obscure more than they illuminate (O'Loughlin et al. 2012). At the same time, many aspects of the climate-migration relationship remain unclear. What contextual features explain the divergent temperature effects observed here? Can inconsistency in the precipitation effects be partly explained by data quality issues in CRU and MERRA? Will these results generalize to other time periods? To address these issues, future studies should seek out additional cross-national migration data sources, continue to explore various climate data sources and model specifications, and directly test for interactions of climate with contextual characteristics of place and period.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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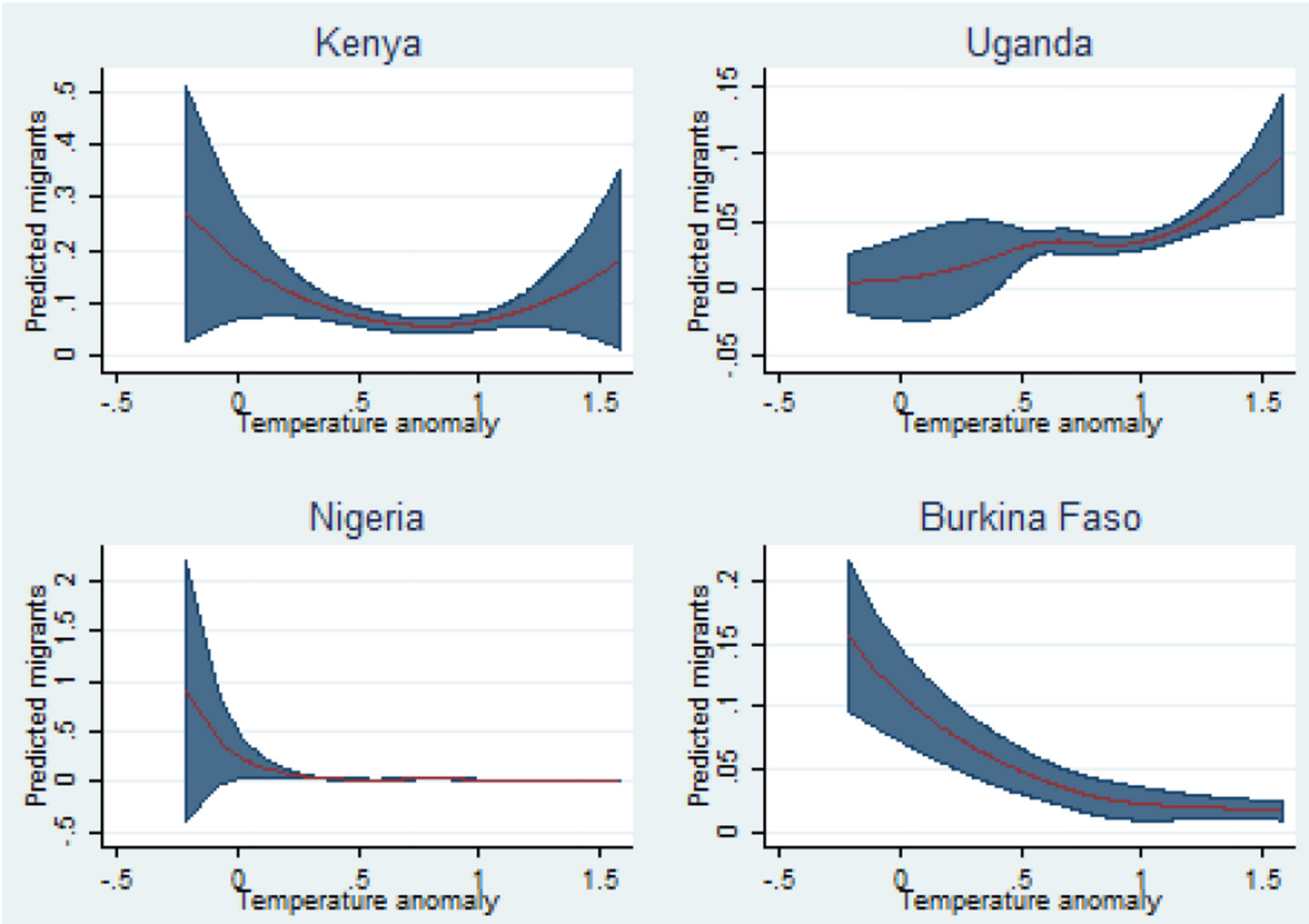
Kenya
Uganda
Nigeria
Burkina Faso
Predicted migrants
Temperature anomaly
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0
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Figure 1.

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Table 1

Sample sizes.

Sample size	Kenya	Uganda	Nigeria	Burkina Faso	Senegal
Migrants	1,390	994	2,005	1,158	1,274
Internal	768	790	1,517	583	672
International	615	204	487	574	602
Male	805	562	1,230	1,012	1,002
Female	585	432	769	146	272
Labor	794	518	910	894	913
Non-labor	594	476	1,087	259	361
Households	1,871	1,762	2,188	2,048	1,943
Rural	957	972	1,112	1,921	661
Urban	914	790	1,076	127	1,282
Primary sector	309	752	509	1,819	399
Other sector	1,562	1,010	1,679	229	1,544
Sent migrant	944	634	1,073	830	857
Sent internal	519	504	780	465	485
Sent international	486	171	384	408	454
Sent male	646	428	834	764	709
Sent female	454	309	498	116	224
Sent labor	599	384	583	674	652
Sent non-labor	436	323	667	205	279
Household-years	11,226	10,572	13,134	12,288	11,658
Districts	17	67	17	10	29
District-years	102	402	102	60	174

Table 2

Descriptive values of socio-demographic control variables at the household level.

Predictor	Kenya				Uganda				Nigeria				Burkina Faso				Senegal			
	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min
Characterisics of head																				
Female	0.22	0.41	1	0	0.25	0.43	1	0	0.06	0.25	1	0	0.04	0.21	1	0	0.17	0.37	1	0
Age	46.1	14.6	100	25	46.0	14.7	99	25	46.5	12.6	100	25	47.9	14.9	100	25	52.5	13.7	97	25
Born in rural area	0.72	0.45	1	0	0.86	0.34	1	0	0.67	0.47	1	0	0.92	0.27	1	0	0.61	0.49	1	0
Years of education	8.33	5.23	23	0	7.24	5.36	24	0	7.41	6.14	24	0	0.78	2.39	17	0	2.51	4.35	17	0
Primary sector occupation	0.17	0.38	1	0	0.58	0.49	1	0	0.31	0.46	1	0	0.90	0.29	1	0	0.24	0.43	1	0
Characteristics of household																				
Number of children (<15 years old)	1.61	1.66	13	0	2.54	2.03	14	0	2.89	2.46	18	0	3.79	2.62	21	0	3.49	2.88	27	0
Number of adult men	1.28	0.95	9	0	1.31	1.01	9	0	1.72	1.26	10	0	1.81	1.21	9	0	2.37	1.66	16	0
Number of adult women	1.40	0.91	6	0	1.37	0.87	9	0	1.55	1.05	14	0	2.06	1.31	11	0	2.59	1.71	14	0
Migrants prior to 2004	0.21	0.61	6	0	0.30	0.91	9	0	0.23	0.76	18	0	0.49	0.90	11	0	0.40	0.78	12	0
Rural location	0.49	0.50	1	0	0.83	0.38	1	0	0.54	0.50	1	0	0.93	0.25	1	0	0.49	0.50	1	0

Table 3

Descriptive values of climate variables at the province-year level.

Specification	Predictor	Kenya				Uganda				Nigeria				Burkina Faso				Senegal			
		Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min
CRU anomalies, years 0–1	Precipitation	−0.07	0.49	0.95	−1.18	0.03	0.73	1.57	−1.38	0.48	0.57	1.68	−0.86	0.44	0.50	1.45	−0.59	0.51	0.55	1.84	−0.75
	Temperature	0.77	0.24	1.25	0.21	0.95	0.26	1.58	0.39	0.67	0.20	1.17	0.21	0.66	0.43	1.35	−0.22	0.67	0.31	1.47	−0.03
CRU raw values, years 0–1	Precipitation (dm)	11.87	3.61	19.49	4.13	12.40	1.65	16.55	7.61	16.13	6.78	27.87	5.27	7.82	1.23	10.25	5.81	6.73	2.77	16.74	2.63
	Temperature (Cx10)	220	34	284	162	238	17	271	170	272	4	284	264	289	3	295	282	276	13	302	255
	Precip. timing (mo)	6.99	0.86	8.00	5.50	5.83	0.78	8.00	4.00	5.69	0.37	6.50	5.00	5.31	0.32	6.00	5.00	4.98	0.18	5.50	4.50
MERRA anomalies, years 0–1	Precipitation	−0.27	0.62	1.44	−1.29	−0.47	0.55	1.18	−1.62	−0.05	0.55	1.44	−1.63	0.18	0.43	1.21	−0.62	0.42	0.61	2.21	−0.54
	Temperature	0.14	0.80	1.61	−1.45	0.54	0.68	1.66	−1.63	0.74	0.62	2.01	−0.61	0.31	1.01	1.77	−1.25	−0.11	0.61	1.13	−1.62
CRU anomalies, years 0–3	Precipitation	−0.01	0.30	0.54	−0.73	0.03	0.39	0.96	−1.11	0.30	0.30	1.12	−0.32	0.27	0.30	0.93	−0.30	0.31	0.43	1.44	−0.66
	Temperature	0.88	0.24	1.32	0.36	1.08	0.25	1.52	0.63	0.61	0.19	0.94	0.01	0.77	0.26	1.29	0.18	0.67	0.19	1.13	0.01

Table 4

Alternative specifications of the effects of climate variability on migration (incident rate ratios, confidence intervals and significance tests).

Specification	Predictor	Kenya	Uganda	Nigeria	Burkina Faso	Senegal
		Effect of climate on migration				
A. CRU anomalies, years 0–1	Precipitation	1.15	1.13	1.30 +	0.79	0.95
		[0.95,1.39]	[0.94,1.37]	[0.98,1.73]	[0.56,1.11]	[0.75,1.20]
	Temperature	0.58 **	2.23 **	0.58	0.29 ***	1.14
		[0.40,0.83]	[1.23,4.01]	[0.18,1.82]	[0.18,0.46]	[0.52,2.51]
	Joint test	**12.0** **	**7.3** *	**17.2** ***	**28.2** ***	**0.3**
B. CRU raw values, years 0–1	Precipitation	1.06	1.07	1.14 *	0.81	0.99
		[0.96,1.16]	[0.96,1.18]	[1.01,1.29]	[0.59,1.11]	[0.84,1.17]
	Temperature	0.93 *	1.13 **	0.83	0.74 ***	1.01
		[0.86,1.00]	[1.04,1.23]	[0.57,1.21]	[0.63,0.85]	[0.85,1.20]
	Joint test	**6.6** *	**7.9** *	**24.4** ***	**16.9** ***	**0.0**
C. CRU raw values, years 0–1, plus timing of precipitation	Precipitation	1.16 **	1.08	1.11	0.81	1.03
		[1.05,1.27]	[0.95,1.23]	[0.96,1.28]	[0.60,1.10]	[0.86,1.22]
	Temperature	0.91 *	1.14 **	0.79	0.74 ***	1.01
		[0.84,0.99]	[1.04,1.25]	[0.52,1.19]	[0.64,0.85]	[0.85,1.20]
	Precip. timing	1.37 **	1.08	0.63	0.92	0.57 +
		[1.10,1.71]	[0.81,1.42]	[0.34,1.18]	[0.56,1.51]	[0.31,1.04]
	Joint test	**13.5** **	**7.7** +	**20.8** ***	**19.9** ***	**3.5**
D. MERRA anomalies, years 0–1	Precipitation	0.98	1.12	1.21 *	0.64 **	0.91
		[0.88,1.09]	[0.77,1.63]	[1.03,1.40]	[0.48,0.84]	[0.71,1.16]
	Temperature	0.77 **	1.22 +	0.40 ***	0.51 ***	1.00
		[0.65,0.92]	[0.97,1.55]	[0.29,0.56]	[0.35,0.75]	[0.65,1.53]
	Joint test	**12.3** **	**3.3**	**61.4** ***	**16.1** ***	**0.6**
E. CRU anomalies, years 0–3	Precipitation	0.87	0.95	0.25 ***	0.50 +	1.35
		[0.63,1.19]	[0.50,1.80]	[0.11,0.54]	[0.23,1.09]	[0.68,2.65]
	Temperature	0.21 ***	0.90	0.06 ***	0.14 ***	1.75
		[0.11,0.41]	[0.28,2.88]	[0.02,0.19]	[0.07,0.27]	[0.69,4.42]

Specification	Predictor	Effect of climate on migration				
		Kenya	**Uganda**	**Nigeria**	**Burkina Faso**	**Senegal**
	Joint test	**21.5** ***	**0.0**	**23.5** ***	**37.1** ***	**2.1**
F. CRU anomalies, years 0–1, no time trend	Precipitation	1.14	1.28 **	0.70 ***	0.60 +	1.10
		[0.93,1.39]	[1.09,1.51]	[0.58,0.84]	[0.35,1.03]	[0.92,1.32]
	Temperature	0.58 **	1.15	0.44 *	0.69	1.46
		[0.41,0.82]	[0.70,1.87]	[0.21,0.93]	[0.44,1.09]	[0.83,2.58]
	Joint test	**13.4** **	**11.0** **	**14.5** ***	**3.4**	**2.6**

Results from negative binomial regressions at the household-year level of the number of departed migrants. Controls, missing indicators and fixed effects are included but not shown. Joint tests are Wald tests of the climate variables.

+ $p<0.10$,

* $p<0.05$,

** $p<0.01$,

*** $p<0.001$

Table 5

Predicted number of migrants under various climate conditions (Specification G, predicted values and standard errors).

Country	Precipitation anomaly	Temperature anomaly 0.00		Temperature anomaly 0.75		Temperature anomaly 1.50	
	−1.00	0.12	(0.04)	0.03	(0.01)	0.16	(0.05)
Kenya	**0.25**	0.21	(0.07)	0.04	(0.00)	0.13	(0.05)
	1.50	0.37	(0.15)	0.05	(0.02)	0.12	(0.09)
	−1.00	0.05	(0.08)	0.02	(0.01)	0.07	(0.02)
Uganda	**0.25**	0.05	(0.04)	0.02	(0.00)	0.07	(0.03)
	1.50	0.07	(0.04)	0.03	(0.01)	0.08	(0.12)
	−1.00	0.24	(0.19)	0.01	(0.01)	0.06	(0.07)
Nigeria	**0.25**	0.13	(0.10)	0.02	(0.00)	0.34	(0.48)
	1.50	0.10	(0.07)	0.05	(0.01)	2.73	(4.61)
	−1.00	0.20	(0.36)	0.09	(0.07)	0.06	(0.03)
Burkina Faso	**0.25**	0.12	(0.04)	0.04	(0.00)	0.02	(0.01)
	1.50	0.14	(0.02)	0.04	(0.02)	0.02	(0.02)
	−1.00	0.03	(0.02)	0.06	(0.02)	0.04	(0.03)
Senegal	**0.25**	0.04	(0.02)	0.07	(0.01)	0.04	(0.01)
	1.50	0.04	(0.02)	0.07	(0.01)	0.04	(0.02)

Predicted number of migrants under various climate conditions with mean values of the other predictors from a model in which rainfall and temperature effects are allowed to be nonlinear and interact.

Table 6

The effects of climate variability on alternative measures of migration (incident rate ratios, confidence intervals and significance tests).

Outcome	Predictor	Effect of climate on migration				
		Kenya	**Uganda**	**Nigeria**	**Burkina Faso**	**Senegal**
H. Internal migrants	Precipitation	1.22 +	1.14	1.29 +	1.20	0.84
		[0.98,1.52]	[0.94,1.40]	[0.95,1.75]	[0.76,1.89]	[0.61,1.16]
	Temperature	0.55 **	2.11 *	0.54	0.49 *	0.86
		[0.36,0.85]	[1.11,3.98]	[0.16,1.83]	[0.26,0.94]	[0.37,2.02]
	Joint test	**11.0** **	**5.5** +	**16.5** ***	**6.6** *	**1.5**
I. International migrants	Precipitation	0.88	1.02	1.53 ***	0.55 **	1.05
		[0.64,1.20]	[0.64,1.61]	[1.21,1.93]	[0.37,0.82]	[0.74,1.51]
	Temperature	0.76	2.24	1.17	0.19 ***	1.81
		[0.32,1.78]	[0.44,11.42]	[0.54,2.53]	[0.11,0.32]	[0.67,4.91]
	Joint test	**1.3**	**1.0**	**14.1** ***	**38.4** ***	**1.4**
J. Male migrants	Precipitation	1.09	1.04	1.34	0.76	1.02
		[0.86,1.40]	[0.83,1.31]	[0.90,1.98]	[0.52,1.12]	[0.76,1.36]
	Temperature	0.53 *	1.69	0.64	0.30 ***	1.14
		[0.28,0.98]	[0.85,3.34]	[0.24,1.72]	[0.18,0.52]	[0.40,3.29]
	Joint test	**4.2**	**2.3**	**9.9** **	**18.8** ***	**0.1**
K. Female migrants	Precipitation	1.25	1.26	1.29	0.96	0.74 +
		[0.85,1.85]	[0.95,1.66]	[0.94,1.76]	[0.37,2.52]	[0.54,1.02]
	Temperature	0.63	2.97 *	0.56	0.20 ***	1.20
		[0.30,1.29]	[1.24,7.14]	[0.10,3.22]	[0.10,0.40]	[0.38,3.73]
	Joint test	**2.0**	**6.7** *	**19.3** ***	**33.3** ***	**5.8** +
L. Labor migrants	Precipitation	1.13	0.94	1.37 +	0.79	0.94
		[0.93,1.38]	[0.72,1.23]	[0.97,1.93]	[0.51,1.22]	[0.71,1.25]
	Temperature	0.50 **	1.07	0.82	0.31 ***	1.12
		[0.33,0.76]	[0.42,2.70]	[0.37,1.84]	[0.17,0.54]	[0.37,3.36]
	Joint test	**11.0** **	**0.3**	**5.8** +	**16.2** ***	**0.2**

Outcome	Predictor	Effect of climate on migration				
		Kenya	Uganda	Nigeria	Burkina Faso	Senegal
M. Non-labor migrants	Precipitation	1.15	1.38 *	1.29 +	0.78	0.97
		[0.81,1.63]	[1.03,1.85]	[0.98,1.71]	[0.52,1.19]	[0.64,1.46]
	Temperature	0.72	4.88 ***	0.46	0.24 **	1.18
		[0.38,1.36]	[2.41,9.88]	[0.12,1.80]	[0.09,0.67]	[0.47,2.94]
	Joint test	**1.5**	**19.4** ***	**22.3** ***	**7.5** *	**0.1**

Results from negative binomial regressions at the household-year level of the number of departed migrants. Controls, missing indicators and fixed effects are included but not shown. Joint tests are Wald tests of the climate variables.

+ $p<0.10$,

* $p<0.05$,

** $p<0.01$,

*** $p<0.001$