Country-Specific Effects of Climate Variability on Human Migration

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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 sophistication in the use of climate data and lack of access to high-quality, cross-national data on migration. To address these limitations, we link data on internal and international migration over a 6-year period from 7624 origin households in Kenya, Uganda, Burkina Faso and Senegal to high-resolution gridded climate data from both station and satellite sources. Analyses of these data reveal that climate variability has country-specific effects on migration: Migration increases with temperature anomalies in Uganda, decreases with temperature anomalies in Kenya and Burkina Faso, and shows no relationship with temperature in Senegal. Consistent with previous studies, rainfall shows only weak relationships with migration across countries. These results challenge generalizing narratives that foresee a consistent migratory response to climate change across the globe.

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 tested climate-migration hypotheses using multivariate approaches that account for potential confounders (Gray & Mueller 2012ab; Hunter et al. 2013; Bohra-Mishra et al. 2014; 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. Specifically, the effects of climate variability on migration are often larger for short-distance or temporary moves (Gray & Mueller 2012b), the effects of rainfall (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 & Mueller 2012a).

These findings support a revised view of climate-induced migration that recognizes the importance of (1) social and economic barriers to long-distance migration in the developing world, (2) the many local adaptation strategies available to rural households, and (3) the potential for climate-migration relationships to be contextually specific and vary across space. To date, however, our ability to more broadly test for these patterns has been limited 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 (e.g., Marchiori et al. 2012). Previous studies have also typically made use of a single climate data source and many have focused on rainfall, ignoring evidence that climate fluctuations are often poorly correlated across alternative data sources (Auffhammer et al. 2013) and that temperature often has large effects on migration relative to rainfall (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, Burkina Faso and Senegal in 2009-10, along with two high-resolution gridded climate datasets derived from both station and satellite data. These four 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. Migration data are derived from the World Bank's African Migration and Remittances Surveys (AMRS), which collected standardized retrospective data on international and internal migration in Kenya, Uganda, Burkina Faso and Senegal for ~2,000 households per country, using an innovative sampling design that oversampled migrant-sending households (Plaza et al. 2011; see Methods). Retrospective household-level data such as these have a long history of successful use for investigating the determinants of migration in the developing world (Smith & 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 or in the five years prior (2004-09).

We use these data to create a household-year dataset covering 7,624 households over a 6 year period (2009-2004) (Table S1). Migration is measured as the number of migrants sent by the household in year *t*, a count which is subsequently decomposed by migrant destination, gender and reported motivation. Households in this dataset were linked to climate by their district-level administrative unit of residence, for a total of 123 such units. The following climate data were extracted as spatial means for these units: 1) the Climatic Research Unit's (CRU) high-resolution monthly precipitation and temperature, derived from weather stations (CRU 2013); and 2) monthly mean land surface temperature and total surface precipitation from the NASA Modern Era-Retrospective Analysis for Research and Applications (MERRA), derived from weather satellites (Reichle et al., 2011). From these sources we calculate annual values of mean temperature and total precipitation as well as climate anomalies standardized to a 1981-2010 base period. Because previous studies have shown that climate can 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 and test for longer lags.

To test for climatic effects on migration while accounting for potential confounders, we estimate country-specific negative binomial regression models of the number of migrants sent per household-year. 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. Negative binomial regression is appropriate for count outcomes and has been previously used to model migration (Taylor et al. 2003). Standard errors are corrected for clustering at the level of the district-level unit, and all results are weighted using sampling weights.

Building on previous studies which have validated CRU, used climate anomalies as the measure of temporal variation, and identified two-year lags in climatic effects on migration, our core specification of climate includes linear measures of rainfall and temperature anomalies derived from CRU and averaged over years *t* and *t*-1 (Table S2). Temperature anomalies have been shown to have robust negative effects on agricultural output across Sub-Saharan Africa, while rainfall tends to have positive effects (Seo et al. 2009). We also test additional plausible specifications of climate as described below. 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 S3). 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. We also test the alternative inclusion of linear and cubic time trends. With inclusion of the time trend, the effects of climate variables are identified by local deviations of climate from the national-scale trend.

Results of the main specifications are shown in Table 1, 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. As described above, our core model (specification A) includes rainfall and temperature anomalies averaged over years *t* and *t*-1 and measured from CRU. 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 rainfall, specification C uses MERRA data in place of CRU, specification D extends the lag to cover years *t* though *t*-3, and specifications E and F replace the quadratic time trend with a linear and a cubic time trend, respectively.

Consistent with previous studies focusing on single countries, this approach reveals important effects of temperature on migration and only weak effects of rainfall. However, novel to this literature, we show using a consistent methodological approach 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 Senegal (p = 0.75). The direction and significance of these effects are largely robust across alternative specifications B-E with a few exceptions. In Uganda the temperature effect becomes non-significant when a four-year measure is used (D), suggesting that migration may be an immediate response to temperature that is compensated by lower migration over time. In Kenya and Burkina Faso, adding a cubic term for the year (E) renders the temperature effect non-significant, indicating that year-to-year variation in climate at the national scale is an important component of our ability to identify the effects in specification A. In Kenya and Burkina Faso, the effect of rainfall becomes statistically significant in particular specifications. We further investigate both rainfall and temperature through an additional interactive specification as described below.

To further test the robustness of these results to alterative assumptions we allow the effects of rainfall and temperature to be nonlinear using two approaches, maintaining the use of CRU anomalies averaged over two years as described above. First we allow the effects of rainfall and temperature to each be nonlinear via restricted cubic splines (Buis 2009). Consistent with the linear specification, the nonlinear effects of temperature (Figure 1) are jointly significant in Kenya ($p < 0.001$), Uganda ($p < 0.001$) and Burkina Faso ($p < 0.001$), but non-significant in Senegal ($p = 0.18$), and the nonlinear effects of rainfall are significant only for Uganda (Figure S1 in preparation). Migration increases most notably with the highest observed temperatures in Uganda versus with the lowest observed temperatures in Burkina Faso, and at both ends of the temperature spectrum in Kenya. Second, we allow the rainfall and temperature effects to continue to be nonlinear via a quadratic specification while also allowing rainfall and temperature to interact. As observed for the first nonlinear specification, these effects are jointly significant for Kenya ($p < 0.001$), Uganda ($p = 0.003$) and Burkina Faso ($p < 0.001$), but non-significant for Senegal (0.54). In Table 2, we present these results in the form of the predicted number of migrants for nine combinations of rainfall and temperature anomalies (Table 2). The climate conditions producing the highest levels of migration are cool and rainy in Kenya, warm and rainy in Uganda, 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 the nature of temperature effects differs strongly across countries, though with the existence of significant nonlinearities.

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 3). This analysis reveals that the effects of climate are most important for internal, male and labor migrants in Kenya; internal, female and non-labor migrants in Uganda; and are jointly significant for all migration flows in Burkina Faso. Additionally, we tested for two-way interactions from rainfall and temperature to education, employment in the primary sector, rural location, and location in a low-rainfall area, but, consistent with previous studies (Gray & Mueller 2012ab; Mueller et al. 2014), we find that these interactions are largely non-significant (Table S4 in preparation).

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 climate is more important for internal than international moves, and that variations in rainfall only have weak 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 rainfall, drive internal labor-related moves by men. This finding is consistent with views of migration as a household investment strategy (Stark & Bloom burkj1985), 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). This again suggests an investment dynamic. Finally in Senegal, where the sample is majority urban, there are no robust effects of climate on migration, suggesting that the population is more insulated from climate variation.

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).

Methods

Sampling: In Uganda and Senegal the household sample is nationally representative. In Kenya and Burkina Faso, 10 provinces and 17 districts respectively were included as the most important sources of migrants identified by census data. 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 (Plaza et al. 2011). Survey weights are used 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.

Survey data: Household composition at the beginning of 2004 was estimated by adding household members born before 2004 to migrants who departed during the study period, and adjusting individual ages appropriately. 245 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 126 households. These values were interpolated to the country median and this interpolation was accounted for through the inclusion of missing indicators in the regression analysis.

Climate data: CRU is derived from over 4000 weather stations, including a large number in Sub-Saharan Africa, by combining a spatial statistical approach and an underlying static climatology. This produces a monthly global dataset at 0.5° resolution (~50km at the equator) (Harris et al. 2014). MERRA uses a reanalysis approach to integrate data from NASA's collection of earth-observing satellites in a way that is consistent with physical models of the earth system. This produces sub-daily data at 0.5° x 0.67° lat-long resolution (Rienecker et al. 2011). These data were extracted at the district-year level as spatial means and linked to households by their district-level unit of residence, with the latter defined as districts in Kenya and Uganda, provinces in Burkina Faso and departments in Senegal.

References

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. Review of Environmental Economics and Policy, 7 (2): 181-198..

Black, R., Bennett, S., Thomas, S., & Beddington, J. (2011). Climate change: Migration as adaptation. Nature, 478, 447–449.

Bohra-Mishra, P., Oppenheimer, M., & Hsiang, S. M. (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. Proceedings of the National Academy of Sciences, 111(27), 9780–9785.

Buis, M. (2009). POSTRCSPLINE: Stata module containing post-estimation commands for models using a restricted cubic spline. http://ideas.repec.org/c/boc/bocode/s456928.html

CRU. (2013). CRU TS3.21: Climatic Research Unit (CRU) Time-Series (TS) Version 3.21 of High Resolution Gridded Data of Month-by-month Variation in Climate (Jan. 1901- Dec. 2012). NCAS British Atmospheric Data Centre, 24th September 2013. doi:10.5285/D0E1585D-3417-485F-87AE-4FCECF10A992.

Gray, C. L. & Bilsborrow, R. (2013). Environmental influences on human migration in rural Ecuador. Demography, 50(4): 1217-1241.

Gray, C. L., & Mueller, V. (2012a). Drought and population mobility in rural Ethiopia. World Development, 40 (1), 134–145.

Gray, C. L., & Mueller, V. (2012b). Natural disasters and population mobility in Bangladesh. Proceedings of the National Academy of Sciences, 109(16), 6000-6005.

Houghton, J. T., Callander, B. A., & Varney, S. K. (1992). Climate change 1992: the supplementary report to the IPCC scientific assessment. Cambridge University Press.

Hunter, L., Murray, S., & Riosmena, F. (2013). Rainfall patterns and U.S. migration from rural Mexico. International Migration Review, 47(4), 874–909.

IPCC. (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Marchiori, L., Maystadt, J. F., & Schumacher, I. (2012). The impact of weather anomalies on migration in sub-Saharan Africa. Journal of Environmental Economics and Management, 63(3), 355-374

Myers, N. (2002). Environmental refugees: a growing phenomenon of the 21st century. Philosophical Transactions of the Royal Society B: Biological Sciences, 357(1420), 609-613.

Mueller, V., Gray, C., & Kosec K. (2014). Heat stress increases long-term human migration in rural Pakistan. Nature Climate Change, 4(3), 182-185.

Müller, C., Cramer, W., Hare, W. L., & Lotze-Campen, H. (2011). Climate change risks for African agriculture. Proceedings of the National Academy of Sciences, 108(11), 4313-4315.

O'Loughlin, J., Witmer, F. D., Linke, A. M., Laing, A., Gettelman, A., & Dudhia, J. (2012). Climate variability and conflict risk in East Africa, 1990–2009. Proceedings of the National Academy of Sciences, 109(45), 18344-18349.

Plaza, S., Navarrete, M., & Ratha, D. (2011). Migration and Remittances Household Surveys in Sub-Saharan Africa—Methodological Aspects and Main Findings. World Bank, Washington, DC.

Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., ... & Woollen, J. (2011). MERRA: NASA's modern-era retrospective analysis for research and applications. Journal of Climate, 24(14), 3624-3648.

Seo, S. N., Mendelsohn, R., Dinar, A., Hassan, R., & Kurukulasuriya, P. (2009). A Ricardian analysis of the distribution of climate change impacts on agriculture across agro-ecological zones in Africa. Environmental and Resource Economics, 43(3), 313-332.

Smith, J. P., & Thomas, D. (2003). Remembrances of things past: Test–retest reliability of retrospective migration histories. Journal of the Royal Statistical Society: Series A (Statistics in Society), 166(1), 23-49.

Stark, O., & Bloom, D. E. (1985). The new economics of labor migration. The American Economic Review, 173-178.

Taylor, J. E., Rozelle, S., & De Brauw, A. (2003). Migration and incomes in source communities: A new economics of migration perspective from China. Economic Development and Cultural Change, 52(1), 75-101.

Table 1. Alternative specifications of the effects of climate variability on migration (incident rate ratios and significance tests).

Specification	**Predictor**	Kenya	Uganda	Burkina Faso	Senegal
A. CRU anomalies, years 0-1	Rainfall	1.15	1.13	0.79	0.95
	Temperature	0.58 **	2.23 **	0.29 ***	1.14
	Joint test	**12.0 ** **	**7.3 * **	**28.2 *** **	**0.3**
B. CRU raw values, years 0-1	Rainfall	1.06	1.07	0.81	0.99
	Temperature	0.93 *	1.13 **	0.74 ***	1.01
	Joint test	**6.6 * **	**7.9 * **	**16.9 *** **	**0.0**
C. MERRA anomalies, years 0-1	Rainfall	0.98	1.12	0.64 **	0.91
	Temperature	0.77 **	1.22 +	0.51 ***	1.00
	Joint test	**12.3 ** **	**3.3**	**16.1 *** **	**0.6**
D. CRU anomalies, years 0-3	Rainfall	0.87	0.95	0.50 +	1.35
	Temperature	0.21 ***	0.90	0.14 ***	1.75
	Joint test	**21.5 *** **	**0.0**	**37.1 *** **	**2.1**
E. CRU anomalies, years 0-1, linear year	Rainfall	1.25 *	1.20 +	0.56 *	1.00
	Temperature	0.40 ***	1.54 +	0.41 ***	1.74 +
	Joint test	**44.9 *** **	**4.5**	**13.5 ** **	**2.9**
F. CRU anomalies, years 0-1, cubic year	Rainfall	0.89	1.02	0.78	1.20
	Temperature	0.81	2.55 **	0.43 +	1.42
	Joint test	**2.8**	**9.5 ** **	**3.2**	**2.7**

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 2. Predicted number of migrants under various climate conditions (estimates and standard errors).

Country	**Rainfall anomaly**	**Temperature anomaly** 0.00	**0.75**	**1.50**
Kenya	**-1.00**	0.12 (0.04)	0.03 (0.01)	0.16 (0.05)
	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)
Uganda	**-1.00**	0.05 (0.08)	0.02 (0.01)	0.07 (0.02)
	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)
Burkina Faso	**-1.00**	0.20 (0.36)	0.09 (0.07)	0.06 (0.03)
	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)
Senegal	**-1.00**	0.03 (0.02)	0.06 (0.02)	0.04 (0.03)
	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 and mean values of other predictors from a model in which rainfall and temperature effects are allowed to be nonlinear and interact.

Table 3. The effects of climate variability on alternative measures of migration (incident rate ratios and significance tests).

Outcome	Predictor	Risk of sending a migrant Kenya	Uganda	Burkina Faso	Senegal
All migrants	Rainfall	1.15	1.13	0.79	0.95
	Temperature	0.58 **	2.23 **	0.29 ***	1.14
	Joint test	**12.0 ****	**7.3 ***	**28.2 *****	**0.3**
Internal migrants	Rainfall	1.22 +	1.14	1.20	0.84
	Temperature	0.55 **	2.11 *	0.49 *	0.86
	Joint test	**11.0 ****	**5.5 +**	**6.6 ***	**1.5**
International migrants	Rainfall	0.88	1.02	0.55 **	1.05
	Temperature	0.76	2.24	0.19 ***	1.81
	Joint test	**1.3**	**1.0**	**38.3 *****	**1.4**
Male migrants	Rainfall	1.09	1.04	0.76	1.02
	Temperature	0.53 *	1.69	0.30 ***	1.14
	Joint test	**4.2**	**2.3**	**18.8 *****	**0.1**
Female migrants	Rainfall	1.25	1.26	0.96	0.74 +
	Temperature	0.63	2.97 *	0.20 ***	1.20
	Joint test	**2.0**	**6.7 ***	**33.3 *****	**5.8 +**
Labor migrants	Rainfall	1.13	0.94	0.79	0.94
	Temperature	0.50 **	1.07	0.31 ***	1.12
	Joint test	**11.0 ****	**0.3**	**16.2 *****	**0.2**
Non-labor migrants	Rainfall	1.15	1.38 *	0.78	0.97
	Temperature	0.72	4.88 ***	0.24 **	1.18
	Joint test	**1.5**	**19.4 *****	**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

Figure 1. Nonlinear effects of temperature on migration in Uganda, Senegal, Kenya and Burkina Faso.

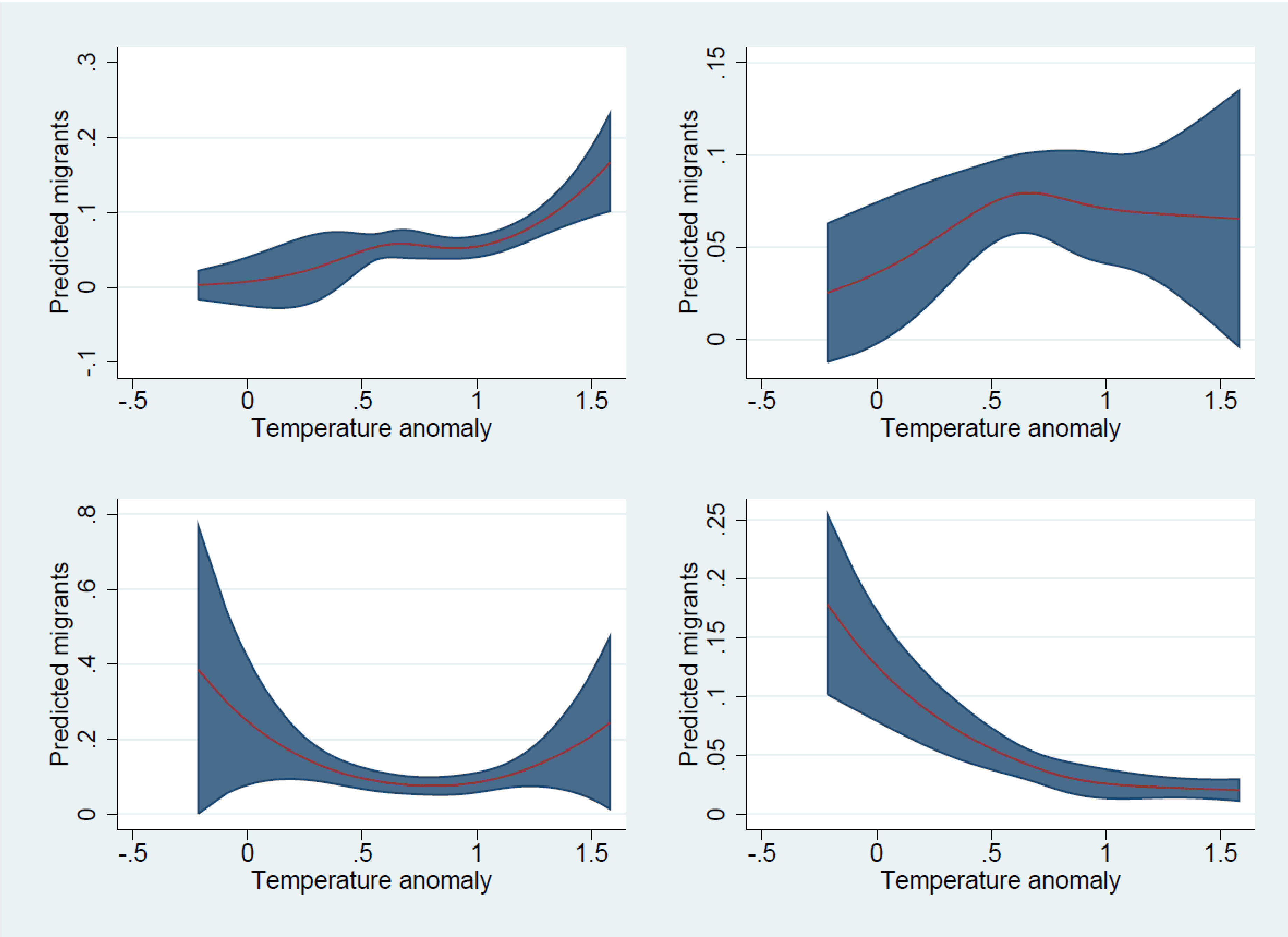

Table S1. Sample sizes.

Sample size	Uganda	Kenya	Burkina Faso	Senegal
Migrants	994	1,390	1,158	1,274
Internal	790	768	583	672
International	204	615	574	602
Male	562	805	1,012	1,002
Female	432	585	146	272
Labor	518	794	894	913
Non-labor	476	594	259	361
Households	1,762	1,871	2,048	1,943
Rural	972	957	1,921	661
Urban	790	914	127	1,282
Primary sector	752	309	1,819	399
Other sector	1,010	1,562	229	1,544
Household-years	10,572	11,226	12,288	11,658
Districts	67	17	10	29
District-years	402	102	60	174

Table S2. Descriptive values of climate variables at the province-year level.

Specification	Predictor	Uganda				Kenya				Burkina Faso				Senegal			
		Mean	**SD**	**Max**	**Min**	**Mean**	**SD**	**Max**	**Min**	**Mean**	**SD**	**Max**	**Min**	**Mean**	**SD**	**Max**	**Min**
CRU anomalies, years 0-1	Rainfall	0.03	0.73	1.57	-1.38	-0.07	0.49	0.95	-1.18	0.44	0.50	1.45	-0.59	0.51	0.55	1.84	-0.75
	Temperature	0.95	0.26	1.58	0.39	0.77	0.24	1.25	0.21	0.66	0.43	1.35	-0.22	0.67	0.31	1.47	-0.03
CRU raw values, years 0-1	Rainfall (dm)	12.40	1.65	16.55	7.61	11.87	3.61	19.49	4.13	7.82	1.23	10.25	5.81	6.73	2.77	16.74	2.63
	Temperature (K)	238	17	271	170	220	34	284	162	289	3	295	282	276	13	302	255
MERRA anomalies, years 0-1	Rainfall	-0.47	0.55	1.18	-1.62	-0.27	0.62	1.44	-1.29	0.18	0.43	1.21	-0.62	0.42	0.61	2.21	-0.54
	Temperature	0.54	0.68	1.66	-1.63	0.14	0.80	1.61	-1.45	0.31	1.01	1.77	-1.25	-0.11	0.61	1.13	-1.62
CRU anomalies, years 0-3	Rainfall	0.03	0.39	0.96	-1.11	-0.01	0.30	0.54	-0.73	0.27	0.30	0.93	-0.30	0.31	0.43	1.44	-0.66
	Temperature	1.08	0.25	1.52	0.63	0.88	0.24	1.32	0.36	0.77	0.26	1.29	0.18	0.67	0.19	1.13	0.01

Table S3. Descrptive values of socio-demographic control variables at the household level.

Predictor	Uganda				Kenya				Burkina Faso				Senegal			
	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min
Characterisics of head																
Female	0.25	0.43	1	0	0.22	0.41	1	0	0.04	0.21	1	0	0.17	0.37	1	0
Age	46.0	14.7	99	25	46.1	14.7	116	25	47.9	15.0	125	25	52.5	13.7	97	25
Born in rural area	0.86	0.34	1	0	0.72	0.45	1	0	0.92	0.27	1	0	0.61	0.49	1	0
Years of education	7.25	5.38	32	0	8.33	5.23	23	0	0.78	2.39	17	0	2.51	4.35	17	0
Primary sector occupation	0.58	0.49	1	0	0.17	0.38	1	0	0.90	0.29	1	0	0.24	0.43	1	0
Characteristics of household																
Number of children (<15 years old)	2.54	2.03	14	0	1.61	1.66	13	0	3.79	2.62	21	0	3.49	2.88	27	0
Number of adult men	1.31	1.01	9	0	1.28	0.95	9	0	1.81	1.21	9	0	2.37	1.66	16	0
Number of adult women	1.37	0.87	9	0	1.40	0.91	6	0	2.06	1.31	11	0	2.59	1.71	14	0
Sent migrant prior to 2004	0.30	0.91	9	0	0.21	0.61	6	0	0.49	0.90	11	0	0.40	0.78	12	0
Rural location	0.83	0.38	1	0	0.49	0.50	1	0	0.93	0.25	1	0	0.49	0.50	1	0

Table S4. Results for Kenya and Uganda of the specifications presented in Table 1 including control variables (incident rate ratios and significance tests).

Predictor	Kenya						Uganda					
	A	B	C	D	E	F	A	B	C	D	E	F
Climate variables												
CRU anomalies, years 0-1, rainfall	1.15	-	-	-	1.25 *	0.89	1.13	-	-	-	1.20 +	1.02
CRU anomalies, years 0-1, temperature	0.58 **	-	-	-	0.40 ***	0.81	2.23 **	-	-	-	1.54 +	2.55 **
CRU raw values, years 0-1, rainfall	-	1.06	-	-	-	-	-	1.07	-	-	-	-
CRU raw values, years 0-1, temperature	-	0.93 *	-	-	-	-	-	1.13 **	-	-	-	-
MERRA anomalies, years 0-1, rainfall	-	-	0.98	-	-	-	-	-	1.12	-	-	-
MERRA anomalies, years 0-1, temperature	-	-	0.77 **	-	-	-	-	-	1.22 +	-	-	-
CRU anomalies, years 0-3, rainfall	-	-	-	0.87	-	-	-	-	-	0.95	-	-
CRU anomalies, years 0-3, temperature	-	-	-	0.21 ***	-	-	-	-	-	0.90	-	-
Controls												
Female	1.24 *	1.24 *	1.24 +	1.24 +	1.24 *	1.24 +	1.06	1.06	1.06	1.06	1.06	1.06
Age	1.07 ***	1.07 ***	1.07 ***	1.07 ***	1.07 ***	1.07 ***	1.00	1.00	1.00	1.00	1.00	1.00
Age squared	1.00 **	1.00 **	1.00 **	1.00 **	1.00 **	1.00 **	1.00	1.00	1.00	1.00	1.00	1.00
Born in rural area	1.00	1.00	1.00	1.00	1.00	1.00	0.91	0.91	0.91	0.91	0.91	0.91
Years of education	1.02	1.02	1.02	1.02	1.02	1.02	1.04 +	1.04 +	1.04 +	1.04 +	1.04 +	1.04 +
Years of education squared	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Primary sector occupation	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Number of children (<15 years old)	1.07 *	1.07 *	1.08 *	1.07 *	1.07 *	1.08 *	1.11 ***	1.11 ***	1.11 ***	1.11 ***	1.11 ***	1.11 ***
Number of adult men	1.56 ***	1.56 ***	1.56 ***	1.56 ***	1.56 ***	1.56 ***	1.41 ***	1.41 ***	1.41 ***	1.41 ***	1.41 ***	1.41 ***
Number of adult women	1.54 ***	1.54 ***	1.54 ***	1.55 ***	1.54 ***	1.55 ***	1.51 ***	1.50 ***	1.50 ***	1.50 ***	1.51 ***	1.50 ***
Sent migrant prior to 2004	1.08	1.08	1.08	1.08	1.08	1.08	0.96	0.96	0.96	0.96	0.96	0.96
Rural location	0.98	0.98	0.98	0.98	0.98	0.98	1.08	1.08	1.08	1.08	1.08	1.08
Year	1.37 **	1.42 ***	1.54 ***	1.52 ***	1.11 **	3.95 ***	1.16	1.17	1.05	1.03	0.89 **	1.70 +
Year squared	0.95 *	0.94 **	0.93 ***	0.96 *	-	0.57 ***	0.94 *	0.94 *	0.97 +	0.97	-	0.77 +
Year cubed	-	-	-	-	-	1.07 ***	-	-	-	-	-	1.03

Results from negative binomial regressions at the household-year level of the number of departed migrants. Missing indicators and fixed effects are included but not shown.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table S5. Results for Burkina Faso and Sengal of the specifications presented in Table 1 including control variables (incident rate ratios and significance tests).

Predictor	Burkina Faso						Senegal					
	A	B	C	D	E	F	A	B	C	D	E	F
Climate variables												
CRU anomalies, years 0-1, rainfall	0.79	-	-	-	0.56 *	0.78	0.95	-	-	-	1.00	1.20
CRU anomalies, years 0-1, temperature	0.29 ***	-	-	-	0.41 ***	0.43 +	1.14	-	-	-	1.74 +	1.42
CRU raw values, years 0-1, rainfall	-	0.81	-	-	-	-	-	0.99	-	-	-	-
CRU raw values, years 0-1, temperature	-	0.74 ***	-	-	-	-	-	1.01	-	-	-	-
MERRA anomalies, years 0-1, rainfall	-	-	0.64 **	-	-	-	-	-	0.91	-	-	-
MERRA anomalies, years 0-1, temperature	-	-	0.51 ***	-	-	-	-	-	1.00	-	-	-
CRU anomalies, years 0-3, rainfall	-	-	-	0.50 +	-	-	-	-	-	1.35	-	-
CRU anomalies, years 0-3, temperature	-	-	-	0.14 ***	-	-	-	-	-	1.75	-	-
Controls												
Female	1.30	1.30	1.29	1.31	1.30	1.29	1.34 +	1.34 +	1.34 +	1.34 +	1.34 +	1.34 +
Age	1.06 **	1.06 **	1.06 **	1.06 **	1.06 **	1.06 **	1.01	1.01	1.01	1.01	1.01	1.01
Age squared	1.00 *	1.00 *	1.00 *	1.00 *	1.00 *	1.00 *	1.00	1.00	1.00	1.00	1.00	1.00
Born in rural area	0.62 *	0.62 *	0.62 *	0.62 *	0.63 *	0.62 *	1.21	1.21	1.21	1.21	1.21	1.21
Years of education	1.14 ***	1.14 ***	1.14 **	1.14 ***	1.14 **	1.14 **	1.01	1.01	1.01	1.01	1.01	1.01
Years of education squared	0.99 *	0.99 *	0.99 *	0.99 *	0.99 *	0.99 *	1.00	1.00	1.00	1.00	1.00	1.00
Primary sector occupation	1.50	1.49	1.50	1.49	1.48	1.50	1.45	1.45	1.45	1.45	1.45	1.46
Number of children (<15 years old)	1.04	1.04	1.04	1.04	1.04	1.04	0.96 *	0.96 *	0.96 *	0.96 *	0.96 *	0.96 *
Number of adult men	1.54 ***	1.54 ***	1.54 ***	1.54 ***	1.54 ***	1.54 ***	1.30 ***	1.30 ***	1.30 ***	1.30 ***	1.30 ***	1.30 ***
Number of adult women	1.00	1.00	1.00	1.00	1.00	1.00	1.17 ***	1.17 ***	1.17 ***	1.17 ***	1.17 ***	1.17 ***
Sent migrant prior to 2004	1.07 *	1.07 *	1.08 *	1.07 *	1.07 *	1.07 *	1.00	1.00	1.00	1.00	1.00	1.00
Rural location	1.29	1.28	1.29	1.29	1.29	1.29	1.02	1.02	1.03	1.03	1.02	1.02
Year	3.34 ***	3.23 ***	4.19 ***	4.34 ***	1.15 ***	4.51 ***	1.45 +	1.48 +	1.48 *	1.31	0.94 +	3.04 ***
Year squared	0.84 ***	0.84 ***	0.82 ***	0.78 ***	-	0.67 +	0.92 *	0.92 *	0.92 **	0.95	-	0.60 ***
Year cubed	-	-	-	-	-	1.03	-	-	-	-	-	1.06 **

Results from negative binomial regressions at the household-year level of the number of departed migrants. Missing indicators and fixed effects are included but not shown.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001