Large rural-urban wage gaps observed in many developing countries are suggestive of barriers to migration that keep potential migrants in rural areas. Using long panel data spanning nearly two decades, I study the extent to which migration rates are constrained by liquidity constraints in rural Tanzania. The analysis begins by quantifying the impact of weather variation on household welfare. The results show how household consumption co-moves with temperature, rendering households vulnerable to local weather events. These temperature-induced income shocks are then found to inhibit long-term migration among men, thus preventing them from tapping into the opportunities brought about by geographical mobility.

Key words: Liquidity constraints, Africa, growing degree days, duration models.

JEL codes: O12, O15, Q54, R23.

Internal migration typically takes center stage when underdeveloped countries modernize and move away from subsistence agriculture (Lewis 1954; Ranis and Fei 1961; Chenery and Syrquin 1975; Collier and Dercon 2014). A recent case in point is China, where the share of people living in urban areas rose from 20% in 1980 to 50% in 2011 (United Nations 2012). Another example is provided by the United Nations Organization for Education, Science, and Culture (UNESCO), which reports that more than 30% of India’s 1.21 billion people were internal migrants in 2011 (UNESCO 2013). This demographic process is also likely to accelerate in sub-Saharan Africa in the next few decades if its emerging countries maintain their rapid economic growth.1

Despite continued growth and increased geographical mobility, large wage-gaps exist between sectors in many developing countries. Both Young (2013) and Gollin, Lagakos, and Waugh (2014) show how labor productivity in the urban (non-agricultural) sector is much larger than in the rural (agricultural) sector. This agricultural productivity gap is suggestive of some type of barrier to internal migration that prevents potential migrants from exploiting this apparent arbitrage opportunity. Alternatively, as argued by Young (2013), the gap is an outcome of an

1 For more details on the “African Growth Miracle,” see Radelet (2010), Young (2012), McKay (2013), and McMillan and Harttgen (2014).
efficient geographical sorting of observed and unobserved skill within the economy. In this case, “... the urban-rural gap is not in and of itself a distortion, it simply reflects efficient sorting conditional on unobserved characteristics of urban-rural life” (Young 2013).

Identifying which of the above explanations is the correct one has important implications for policy. If barriers to migration exist, removing them would lead to better allocation of labor and presumably to better aggregate productivity. It would also reduce spatial inequalities within countries. However, if labor is already allocated efficiently, then there is no market failure to address.

I revisit this question by investigating whether financial constraints in rural areas act as a barrier to migration. The article views long-term migration as an investment. Migration is associated with various costs—for example, travel expenses and search costs in the destination area (Franklin 2015; Morten and Oliveira 2016)—that are borne up front. In the presence of credit constraints, potential migrants can only finance migration by accumulating enough savings before migrating. Furthermore, approximately 97% of African crop land is rainfed (Faurès and Santini 2008), rendering the livelihoods of rural households extremely vulnerable to weather variation. If incomes, and therefore savings, co-move with weather (temperature and precipitation) then migration rates should also respond to weather variation. If liquidity constraints bind, migration rates decrease with negative weather shocks. Such a correlation should not exist in the absence of binding liquidity constraints.

The empirical part of the article sets out to test this hypothesis by exploiting a two-decade long panel data set from the Kagera region in Tanzania. The survey provides baseline data based on a comprehensive household questionnaire administered from 1991 to 1994. A further round of the survey conducted in 2010 attempted to track all individuals, irrespective of whether they still resided in their original baseline village or not. In this follow-up round we also collected detailed information on migration histories since 1994. The migration data were then linked to historical temperature and precipitation records in an attempt to shed light on how local weather shocks shape long-term migration decisions in a context of mass migration.

The analysis begins by documenting how household welfare co-moves with local weather events. Controlling for precipitation, household fixed effects, and various time-varying factors, I find that a one standard deviation increase in the mean monthly growing season temperature decreases household per capita consumption by 4.9%, on average. Having established that household incomes co-move with weather outcomes, I then model migration decisions using temperature changes as a proxy for income shocks. More specifically, I use discrete time duration models (Allison 1982; Jenkins 1995) to test whether these local weather shocks affect long-term migration decisions in Tanzania. I find that adverse temperature shocks reduce long-term migration among men. A one standard deviation increase in the previous year’s average monthly growing season temperature reduces the overall male migration rate by about 13%. Female migration is not affected by these shocks, possibly due the fact that it is largely motivated by marriage and family in this context. Further investigation reveals that the migration choices of men originating from wealthier households are less constrained by these temperature shocks.

This article speaks to the emerging evidence on “geographic poverty traps” (Jalan and Ravallion 2002; De Weerdt 2010). The literature on poverty traps identifies geographic location as a factor that locks people into poverty, which results in a puzzle: Why do more people not migrate away from these remote areas (Kraay and McKenzie 2014)? The same question is also raised by Beegle, De Weerdt, and Dercon (2011) who, using the same data as the current article, find that internal migration comes with high returns in Tanzania. Liquidity constraints coupled with high migration costs seem to emerge as a part of the answer. In an insightful study, Bryan, Chowdhury, and Mobarak (2014) use an

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1 I only consider long-term internal migration spells. This is in part motivated by the data used in this article, where the average migration spell is more than 8 years.

2 More than 50% of the original panel respondents (who were still alive in 2010) had out-migrated from their baseline villages by 2010. For more details, see De Weerdt and Hirvonen (2016).

3 This analysis borrows techniques from an emerging body of literature that studies how migration rates respond to weather shocks in different contexts (Barrios, Bertinelli, and Strobl 2006; Feng, Krueger, and Oppenheimer 2010; Dillon, Mueller, and Salau 2011; Gray and Mueller 2012b, 2012a; Marchiori, Maystadt, and Schumacher 2012; Mueller, Gray, and Kosec 2014). For recent reviews of this literature, see Lilleør and Van den Broeck (2011), Maystadt and Mueller (2012) and Marchiori, Maystadt, and Schumacher (2013).
experimental setting in Bangladesh to explore the role of liquidity constraints on seasonal migration decisions. These authors randomly allocated a small incentive to households to out-migrate during the off-season, and found that seasonal migration rates increase considerably in the treatment villages. These authors also found that households close to subsistence were most responsive to the intervention. This suggests that liquidity constraints play a role in preventing individuals from engaging in seasonal migration. Still, as argued by Munshi and Rosenzweig (2016), temporary migration cannot entirely close the agricultural productivity gap because it is mostly seasonal and because many jobs in the non-agricultural sector require long-term contracts. The strength of this article lies in its ability to shed light on this issue by using “real-world” data over a long time period.

Data

Context

Kagera is a region in the northwestern part of Tanzania, bordering Uganda, Rwanda, and Lake Victoria. According to the 2012 Tanzanian Census, the region has a population of roughly 2.5 million people (The United Republic of Tanzania 2013). The region is overwhelmingly rural and relatively remote. Of all regions in Tanzania, Kagera is the farthest from Dar es Salaam, which is the commercial capital of the country. According to the United Republic of Tanzania (URT), more than 80% of the economically active population engage in agricultural production (URT 2012). The main food crops are bananas, beans, maize, and cassava, while coffee, tea, and cotton are important cash crops. Only 2% of agricultural households reported having access to irrigation in 2007/08 (URT 2012).

Kagera has two rainy seasons in which agricultural production takes place. The long rainy season (Masika) usually occurs between March and May, while the short rainy season (Vuli) comes between October and December. Earlier literature has documented how poor rainfall (i.e., droughts) can have serious consequences for incomes in this context (Bengtsson 2010). Excess rains are less of a problem due to the emphasis of the production in tree crops and also because the terrain is relatively undulating. Despite its close proximity to the Equator, temperatures in the region are moderate, with average monthly temperatures ranging between 21–23.5 °C. These moderate temperatures are partly due to high elevation, with altitudes ranging between 1–2 km above sea level. The online supplementary appendix provides the average monthly precipitation and temperature patterns in the region.

Survey

The Kagera Health and Development Survey (KHDS) was originally designed and implemented by the World Bank and the Muhimbili University College of Health Sciences. The baseline survey consisted of 915 households from 51 villages that were interviewed up to four times between autumn 1991 and January 1994 (see World Bank 2004, for more details). The 2004 and 2010 follow-up surveys attempted to re-interview all individuals that were interviewed at the baseline and were still alive at the time of the re-survey. A full household questionnaire was administered in a household where a panel respondent was found residing. Due to household dynamics (e.g., children leaving the households), the sample size increased to more than 2,700 households in 2004 (see Beegle, De Weerdt, and Dercon 2006, for more details) and to more than 3,300 in 2010 (see De Weerdt et al. 2012, for more details). The household re-contact rates are exceptionally high by the standards of such panels (Alderman et al. 2001). Excluding households for which all previous members were deceased, the re-contact rate was 93% in 2004 and 92% in 2010. At the individual level, the re-interview rates among surviving panel respondents were 82% in 2004 and 85% in 2010.7

5 In the international migration context, Angelucci (2015) and Bazzi (2013) also find evidence that liquidity constraints may inhibit migration.

6 The “as the crow flies” distance from the region’s capital (Bukoba) to Dar es Salaam is more than 1,000 km.

7 For about 40% of the individuals (out of 752) who were not interviewed in 2010, I know the year in which they out-migrated (through secondary sources). Including these individuals in the sample and re-running the migration regressions without the time-varying control variables (for which the key source is the 2010 data round) yields very similar coefficients (results are reported in the online supplementary appendix). This suggests that attrition at the individual level is not a major concern to the analysis.
Migration

Table 1 provides an overview of the migration patterns at the individual level. By 2010, more than half of the re-interviewed panel respondents were located in their 1991–94 baseline community; 9% had relocated to a nearby village and 24% lived elsewhere in Kagera. About 14% of the re-contacted respondents were found elsewhere in Tanzania. We also tracked respondents in Uganda, where 1% of the interviewed panel respondents were found. Transforming the data to the household level reveals that 84% of the re-contacted baseline households had at least one migrant member in 2010.

Earlier work using these data report large income gains from internal migration. Using the 1991–2004 panel of the survey, Beegle, De Weerdt, and Dercon (2011) find that migrants enjoy a 36 percentage point growth premium over non-migrants—even after addressing selection on unobservable traits. Table 2 shows that despite minor differences in welfare in the early 1990s, those who migrated out of the village by 2010 became richer than those who decided to stay. Panel respondents who moved out of their original baseline district saw their consumption more than double over the 19-year period. The poverty head count rate also declined most among this group compared to those who stayed or moved within their baseline district.

The 2010 questionnaire collected detailed information about migration histories; the migration module focused on long-term migration spells of at least six months. Each panel respondent was asked how many times they had migrated, as well as the year they first left the baseline village. For return migrants, the year of return to the baseline village is also known. The recall nature of the questionnaire is less of a concern here. First, as we tracked individuals who migrated, these questions were asked directly from the migrants and not, as is often the case, from those who stayed behind. Second, the questionnaire focused on long-term migration spells. Psychological and survey methodological literature suggests that individuals are (more) likely to remember salient events (Dex 1995) such as weddings or long-term migration spells. This is further confirmed by Smith and Thomas (2003), who employ matched migration history data from Malaysia to model recall bias associated with migration. These authors find that the length of the migration spell was positively associated with the likelihood that the respondent reported to have migrated, and recommend that migration history modules should focus on moves that lasted at least six months.

Table 3 provides a summary of the reasons for leaving the baseline village. More than one-third of the female respondents (but none of the male respondents) cited marriage as the reason for migrating, which is what one would expect in a culture with patrilocal marriages. Typically, the future husband and his household are responsible for the bride price. Therefore, it is anticipated that female migration patterns are less affected by weather-related shocks.10 Less than 15% of the female respondents reported that they left because of work. In contrast, almost 45% of the male migrants reported moving because they had found work or went looking for work. Given these differences in out-migration motives, I analyze the impact of weather shocks on

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Table 1. KHDS 2010 Migration Patterns

| Location                  | %  |
|---------------------------|----|
| Same community            | 52 |
| Nearby village            | 9  |
| Elsewhere in Kagera       | 24 |
| Other region              | 14 |
| Uganda                    | 1  |
| **Total**                 | **100** |

| Number of individuals     | 4,336 |

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8 Hirvonen and Lilleør (2015) offer a descriptive analysis on return migration in this context using the same data.

9 The maximum observed migration spell is 16 years (individuals who left in 1994 and have not returned by 2010). The migration spells are longer for women (9.1 years) and individuals who left because of schooling (11.4 years).

10 In a seminal paper, Rosenzweig and Stark (1989) find that marriage-related female migration in rural India is used to mitigate ex ante risk. Households pool risk with distant households connected by marriage. The focus here is different: in this article I study the role of ex post shocks on migration rates.
Migration patterns separately for men and women. Age is one of the main determinants of migration decisions. According to these data, most migration occurs when individuals turn 15 and before they turn 40. This motivates restricting the migration analysis to individuals aged 15–39. Education is another important determinant of out-migration; individuals with secondary education degrees are more likely to leave. The online supplementary appendix shows the annual migration rates for each age group and level of education by gender.

Temperature and Precipitation Data

For a given geographical area, the quality of the weather data typically depends on the number of active weather stations. In poor countries, the collection of accurate weather data may not always be a priority. In Africa, like other continents, the number of active weather stations has been in steady decline over the past decades (Lorenz and Kunstmann 2012). Thus, the so-called re-analysis data based on combining satellite and in situ observations provide a valuable resource for regions with a sparse station network.

The temperature data come from NASA’s Modern-Era Retrospective analysis for Research and Applications (MERRA), which is a global, gridded data set based on retrospective analysis of historical weather data obtained from satellite images and weather stations (Rienecker et al. 2011). I use GPS coordinates to link the gridded temperature data to the baseline villages. The data set provides daily temperature measures aggregated into grids that are 1/2° in latitude by 2/3° in longitude (roughly 55 km x 75 km at the equator).

I also use data on precipitation. Temperature and precipitation are likely to be correlated, and without the inclusion of one or the other, the identification may suffer from the classic omitted variable bias (Auffhammer et al. 2013). For precipitation I can exploit data based on a dense station network.

Table 2. Consumption and Poverty Dynamics of the Panel Respondents between 1991 and 2010, by Migration Status

| Reason | N | Mean 1991 | Mean 2010 | difference |
|--------|---|-----------|-----------|------------|
| Non-migrant | 2,224 | 343,718 | 492,398 | 148,680*** |
| Migrant: within district | 941 | 347,329 | 559,480 | 212,150*** |
| Migrant: out of district | 1,106 | 387,790 | 1,015,192 | 627,402*** |
| Full Sample | 4,271 | 355,926 | 642,558 | 286,632*** |

Note: All consumption values have been temporally and spatially deflated using data from a price questionnaire included in the survey. The consumption values here are in annual per capita terms and expressed in 2010 Tanzanian shillings. Significance of the difference in means based on a t-test; *** = p<0.01.

Table 3. Reasons for Leaving the Baseline Village (Full Sample)

| Reason | Males (%) | Females (%) |
|--------|-----------|-------------|
| To look for work | 29.8 | 7.5 |
| Own schooling | 16.0 | 10.3 |
| Found work | 15.1 | 6.7 |
| To live in a healthier environment | 10.4 | 11.7 |
| Marriage | 0.0 | 38.9 |
| Other reason | 28.8 | 24.9 |
| Total | 100.0 | 100.0 |

Note: This table also appears in De Weerdt and Hirvonen (2016).

11 Moreover, dropping the individuals who migrated because of schooling does not change the findings. See the online supplementary appendix.

12 Also previous studies have focused on this age group (e.g., Gray and Mueller 2012b).

13 The mean within-village correlation coefficient between the growing season temperature and precipitation from 1990–2009 is -0.317 with a standard deviation of 0.208.

14 The network of stations that provide temperature data for Tanzania is sparse. For example, a widely used global gridded data set provided by the Climate Research Unit (CRU), hosted by the University of East Anglia, uses only three weather stations from Tanzania (Rowhani et al. 2011)—none of them from Kagera. This motivates the reliance on re-analysis data.

Electronic copy available at: https://ssrn.com/abstract=3576002
historical precipitation data from the Tanzanian Meteorological Agency for gauges in more than 200 weather stations in Tanzania. For Kagera, I take all weather stations within a 100-km radius from each village (17 stations in total) and link the precipitation data to each village using an inverse distance weighing method.\(^{15}\)

All weather data sets span the entire study period. Precipitation is measured as the total precipitation during the two rainy seasons.\(^{16}\) For temperature, I consider two different measures, both attempting to capture farming conditions during the rainy seasons.\(^{17}\) The first measure is the mean monthly temperature during the previous two rainy seasons. The second is the number of growing degree days (GDDs), often used in the agronomical literature to capture temperature’s apparent non-linear relationship with plant growth (e.g., Ritchie and NeSmith 1991; Schlenker and Roberts 2009). Recent studies in economics and climate change research have also adopted this measure (Schlenker, Hanemann, and Fisher 2006; Schlenker and Roberts 2009; Schlenker and Lobell 2010; Burke et al. 2011; Dillon, Mueller, and Salau 2011; Fisher et al. 2012). The MERRA data set provides daily minimum and maximum temperatures. I approximate the diurnal temperature distribution by interpolating between the minimum and maximum temperature values using a sinusoidal curve (Baskerville and Emin 1969; Snyder 1985). Growing degree days are then measured by the time of exposure to a certain temperature range. I set the lower bound to 8°C and the upper bound to 34°C. Exposure to temperatures above this range is considered harmful for agricultural yields.

Table 4 provides the summary statistics of weather variables over the two decades. The average monthly growing season temperature across the villages is 23°C. The standard deviation stands at 1.28°C but this variation mainly originates from the differences between the villages. The within-village standard deviation is 0.33°C, implying that temperatures remain fairly stable over time. The empirical strategies exploit this temporal variation within each village. Therefore, in what follows, I will interpret the impact of temperature shocks with respect to the within-village standard deviation (0.33°C).\(^{18}\)

The number of growing degree days in the data is 2,735, with a within-village standard deviation of 57.1. Temperatures above 34°C are rare. The mean degree days above this threshold is 0.02 degree days, with a within-village standard deviation of 0.118. The mean growing season precipitation is 87.2 cm (within-village standard deviation: 13 cm). Finally, the data based on self-reports suggest that weather-related shocks are common reasons for income fluctuations in Kagera. The 2004 and 2010 rounds collected extensive retrospective information about the income shocks experienced by the panel respondents. Nearly 60% of the respondents reported having experienced at least one shock between 1994 and 2009. As documented in De Weerdt and Hirvonen (2016), the most frequently reported shocks were the death of a family

\(^{15}\) The method involves estimating precipitation for each village using all available data from the stations. A village-specific monthly precipitation value is calculated by weighing each monthly precipitation reading with the inverse of the distance to the weather station where it was recorded.

\(^{16}\) Defining precipitation as a monthly mean during the previous two rainy seasons yields near-identical findings.

\(^{17}\) For temperature this means first calculating the mean daily temperature for each growing season month (March, April, May, October, November, and December), and then taking the mean over these to construct an annual measure. For precipitation, I first calculate the total precipitation for each growing season month and then take a mean over these.

\(^{18}\) Note that, for example, a growing season that has four average growing season months and 2 growing season months in which the temperature is 1°C above the mean would produce such a 0.33°C departure from the long-run mean.
member (27% of all shocks), poor harvest due to bad weather (21%), and serious illness (19%).

Weather Shocks and Consumption

As only very few households have access to irrigation (see above), I expect the weather conditions in the growing season to largely determine the contemporaneous incomes. The econometric analysis begins by estimating the impact of weather shocks on household consumption. I use the four waves of the household panel survey administered in 1991–94. This baseline survey consisted of 915 households that were interviewed up to four times. After dropping households that were interviewed only once, as well as a small number of households with missing consumption data, I am left with 3,277 observations from 912 households.

These early rounds of the survey also collected data on incomes. However, measuring income in a context where most households engage in self-employed agriculture is difficult and subject to a large margin of error (Deaton 1997). In such a setting, consumption has been viewed as providing a more reliable measure of welfare (e.g., Deaton and Grosh 2000). This motivates the use of consumption as the outcome variable to estimate the impact of weather shocks on household welfare.

The consumption data originate from extensive food and non-food consumption modules in the survey. The consumption basket includes 97 food items (home produced and purchased) and 36 non-food items. The aggregates are temporally and spatially deflated using data from a price questionnaire included in the survey. Consumption is expressed in per capita terms using 1991 Tanzanian shillings (Tsh). The mean household per capita consumption for the pooled sample is 34,191 Tsh, with a standard deviation of 26,914 Tsh. The econometric strategy described below controls for any questionnaire-specific traits and seasonality aspects of consumption through the inclusion of controls for wave and the quarter of year when the interview took place.

I use a fixed-effects approach (Burke et al. 2011; Dell, Jones, and Olken 2012; Fisher et al. 2012; Dell, Jones, and Olken 2013) to identify the effect of weather changes on household consumption. Using household and year fixed effects, the impact of the weather changes is identified from village-specific deviations in weather while controlling for annual shocks common to all villages.

Building on the work in Bengtsson (2010), the natural log of per capita consumption for household \( h \) in village \( v \) in wave \( t \) (\( \ln c_{hvt} \)) is modeled as:

\[
\ln c_{hvt} = \beta_1 T_{v,t-1} + \beta_2 R_{v,t-1} + \gamma_h + q_{hvt} + w_t + \epsilon_{hvt}
\]

where \( t = 1, \ldots, 4 \). The term \( T_{v,t-1} \) captures the temperature and \( R_{v,t-1} \) the precipitation during the rainy season months in the 12 months preceding the interview. The term \( q_{hvt} \) is a set of dummies controlling for the quarter of year when the interview took place. Wave dummies are captured by \( w_t \). The term \( \gamma_h \) represents household fixed effects capturing all time-invariant characteristics of the households. Both cluster as well as spatially robust standard errors are reported. For the latter, I use the Conley (1999) standard errors that are robust to spatial autocorrelation and heteroskedasticity. The computation is based on a weighing matrix that places more weight on observations that are closer to each other. The weights decay to zero after a pre-specified distance cut-off is met. I report the Conley (1999) standard errors based on the following cut-off points: 25, 50, 75, 100, and 125 km.

Besides the wave fixed effects, the survey design permits the further control for unobserved time-variant effects (Bengtsson 2010). The mean

\[\text{The Ordinary Least Squares (OLS) estimate for temperature is statistically significant and negative when household per capita income or agricultural income is used as the outcome variable. However, the estimated impacts are implausibly large. The median quantile regression produces more similar (and statistically significant) temperature estimates compared to the consumption models. This suggests, as discussed in Bengtsson (2010) and confirmed by graphical analysis done by the author (not reported), that the income data are characterized by numerous outliers. Therefore, the OLS results based on the income data should be interpreted with extreme caution.}\]

\[\text{Note that the recall period was 12 months in the first wave (administered usually in 1991 or 1992). Waves 2, 3, and 4 were administered 6 to 7 months after the previous wave and therefore the recall period in the consumption module was six months. Following Bengtsson (2010), the consumption values are normalized by dividing the annual value in wave 1 by two.}\]

\[\text{The average distance between the 51 villages is 88 km, with a standard deviation of 68 km. This procedure is implemented in Stata 13.1 following Hsiang (2010) and using the “reg2hdfepatial” command written by Thiemo Fetzer.}\]
First, the wave does not fully correspond to the month or even to the calendar year of the interview. This was because the survey team visited the baseline villages at different times of the year and sometimes even in different calendar years within waves. For example, in the first wave, 47% of the households were interviewed in 1991, 50% in 1992, and 3% in 1993. Furthermore, the weather variables are constructed so that they capture the conditions in the growing season months in the 12 months prior to the interview month. These two features induce additional random cross-sectional variation to the data. The first additional specification includes a set of year dummies ($h_t$) that capture any macro-level shocks specific to the calendar year. I then replace these with district by year interaction terms ($d_h \times \theta_t$). While these interaction terms capture district-specific trends such as district-level price effects, they come with a cost of absorbing a large amount of the variation in the temperature data.

Table 5 reports the results based on equation (1) using the mean monthly growing season temperature in the past 12 months before the interview date. Furthermore, column 1 controls for time effects only through wave dummies. Column 2 adds the year dummies and column 3 replaces these with district by year interaction terms. The temperature variables appear with negative coefficients in all specifications. The impact of a one standard deviation (0.33°C) increase in average monthly growing season temperature decreases household per capita consumption by 4.9%–5.5% (on average, and ceteris paribus) depending on the specification. The spatially robust Conley (1999) standard errors are

### Table 5. Impact of Temperature Changes on Household Consumption

|                      | 1             | 2             | 3             |
|----------------------|---------------|---------------|---------------|
| **Temperature (°C)** | -0.148        | -0.147        | -0.168        |
| Cluster-robust standard errors $^a$) | (0.060)**      | (0.060)**      | (0.095)*      |
| Conley (1999), 25 km cut-off | (0.061)**      | (0.063)**      | (0.085)**      |
| Conley (1999), 50 km cut-off | (0.059)**      | (0.058)**      | (0.085)**      |
| Conley (1999), 75 km cut-off | (0.056)**      | (0.052)**      | (0.085)**      |
| Conley (1999), 100 km cut-off | (0.054)**      | (0.048)**      | (0.085)**      |
| Conley (1999), 125 km cut-off | (0.051)**      | (0.045)**      | (0.086)*       |
| **Precipitation (cm)** | -0.000        | -0.001        | 0.001         |
| Cluster-robust standard errors $^a$) | (0.001)        | (0.001)        | (0.001)       |
| Conley (1999), 25 km cut-off | (0.001)        | (0.001)        | (0.001)       |
| Conley (1999), 50 km cut-off | (0.001)        | (0.001)        | (0.001)*      |
| Conley (1999), 75 km cut-off | (0.001)        | (0.001)        | (0.001)*      |
| Conley (1999), 100 km cut-off | (0.001)        | (0.001)        | (0.001)*      |
| Conley (1999), 125 km cut-off | (0.001)        | (0.001)        | (0.001)***    |

| **Household fixed effects** | yes         | yes         | yes         |
| **Year dummies**            | no          | yes         | no          |
| $\gamma^2 (2) = 4.87$       |             |             |             |
| **District by year interactions** | no         | no          | yes         |
| $\gamma^2 (17) = 51.03$     |             |             |             |
| **Wave dummies**            | yes         | yes         | yes         |
| $\gamma^2 (3) = 121.9$      |             |             |             |
| **Quarter of year dummies** | yes         | yes         | yes         |
| $\gamma^2 (3) = 2.82$       |             |             |             |
| **Number of observations**  | 3,277        | 3,277        | 3,277        |
| **Adjusted R\(^2\)**        | 0.175        | 0.176        | 0.190        |
| R\(^2\)
| 0.177                      | 0.179        | 0.195        |

Note: Asterisks indicate the following: ** = $p<0.01$, * = $p<0.05$, and * = $p<0.1$. Superscript * indicates that cluster-robust standard errors are clustered at the village level.

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22 The visits across villages were randomized at the first round of interviews (World Bank 2004).

23 If a household dropped out from the survey it was replaced with another household. This explains why few households were interviewed in 1993.

24 The 51 villages group into six districts.
generally somewhat smaller than the standard errors based on (village-level) clustering. In the preferred specification, which contains the household fixed effects with year dummies (column 2), a one standard deviation increase in temperature decreases household per capita consumption by 4.9%. The 95% confidence interval (based on the cluster-robust standard errors) for this negative effect is [0.9; 8.8].

Column 3 (table 5) includes the district-by-year interaction terms. The coefficient on the temperature variable is of similar magnitude as in other columns, although, as expected, is somewhat less precisely estimated. This suggests that the channel through which temperature affects consumption is not mediated through the local, district-level price effects.25

Finally, I do not find robust evidence that precipitation has an impact on consumption after temperature is controlled for. The estimate in column 3 based on spatially robust standard errors appears statistically significant at the 10% level, but the estimated impact is small: a one standard deviation increase in average monthly growing season precipitation (13.1 cm) increases consumption by 1.3%.

The outcome variable in equation (1) is assumed to have a linear relationship with temperature and precipitation. The evidence from previous studies suggests that extreme temperatures and precipitation have more severe negative welfare impacts (Schlenker and Roberts 2009; Porter 2012; Mueller, Gray, and Kosec 2014). I test this using a spline function of the GDD variable. The first part of this variable captures temperature exposure between 8–34°C and the second exposure to temperatures above 34°C. Table 6 presents the results. As before, column 1 controls for time effects only through wave dummies, column 2 adds the year dummies, and columns 3 replaces these with district-by-year interaction terms. The magnitudes of the coefficients suggest that the exposure to extreme temperatures is more harmful for consumption. However, while both temperature terms appear with negative signs in all columns, the coefficients are mostly statistically insignificant. This could be due to small cell sizes in the extreme temperature segment of the spline. Also, the joint-significance test signals that we cannot reject the null that the joint effect is zero in the first two columns. Only in column 3 does the coefficient capturing the impact of extreme temperatures appear statistically significant (based on the spatially robust standard errors). Here, one standard deviation (0.118) increase in the exposure to this temperature range reduces household per capita consumption by 5.7%, on average, and ceteris paribus. This estimate is very close to the temperature estimate obtained in the previous table, suggesting that it is the extreme temperatures that are driving the results in table 5.

I explored the robustness of these results in a number of different ways. First, off-season temperature does not exert an independent effect on household consumption, further supporting the notion that temperature affects consumption through the agricultural yield channel. Second, quantile regressions show that the estimated impacts are similar across the (conditional) consumption distribution results. Moreover, as the median and the corresponding OLS regression produce broadly similar temperature coefficients it is unlikely that outliers are driving the results (Koenker and Hallock 2001). Finally, the results are robust to using a Standardized Precipitation-Evapotranspiration Index (SPEI; Vicente-Serrano, Begueria, and López-Moreno 2010) instead of rainfall and temperature. These robustness tests are presented and further discussed in the online supplementary appendix.

The foregoing has established that temperature shocks induce considerable fluctuations in household consumption. The next section investigates the role of household wealth on migration rates, followed by a section analyzing the impact of these temperature shocks on long-term migration decisions.

Migration and Household Wealth

One way to establish whether liquidity constraints play a role on migration decisions is to study how initial wealth affects migration rates. Indeed, if liquidity constraints bind for some households but not for all, then we should expect that migration rates have a non-linear relationship with household wealth (McKenzie and Rapoport 2007). This section tests this hypothesis.

25 More specifically, I expect that the district-year interactions capture the changes in prices of the cash crops that vary little across villages within the same district.
The data consist of 1,662 women and 1,578 men who were interviewed in the first wave of the survey and were aged between 15–39 at some point between 1994 and 2010. Out of these individuals, 60% of the women and 48% of the men out-migrated at least once for more than a six-month period between 1994 and 2010. I regress the binary migration variable on individual and household characteristics.\(26\) I use the logged per capita value of land as a measure for wealth at the baseline.\(27\) The mean of this variable is 10.70 with a standard deviation of 1.41. I explore non-linearities in the migration-wealth relationship using a spline function that consists of five linear segments and threshold values.

\(\text{Table 6. Impact of Temperature Changes on Household Consumption—GDD}\)

| Dependent variable: (logged) household per capita consumption | 1      | 2      | 3      |
|---------------------------------------------------------------|--------|--------|--------|
| Number of growing degree days (8-34 °C)                       | -0.0005| -0.0005| -0.0004|
| \textit{Cluster-robust standard errors}\(^{a)}\)              | (0.0004)| (0.0004)| (0.0005)|
| \textit{Conley (1999), 25 km cut-off}                         | (0.0003)| (0.0004)| (0.0004)|
| \textit{Conley (1999), 50 km cut-off}                         | (0.0003)*| (0.0004)| (0.0004)|
| \textit{Conley (1999), 75 km cut-off}                         | (0.0003)*| (0.0003)| (0.0004)|
| \textit{Conley (1999), 100 km cut-off}                        | (0.0003)**| (0.0003)**| (0.0004)|
| \textit{Conley (1999), 125 km cut-off}                        | (0.0002)**| (0.0003)**| (0.0004)|
| Number of 34+ °C degree days                                  | -0.2051| -0.2435| -0.4915|
| \textit{Cluster-robust standard errors}\(^{a)}\)              | (0.1562)| (0.1636)| (0.3126)|
| \textit{Conley (1999), 25 km cut-off}                         | (0.2633)| (0.1712)| (0.2249)**|
| \textit{Conley (1999), 50 km cut-off}                         | (0.2604)| (0.1680)| (0.2061)**|
| \textit{Conley (1999), 75 km cut-off}                         | (0.2600)| (0.1641)| (0.2019)**|
| \textit{Conley (1999), 100 km cut-off}                        | (0.2610)| (0.1640)| (0.1965)**|
| \textit{Conley (1999), 125 km cut-off}                        | (0.2636)| (0.1657)| (0.1933)**|
| Precipitation (cm)                                            | -0.0003| -0.0111| 0.0017 |
| \textit{Cluster-robust standard errors}\(^{a)}\)              | (0.0011)| (0.0011)| (0.0011)|
| \textit{Conley (1999), 25 km cut-off}                         | (0.0012)| (0.0011)| (0.0009)*|
| \textit{Conley (1999), 50 km cut-off}                         | (0.0011)| (0.0011)| (0.0008)**|
| \textit{Conley (1999), 75 km cut-off}                         | (0.0009)| (0.0011)| (0.0007)**|
| \textit{Conley (1999), 100 km cut-off}                        | (0.0008)| (0.0011)| (0.0007)**|
| \textit{Conley (1999), 125 km cut-off}                        | (0.0007)| (0.0010)| (0.0007)**|
| F-test on the joint effect of the GDD coefficients.            |        |        |        |
| \textit{cluster-robust standard errors}                       | 0.1932 | 0.1416 | 0.1216 |
| \textit{Conley (1999), 25 km cut-off}                         | 0.4346 | 0.1536 | 0.0287 |
| \textit{Conley (1999), 50 km cut-off}                         | 0.4296 | 0.1460 | 0.0170 |
| \textit{Conley (1999), 75 km cut-off}                         | 0.4287 | 0.1367 | 0.0148 |
| \textit{Conley (1999), 100 km cut-off}                        | 0.4306 | 0.1364 | 0.0123 |
| \textit{Conley (1999), 125 km cut-off}                        | 0.4351 | 0.1406 | 0.0109 |
| Household fixed effects                                       | yes    | yes    | yes    |
| \(\chi^2\) (869) = 5681.2                                     |        |        |        |
| Year dummies                                                  | no     | yes    | no     |
| \(\chi^2\) (2) = 4.87                                        |        |        |        |
| District by year interactions                                 | no     | no     | yes    |
| \(\chi^2\) (17) = 51.03                                       |        |        |        |
| Wave dummies                                                  | yes    | yes    | yes    |
| \(\chi^2\) (3) = 121.9                                       |        |        |        |
| Quarter of year dummies                                       | yes    | yes    | yes    |
| \(\chi^2\) (3) = 2.82                                        |        |        |        |
| Number of observations                                        | 3,277  | 3,277  | 3,277  |
| Adjusted R\(^2\)                                              | 0.175  | 0.176  | 0.190  |
| R\(^2\)                                                       | 0.177  | 0.179  | 0.195  |

Note: Asterisks indicate the following: *** = \(p<0.01\), ** = \(p<0.05\), and * = \(p<0.1\). Superscript * indicates that cluster-robust standard errors are clustered at the village level.

\(26\) I use the linear probability model (LPM) here to better accommodate the village fixed effects in this cross-sectional regression. The Logit model provides similar estimates.\(27\) To address measurement error concerns, I took the mean land value over the four baseline survey rounds in 1991–94.
Table 7. Migration and Initial Wealth

| (Log) Land value per capita spline: | Pooled | Males | Females |
|-----------------------------------|--------|-------|---------|
| 0–20 percentile                   | −0.001 | −0.006 | 0.002   |
|                                  | (0.011)| (0.013)| (0.015) |
| 20–40 percentile                  | 0.031  | −0.007 | 0.111   |
|                                  | (0.060)| (0.115)| (0.077) |
| 40–60 percentile                  | −0.020 | −0.077 | −0.060  |
|                                  | (0.072)| (0.144)| (0.086) |
| 60–80 percentile                  | 0.086  | 0.207**| 0.016   |
|                                  | (0.056)| (0.092)| (0.079) |
| 80–100 percentile                 | −0.061*| −0.093**| −0.031  |
|                                  | (0.036)| (0.046)| (0.042) |

Note: Asterisks indicate the following: *** = p<0.01, ** = p<0.05, and * = p<0.1. Linear Probability Model. Cluster robust standard errors are in parentheses. The dependent variable obtains a value of 1 if the person migrated for more than 6 months between 1991 and 2010 (zero otherwise).

(0.036) (0.046) (0.042)

(0.036) (0.046) (0.042)

(0.036) (0.046) (0.042)

These temperature-induced income shocks constrain out-migration.

I employ duration analysis based on discrete time methods (Allison 1982; Jenkins 1995) to study how annual migration rates respond to weather variation in Kagera. The duration modeling framework allows for the inclusion of time-varying explanatory variables such as temperature and precipitation. It also accommodates the apparent (independent) censoring of the data. The procedure involves the transformation of the data to person-year level. I consider mobility between 1994 and 2009. Furthermore, given the age restriction, individuals enter the data set when they turn 15 and leave when they migrate or turn 40. This yields an unbalanced data set of 24,962 person-year observations. The total number of individuals is 3,240 (1,662 women and 1,578 men), with 1,480 right-censored individuals, those who had not migrated by 2009. Because the migration motives are different for men and women, the analysis is separated by gender.

The discrete time duration analysis typically adopts the logit model. The logit model constrains the probability to a [0,1] interval by assuming a cumulative density function that follows a logistic distribution. Here, the estimated model can be formulated as

\[ \ln \left( \frac{M_{ivt}}{1 - M_{ivt}} \right) = \beta T_{v,t-1} + x'_{ivt} \delta + \theta_t + \vartheta_v. \]

The out-migration event of an individual i is captured by the binary variable \( M_{ivt} \) that assumes a value of 1 if the person migrates from village \( v \) at a year \( t \), and zero otherwise. Further, \( T_{v,t-1} \) captures the mean monthly growing season temperature, or the number of growing degree days in the previous year in the village. If liquidity constraints bind, we expect \( \beta < 0 \).

The term \( \vartheta_v \) represents a set of village dummies, while \( \theta_t \) represents year dummies. The standard errors are clustered at the village level. The vector \( x_{ivt} \) captures individual and village fixed effects.

Migration and Weather Shocks

Earlier I showed how temperature shocks result in large fluctuations on household consumption. In this section, I study whether
Table 8. Summary Statistics

|                      | All         | Males       | Females     |
|----------------------|-------------|-------------|-------------|
|                      | Mean        | Std. dev.   | Mean        | Std. dev.   | Mean        | Std. dev.   |
| **Time-variant variables:** |             |             |             |             |             |             |
| Temperature (°C)      | 22.61       | 1.290       | 23.81       | 6.568       | 24.01       | 6.918       |
| Number of growing degree days (8-34 °C) | 2721.9 | 203.03 | 286.4 | 45.2 | 286.4 | 45.2 |
| Number of 34+ °C degree days | 0.024 | 0.150 | 0.026 | 0.152 | 0.026 | 0.152 |
| Precipitation (cm)   | 83.76       | 40.66       | 83.76       | 40.66       | 83.76       | 40.66       |
| Age in years         | 23.90       | 6.735       | 23.81       | 6.568       | 24.01       | 6.918       |
| Less than primary education (reference) | 0.297 | 0.457 | 0.286 | 0.452 | 0.310 | 0.462 |
| Primary education    | 0.656       | 0.475       | 0.661       | 0.473       | 0.651       | 0.477       |
| Secondary education  | 0.046       | 0.210       | 0.052       | 0.223       | 0.040       | 0.195       |
| **Time-invariant variables:** a |             |             |             |             |             |             |
| Male                 | 0.530       | 0.499       | 0.530       | 0.499       | 0.510       | 0.500       |
| Head or spouse       | 0.127       | 0.332       | 0.087       | 0.282       | 0.171       | 0.376       |
| Child of head        | 0.583       | 0.493       | 0.646       | 0.478       | 0.513       | 0.500       |
| Grandchild of head   | 0.115       | 0.319       | 0.116       | 0.320       | 0.115       | 0.319       |
| Other relation to the head (reference) | 0.175 | 0.380 | 0.151 | 0.358 | 0.201 | 0.401 |
| Male head of the household | 0.786 | 0.410 | 0.786 | 0.410 | 0.786 | 0.410 |
| Age of the head      | 47.95       | 16.10       | 47.95       | 16.10       | 47.95       | 16.10       |
| Land size (acres)    | 5.086       | 5.017       | 5.086       | 5.017       | 5.086       | 5.017       |
| Number of males 0-5 years | 0.715 | 0.877 | 0.715 | 0.877 | 0.715 | 0.877 |
| Number of males 6-15 years | 1.301 | 1.158 | 1.301 | 1.158 | 1.301 | 1.158 |
| Number of males 16-60 years | 1.426 | 1.020 | 1.426 | 1.020 | 1.426 | 1.020 |
| Number of males 61+ years | 0.187 | 0.390 | 0.187 | 0.390 | 0.187 | 0.390 |
| Number of females 0-5 years | 0.737 | 0.916 | 0.737 | 0.916 | 0.737 | 0.916 |
| Number of females 6-15 years | 1.315 | 1.292 | 1.315 | 1.292 | 1.315 | 1.292 |
| Number of females 16-60 years | 1.769 | 1.257 | 1.769 | 1.257 | 1.769 | 1.257 |
| Number of females 61+ years | 0.184 | 0.403 | 0.184 | 0.403 | 0.184 | 0.403 |
| Baseline Assets: b  |             |             |             |             |             |             |
| Log per capita value of land | 10.70 | 1.407 | 10.70 | 1.407 | 10.70 | 1.407 |
| Log per capita value of durable goods | 5.010 | 3.877 | 5.010 | 3.877 | 5.010 | 3.877 |
| **Number of person-years** | **24,962** | **13,225** | **24,962** | **13,225** | **24,962** | **13,225** |

Note: Gender disaggregated statistics are reported only for the individual-level variables. Superscript a: measured in wave 1 (usually administered in 1991 or 1992); baverage over the four baseline survey rounds 1991–94.

The identification strategy here is similar to the fixed effects approach employed earlier. Village dummies absorb the spatial variation in these data, so only the within-village variation in temperatures over time is exploited. The year dummies control for any annual macro-level shocks common to all villages.
Results

Table 9 provides the results. All coefficients are marginal effects from the logit model. The first two columns provide the results for men and the last two for women. In the odd columns, temperature is measured using the average monthly growing season temperature from the previous year. In even columns, temperature is defined as degree days.

Focusing first on the control variables, we see that, as anticipated, education increases the risk of migrating. The coefficients on the age dummies reflect the age-dynamics documented in the online supplementary appendix. Furthermore, the ties to the household head are important predictors of migration. Other things being equal, the closer the familial ties are to the head, the less likely the individual is to migrate. This finding is in line with previous research in Tanzania (Beegle, De Weerdt, and Dercon 2011) and Malawi (Beegle and Poulin 2013).

Our attention now shifts to the weather variables. We see that an increase in the mean temperature in the previous year’s growing season decreases the probability of migrating. In column 1, a one standard deviation (0.33 °C) increase in the previous year’s average monthly growing season temperature decreases the probability of migrating by 0.76 of a percentage point, on average, and ceteris paribus. This corresponds to a reduction in...

### Table 9. Impact of Temperature Changes on Migration

|                | 1 Males                  | 2 Males                  | 3 Females            | 4 Females            |
|----------------|--------------------------|--------------------------|----------------------|----------------------|
| Temperature (°C) | -0.0233*** (0.0072)     | n/a                      | -0.0011 (0.0141)    | n/a                  |
| Growing degree days (8-34 °C) | n/a                      | -0.0001** (0.0001)      | n/a                  | -0.0000 (0.0001)     |
| Degree days (34+ °C) | n/a                      | -0.0502** (0.0223)      | n/a                  | 0.0118 (0.0158)      |
| Precipitation (cm) | -0.0000 (0.0001)         | -0.0000 (0.0001)        | -0.0002 (0.0001)     | 0.0118 (0.0158)      |
| Secondary education | 0.0869*** (0.0079)       | 0.0870*** (0.0080)      | 0.0605*** (0.0111)  | 0.0605*** (0.0111)   |
| Primary education | 0.0176*** (0.0057)       | 0.0175*** (0.0057)      | 0.0222*** (0.0062)  | 0.0221*** (0.0062)   |
| Less than primary education | reference               | reference               | reference            | reference            |
| Age: 15-19 | reference               | reference               | reference            | reference            |
| Age: 20-24 | -0.0015 (0.0064)         | -0.0015 (0.0064)        | 0.0104 (0.0078)     | 0.0104               |
| Age: 25-29 | -0.0307*** (0.0082)      | -0.0307*** (0.0082)     | -0.0247** (0.0105)  | -0.0247** (0.0105)   |
| Age: 30-34 | -0.0389*** (0.0082)      | -0.0389*** (0.0082)     | -0.0454*** (0.0109) | -0.0454*** (0.0109)  |
| Age: 35-39 | -0.0515*** (0.0116)      | -0.0513*** (0.0115)     | -0.0834*** (0.0165) | -0.0834*** (0.0165)  |
| Head or spouse | -0.0355*** (0.0113)     | -0.0356*** (0.0113)     | -0.0682*** (0.0135) | -0.0682*** (0.0135)  |
| Child of head | -0.0330*** (0.0053)      | -0.0330*** (0.0053)     | -0.0013             | -0.0013             |
| Grandchild of head | -0.0164** (0.0074)    | -0.0162** (0.0074)      | 0.0054              | 0.0054              |
| Other relation to the head | reference               | reference               | reference            | reference            |
| Household level controls | yes                     | yes                     | yes                  | yes                  |
| Village dummies | yes                     | yes                     | yes                  | yes                  |
| Year dummies | yes                      | yes                     | yes                  | yes                  |
| Observations | 13,225                   | 13,225                   | 11,737               | 11,737               |
| Pseudo-Log likelihood | -2,685.4                 | -2683.7                 | -3,225.6             | -3,225.5             |

Note: Asterisks indicate the following: *** = p<0.01, ** = p<0.05, and * = p<0.1. Coefficients are marginal effects. Standard errors (in parentheses) are clustered at the village level, and calculated using the delta method. The household-level controls are measured in wave (i.e., before 1994) and include head’s characteristics (gender, age, and education), household composition (number of males and females of certain age), and land ownership (acres).
the overall male migration rate of about 13%. The estimate is significant at the 1% level. Using growing degree days reveals that the temperature effects are driven by extreme temperatures. While the coefficient on the first part of the GDD spline is negative and statistically significant at the 5% level, the coefficient on the segment that captures the exposure to 34°C is considerably larger.

Precipitation in the previous year’s growing season does not exert an independent impact on migration decisions.

Columns 3 and 4 provide the results for women. The coefficients on the temperature variables appear insignificant in all columns. This confirms the established prior result that female migration is less responsive to income shocks induced by weather because it is largely motivated by marriage and family.

The survey also provides information on the locality the individuals first migrated to. Using a multinomial logit approach, I next break the migration decision to moves within the same district and to outside the district. This permits the comparison of the impact of temperature between short and long distance moves. Table 10 shows that for men, temperature increases have a negative effect to both short and long distance moves. The comparison of the temperature coefficients suggests that temperature shocks particularly inhibit out of district migration. This is in line with the prior result that the migration costs increase with the distance migrated. However, due to the reduction in cell sizes in the outcome variable, the observed difference between the temperature coefficients is not statistically different from zero. The specification based on growing degree days again suggest that extreme temperatures are driving the results. However, due to the (further) reduction in cell sizes, the point estimates are imprecisely estimated.

For women, table 11 shows that the coefficients on the temperature variable appear insignificant for both short and long distance moves. Interestingly, precipitation exerts a statistically significant and negative impact on women’s long distance migration. The interpretation of this effect is difficult however, due to the fact that precipitation does not exert an independent and robust impact on household consumption (see table 5).

Table 10. Short vs. Long Distance Moves–Males

|                     | Temperature (°C) | Number of growing degree days (8-34°C) | Number of 34+ °C degree days | Precipitation (cm) | Secondary education | Primary education | Less than primary education |
|---------------------|------------------|----------------------------------------|-----------------------------|-------------------|--------------------|---------------------|-----------------------------|
|                     | No migration     | Within district                        | Outside district            | No migration     | Within district    | Outside district    | Observations |
| Temperature         | b                | −0.007*                                | −0.018**                    | b                 | −0.0000           | −0.0001             | 13,225         |
|                     | (0.004)          | (0.008)                                |                             | (0.0000)          | (0.0000)           | (0.0000)            |               |
| Number of growing degree days (8-34°C) | b                | 0.014**                                | 0.071***                    | b                 | 0.0139**          | 0.0713***           |               |
|                     | (0.005)          | (0.007)                                |                             | (0.0005)          | (0.0000)           | (0.0000)            |               |
| Precipitation (cm) | b                | −0.001                                 | 0.022***                    | b                 | −0.0011           | 0.0216***           |               |
|                     | (0.004)          | (0.005)                                |                             | (0.0004)          | (0.0005)           | (0.0005)            |               |
| Secondary education | b                | 0.014**                                | 0.071***                    | b                 | 0.0139**          | 0.0713***           |               |
|                     | (0.005)          | (0.007)                                |                             | (0.0005)          | (0.0000)           | (0.0000)            |               |
| Primary education   | b                | −0.001                                 | 0.022***                    | b                 | −0.0011           | 0.0216***           |               |
|                     | (0.004)          | (0.005)                                |                             | (0.0004)          | (0.0005)           | (0.0005)            |               |
| Less than primary education | b | reference                             | reference                   | b                 | reference         | reference           |               |
| Observations        | 13,225           | 13,225                                 | 13,225                      |                   |                    |                    |               |
| Pseudo-Log likelihood | −3,101.1         | −3,101.1                               | −3,101.3                   |                   |                    |                    |               |

Note: Asterisks indicate the following: *** = p<0.01, ** = p<0.05, and * = p<0.1. Coefficients are marginal effects. Standard errors (in parentheses) are clustered at the village level, and calculated using the delta method. For information about the control variables used and for other notes, see table 9.

35 The annual male migration rate is 5.8% (see the online supplementary appendix).

36 One standard deviation (13 cm) increase in precipitation decreases out-of-district migration rates by 0.13 of a percentage point. As the annual out-of-district migration rate for women is 0.04, this corresponds to a 3% reduction in the migration rate in this category.
I conducted a host of tests to explore the robustness of these results. First, the results are robust to replacing the year dummies with spell at-risk variables that are often used in the duration modeling framework to measure the time to migration. Second, a concern in the heavy use of village fixed effects is that perhaps the observed effects originate from a single village that does not conform to the general pattern in the region. I addressed this by omitting each village in turn from the sample. The estimated coefficients remain remarkably similar across these 51 regressions. Third, results are robust to replacing village fixed effects with individual-level fixed effects. Fourth, applying Conley (1999) standard errors instead of the clustered ones yields near-identical standard errors in all models. Finally, the results are robust to dropping those individuals who migrated because of schooling. These results are available in the online supplementary appendix.

Heterogeneity

The foregoing econometric results suggest that negative income shocks make liquidity constraints on migration more binding. However, this observed pattern should not be homogenous across all households. In particular, we should expect to see that the migration decisions of individuals originating from wealthier households are less affected by adverse weather shocks. In this penultimate section, I test this hypothesis by interacting the weather shock variables with household wealth at the baseline.

I proxy household wealth here using the logged per capita value of land at the baseline.37 Columns 1 and 2 in table 12 provide the results for the male sample.38 We see that the coefficient on the interaction between the temperature and the household assets appears positive and significant at the 10% level. This finding implies that the migration decisions of men originating from wealthier households are less affected by temperature shocks.

The land markets in Kagera are thin and as a consequence the reported land values may be measured with considerable error.39 According to earlier anthropological research in this area (Reining 1962), most land is owned by the clan and the land allocation is based on strict traditional laws. Importantly, this ‘clan land’ cannot be sold without the permission of the clan. Moreover, clan land is treated less like private property and more like land that one uses during their life time and passes onto their children. Other, more recent studies, make similar remarks about the land allocation in Kagera, see De Weerdt (2010); Kudo (2015).

Table 11. Short vs. Long Distance Moves–Females

|                         | Temperature                  | Degree days                  |
|-------------------------|------------------------------|------------------------------|
|                         | No migration                 | Within district              | Outside district             | No migration | Within district | Outside district |
| Temperature (°C)        | b 0.0043 (0.0119)            | −0.0048 (0.0070)             | b 0.0000 (0.0000)            | −0.0000       |
| Number of growing degree days (8-34 °C) | b 0.0000 (0.0001) | −0.0001*** (0.0000) | b 0.0000 (0.0001) | −0.0001*** (0.0000) |
| Number of 34+ °C degree days | b 0.0149 (0.0091) | 0.0408*** (0.0083) | b 0.0148 (0.0091) | 0.0408*** (0.0083) |
| Precipitation (cm)      | b 0.0000 (0.0001) | −0.0001*** (0.0000) | b 0.0000 (0.0001) | −0.0001*** (0.0000) |
| Secondary education     | b 0.0090* (0.0048) | 0.0136*** (0.0048) | b 0.0090* (0.0048) | 0.0136*** (0.0048) |
| Primary education       | b reference (reference)     | reference (reference)       | b reference (reference)     | reference (reference) |
| Less than primary education | b reference (11,737) | reference (11,737) | b reference (11,737) | reference (11,737) |
| Pseudo-Log likelihood   | −3,803.7                     | −3,803.7                     |

Note: Asterisks indicate the following: *** = p<0.01, ** = p<0.05, and * = p<0.1. Coefficients are marginal effects. Standard errors (in parentheses) are clustered at the village level, and calculated using the delta method. For information about the control variables used and for other notes, see table 9.

37 I do not consider the GDD spline variable for the exercise because interpreting the multiple interactions would be cumbersome.
38 The temperature coefficients, including the one on the interaction term, do not appear statistically significant in the female sample. The regression results are omitted to conserve space.
39 According to earlier anthropological research in this area (Reining 1962), most land is owned by the clan and the land allocation is based on strict traditional laws. Importantly, this ‘clan land’ cannot be sold without the permission of the clan. Moreover, clan land is treated less like private property and more like land that one uses during their life time and passes onto their children. Other, more recent studies, make similar remarks about the land allocation in Kagera, see De Weerdt (2010); Kudo (2015).
Beegle, Dehejia, and Gatti (2006) show how durable assets often serve as a collateral for loans. This suggests that the values of these assets are better known by the households. Columns 3 and 4 show that using the logged per capita value of durable goods per household member instead of the land-based measure provides similar results. As expected, this somewhat improves the precision: the coefficient on the interaction term is now significant at the 5% level.

**Conclusions**

Despite the high returns to internal migration (Beegle, De Weerdt, and Dercon 2011), many people remain in poor rural areas, which results in large rural-urban wage gaps. This is suggestive of barriers to migration that prevent potential migrants from exploiting the apparent arbitrage opportunity. Alternatively, these spatial inequalities may also be an outcome of efficient sorting of labor based upon unobserved skill, in which case there is no market failure for policies to address (Young 2013).

The findings in this article suggest that the low rates of internal migration in Tanzania can, at least partly, be explained by liquidity constraints. This implies that the spatial inequalities observed in the country are not only due to the efficient allocation of unobserved skills across space. Moreover, these liquidity constraints seem more pertinent to the poorest segments in the rural villages: those with higher initial assets have a better chance to move and economically advance in life.

These results then have important implications for policy. Internal migration out of the poor rural areas is one of the key ways of escaping poverty in rural Tanzania (Beegle, De Weerdt, and Dercon 2011; Christiaensen, De Weerdt, and Todo 2013). Policies that facilitate geographical mobility may come with a great potential for poverty reduction. Furthermore, the more efficient allocation of labor is also likely to lead to a better aggregate productivity. Reducing the costs associated with internal migration—coupled with careful urban planning—is one policy tool for achieving this.

Finally, the finding that weather shocks limit migration is also relevant to climate change policy. Long-term temperature increases are likely to make some areas less suitable and in turn make some areas more suitable for crop-production (Mendelsohn 2008). If this type of “spatial-shifting” of agricultural production zones becomes a reality in developing countries, then migration either to these new production zones or to urban areas would be a key adaption strategy. However, if migration is costly and liquidity constraints bind, households and individuals would be locked into these low productivity areas. Public policy could then have an important role to play in facilitating migration—and thereby in adaptation to the adverse impacts of global warming.

**Supplementary Material**

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/.

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**Table 12. Interacting the Weather Variables with Baseline Wealth**

| Asset: value of land per capita | Asset: value of durable goods per capita |
|--------------------------------|----------------------------------------|
| 1 males                        | 2 males                                 |
|--------------------------------|----------------------------------------|
| Temperature (°C)               | −0.056*** (0.019)                       | −0.030*** (0.007) |
| * (log) value of assets        | 0.003* (0.002)                          | 0.001** (0.001)  |
| Precipitation (cm)             | 0.000                                  | 0.000            |
| * (log) value of assets        | −0.000                                 | −0.000           |
| (log) value of assets          | −0.070** (0.036)                        | −0.024* (0.013)  |
| Observations                   | 13,225                                 | 13,225           |
| Pseudo-Log likelihood          | −2,681.8                               | −2,682.6         |

Note: Asterisks indicate the following: *** = p < 0.01, ** = p < 0.05, and * = p < 0.1. In columns 1 and 2, assets are measured using logged per capita land value. In columns 3 and 4, the asset variable is based on logged per capita value of durable goods. The table shows marginal effects based on a logit model. Standard errors (in parentheses) are clustered at the village level and computed using the delta method. For information about the control variables used and for other notes, see table 9.
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