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Weather Shocks, Agricultural Production and Migration: Evidence from Tanzania

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ABSTRACT *We analyse whether Tanzanian rural households engage in internal migration as a response to weather-related shocks. We hypothesise that, when exposed to such shocks and a consecutive crop yield reduction, rural households use migration as a risk management strategy. Our findings confirm that for an average household, a 1 per cent reduction in agricultural income induced by weather shock increases the probability of migration by 13 percentage points on average within the following year. However, this effect is significant only for households in the middle of wealth distribution, suggesting that the choice of migration as an adaptation strategy depends on initial endowment. What is more, the proposed mechanism applies to households whose income is highly dependent on agriculture, but is not important for diversified livelihoods.*

Introduction

There is a substantial evidence that climate has been changing in recent decades, both in terms of its means and extremes, and this trend will not only persist, but will intensify in the near future (IPCC, 2007). According to recent estimates, this unprecedented climate variability will first occur in the tropics and among low-income countries, where the projected mean climate may continuously move outside the bounds of historical variability already in 2034, about 17 years earlier than the global average (Mora et al., 2013). Through their implications for agricultural production, these changes will exert additional pressure on populations in developing countries, both because a majority of the poor rely on rain-fed agriculture and because the share of food in their budget may amount to two-thirds (Cranfield, Eales, Hertel, & Preckel, 2003). Therefore, climate change and climate variability should be perceived as an important source of risk for rural households in developing countries.

The link between climate and agricultural productivity has been thoroughly analysed. Despite calibration caveats or data limitations, both crop growth simulation models and statistical studies reveal that whereas some yield gains are likely under global warming in temperate regions, the lowest income countries will experience the sharpest losses (Deryng, Sacks, Barford, & Ramankutty, 2011). In particular, cereals, the staple food in most of the developing world, show the greatest potential to be adversely affected by climate change (Schlenker & Roberts, 2009) and according to Schlenker and Lobell (2010), yields will decline by about 10 per cent by 2050 in nearly all countries in Sub-Saharan

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Africa. Schlenker and Roberts (2009) identified a threshold at 30°C for maize, after which additional increments to temperature result in a sharp reduction in yields. This type of nonlinearity can therefore have important consequences should the climate change lead to an increase in the intensity and frequency of extreme heat events (Easterling et al., 2000).

Even though the implications of climate anomalies may have a much broader range than distortions of crop output, we focus our attention on weather variability as a risk factor in agriculture. In particular, we investigate the extent to which rural households engage in internal migration to ensure against agricultural weather-related risk.

The literature suggests a range of mechanisms that households living in risky environments have developed to shield their consumption from risk, including income smoothing, self-insurance, and social insurance arrangements, particularly important in the absence of formal insurance or credit markets. Much emphasis has been put on households depleting their productive assets (Fafchamps, Udry, & Czukas, 1998; Kazianga & Udry, 2006), making low-risk, low-return investments (Rosenzweig & Binswanger, 1993), diversifying their income sources (Dercon, 1996) or diversifying landholdings into various spatially separated plots and into various crops (Townsend, 1994). However, these studies point towards limited effectiveness of risk-bearing institutions in protecting consumption against income shocks both over time and within local communities (Kazianga & Udry, 2006). The effectiveness of these risk-bearing institutions is hindered by the fact that weather risk is spatially covariant. Therefore, even though some of these mechanisms may be useful in case of idiosyncratic risk, they may not be effective when the whole village experiences the same climatic stress.

In this context, we hypothesise that households exposed to increased weather risk may consider migration as spatial diversification of income. Since interhousehold family transfers are an important source of insurance in low-income countries, a household, as long as it can afford the cost of migration, may decide to relocate one or more members in order to reduce the correlation between origin and destination income shocks (Rosenzweig & Stark, 1989). Therefore, a better understanding of the effectiveness and limitations of migration as a risk management strategy may inform us about households' ability to adapt to weather-related risk, and, potentially, inform policy design in the context of increasing occurrence and intensity of climatic stress in developing countries.

A growing literature has investigated the use of migration as a response to climate change or climate variability. Starting with Rosenzweig and Stark's (1989) seminal paper on India, some evidence of environmentally induced migration has been found for both low-income (Ezra & Kiros, 2001; Findley, 1994; Henry, Schoumaker, & Beauchemin, 2004; Meze-Hausken, 2000) and high-income countries (Feng, Krueger, & Oppenheimer, 2010; McLeman & Smit, 2006).

However, the environmentally induced migration is a highly contextual phenomenon, depending on particular agroecological conditions or cultural norms, as in the case of female migration (Curran & Rivero-Fuentes, 2003), and therefore different studies produce different, sometimes conflicting, results. For example, Gray and Bilsborrow (2013) emphasise the importance of international migration as a response to agricultural shocks in Ecuador, whereas Findley (1994) and Henry et al. (2004) suggest that in West Africa, migrants choose short-distance destinations. Similarly, both Findley (1994) and Henry et al. (2004) show that mobility takes place primarily within rural zones. On the other hand, Barrios, Bertinelli, and Strobl (2006) and Marchiori, Maystadt, and Schumacher (2012) propose a model where environmental factors lead to urban migration. Other inconsistencies occur with respect to the role of female migration (Findley, 1994; Gray & Mueller, 2011), the impact of natural disasters versus slow-onset climatic changes (Gray & Mueller, 2012; Halliday, 2006), or even sign of the relation between climatic factors and migration (see Black, Kniveton, & Schmidt-Verkerk, 2011; Feng et al., 2010; Munshi, 2003; for Mexico example).

What is more, a closer examination of the literature suggests that important data issues may be at stake. First, a great number of studies are based on surveys covering a very limited number of individuals, households, and communities, which significantly hinders statistical inference. Second, climatic data itself has not always been available nor reliable, and covers a limited time span in many developing countries, forcing researchers to base their estimations on merely a decade of observations, or on highly extrapolated data. Finally, many studies use rainfall data only, whereas the impact of temperature extremes is found to be much more detrimental to agriculture (Ahmed et al., 2011). Therefore, despite substantial progress in the field of environmental migration, the hybrid narrative of environmental migration requires further investigation.

In this paper, we attempt to address these challenges in a number of ways. Our contribution to the existing literature is threefold. First of all, we employ standardised precipitation evapotranspiration index (SPEI) as our principal measure of weather conditions, which is a big improvement over previous studies using temperature or rainfall data only. Recent studies (Vicente-Serrano, Beguería, & López-Moreno, 2010; Vicente-Serrano, Zouber, Lasanta, & Pueyo, 2012) reveal that this index tracks dry or wet conditions better than traditional indices like the Standardised Precipitation Index (SPI) or Palmer Drought Severity Index (PDSI); besides, by incorporating temperature and precipitation, it covers the whole range of the potential impacts of temperature, rainfall, and their interactions on crop output. To our knowledge, our paper is the second in the literature on environmental migration that uses SPEI (see Mueller, Gray, & Kosec, 2014). Besides, we base our estimations on high-quality household survey data on Tanzania, covering a large representative sample of households from the whole country. Second, Tanzania agroecological diversity, spanning from semiarid to humid areas, provides enough variation in weather conditions, which is necessary for statistical purposes. Finally, we propose a model in which adverse weather conditions, by reducing agricultural output, prompt households to send their members away in order to secure income sources. Our results suggest that a 1 per cent reduction in agricultural output instrumented with weather shock increases the probability of migration by 13 percentage points on average.

Background

Tanzania is a pertinent case study for the analysis of the link between weather, agricultural yields and human mobility. In a recent dataset prepared by the Center for Global Development (Wheeler, 2011), the country has been ranked 20th in the world in terms of the extreme weather vulnerability.[1] In the last decade, Tanzania registered two important drought events which led to severe losses in some regions whereas other parts of the country are subject to recurrent flooding. The aggregate indices thus hide important heterogeneity in terms of both current agroclimatic conditions,[2] but also future predictions of climate change impacts.

An empirical analysis of rainfall and temperature suggests a trend of decreasing rainfall between 1922 and 2007, whereas temperature mean and extremes increased by 1.9 and 0.2°C respectively over that period (Mary & Majule, 2009). The same trend can be seen in our data. Several future projections using general circulation models indicate that the interior of the country will experience a 20 per cent decrease in rainfall in June–August season, shortening the rainy season and increasing the risk of drought, whereas precipitation is expected to increase by up to 50 per cent in eastern Tanzania and the Lake Victoria region (Hulme, Doherty, Ngara, New, & Lister, 2001). Temperatures are projected to increase by up to 2.2°C by 2100 (Agrawala et al., 2003). Climate change should therefore be considered an important challenge which Tanzanian households will be about to face in the near future. Even in the short run, they have already been exposed to altered weather patterns: erratic and poorly distributed rainfall, shorter and hotter growing season, and unpredictable start and end of the rainy season, with detrimental consequences for agricultural productivity (Kijazi & Reason, 2012).

Tanzania, like many Sub-Saharan countries, seems to be particularly vulnerable to increased weather variability because of the role that agriculture plays in the economy and livelihoods: it accounts for about half of gross production, and employs about 80 per cent of the labour force (Thurlow & Wobst, 2003). Agriculture in Tanzania is primarily rain-fed, with only 2 per cent of arable land having irrigation facilities (FAO, 2009), making yields dependent on weather realisation. In a recent study, Rowhani, Lobell, Linderman, and Ramankutty (2011) predict that by 2050, the projected seasonal temperature increase by 2°C in Tanzania will reduce average maize, sorghum, and rice yields by 13, 8.8, and 7.6 per cent respectively. Ahmed et al. (2011) model a spillover effect that this decrease in crop yields will have on other sectors, and especially on food prices, leading to an increase in poverty headcount.

Data

We base our analysis on high quality household survey data. We use the Tanzania National Panel Survey (TZNPS) collected by the National Bureau of Tanzania as part of nationally representative living standard survey (WB's LSMS-ISA). The extensive focus of the survey on agriculture offers a wealth of data. TZNPS include a range of data on 16,709 individuals from 3,265 households. However, since our focus is on households involved in agricultural activities, we end up with a sample of 1,583 farm households for which we have full data. We conduct the analysis at the cross-sectional level, using the first 2008/2009 wave as the baseline from which we take pre-migration household characteristics and agricultural production data. Since there is no explicit question on permanent migration in the dataset, the second wave of the survey serves to identify migrants.

For the purpose of this study, we adopt the New Economics of Migration approach (Katz & Stark, 1986; Lucas & Stark, 1985; Stark & Bloom, 1985; Stark & Levhari, 1982) where migration is a collective and not an individual decision; household is therefore the unit of observation. Our dependent variable is a migration dummy for households which sent at least one migrant between the two waves. We identify such households by comparing the place of residence of all households members in the first and the second waves of the survey; thus migration dummy equals one for households with at least one member who permanently moved out of the original village between 2008/09 and 2010/11.[3] Despite the fact that we are interested in economically-driven migration, we do not restrict the sample to working-age individuals: the 2006 Integrated Labour Force Survey suggests that 32 per cent of children aged 5–17 years were employed in economic activities; and nearly half of children were engaged in households tasks. Our results remain unchanged when we exclude children from the analysis.

TZNPS provides a range of household characteristics which we use in our estimations (see table A1 in the Online Appendix for details): household labour, that is the number of household members in working age (15 to 64), dummy for female headed households, the highest level of education in the household in years of schooling, physical assets – that is dwelling and other durables possessed – cattle units,[4] and dummy for previous migration experience, which equals one if any household member had previously moved out or into the current location. Detailed agricultural data is also available; for the purpose of this study we use land area in acres and land characteristics such as terrain slope in the agricultural production equation. We use the data on distance to the district capital as a proxy of connectedness or cost of migration. The data on 2008/2009 income (total income and agricultural income) and value of crop production (all aggregates in thousands of Tanzanian shillings) come from the FAO Rural Income Generating Activities (RIGA) database.[5] The RIGA database covers all agricultural households from the TZNPS and all variables available in RIGA were computed based on the original TZNPS dataset.[6]

Since the TZNPS provides the GPS coordinates of the households,[7] we are able to match the households from the survey with the corresponding weather data. In our analysis, we employ the SPEI index from the high-resolution (0.5x0.5 degree) gridded dataset by Vicente-Serrano et al. (2010). SPEI is an index of deviations from the average water balance, that is precipitations minus potential evapotranspiration. The novelty lies in the fact that 'SPEI includes the role of temperature in drought severity by means of its influence on the atmospheric evaporation demand' (Vicente-Serrano et al., 2010). Even though SPEI is oftentimes used as a drought index, we do not put any threshold to assign drought conditions; instead, we use the whole continuum of possible outcomes for both dry (negative values) and wet (positive values) conditions. We apply this measure to the growing season. Tanzania is characterised by both unimodal (November–April) and bimodal rainfall patterns (March–May and October–December); the hottest period occurs between November and February, and the coldest between May and August. In order to account for all these factors, we take the average value of SPEI index for months from January to June.[8] Since we don't know the distribution of households between the two rainfall regimes, we check our results using the average for March–May only, which corresponds to the long *masika* season in bimodal areas. Alternatively, we use monthly temperature and precipitation from a high-resolution[9] gridded dataset by the Climate Research Unit of the

University of East Anglia (Harris, Jones, Osborn, & Lister, 2014). We employ them in levels (seasonal mean temperature and precipitation, and squared terms), but we also construct temperature and precipitation shocks, which we define as residual from the 30-year trend modelled with harmonic regression proposed by Helsel and Hirsch (2002).

Two caveats related to the weather data we use have to be taken into account. First, both SPEI and CRU are gridded datasets obtained by means of extrapolation of the data available from meteorological stations. The availability and accuracy of such data in developing countries may be questionable. However, we only use the last 30 years of data, and, as documented in CRU, the number of stations, and therefore the quality of data, improved significantly over that period in comparison to previous years.[10]

Second, the use of gridded data implies the possibility of a number of enumeration areas[11] having the same weather observations. In particular, this problem relates to Dar es Salaam. However, since we focus here on agricultural households only, the large majority of households from Dar es Salaam are excluded from our sample. Overall, we find from 1 to 32 households within the same grid cell; however, in 80 per cent of cases, a maximum of three enumeration areas (which corresponds to around 21–23 households) fall into the same cell. We correct this by applying cluster and Moulton correction options.

14 per cent of households sent at least one migrant between the two waves (table A1 in the Online Appendix). Even though this figure may seem to be low, and indeed, both quantitative and qualitative studies have documented reluctance towards migration in Tanzania (Beegle, De Werdt, & Dercon, 2011; Mary & Majule, 2009), note that in this study we measure migration flow, that is the proportion of households which sent at least one member away between 2008/2009 and 2010/2011. In particular, if we take into account that TZNPS is a representative survey for the whole country, it would suggest that almost three million people moved in Tanzania just within one year. Note that only 12 per cent of moves are explicitly related to marriage. Besides, as suggested by Rosenzweig and Stark (1989), environmental factors may also play a role in marriage migration decisions. In our dataset, we observe internal migration only. This is consistent with the migration patterns observed in a different household survey conducted in the Kagera region of Tanzania (Kagera Health and Development Survey) which shows that only nine out of 6,000 individuals tracked moved out of the country over the 10- year period.

Some important differences can be observed between households with and without new migrants (Table 1). In particular, lower values of 6- and 12-month SPEI point towards more pronounced dry conditions that migrant-sending households experienced in 2008. According to our hypothesis, this is exactly what could have pushed them to relocate some of their members. These households are wealthier, both in terms of current income and assets, proxied by the total livestock units, which is not only a wealth indicator, but also constitutes an important productive asset in Sub-Saharan Africa. Much fewer households in this group are subsistence farmers.[12] Similarly, households who sent migrants are less financially constrained, since they have better access to credit and are more involved in informal assistance groups (SACCOS), even though these differences are not or are barely statistically significant. This may suggest that migration is costly, and that poor households cannot afford it. Finally, households that sent their members away differ significantly along the lines of traditional migration drivers: they are of bigger size and are better educated. On average, more households from this group already have previous migration experience, and the value of remittances they receive in the baseline year is higher than among households that did not send any migrants after 2008.

Estimation Strategy

Our specification is motivated by the literature on the New Economics of Migration (Katz & Stark, 1986; Lucas & Stark, 1985; Stark & Bloom, 1985; Stark & Levhari, 1982). A central tenet of this approach is that families evolve economic strategies not only to maximise household earnings, as in

Table 1. Characteristics of Migrant-Sending Households

	Households without new migrants	Households with new migrants	Difference
SPEI01	−0.158	−0.175	0.0161
SPEI06	−0.108	−0.246	0.138***
SPEI12	−0.247	−0.343	0.0961**
SPEI24	0.697	0.721	−0.0237
SPEI48	0.158	0.13	0.0284
Temperature mean	22.76	23.14	−0.380*
Temperature	22.78	23.2	−0.417**
Temperature shock	−1.715	−1.298	−0.417**
Precipitation mean	708.7	718.4	−9.677
Precipitation mean	661.1	660.6	0.5
Precipitation shock	−10.69	−10.77	0.0834
Agricultural production	707.3	713	−5.665
Crop production	560	551.4	8.545
Livestock production	147.3	161.5	−14.21
Total income	891.4	1197.8	−306.4**
Farm income	409.3	438.6	−29.33
Crop income	242.6	273.6	−31.02
Off-farm income	482.2	759.2	−277.1**
Farm specialiser	0.53	0.473	0.0575
Subsistence specialiser	0.417	0.338	0.0788*
HH size	5.259	6.459	−1.201***
HH labour	2.435	3.275	−0.840***
Female head	0.242	0.275	−0.033
Education	5.913	6.937	−1.024***
Credit	0.0632	0.0811	−0.0179
Saccos	0.0397	0.0721	−0.0324*
Distance	36.04	32.01	4.03
Migration experience	0.442	0.559	−0.116**
Remittances	47.35	68.93	−21.58***
Cattle	1.456	2.662	−1.206**
Livestock	1.846	3.008	−1.162**
Land	6.359	6.266	0.0936
Number of observations	1,361	222	

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Harris and Todaro's (1970) model, but also to minimise risk. In our model, which applies to agricultural households in developing countries, the principal source of risk is weather. Like in Feng et al. (2010), the main assumption here is that weather does not impact migration decisions directly, for example through its amenity value or through household preferences for a given climatic setting, and the results from the reduced-form probit regression of SPEI on migration decisions seem to support this hypothesis. In most cases, the coefficients of SPEI are insignificant, both in statistical as well as economic terms, with the only exception of 12-month SPEI significant at 10 per cent level (see table A2 in the Online Appendix). Instead, we posit that weather shocks affect mobility patterns solely through their detrimental impact on agricultural yields. Indeed, since income derived from farming activities constitutes a big share of total income,[13] a negative weather shock not only translates directly into the income shock, but may also have important implications for food security, in particular for subsistence farmers.[14] This, in turn, may prompt households to send some of their members away in order to diversify income sources.

Our empirical strategy, therefore, consists of two steps. First, we analyse weather as a risk factor in agriculture and we estimate crop production function. We use the value of agricultural production and not agricultural income since on the one hand, the output is directly affected by weather shocks while income is affected by the corresponding price dynamics in the local markets, and on the other, it allows us to minimise the measurement error associated with income computation based on recall data. We also focus on crop rather than livestock production because in our sample, this is the dominant farming activity: not only 95 per cent of households cultivate crops, but crop production also constitutes by far the largest part in total agricultural production with the median share amounting to 98 per cent. Besides, even though livestock production is certainly affected by climate change, the mechanisms of these changes may not be the same as in cases of plant growth.[15] We model crop production as in Equation (1):

$$Y_{crop,ij} = f\left(N_{ij}, L_{ij}, LS_{ij}, S_{ij}, Shock_j\right) + \epsilon_{ij} \tag{1}$$

where logarithm of crop output is determined as a function of weather shock in a village j, and as a function of household i's number of labourers N_{ij}, land units L_{ij}, livestock units LS_{ij}, and land slope S_{ij}. As in a typical production function approach, the underlying assumption is that the adaptive capacities within agriculture are low. In the context of our study, this assumption seems to be justified given the short time span of our dataset which is not long enough to adapt productive technology. The observed level of potential adjustments to changing climate is negligible: only 2 per cent of plots are irrigated; fertilisers, pesticides, herbicides, and improved seeds are used on 9 per cent of plots. With respect to technology employed, hand power is still dominant with 90 per cent of farmers using hand tools only, and with a mere 0.3 per cent of farmers resorting to mechanic power. As anywhere in the developing world, this may be explained by limited access to finance: only 6 per cent of households in our sample have access to formal credit, and only 5 per cent are involved in savings and credit cooperative organisations, SACCOS.[16]

Second, we proceed to estimating migration probability. In light of the assumptions of the model discussed above, weather does not appear in the migration equation directly, but serves as an instrument for agricultural income that is the main explanatory variable in migration decisions. Thus, we apply an IV probit model where Equation (2) estimates the determinants of the household i in a village j sending at least one migrant M between 2008 and 2010:

$$M_{ij} = f\left(Y_{crop,ij}, X_{ij}, C_j\right) + \varepsilon_{ij} \tag{2}$$

$Y_{crop,ij}$ is the logarithm of crop production in 2008, one year prior to migration decision. The vector X refers to pre-migration household characteristics at the baseline (2008/2009), such as size of available household labour, gender of household head, the highest level of education within a household, livestock assets, and landholdings. We include these variables to reflect initial endowments that influence the decision to send migrants and are uncorrelated with climate fluctuations. C_j denotes cost of migration, proxied by the distance from the village to a district capital. In order to account for the main mechanism in our model, but also to take into account the endogeneity in Equation (2), we instrument crop production with weather shock and land slope; the other production factors from Equation (1) appear directly as exogenous variables in Equation (2). Technically, therefore, by employing the IV probit method, we calculate the marginal contribution of weather shock, in the main specification proxied by SPEI, to crop production, and use this variable to explain migration decision within a household.

One potential caveat in our approach is that weather may affect migration decision through channels other than crop production, such as livelihoods, animal production or off-farm labour productivity. If this is the case, then the assumptions of our model will be violated. However, in the estimation strategy we do not employ baseline climate variables, such as temperature and precipitation, long-term means or coefficients of variation, that could be associated with many unobserved socio-ecological characteristics affecting migration propensity within local communities. Second, we conduct parallel analyses for livestock production and off-farm income (see table A4 in the Online Appendix for off-farm income regression), and the results point to the fact that even though weather anomalies have a direct impact on both livestock production and off-farm income, these are not the channels through which weather shocks affect migration propensity.

Crop Production Function

First, we estimate the impact of weather shock on crop production as in Equation (1). As a starting point, we use SPEI at different timescales (1, 6, 12, 24, and 48 months) as our principal weather variable. These timescales allow for identifying various types of drought that affect different usable water resources.[17] Recall that SPEI index is normalised with mean zero and standard deviation one, and that negative values indicate drought conditions.[18] Results in Table 2 confirm strong negative impact of drought conditions on crop production. The increase in water deficit by one standard deviation results in a crop production decline by 20 to 30 per cent according to different timescales. The magnitude of SPEI coefficient is thus very important, even if in practice, one standard deviation change in SPEI would entail an important shift in weather conditions; for example, in 2008, the values observed in our dataset ranged from −1.03 to 1.10 in the growing season. Interestingly, statistical significance of SPEI coefficients increases along timescales. This result becomes more apparent when we correct standard errors with cluster[19] and Moulton correction options in order to account for the fact that weather data we use is aggregated at the grid cell level, whereas our estimation is done at the household level. While coefficients for short time scales are not significant at all or are significant only at the 10 per cent level (for sake of brevity, results for short-time scales are not reported here), the results for longer time scales remain highly significant at the 1 or 5 per cent level, as in columns (6) to (8). This is consistent with Vicente-Serrano et al.'s (2012) findings, according to which vegetation in semiarid and subhumid areas, which are the focus of our study, tends to respond to drought at longer timescales. 'Vegetation of these regions is adapted to tolerate regular periods of water deficit and has physiological mechanisms to cope with these conditions' (Vicente-Serrano et al., 2012). Based on these findings, we choose to include longer timescale SPEI in our preferred specification (12-, 24-, and 48-month indices).

In order to make a reference to previous studies, we also check the impact of weather on crop production using standard weather variables: temperature and precipitation. We draw on studies that use weather variables in levels (Mendelsohn, Nordhaus, & Shaw, 1994) and weather shocks (Feng et al., 2010; Kelly, Kolstad, & Mitchell, 2005). Columns (4) and (9) in Table 2 present the results for temperature and temperature squared in the 2008 growing season and confirm the nonlinear inverted-U shape found in previous studies (Schlenker & Roberts, 2009). We also include precipitation and precipitation squared,[20] but they are not statistically significant. First, as explained by Rowhani et al. (2011), the CRU dataset overestimates rainfall in comparison to data obtained from meteorological stations, while temperature measures are much more consistent. Also, rainfall patterns show much greater spatial heterogeneity than temperature, and such heterogeneity is not fully captured by extrapolated data. Second, recent studies suggest that temperature extremes may be much more detrimental for plant growth than precipitations (Schlenker, Hanemann, & Fisher, 2006). Finally, in columns (5) to (10) we also test the impact of temperature and precipitation shocks on crop production. Despite the statistically significant coefficient for the temperature shock, it is worth noting that its magnitude is much smaller than those of SPEI coefficients. The impact of precipitation shock, again, is not significant. These results suggest that the range of weather conditions captured by SPEI is more pertinent to crop growth than a single weather factor.

Migration

Table 3 displays the main results for migration IV probit model. For agricultural households, weather shocks appear to be an important migration driver through their impact on crop production. When we apply our preferred specification with long timescales SPEI indices as in columns (1) to (3), the results suggest that a 1 per cent decrease in crop production induced by a weather shock increases the

Table 2. Crop Production

Dependent variable: logarithm of crop production	OLS					Moulton				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HH labour	0.138***	0.128***	0.134***	0.130***	0.133***	0.138***	0.128***	0.134***	0.130***	0.133***
	(0.0189)	(0.0188)	(0.0189)	(0.0190)	(0.0190)	(0.0200)	(0.0200)	(0.0200)	(0.0201)	(0.0201)
Land	0.00421***	0.00391**	0.00396**	0.00425***	0.00421***	0.00421**	0.00391**	0.00396**	0.00425**	0.00421**
	(0.00155)	(0.00155)	(0.00155)	(0.00156)	(0.00156)	(0.00185)	(0.00185)	(0.00185)	(0.00185)	(0.00186)
Cattle	0.0246***	0.0216***	0.0229***	0.0217***	0.0221***	0.0246***	0.0216***	0.0229***	0.0217***	0.0221***
	(0.00574)	(0.00573)	(0.00573)	(0.00584)	(0.00583)	(0.00639)	(0.00639)	(0.00639)	(0.00651)	(0.00652)
Slope	0.0196***	0.0262***	0.0252***	0.0195***	0.0189***	0.0196***	0.0262***	0.0252***	0.0195***	0.0189***
	(0.00464)	(0.00469)	(0.00465)	(0.00472)	(0.00471)	(0.00672)	(0.00682)	(0.00676)	(0.00687)	(0.00690)
SPEI12	0.310***					0.310***				
	(0.0686)					(0.115)				
SPEI24		0.241***					0.241**			
		(0.0569)					(0.0954)			
SPEI48			0.286***					0.286**		
			(0.0676)					(0.113)		
Temperature				0.459*					0.459	
				(0.241)					(0.403)	
Temperature squared				−0.0112**					−0.0112	
				(0.00529)					(0.00887)	
Temperature shock					−0.0469***					−0.0469**
					(0.0135)					(0.0229)
Constant	12.31***	12.06***	12.17***	7.806***	12.19***	12.31***	12.06***	12.17***	7.806*	12.19***
	(0.0633)	(0.0752)	(0.0635)	(2.820)	(0.0636)	(0.106)	(0.126)	(0.106)	(4.725)	(0.107)
Observations	1,583	1,583	1,583	1,583	1,583	1,583	1,583	1,583	1,583	1,583
R-squared	0.082	0.081	0.081	0.081	0.078	0.082	0.081	0.081	0.081	0.078

Notes: Coefficients for precipitation and precipitation squared (col. 4 and col. 9), and precipitation shock (col. 5 and col.10) not reported. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3. Migration

Dependent variable: probability of migration	SPEI12 (1)	SPEI24 (2)	SPEI48 (3)	Temperature precipitation (4)	Temperature precipitation shock (5)
Logarithm of crop production	−0.129***	−0.0942**	−0.107***	−0.110**	−0.139***
	(0.0333)	(0.0430)	(0.0393)	(0.0547)	(0.0513)
HH labour	0.0404***	0.0384***	0.0393***	0.0394***	0.0408***
	(0.00545)	(0.00618)	(0.00584)	(0.00625)	(0.00556)
Education	0.00816***	0.00838***	0.00833***	0.00832***	0.00806***
	(0.00293)	(0.00298)	(0.00297)	(0.00298)	(0.00297)
Female head	0.0126	0.0270	0.0223	0.0211	0.00893
	(0.0246)	(0.0267)	(0.0259)	(0.0301)	(0.0300)
Cattle	0.00472***	0.00408**	0.00430***	0.00429**	0.00477***
	(0.00157)	(0.00169)	(0.00164)	(0.00175)	(0.00167)
Migration experience	0.0402**	0.0411**	0.0413**	0.0409**	0.0397**
	(0.0170)	(0.0173)	(0.0172)	(0.0172)	(0.0171)
Distance	−0.000244	−0.000234	−0.000237	−0.000240	−0.000244
	(0.000213)	(0.000220)	(0.000217)	(0.000218)	(0.000210)
Observations	1,583	1,583	1,583	1,583	1,583
Wald test of exogeneity Prob>chi2	0.0012	0.046	0.0158	0.0774	0.0294

Notes: Instrumented: logarithm of crop production. Main instrument(s):SPEI12 (col.1), SPEI24 (col.2), SPEI48 (col.3), temperature, temperature squared, precipitation, precipitation squared (col.4), temperature and precipitation shock (col.5). Results presented in terms of the average marginal effects. First-stage regressions omitted. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

probability of migration within the following year by 9 to almost 13 percentage points on average,[21] depending on the time-scale used. Not only the magnitude, but also the statistical significance of the main coefficient is highest when the weather shock is defined by the SPEI capturing water balance conditions during 12 months. We find the significant impact of crop output deviations on migration decision when we use temperature and precipitation and the squared terms as in column (4), and deviation from the trend as in column (5) as well. Findings in column (4) should be treated with caution, however, since the results for the temperature and precipitation in levels in the agricultural production equation are not robust to different specifications (Table 2). The estimates in Table 3 confirm the importance of traditional migration drivers: labour force availability, education level and previous migration experience increase the probability of migration, but the magnitude of this impact is much smaller than that of crop production shock. Surprisingly, the effect of the distance to the district capital is almost negligible. On the other hand, as expected, the initial endowment, proxied here by the total livestock units of cattle, turns out to be a significant factor in migration process.

Taking into account the role that initial endowments may play in migration, especially in the context of low income and important financial constraints, we explore this issue in detail in Table 4. We divide our sample into three wealth categories and conduct separate estimations for each of them. We apply two measures of wealth: an asset-based wealth index which we constructed by applying Kolenikov and Angeles (2004) polychoric principal component analysis as in columns (1) to (3), and expenditures per capita.[22] Independent of the wealth measure used, the results show an interesting pattern: weather-induced crop output shock is an important predictor of migration probability only for households in the middle of the wealth distribution, whereas it is insignificant for the poorest and the richest households. We may expect that the poorest households cannot afford migration costs, while the richest ones may prefer and also afford *in-situ* adaptation strategies, such as irrigation or drought-resistant crops.

Table 4. Migration, Initial Endowment and Specialisation

Dependent variable: probability of migration	Wealth tertiles			Specialisation	
	1st	2nd	3rd	Farm specialisers	Diversified
	(1)	(2)	(3)	(4)	(5)
Logarithm of crop production	−0.116	−0.165***	−0.0658	−0.220***	−0.0913*
	(0.0865)	(0.0383)	(0.0609)	(0.0692)	(0.0494)
HH labour	0.0600***	0.0398***	0.0283***	0.0512***	0.0332***
	(0.0154)	(0.00791)	(0.0102)	(0.00775)	(0.00859)
Education	0.00801	0.00476	0.0195***	0.00676	0.0142***
	(0.00534)	(0.00525)	(0.00683)	(0.00443)	(0.00430)
Female head	0.0181	0.0108	0.0690	0.0292	0.0238
	(0.0443)	(0.0346)	(0.0542)	(0.0325)	(0.0377)
Cattle	0.00180	0.00495**	0.00514*	0.00335*	0.00290
	(0.00304)	(0.00249)	(0.00294)	(0.00174)	(0.00357)
Migration experience	0.0535*	0.0512*	0.0305	0.0315	0.0458*
	(0.0311)	(0.0273)	(0.0387)	(0.0233)	(0.0259)
Distance	−0.000433	−0.000222	−6.12e-05	0.000172	−0.000738*
	(0.000379)	(0.000302)	(0.000547)	(0.000327)	(0.000404)
Observations	564	593	426	827	756
Wald test of exogeneity Prob>chi2	0.1944	0.0006	0.5326	0.0099	0.0800

Notes: Instrumented: logarithm of crop production. Main instrument: SPEI12. Wealth tertiles based on asset-based index based on the polychoric principal component analysis (Kolenikov & Angeles, 2004). Farm specialiser: hh deriving >75 per cent of income from agriculture. Results presented in terms of the average marginal effects. First-stage regressions omitted. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Finally, in order to test the validity of the agricultural productivity mechanism in our model, we estimate Equation (2) separately for households specialised in agriculture, which we define as those households that derive at least 75 per cent of their income from agriculture, and diversified households. The results in columns (4) and (5) confirm our expectations. Weather-induced negative crop output shocks play a much more important role for households dependent on agriculture: the coefficient in column (4) is more than twice as high than in column (5), both in terms of its magnitude and statistical significance. A similar pattern is observed when we use temperature and precipitation shocks as instruments for crop output,[23] even though the coefficients and their statistical significance are lower, consistent with the previous results. This clearly suggests that farmers specialised in agriculture, who constitute about half of our sample, are the most vulnerable to the impact of deviations in weather patterns.

Robustness

As a robustness check, we employ a set of estimations using a constrained definition of dependent variable, as well as alternative measures of the main explanatory variable (Table 5). In column (1), we recall our principal results. In column (2), we estimate our model for migrants defined as those individuals who moved a distance greater than 10 km. With this threshold, we exclude very short-distance moves within or in the vicinity of the village of origin. In column (3), we include only individuals of working age (15-year old and older) in order to put emphasis on the economic motivations of migration. For the sake of brevity, we present results only for crop production instrumented with 12-month SPEI. Finally, in columns (4) to (6), we instrument crop output with SPEI measured uniquely for the long *masika* season, the most important growing season in regions characterised by bi-modal rainfall patterns. Our principal

Table 5. Robustness Check

Dependent variable: probability of migration	Basic model (1)	Migrants >10 km (2)	Migrants in working age (3)	Masika season SPEI12 (4)	Masika season SPEI24 (5)	Masika season SPEI48 (6)
Logarithm of crop production	−0.129***	−0.111***	−0.131***	−0.146***	−0.106**	−0.104***
	(0.0333)	(0.0360)	(0.0333)	(0.0309)	(0.0430)	(0.0400)
HH labour	0.0404***	0.0354***	0.0413***	0.0409***	0.0392***	0.0391***
	(0.00545)	(0.00566)	(0.00532)	(0.00531)	(0.00594)	(0.00590)
Education	0.00816***	0.0104***	0.00715**	0.00799***	0.00835***	0.00835***
	(0.00293)	(0.00285)	(0.00287)	(0.00290)	(0.00297)	(0.00297)
Female head	0.0126	0.0220	0.00428	0.00511	0.0222	0.0233
	(0.0246)	(0.0244)	(0.0236)	(0.0240)	(0.0269)	(0.0261)
Cattle	0.00472***	0.00389**	0.00485***	0.00498***	0.00432***	0.00425***
	(0.00157)	(0.00156)	(0.00153)	(0.00154)	(0.00167)	(0.00165)
Migration experience	0.0402**	0.0323*	0.0382**	0.0390**	0.0409**	0.0413**
	(0.0170)	(0.0165)	(0.0167)	(0.0168)	(0.0172)	(0.0172)
Distance	−0.000244	−0.000196	−0.000241	−0.000244	−0.000238	−0.000237
	(0.000213)	(0.000205)	(0.000211)	(0.000208)	(0.000218)	(0.000218)
Observations	1,583	1,583	1,583	1,583	1,583	1,583
Wald test of exogeneity Prob>chi2	0.0012	0.0065	0.0011	0.0002	0.0278	0.0199

Notes: Instrumented: logarithm of crop production. Main instrument(s): SPEI12 (col. 1–3), SPEI12 masika (col.4), SPEI24 masika (col. 5), SPEI48 masika (col.6). Results presented in terms of the average marginal effects. First-stage regressions omitted. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

findings turn out robust to these changes. The magnitude of the coefficients moves only slightly, while their statistical significance remains high at 1 per cent.

Finally, we conduct the attrition analysis (see the Online Appendix). Even though low in comparison to most longitudinal surveys (4.5% of individuals from our target sample), the attrition observed in the TZNPS may potentially constitute a serious problem for the analysis of migration. Since residential moves are typically one of the main reasons for non-response in panel surveys (Fitzgerald, Gottschalk, & Moffitt, 1998), it is plausible that attrition in our dataset is not random but instead is systematically associated with the covariates explaining migration decisions. If this were the case, then our estimates based on a sample of non-attritors would be biased. However, we show that despite being non-random, the attrition observed in the sample does not consistently bias our results. The only caveat is that by conducting the analysis based on the sample of non-attritors, we may potentially underestimate the magnitude of our findings.

Conclusion

We investigate whether Tanzanian households respond to weather risk. We test an IV probit model where migration decision is determined by agricultural income instrumented with standardised precipitation evapotranspiration index (SPEI), but also temperature and precipitation shocks. Our results suggest that weather shocks have a significant negative impact on crop production. As a consequence, a 1 per cent reduction in agricultural income induced by weather shock increases the probability of migration by 13 percentage points on average within the following year. Interestingly, migration decision appears to be conditional on initial endowment, since only households in the middle of the wealth distribution respond to the weather shock by spatially diversifying their income sources. What is more, such a mechanism where climate variability affects household migration decision through agricultural channel is valid only for households whose income is highly dependent on agriculture, while the results are not significant for diversified livelihoods.

To our knowledge, this study is the second to use SPEI index in the literature on environmental migration. Our results showed some important advantages of this multi-scalar index over different measures of temperature and precipitation. SPEI encompasses the whole spectrum of water balance, including the effects of temperature, and is therefore better suited to capture meteorological conditions that have an impact on plant growth and agricultural output.

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Notes

1. http://www.cgdev.org/page/mapping-impacts-climate-change [15.10.2014].
2. The diversity of agroecological zones in Tanzania ranges from arid or semiarid zones, sub-humid highlands, plateaux, to alluvial plains and coastal zones (de Pauw, 1984).
3. We identify residential moves based on the GPS coordinates of place of origin and destination.
4. Number of cows, calves, bulls, and steers expressed as tropical livestock units (TLU). For conversion factors, see Chilonda and Otte (2006).
5. www.fao.org/economic/riga/riga-database/en/ [11.11.2013].
6. For methodology, see FAO (2012).
7. For confidentiality reason, these are the averages of household GPS coordinates in each enumeration area, to which a random offset within a specified range has been applied. Spatial queries using medium- or low-resolution datasets should be minimally affected by the offsets.
8. This approach has been adopted in climatology literature, see Ahmed et al. (2011).
9. SPEI dataset is computed based on the data from CRU, therefore, both datasets have the same resolution.
10. We conducted separate analysis using longer timespans of 50 and 80 years, but we didn't find any significant results.
11. Enumeration area refers to a village in rural areas and to a neighbourhood in urban areas.
12. Subsistence farming is a form of agriculture where almost all production is consumed by the household.
13. In our sample, farm income amounts to more than 60 per cent of total income on average.
14. Subsistence farmers constitute 40 per cent of our sample.
15. See Thornton et al. (2008) for reference.
16. This low engagement in cooperative credit solutions may seem surprising especially when compared to neighbouring Kenya. According to J.D. Barkan, this results from the socialist past, where '[the ruling party's] monopolization over rural associative life [. . .] inhibited, indeed actively discouraged, the emergence of self help community development organizations of the type that flourished in Kenya' (Barkan, 1994, p. 21).

17. 'Short time scales are mainly related to soil water content and river discharge in headwater areas, medium time scales are related to reservoir storages and discharge in the medium course of the rivers, and long time scales are related to variations in groundwater storage' (Vicente-Serrano et al., 2010).
18. A SPEI equal to zero indicates a value corresponding to 50 per cent of the cumulative probability of water deficit/water surplus according to log-logistic distribution (Vicente-Serrano et al., 2010).
19. Results for cluster option available upon request; they confirm all the results obtained with the OLS.
20. Not reported here.
21. Results are presented in terms of the average marginal effects. First-stage regressions are omitted.
22. Not reported here.
23. Not reported here.

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