Internal Migration and Vulnerability to Poverty in Tanzania

REBECCA PIETRELLI
PASQUALE SCARAMOZZINO

Introduction

ACCORDING TO THE traditional approach, individuals chose to migrate with the expectation of earning better wages at their destination than they earn at their origin. In their seminal contribution, Harris and Todaro (1970) proposed a dual model of the labor market, with a traditional (agricultural/rural) sector that pays a subsistence wage and a modern (industrial/urban) sector characterized by a higher marginal product of labor. Migration is the mechanism through which the labor force moves toward the more productive sectors of the economy, thereby ensuring a more efficient allocation of labor.

This analysis is based on two key assumptions. First, migration is an individual decision. There is no explicit consideration that migration decisions are possibly made at the household level—with some members remaining in the region of origin and others migrating and then pooling resources with their family. Second, the decision to migrate is based solely on the expected value of the migrants' wage at the destination relative to the wage at the origin—without consideration of the risks associated with their decision.

The New Economics of Labor Migration (NELM) addresses the first issue by focusing on the household as the unit where the migration decision is made (Stark and Levhari 1982; Stark and Bloom 1985; Oded 1991). Some family members may decide to migrate and then remit back a share of their labor income to the original family. More generally, migration can act as an insurance mechanism, which enables the household to reduce its vulnerability to adverse shocks in the absence of fully developed insurance markets (Ray 1998, chapter 15; Bardhan and Udry 1999, chapter 8).

The role of uncertainty is increasingly seen as crucial for understanding migration decisions in low-income countries. Rosenzweig and Stark (1989) show that migration associated with marital arrangements among Indian households can reduce income uncertainty and help smooth household consumption in the presence of spatially covariant risks. More recently, the role of uncertainty in migration decisions has been studied by Burda (1995) in the context of real options theory (Dixit and Pindyck 1994). Income in both the region of origin and the region of destination is risky, and migration involves a sunk cost that cannot be recovered if the decision is reversed at a later date. Under these conditions, the option to migrate should only be exercised when a further delay would not be optimal. For instance, a reduction in income uncertainty in the destination might lead the household to bring forward the migration decision.[1] In this framework, migration can be seen as a key element of household risk management strategy. When income is pooled within the family, migration by some household members can be an effective tool to diversify the household's income across different sources, thereby reducing its overall risk.

In spite of its potential relevance, empirical analysis of the risk-mitigating aspects of migration is still very limited because of the difficulty in controlling the endogeneity of the migration decision, and because of the lack of experimental data. In this article, we are able to identify the risk-reducing effects of migration, thanks to an extreme meteorological event that took place in Tanzania. The country exhibits two rainfall regimes: unimodal (which covers the areas in the south, center, and west) and bimodal (in the north, the northern coast, and the north-west). The unimodal regions experience only one long rainy season during the agricultural year, whereas the bimodal regions have two short rainy periods. During the 2008–2009 season, the bimodal regions suffered an extreme drought. This shock affected eastern African countries and was described as "one of the worst in living memory" (IDRC 2010). However, unimodal regions were not affected. We look at this extreme natural event to examine how households in the region of origin were affected by the migration of household members. In particular, we analyze whether migration had a different effect on the household of origin depending on whether it had been directed toward a unimodal or a bimodal region.

We adopt a stochastic outcome approach to examine how migration may have contributed to reducing household vulnerability. Specifically, we follow Chaudhuri (2000); Chaudhuri, Jalan, and Suryahadi (2002); and Günther and Harttgen (2009) and estimate the household's vulnerability to expected poverty (VEP) as a measure of the effects of migration on family welfare. This approach to the analysis of household poverty is intrinsically dynamic and forward-looking, since vulnerability is defined as the probability that the household might fall below a critical poverty line as a result of unfavorable shocks. The approach is also consistent with the World Bank's "Social Risk Management" framework, which regards the ability of a community to manage risks as the main source of vulnerability (World Bank 2005).

The choice of focusing on internal migration allows us to contribute to this emerging literature. From the seminal work on internal migration in developing countries by Lucas (1997), the debate on the implications of internal migration for poverty alleviation and development has grown but there is still a lack of "adequate knowledge on the benefits gained from internal migration" (Vargas-Lundius 2018). On the other hand, the effects of international migration have been extensively investigated (see Ratha, Plaza, and Ozden (2016) for a recent review of the benefits of international migration for both destination and origin countries) and have been shown to be larger compared to internal migration (e.g., Castaldo, Deshingkar, and McKay (2012) and McKay and Deshingkar (2014) show that international migrants remit more and to richer households).

We use a comprehensive data set from surveys carried out over the period 2004–2010 in the region of Kagera in Tanzania. Individual household members are tracked over time, and the migrants' destination area is recorded. Alongside that information, facts about both the original family and the new family in the destination region are also recorded. It is thus possible to measure changes in the vulnerability of the original household in a fully dynamic setting. Specifically, we examine whether households whose members had migrated to a unimodal region of the country experienced a reduction in their VEP relative to households whose members had migrated to a bimodal region, which was affected by the drought. An *ex ante* unanticipated shock would have resulted in changes in the *ex post* vulnerability of the household.

The main empirical results are consistent with migration as an insurance mechanism for the household. First, we adopt a matching approach to examine the differential changes in the vulnerability to basic needs and food insecurity by households with and without migrants, and show that migration by some family members to unimodal regions significantly reduced the vulnerability of the household of origin. Next, we exploit the "natural experiment" of the drought in the bimodal meteorological regions in Tanzania to control for time-varying, unobserved heterogeneity, and observe that migration to the drought-free unimodal zones resulted in a significant decline in vulnerability for the household of origin. These novel empirical results show that migration did enable households to mitigate their risks.

Our results are consistent with those of Hirvonen and Lilleør (2015) and De Weerdt and Hirvonen (2016), who used the same data set for Kagera. Hirvonen and Lilleør (2015) established the existence of links between migrants and their home communities, both during the migration spell and following the return migration. De Weerdt and Hirvonen (2016) find evidence that migrants feel an obligation toward family members who remain at home, consistent with social norms associated with kinship (Lévi-Strauss 1969). Those who remain at home benefit from the migrants' positive shocks and receive some insurance against their own negative shocks, but do not suffer from the migrants' negative shocks.

The structure of the article is as follows. The next section provides background information on the Kagera region and on the severity of the drought of 2008–2009. The third section describes the household sample data used in the analysis and motivates our choice of measure of vulnerability. The fourth section illustrates the matching approach adopted in the article and discusses the empirical results of the analysis. The fifth section explains our methodology for the exogenous variation and shows that migration to unimodal zones resulted in a significant decline in vulnerability for the households of origin. Finally, the last section concludes the article.

The Kagera region and the drought of 2009

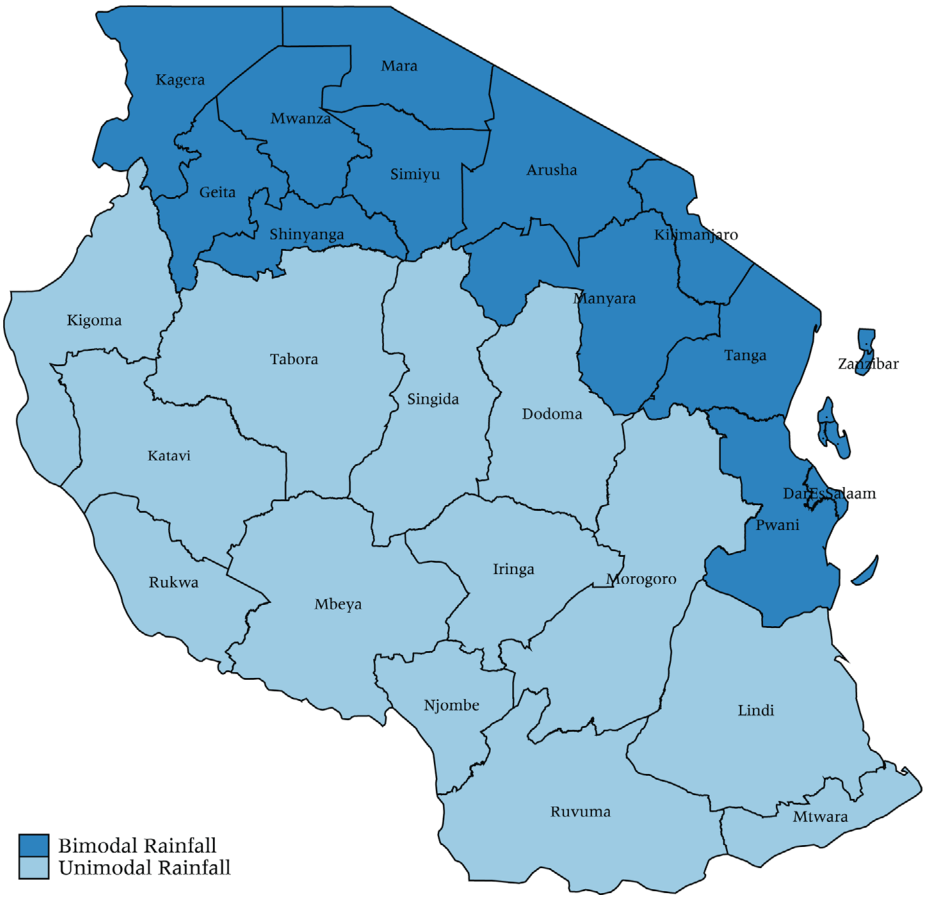
Kagera is the remote north-western region of Tanzania, bordering Lake Victoria, Rwanda, Burundi, and Uganda. The region covers 40,838 km^2 of land surface and 11,885 km^2 of water surface and is overwhelmingly rural. According to the latest Population and Housing Census (2012), the population residing in the region is about 2.5 million. The main ethnic groups of the region are the Haya and Nyambo tribes in the north, and the Subi, Sukuma, Zinza, and Hangaza tribes in the south.

The agricultural sector is dominant in the Kagera economy. The sector accounts for about 50 percent of the regional GDP and employs about 90 percent of the economically-active population in the production of food and cash crops. Bananas, beans, maize, and cassava are the main food crops, whereas coffee, tea, and cotton are the main cash crops. Livestock is the second most important economic activity in the region. Recently, fishing in Lake Victoria has provided an alternative source of income. The industrial base in the region is limited and is mainly comprised of agro-industrial operations (URT 2012). The region is relatively remote and is the farthest of the country from the political and commercial capital, Dar es Salaam.

Tanzania presents two distinct rainfall regimes. The country is accordingly divided into a unimodal zone (covering the south, central, and western regions of the country) and a bimodal zone (extending over the north, northern coast, and north-western areas), as shown in Figure 1. The two zones have different rainy seasons and consequently also different harvesting periods. The unimodal zone experiences only one long rainy season from December to April: sowing takes place in November and harvesting in June and July. The bimodal zone has short rainy seasons from October to December and a long rainy one from March to May. It has a short harvesting period in January/February and a long one in July/August (WFP 2013). As shown in Figure 1, the Kagera region falls in the bimodal rainfall regime.

In 2009, a severe drought hit many countries of East Africa, leading to crop failures and livestock mortality (Goldman and Riosmena 2013). The

FIGURE 1 Map of rainfall regimes in Tanzania

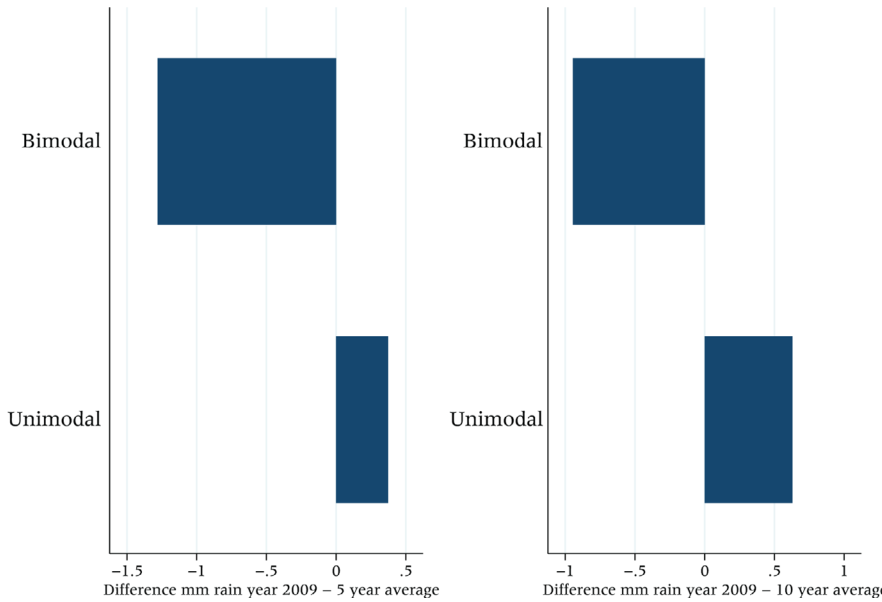


Source: Authors' elaboration using Stata 15.

northern regions of Tanzania were heavily damaged and Kagera was one of the worst-hit regions.

As supported by the FAO-GIEWS[2] data used for measuring rainfall anomaly (Figure 2), the regions under the bimodal rainfall regimes received a significantly lower amount of rain in 2009 compared to the rain received in the long term. As suggested by the meteorological literature, one of the simplest ways to measure the precipitation anomaly is to use the difference between the annual observation and the long-term mean.[3] As expected, the bimodal regions report a decrease between the millimeters of rain received in 2009 and those received in the previous five years as well as in the previous 10 years. These data confirm the severity of the drought experienced by regions with bimodal regimes. By contrast, the unimodal regions of Tanzania report a slight increase in (average) rainfall received in 2009 compared to the previous period.

FIGURE 2 Rainfall anomaly by rainfall regime: average long-term difference of millimeter of rain for regions under bimodal and unimodal regime



Source: Authors' elaboration using FAO-GIEWS data.

Data

Sample

The Kagera Health and Development Survey (KHDS) was designed and implemented by the World Bank and the Muhimbili University College of Health Sciences. It consists of a survey of households living in the Kagera region, originally interviewed in four rounds from 1991 to 1994 (KHDS I). Resurveys were then administered in 2004 (KHDS II) and 2010 (KHDS III) with the aim of re-interviewing all individuals who were interviewed in any round of the KHDS I, the so-called Previous Household Members (PHHMs).[4] The analysis in the present article employs KHDS II and III. Nevertheless, the very low attrition rate in both waves preserves the representativeness of the survey. In KHDS II, the rate of re-contacted original households is 93 percent, whereas in KHDS III, it is equal to 92 percent of the KHDS I household sample. Taking into account the original households whose members were all found to be dead in 2004 (17 cases) and in 2010 (26 cases), the number of untraced households is extremely low: 63 households in the KHDS I and 71 in the KHDS II. This impressive result can be explained by the fact that one of the features of this survey was to trace households irrespective to their location.[5]

For the purposes of the present analysis, the 2004 sample of households is restricted to those residing in the original community (1,083). This allows us to compare households with and without migrants living in the same place (the original community) between 2004 and 2010. Our choice is motivated by (1) shortening the period of the analysis to the shortest one possible (2004–2010)[6] since a vulnerability analysis is more appropriate over a short time period; (2) focusing the analysis on the periods right before and after the drought to exploit this exogenous variation (see the fifth section); (3) ruling out the effect of the previous migration of the entire households since, for households that moved between 1991 and 2004, it is not possible to identify the presence of migrant members between 2004 and 2010.[7] The selected 2004 sample of households residing in the original community is poorer than the sample of households who were able to move between 1991 and 2004 both in terms of food consumption and nonfood consumption (Beegle, De Weerdt, and Dercon 2011). This means our analysis is focused on the effect of having migrants for poorest households of the Kagera region. Following this, a note of caution should be raised concerning the external validity of our findings. The exclusion of the migrant households (between KHDS I and II) hampers our ability to derive consistent estimates for the entire population.

The presence of household split-offs between 2004 and 2010 needs to be taken into consideration. The present analysis has been conducted on two samples of households: the extended sample of 1,238 households including all the splits in 2010, as well as the restricted sample of 881 households with the same head in the two periods. This implies that the impact of migration is tested on the entire network of the households. The latter is in the same spirit as Angelucci et al. (2010). Indeed, the intergenerational family ties between new households of siblings (living together in the previous wave) are considered to form the extended sample. The summary statistics are reported in Table A-1 (in Appendix[8]) for the two samples and by typology of households, with and without migrants.

To define the migrants, this article looks at the household members' localization in 2010 compared to 2004 (which, according to the selected sample of households, corresponds to the original localization in KHDS I). The migrant can be localized in a nearby village, elsewhere in the same region, or elsewhere in Tanzania. The article adopts the definition of migration proposed by Beegle, De Weerdt, and Dercon (2011) and De Weerdt and Hirvonen (2016), according to which a migrant is a household member found not to reside in the baseline community at the end of the sample period in 2010. The subsample of individuals (specifically PHHMs) who moved during the period considered is composed of 197 people and is balanced in terms of gender (53 percent of migrants are females). Since the analysis focuses on internal migration, 62 international migrants are not considered in the analysis.[9] If some selectivity bias may derive from the choice of our sample of analysis, it should be noted that we are focusing on the poorest left-behind households who are able to engage their members in internal migration only.

One of the main limitations of the data set employed is the lack of detailed information on remittances. The household questionnaire for 2010 does not ask questions on the amount of remittances received by the origin households. The only information on remittances is asked for indirectly in the modules on shocks (if current or past years have been good or bad for, respectively, high remittances or low remittances) and on household activities and income (whether received remittances are the first, second, or third most important income source for satisfying the household daily needs).

Finally, this analysis uses two additional data sets provided by the Economic Development Initiatives group.[10] First, the total consumption and food and nonfood consumption data for all the waves have been used in the analysis. Consumption data are expressed in annual per capita terms deflated using information from the KHDS price questionnaire. Second, we control for migration distance by means of a distance matrix, elaborated by Jose Funes and Jean-Francois Maystadt. The matrix contains all distances between all households interviewed in KHDS III. The distances are expressed using the Euclidean metrics (km).

Outcome variable

This article follows the VEP approach proposed by Chaudhuri, Jalan, and Suryahadi (2002), and extended by Günther and Harttgen (2009) to take into account idiosyncratic and covariate shocks. They define vulnerability as "the *ex-ante* risk that a household will, if currently nonpoor, fall below the poverty line, or, if currently poor, will remain in poverty." According to this definition, a household is classified as vulnerable if it has a high probability of being poor in the future. Conversely, a household is classified as not vulnerable if it is not likely to be poor in the future. Formally, the vulnerability level of a household i at time t is defined as the probability that the household will find itself consumption poor at time $t + 1$ (Chaudhuri, Jalan, and Suryahadi 2002).

The VEP measure presents two main attractive features. First, it estimates vulnerability using a single round of cross-sectional data. Second, it is easily interpretable because the results are expressed in terms of the expected value of Foster, Greer, and Thorbecke's (1984) measure of poverty. The VEP measure, generally recognized as one of the fundamental approaches for measuring vulnerability (Gallardo 2017), has been extensively used in the empirical literature, either as the outcome of interest (Khandker 2007; Rayhan and Grote 2007; Imai 2011; Swain 2012; Swain and Floro 2012; Imai, Gaiha, and Thapa 2015; Nguyen, Raabe, and Grote 2015; Cahyadi and Waibel 2016; Magrini and Vigani 2016; Zereyesus et al. 2017) or for testing the link between vulnerability and poverty (Adepoju et al. 2011; Imai, Gaiha, and Kang 2011; Jha and Dang 2010; Feeny and McDonald 2016).

Following the statistical approach proposed by Chaudhuri, Jalan, and Suryahadi (2002), we assume that consumption is log-normally ($ln(c_i)$) distributed across households and compute VEP measure as the estimated probability ($\widehat{Pr}$) that a household with the characteristics X_i will be poor as:

$$V_i = \widehat{\Pr}\left(ln\left(c_i\right) < \ln\left(z\right) | X_i\right) = \Phi\left(\frac{\ln\left(z\right) - X_i\hat{\beta}}{\sqrt{X_i\hat{\theta}}}\right), \tag{1}$$

where Φ denotes the cumulative density of the standard normal random variable while $X_i\hat{\beta}$ and $X_i\hat{\theta}$ are, respectively, the estimates of the mean and the variance of log consumption obtained from a three-step feasible generalized least squares (FGLS) procedure.

Despite its attractive features, the limitations of the VEP approach are well known in the empirical literature (Gallardo 2017). The method relies on strong simplifying assumptions. These require that the probability distribution is (1) log-normal, (2) the same for all the units in the population, (3) invariant in the future (cross-sectional variability proxies intertemporal variance in consumption), and (4) based on a set of observable characteristics. Despite the assumptions used for the estimation of the probability distribution being quite restrictive, there are no specific reasons why they should be valid only for those households with or for those households without migrants. In other words, the (1) log-normality, (3) time stationarity, and (4) conditionality assumptions are not expected to interfere with the migration status of the households' members and therefore with the empirical strategy proposed to assess the effect of migration on vulnerability. On the other hand, the assumption (2) that the same probability distribution is estimated for households with and without migrants is required to smooth any difference detected in the two samples of households.

Additionally, as first pointed out by Hoddinott and Quisumbing (2003), the VEP method has the undesirable feature that the probability of the household being poor decreases when the variability of household consumption around the poverty line increases; in a nutshell, vulnerability is reduced by assigning the household more risk. This undesirable feature is particularly problematic because it is in contrast with the evidence of the poor being more risk averse. Gallardo (2017) illustrates this shortcoming by using an example: if two households have the same expected value of consumption, but different variances, the household with less dispersion in its consumption outcomes is more vulnerable.[11] On the contrary, the household with much dispersed welfare outcomes is less vulnerable. In contrast to the previous simplifying assumptions, this shortcoming of the VEP approach can be problematic in that it specifically applies to one of the two samples of households considered in the analysis. According to the NELM literature, households with migrants are expected to have less consumption variance because of risk pooling. Therefore, as in the example from Gallardo (2017), the VEP approach perversely considers them to be more vulnerable than households with more variance, as the household-less migrants are supposed to be. This means that, if any effect on vulnerability is detected by using the VEP approach, this can be considered a lower bound. In fact, a larger difference between households with and without migrants should be reported if low consumption variance would be translated in less vulnerability rather than more vulnerability.

The VEP measure has been estimated in 2004 and 2010 for all households that did not move relative to their initial location reported in KHDS I. Table A-2 shows the results for total consumption and food consumption models using the FGLS procedure (last step estimations). All coefficients display the expected signs. For example, the age of the household head has a concave impact on food consumption. The proportion of adults of the household has a positive impact on consumption, whereas the number of children has a negative effect.

As shown in Table 1, the vulnerability rates in 2010 are higher than the poverty rates, for both samples and measures. Beside the vulnerability rates, Table 1 presents the estimated expected means and variances of total consumption and food consumption, as well as the vulnerability means. The mean estimates are similar in magnitude for the two groups of households with and without migrants (respectively, 0.41 and 0.43 for basic needs poverty and 0.34 and 0.36 for food poverty) and the hypothesis of their equality in both cases cannot be rejected by a t-test of equality of vulnerability means. The same pattern is confirmed in the case of food and basic needs poverty.

Finally, Table 2 reports the vulnerability variation between 2004 and 2010 for (both extended and same head) households with and without migrants. In the period considered, households with migrants perform better in terms of vulnerability reduction than households without them, both for basic needs and food poverty. For both samples, the vulnerability to food poverty decreases in 2010 relative to 2004, while for households without migrants, it increases. The vulnerability to basic needs poverty decreases in the extended sample for households without and with migrants, but for the latter the decline is larger. The difference in the vulnerability variation between households with and without migrants is statistically significant for basic needs poverty in the extended household sample and for food poverty in the sample of households with the same head.

TABLE 1 Vulnerability to basic needs and food poverty at 2010

	HHs with migrants	HHs without migrants	t-Test[a]
Basic needs			
Poverty rate	0.380	0.380	
Poverty line	12.600	12.600	
Vulnerability mean	0.410	0.430	0.170
	(0.401)	(0.384)	
(Estimated) mean[b]	13.170	13.040	
	(4.288)	(3.731)	
(Estimated) variance[c]	1.010	1.010	
	(0.307)	(0.198)	
Vulnerability rate	0.470	0.530	
Food			
Poverty rate	0.180	0.180	
Poverty line	11.900	11.900	
Vulnerability mean	0.340	0.360	0.240
	(0.415)	(0.385)	
(Estimated) mean[b]	13.200	12.960	
	(6.738)	(12.345)	
(Estimated) variance[c]	1.020	0.990	
	(0.360)	(0.270)	
Vulnerability rate	0.480	0.520	
Observations	325	910	

[a]p-Value of the t-test of equality of vulnerability rates between households with and without migrants. Standard deviation in parenthesis.
[b]The estimates of the mean of log consumption—represented by $X_i\hat{\beta}$ in the VEP formula (1)—are obtained from a three-step feasible generalized least squares procedure.
[c]The estimates of the variance of log consumption—represented by $X_i\hat{\theta}$ in the VEP formula (1)—are obtained from a three-step feasible generalized least squares procedure.
SOURCE: Kagera Health and Development Survey, wave III (2010).

Matching approach

Methodology

It is well known in the development literature[12] that the estimation of the impact of migration on the households of origin (or on the migrants) is made difficult by the issue of endogeneity.[13] Specifically, the outcomes of households with and without migrants are not simply comparable to each other because households self-select into migration. In fact, both observed and unobserved attributes of households are likely to be correlated with the decision to send one member away as well as with the outcome of interest, which in our case is the household's vulnerability to poverty. We propose a valuable approach that allows us to assess the effect of migration without randomized data.

To assess the impact of migration on vulnerability to poverty of origin households, we first consider the following model:

TABLE 2 Vulnerability variation (2010–2004) by categories of households

	Basic needs		Food	
	Extended HHs	HHs with same head	Extended HHs	HHs with same head
With migrants	–0.094	–0.060	–0.002	–0.103
	(0.527)	(0.615)	(0.587)	(0.489)
Without migrants	–0.015	0.001	0.033	0.048
	(0.501)	(0.525)	(0.507)	(0.411)
t-Test[a]	0.025	0.431	0.368	0.000
Observations	1,235	881	1,235	881

[a]p-Value of the t-test of equality of vulnerability variation between households with and without migrants.
Standard deviation in parenthesis.
SOURCE: Kagera Health and Development Survey, wave II (2004) and III (2010).

$$ATT = [Y_t - Y_{t'} | X_{t'}, D = 1] - [Y_t - Y_{t'} | X_{t'}, D = 0], \tag{2}$$

where ATT is the average effect of treatment on the treated. The treatment variable (dummy D) is equal to 1 if the household had any migrant members between the baseline period ($t' = 2004$) and the following interview ($t = 2010$). The outcome of interest is the variation in the VEP by the household between the first ($t' = 2004$) and the second period ($t = 2010$). The VEP variation is measured both in terms of basic needs and food poverty. The main advantage of this method is that it allows for "temporally invariant differences in outcomes between households with and without migrants" (Smith and Todd 2005). Some unobserved attributes of households, such as loss aversion, entrepreneurial ability, or the strength of family ties, may play an important role in migration. For instance, a loss-averse household may be reluctant to encourage migration of its members when this is perceived as a risky strategy.[14] The household may also be reluctant to engage in crop diversification, which may be a useful risk-management strategy against agricultural production risks. On the other hand, a household engaged in crop diversification may reduce its exposure to agricultural product risk, thereby also reducing the gains from migration. In the end, our matching method controls the selection of migrants due to time-invariant unobservable characteristics at the household level.

The model is estimated using a variety of matching estimators. We first use the difference-in-difference with the propensity score matching method[15] (D-i-D PSM) proposed by Smith and Todd (2005). To obtain the propensity score, we estimate a logit model[16] that links the probability of having a migrant in t to household characteristics in t'. The model is defined as:

$$P\left(D_{i,j,t} = 1\right) = F(X_{i,j,t'}, Z_{j,t'}), \tag{3}$$

The dependent variable is the probability that household i in village j has a migrant member in period t. The binary dummy $D_{i,j,t}$ equals one if household i has at least one migrant in period t and zero otherwise. The probability of having a migrant member is a logistic function (F) of household characteristics measured at t'.

Second, we employ the bias-adjusted estimator proposed by Abadie and Imbens (2006) to estimate the ATT. The main advantage of this estimator is that it allows for matching on multiple covariates without imposing parametric assumptions. According to Gibson, McKenzie, and Stillman (2011, 2013), this estimator performs next best after the instrumental variable (IV) estimator among the nonexperimental methods. IV estimation has been avoided in the analysis because of the nature of the dependent variable, which makes the exclusion restriction unlikely to hold.[17]

Third, the coarsened exact matching (CEM) estimator recently developed by Iacus, King, and Porro (2011) has been employed. After preprocessing the data, the vulnerability variation (both for basic needs and food poverty) has been regressed on a migration dummy equal to one if the household had at least one member who migrated between 2004 and 2010, and zero otherwise.

The key element of this strategy is to match households with migrants to those without them with similar pretreatment characteristics measured in 2004. We specifically avoid matching based on characteristics in 2010 because they may be endogenous to migration.[18] The attributes used to match households are aimed to control for the propensity of having migrants in the following years (household size; number of males; number of members with primary education; number of members with secondary education; a dummy for whether the origin household is living in urban Bukoba; number of cattle owned by the household; number of sheep owned by the household; acre of plots owned by the household; dummy for having a bank account; dummy for having experienced a shock; dummy for participating in informal organizations). For example, the amount of assets owned by a farmer household is an observable characteristic that can be correlated both with migration and with vulnerability to poverty. Indeed, the household may decide to sell part of its assets to cover the migration costs. On the other hand, the household may decide to sell some assets after the occurrence of a negative shock as part of a strategy of consumption smoothing, which will in turn affect the probability of the household experiencing consumption below the poverty line.

Results

As described above, matching has been obtained over pretreatment covariates in 2004. These are related to household demographic characteristics that affect the propensity of having migrants and the risk management strategy. The inclusion of a relatively large number of covariates is motivated by the need to satisfy the conditional independence assumption, that is, there are no other observable factors influencing migration and the potential

TABLE 3 The effect of migration (ATT) on VEP variation (2010–2004)

	Extended HHs		HHs with same head	
	(a) Basic needs	(b) Food	(c) Basic needs	(d) Food
Propensity score matching				
Nearest-neighbor	–0.153**	–0.062	–0.014	–0.155**
	(0.062)	(0.066)	(0.051)	(0.061)
Caliper	–0.153**	–0.062	–0.014	–0.155**
	(0.062)	(0.066)	(0.051)	(0.061)
Kernel	–0.088**	–0.024	–0.062*	–0.154***
	(0.035)	(0.036)	(0.037)	(0.038)
Matching on multiple variables				
Mahalanobis distance	–0.106**	–0.035	–0.013	–0.119**
	(0.047)	(0.054)	(0.051)	(0.057)
Euclidean distance	–0.056	–0.025	–0.019	–0.168***
	(0.045)	(0.056)	(0.054)	(0.060)
Inverse variance distance	–0.102**	–0.065	–0.012	–0.150**
	(0.048)	(0.059)	(0.055)	(0.060)
Coarsened exact matching				
	–0.075	–0.029	–0.070**	–0.262***
	(0.073)	(0.059)	(0.030)	(0.057)
Observations	1,325	1,325	881	881
Treated	325	325	195	195
Control	910	910	686	686

Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Matching and bias-adjustment variables: household size; number of males; number of members with primary education; number of members with secondary education; a dummy for whether the origin household is living in Bukoba urban; number of cattle owned by the household; number of sheep owned by the household; acre of plots owned by the household; dummy for having a bank account; dummy for having experienced a shock; dummy for participating in informal organizations.
SOURCE: Kagera Health and Development Survey, wave II (2004) and III (2010).

outcomes that would be obtained in the absence of migration. The balance test is satisfied for all the used covariates for the two samples of households. After matching, baseline variables for the treatment group are well-balanced in both samples (see the p-values for matched and unmatched households in Table A-4).

Before looking at the results, Figure A-1 confirms the common support condition for propensity score matching. The evidence suggests that a large majority of observations are found to be on common support (households with and without migrants are similar in their characteristics and they can be matched), hence they can be compared in a meaningful way.

Table 3 reports the results from all the matching methods employed: propensity score (matching to the nearest neighbor, with the Caliper of 0.2 percent and Kernel), matching on multiple covariates (with three different distance metrics: Mahalanobis, Euclidean, and the inverse variance), and CEM. The results are presented for both samples of households, in columns

(a) and (c) for vulnerability to basic needs poverty and in columns (b) and (d) for vulnerability to food poverty.

The common result that emerges from these findings is that in 2010 households with migrants were, on average, less vulnerable to poverty than households without migrants compared to 2004. The estimated significant gain due to the presence of migrants is a reduction in VEP ranging from 0.09 to 0.15 points for vulnerability to basic needs in the sample of extended households (column a) and from 0.12 to 0.26 points for vulnerability to food poverty in the sample of households with the same head (column d), according to the different methods employed.

An interesting finding is that the results differ for the two samples of households. While for extended households, the migration effect is significant for vulnerability to basic needs poverty (column a) but not for food poverty—for households with the same head in the two periods there is a stronger significant effect for food poverty (column d). This result may be driven by the fact that households with the same head may have members with a higher average age since the younger members may have left the original household.[19] They are thus more likely to be poorer than households resulting from split-offs, as it emerges by the average higher values of food and total consumption for extended households with migrants (Table A-1), and may face barriers to migration. Consequently, whenever they can invest in migration, households with the same head will have a stronger return in terms of reduced vulnerability to food poverty. These results are consistent with those of Skoufias and Quisumbing (2003), who argue that food consumption tends to be given a higher priority in terms of different informal insurance arrangements at the community level relative to nonfood consumption.

Exogenous variation

The results from the matching analysis of the previous section are valuable because they allow us to assess the effects of migration even without randomized data. These results may, however, still be affected by time-varying unobserved heterogeneity across households. To control for this, our analysis takes advantage of a natural event: the drought in the bimodal regions of Tanzania in 2008–2009. As discussed by Rosenzweig and Stark (1989), the covariance of shocks between the area of destination, where migrants live, and the place of origin, where their households reside, has a crucial relevance for risk management. They find that migration contributed to the reduction in the variability of consumption of the household of origin, controlling for the variability of household income from crop production. Furthermore, they find that "households exposed to higher income risk are more likely to invest in longer-distance migration-marriage arrangements" (Rosenzweig and Stark 1989).

The crucial assumption tested in our work is that migration to unimodal zones of the country acted as an insurance mechanism for the households of origin against the effects of the extreme drought. Those migrants who moved from Kagera to unimodal areas of Tanzania can be expected to have been less damaged by the drought than their household of origin. They will therefore have been better able to send remittances back to the Kagera region.[20] Thus, in the subsample of households with migrants, those with members who migrated to the unimodal areas of the country should have become less vulnerable than households with migrants in the bimodal areas. This exogenous variation (the extreme drought) negatively affected, *ceteris paribus*, the households living in Kagera. If households with migrants in unimodal areas are found to perform better in their vulnerability variation than households with migrants in bimodal areas, this can be seen as evidence that migration acted as an effective risk management strategy.

The focus on the subsample of households with migrants allows us to control for unobserved heterogeneity. In fact, households with migrants in unimodal zones are not expected to be structurally different from households with migrants in bimodal areas of the country. A range of t-tests on the observable characteristics (Table A-5) confirms the balance between households with migrants in unimodal areas and households with migrants in bimodal areas. The balance in the observable characteristics supports the presence of a balance in unobserved heterogeneity.

To exploit this exogenous variation, we limit the analysis to the subsample of households having at least one migrant in 2010. Thus, the focus is on the impact of migrants' location on the change of vulnerability to poverty of the household of origin before (2004) and after (2010) the drought. Formally, the following equation is estimated:

$$\Delta Vul_i = \beta_0 + \beta_1 Dist_i + \beta_2 Unim_i + \beta_3 Dist_i * Unim_i + \beta_4 \Delta X_i + \varepsilon_i, \qquad (4)$$

The focus on changes over 2004–2010 in household vulnerability to poverty (ΔVul_i) and attributes (ΔX_i) allows to purge the estimates of household time-invariant heterogeneity. $Dist_i$ measures the distance (in kilometers) between the migrant and the family of origin. Living closer to the original family may facilitate the reception of remittances, cash, and particularly in-kind transfers. The model adopts the linear elasticity form for the distance between migrants' new location and that of origin families.[21] The key variable of this specification is the dummy variable $Unim_i$, which is equal to 1 if the migrant from household i is located in a unimodal zone and 0 otherwise. Finally, $Dist_i * Unim_i$ is an interaction term between the distance and the unimodal dummy. The interaction controls for the potential different effect of migration to unimodal areas depending on the distance that separates the migrant and the household of origin.

If the household has more than one migrant, the $Dist_i$ variable is replaced with the mean distance over all migrants. In this case, the unimodal

TABLE 4 Impact of migrant location on VEP variation of origin households

	VEP variation	
	(a) Basic needs	(b) Food
Distance	0.000	0.000
	(0.000)	(0.000)
Unimodal	–0.419*	–0.551**
	(0.250)	(0.222)
Distance × unimodal	0.000	0.001**
	(0.000)	(0.000)
Number of cattle	–0.002	–0.002
	(0.003)	(0.002)
Acre of owned plots	–0.012*	0.014**
	(0.006)	(0.006)
Number of enterprises	–0.030	0.096***
	(0.0404)	(0.0359)
Toilet	–0.218	–0.317**
	(0.144)	(0.128)
Electricity	0.516**	0.231
	(0.227)	(0.202)
Constant	–0.117***	–0.162***
	(0.045)	(0.040)
Observations	325	325
R-squared	0.077	0.113

Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
All the control variables - number of cattle, acre of owned plots, number of enterprises, toilet, electricity - are expressed as difference (2010-2004).
SOURCE: Kagera Health and Development Survey, wave II (2004) and III (2010).

dummy is equal to 1 if at least one migrant moved to unimodal areas of the country. Table A-6 reports the summary statistics of variables used.

Table 4 reports the impact of migrant location on the change in household VEP, before (2004) and after (2010) the occurrence of the drought, for the subsample of households with migrants.

The distance coefficient is not statistically significant. This can be explained by the low relevance of the distance variable when controlling for the migration to unimodal areas. Furthermore, migrants in unimodal areas are closer to original families (Table A-5). By contrast, the coefficient on the unimodal dummy is highly negative and statistically significant: it translates into a reduction of about 0.42 vulnerability points for basic needs and 0.55 vulnerability points for food. Its effect declines with the distance from the area of origin as indicated by the positive coefficient on the interaction term, though this is only significant for vulnerability to food poverty. The unimodal and the interaction coefficients are, however, jointly significant in both cases: the p-value for the *F* test is 0.0880 for vulnerability to basic needs poverty (column a) and 0.0476 for food poverty (column b).

We can obtain an estimate of the average effect of the unimodal location of migrants on vulnerability to poverty change by considering the mean value of the distance variable in the sample, which is 249 km. At the mean distance, the effect is $0.42 + 0.0002 \times 249 = 0.37$ for vulnerability to basic needs poverty and $0.55 + 0.0006 \times 249 = 0.40$ for vulnerability to food poverty. Migration of family members to unimodal zones of Tanzania is thus associated, on average, with a differential decrease in vulnerability for the household of origin of about 0.40 vulnerability points relative to its pre-shock level.

It is interesting to observe that, for households with the same head, when we explore the effects of the exogenous variation, the presence of migrants to unimodal zones significantly reduces their vulnerability both to basic needs and to food poverty vulnerability. By contrast, the matching methods described in the fourth section do not show a significant reduction in vulnerability to basic needs (Table 3). This different result may be due to the fact that matching methods may not fully capture some of the time-varying characteristics that can instead be controlled for an analysis that exploits the exogenous variation due to the natural event. An example of a time-varying unobservable characteristic can be the variation over time of the informal household network, namely the pool of friends and associations the household can rely on after the occurrence of the drought. On the contrary, the matching method may underestimate the effect of migration by comparing households with migrants with households who rely on alternative coping strategies (unobservable and time-varying). Controlling for the latter, the approach relying on the exogenous variation allows us to compare households with and without migrants to unimodal areas, having, for example, the same type of informal network variation in response to the drought.

Conclusions

Migration can be an important strategy to reduce the risks faced by households, but empirical evidence on the risk-mitigating aspects of migration is still limited. This article investigates how VEP was affected by migration from the Kagera region of Tanzania. The article uses matching methods and exploits an exogenous variation due to an unanticipated drought, which only affected regions with a bimodal rainy pattern. The empirical findings show that VEP was significantly reduced for families whose members migrated to unimodal regions, relative to those whose members migrated to bimodal regions. After controlling for time-varying unobservable factors, we find an effect of migration on vulnerability to basic needs as well as on vulnerability to food poverty of origin households. The evidence, therefore, supports the view that migration acted as an effective risk management strategy for households. We did not enquire as to why this could be the case as this would demand more information about the channels, since migrant remittances and other important personal characteristics of migrants are not available. Our results are, however, consistent with the findings of De Weert and Hirvonen (2016), who show that the presence of migrants provides insurance to the family members who remain at home.

Additionally, a future extension of this research would be to explore further the *ex-ante* cost of migration as a risk management strategy. In fact, in the absence of shocks, migration could have a high cost for the origin households, which is not compensated by higher returns. Finally, resorting to migration could have an opportunity cost in terms of alternative strategies such as crop diversification that could instead be adopted by origin households. This is an important line of research that would be worth exploring in the future.

Notes

1 See also Khwaja (2002), Anam, Chiang, and Hua (2008), Moretto and Vergalli (2008), and Vergalli (2011) for applications of the real options approach to migration. Abel et al. (1996) develop a general approach to the analysis of investment under uncertainty.

2 The FAO-Global Information and Early Warning System collects various information by utilizing remote sensing data. More information is available at: http://www.fao.org/giews/data-tools/en/.

3 Keyantash and Dracup (2002) review and compare the drought indices.

4 The baseline KHDS I sample is composed of 915 households. In 2004, the field team managed to recontact 832 households of the baseline sample. Recontact means that at least one PHHM was re-interviewed in the KHDS II. Because after 13 years, a number of people had moved out of their original households, the new sample consisted of 2,774 households. In 2010, 818 households from KHDS I sample were re-contacted. After 18 years, the new sample of households included 3,313 households compared to the original 915 (De Weerdt et al. 2012).

5 In KHDS II, 49 percent of the households were found in the same village of the original household (Beegle, De Weerdt, and Dercon 2011), whereas in KHDS III, it was 44 percent of households (De Weerdt and Hirvonen 2016).

6 Other possible options would have been to compare (1) households with and without migrants living in the same place between KHDS I (1991) and II (2004); and (2) households with and without migrants living in the same place between KHDS I (1991) and III (2010). In both cases, the time period of the analysis would have been longer and less appropriate for a vulnerability analysis.

7 In fact, focusing on the entire 2004 sample would not allow researchers to establish whether they have members who moved between 2004 and 2010, since localization is reported with respect to KHDS I.

8 Appendixes are available at the supporting information tab at wileyonlinelibrary.com/journal/pdr.

9 By the sampling design, some individuals are not traced between 2004 and 2010; if they are not PHHMs, namely they are new members in 2004, or they are not found to reside with PHHMs in 2010. Additionally, due to the scope of the analysis, entire households migrating between 2004 and 2010 are not considered in the analysis.

10 Additional information on the EDI Group and specifically on KHDS data can be found here: http://edi-global.com/publications/.

11 Gallardo (2017, 19) uses a figure to represent the probability density of consumption of two people with the same

expected value of consumption, which is equal to 0.8. "Person A is better off because she has less dispersion (less variance) in her probable consumption outcomes. However, under the VEP approach, she is more vulnerable than person B because her probability of being poor is greater."

12 Following McKenzie (2015), while the development literature aims to estimate the impact of migration on the welfare of the migrants and their families of origin, the immigration literature focuses on the impact of migration on the outcomes of natives in the destination country.

13 See McKenzie and Yang (2010) for a comprehensive explanation.

14 For the concept of loss aversion and its difference from risk aversion, see Kahneman and Tversky (1979, 1991).

15 The D-i-D PSM estimator requires that: $\mathbb{E}(Y_{0,t} - Y_{0,t'}|P, D = 1) = \mathbb{E}(Y_{0,t} - Y_{0,t'}|P, D = 0)$, (3), where t and $t'$are respectively, the time periods after and before migration; Y_0 is the potential outcome of households with and without migrants; and $P = Prob(D = 1|Z)$ is the conditional probability that there is a migrant in the family. Furthermore, this estimator requires that the support condition holds in both periods $t'$and t: for all the observable conditioning variables Z, there must be a positive probability of $(D = 1)$ or not $(D = 0)$ migrants.

16 We obtain similar results by using a Probit model. The results are presented in Table A-3.

17 McKenzie and Yang (2010) caution against the use of IV to estimate the impact of migration.

18 This was the approach followed by Esquivel and Huerta-Pineda (2007) to assess the effect of remittances on poverty of Mexican households: see also McKenzie and Yang (2010).

19 The average age of the head of extended households with migrants is 50 years, while for the sample of households with the same head with migrant is the average age is 59 years (Table A-1).

20 This is confirmed by the relevance of received remittances for origin households' daily needs to migrants' localization. Only 1.63 percent of households with migrants in bimodal areas consider remittances as the most important income source for meeting their daily needs, whereas 6.67 percent of households with migrants in unimodal areas consider the received remittances as the most important income source. The same pattern is confirmed for the percentages of households ranking remittances as the second most important source of income: 4.25 percent for households with migrants in bimodal areas and 6.67 percent for households with migrants in unimodal areas. The same is true for the third income source: 3.13 percent for households with bimodal migrants and 7.69 percent for households with unimodal migrants.

21 From the seminal paper by Schwartz (1973) to the recent paper by Ingelaere et al. (2018) using the KHDS data.

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