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Migration as an Adaptation Strategy to Weather Variability: An Instrumental Variables Probit Analysis*

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Abstract

There is solid scientific evidence predicting that a large part of the developing world will suffer a greater incidence of extreme weather events, which may increase the incidence of displacement migration. We draw on the new economics of migration to model migration decisions of smallholder and rain-dependent farm households in rural Ethiopia and investigate both the *ex-ante* and *ex-post* impacts of climate variables. Using detailed household survey panel data matched with rainfall data, we show that weather variability - measured by the coefficient of variation of rainfall - has a strong positive impact on the probability of sending a migrant. This implies that households engage in migration to cope with risk *ex-ante*. We also find evidence suggesting that rainfall shocks have *ex-post* impact on households' likelihood of migration, but the effect is not statistically significant at the conventional levels. Instrumental variables probit regression results also show that controlling for endogeneity of income using a credible instrument is important to identify its impact on the decision to send a migrant. Our findings have important implications for policies aiming to improve the capacity of vulnerable households to adapt to climate change.

Keywords: climate change, drought, Ethiopia, household survey, migration, rainfall.

JEL: O15, Q54, R23

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1 Introduction

Global environmental threats, in particular climate change, have been identified as potential causes of large migration flows in the future (UNFPA, 2009; IPCC, 2014). Although the climate is a global good, available projections indicate that climate change damages will differ significantly according to region and will affect developing countries more than developed countries (IPCC, 2014). There is now a large degree of certainty that parts of the developing world will suffer a greater incidence of extreme weather events, which may increase the necessity of displacement migration (Hulme et al., 2001). There are several reasons for this: vulnerability of coastal zones, greater dependence on agriculture, and less adaptive capacity (Tol et al., 2004; Mendelsohn et al., 2006). The term "environmental refugees" was popularized by Myers (see for example Myers, 1997, or Bates, 2002)[1]. The term has since been criticized, in particular because what matters in predicting future migration flows is ultimately identifying vulnerable populations, which is a result of the joint influence of household characteristics, social networks, access to infrastructure, political environment, etc. (Raleigh et al., 2010, Black et al., 2011). More recent credible reports, such as the Stern Report (2007), warn that, by 2050, 200 million people could be at risk of climate events that *may* induce migration.

Certainly, environmental conditions have always influenced habitat, and increased stress on natural resources constitutes an important factor in migration. Some of the most prevalent examples are drought and increased water scarcity and soil erosion, which lead farmers to move away from arid land. Specific types of migration form an integral part of human adaptation to changes in the environment: seasonal or circular migration have very different drivers than displacement migration following a disaster (Adger, 2000; Perch-Nielsen et al., 2008). The most recent literature studies climate change and uses weather factors that are strictly exogenous. In this paper, we investigate both the *ex-ante* and *ex-post* impacts of climate variables on the decision to engage in migration by smallholder farm households in Ethiopia. We use the coefficient of variation of rainfall and objectively defined rainfall shock variables to test our hypotheses on the relationship between weather and migration.

Rural Ethiopia provides a valuable setting to investigate our hypothesis. About 82% of its population depends on rain-fed agriculture, access to irrigation is insignificant (CIA, 2015), and the country has been affected by frequent climatic shocks in recent decades (Dercon, 2004). Future projections show a significant impact on African migration flows, in particular, following climate change-induced water stress (Le Blanc and Perez, 2008). According to the IPCC's 5th Assessment

[1] See UNFPA (2009) for estimations of the numbers of displaced people due to environmental degradation, and CRED (2015) for the numbers of displaced people due to natural disasters.

Report, Sub-Saharan Africa is the region with the highest exposure to drought in the world, in terms of the share of the exposed population (Niang et al., 2014). In this regard, our analysis provides important insights on the possible impacts of climate change on migration flows.

There is a small but growing literature that investigates the link between climate change and migration. Barrios et al., (2006), one of the first studies measured the impact of rainfall on the distribution of population among rural and urban areas in Sub-Saharan Africa, and found a significant effect of rainfall patterns on the population distribution. Some recent studies analyze macro-level data on international migration flows to examine the effect of rainfall and temperature on out-migration from Sub-Saharan Africa (Marchiori et al., 2012), and on in-migration to OECD countries from developing countries (Coniglio and Pesce, 2015). Using yearly migration data from the OECD, Coniglio and Pesce (2015) find that inter-annual rainfall variability increases out-migration from developing countries to OECD countries, especially from countries with large agricultural sectors. Beine and Parsons (2015) include both climate factors and natural disasters in an analysis of international migration flows derived from 10-year interval migrant stock data from the World Bank from 1960 to 2000. On that standardized data, which also include South-South migration, they find no statistically significant long-run average effects of neither climate factors nor natural disasters on international migration flows. They find a statistically significant effect only of natural disasters on internal migration flows, proxied by the rate of urbanization. This result seems compatible with the argument of Marchiori et al. (2012), who find that rainfall and temperature anomalies first increase migration from rural to urban areas, and then, in a second step, also increase international out-migration from Sub-Saharan Africa over the period 1960-2000, depending on the size of urban agglomeration externalities. Recently, Maurel and Tuccio (2016) also find a similar effect on international bilateral migration, using the same standardized data as in Beine and Parsons (2015).

Our paper uses household data to analyze the migration decision in the "new economics of migration" framework (Stark and Bloom, 1985; Stark, 1993). While a study from one country hardly can be used to infer more general conclusions, compared to the studies on international migration flows, the use of detailed household data enables us to disentangle the many factors that interact to explain migration. Early evidence of environmentally induced migration are found in geographical studies from Burkina Faso (Henry et al. 2004a, 2004b), Ethiopia (Ezra-Kiros, 2001; Meze-Hausken, 2000) and Mali (Findley, 1994). Most of these studies use proxies for climate and its consequences - vulnerability to famines, for example, according to an NGO assessment in the Ezra and Kiros (2001) study on Tigray, Northern Ethiopia. Very few of them can therefore separate the impact of household and community characteristics from the possibility of exogenous environmental push factors, such as rainfall variability and rainfall shocks. Our key contribution is thus to assess both the *ex-ante* and the *ex-post* impacts of one of the most relevant climate variables for Sub-Saharan Africa - rainfall - in addition to household socio-economic characteristics, based on detailed and representative household panel data from Ethiopia.

Household data have been used in studies on migration and climate factors on Ecuador (Gray, 2009), Nigeria (Dillon et al., 2011), Malawi (Lewin et al., 2012), Indonesia (Bohra-Mishra et al., 2014), Bangladesh (Gray and Mueller, 2012b) and Ethiopia (Gray and Mueller, 2012a), among others (see the survey in Millock, 2015). Among the few of these studies to use actual rainfall data, Bohra-Mishra et al. (2014) find a significant positive but small effect from rainfall on household permanent migration in Indonesia (and a larger significant effect of temperature); both effects are nonlinear. Below a certain threshold, an increase in rainfall reduces out-migration, whereas an increase in rainfall above that threshold increases out-migration. In an analysis of Malawi, a very poor country, Lewin et al. (2012) find that rainfall shocks lead to a lower probability of migration. This result is consistent with the hypothesis that severe weather shocks reduce a household's income and stock of capital so much that the household does not have the resources necessary to migrate.[2]

The paper that is the most closely related to our paper is Gray and Mueller (2012a). Using the Ethiopian Rural Household Survey (ERHS), which we use in the current paper, these authors investigate the effects of drought on farm households' mobility and document that men migrate more than women following drought. Gray and Mueller (2012a) model migration as an individual decision and use subjective indicators of exposure to drought reported by households. In this paper, we follow the new economics of migration (Stark, 1993) and model migration as a household decision. We also use objectively measured rainfall data to define our key variables of interest: weather variability, as measured by the coefficient of variation of rainfall, and rainfall shocks, constructed as a one standard deviation from the long-term mean two years before migration. This is the second contribution of the current study, since it is plausible to expect that reported shocks would be correlated with household characteristics that determine the migration decision. Our study also extends the analysis of Gray and Mueller (2012a) by taking into account endogeneity of income - an important determinant of migration - using an instrumental variables estimator and the level of rainfall as an instrument.

Instrumental variables probit regression results suggest that the likelihood of sending a migrant increases with rainfall variability measured by the coefficient of variation. This can be interpreted as an *ex-ante* measure of the riskiness of a household's environment.[3] Results also provide suggestive

[2]The analysis relies on cross-sectional data, though, so caution should be taken in interpreting the results.

[3]Dillon et al. (2011) also separate ex ante and ex post risk, but focus on risk from temperature variations, and they could not control for income endogeneity, as they were lacking data on income for the 185 households in Northern Nigeria that were studied.

evidence that households respond to rainfall shocks by sending a migrant, but this effect is not statistically significant at the conventional levels. We also show that controlling for endogeneity of income is important to clearly identify its role in migration. Our findings have important implications for possible future impacts of climate change related to migration and households' adaptation strategies.

The remaining part of the paper is organized as follows: Section 2 describes the relevance of studying the case of Ethiopia. The conceptual framework that defines our hypotheses is outlined in Section 3. The data and the econometric strategy are described in Section 4, and the variables in Section 5. The estimation results are presented and discussed in section 6. Section 7 concludes.

2 Rainfall and agricultural income in Ethiopia

We test the hypothesis that migration is induced by exogenous environmental factors, such as rainfall variability, in a predominantly agrarian country. It is particularly relevant to focus on Africa and especially on Ethiopia since climate change has been shown to affect the less developed countries more, in particular those that are exposed to severe water stress, and where the low level of adaptive capacity may lead to environmentally induced migration (Black et al., 2008). Ethiopia is one Sub-Saharan African country that has been classified as extremely vulnerable to drought and other natural disasters such as floods, heavy rains, frost and heat waves. These extreme weather events cause loss of lives and property and disrupt livelihoods. A large proportion of the population of Ethiopia are heavily dependent on rain-fed agriculture, which is affected by climate change (Kurukulasuriya et al., 2006). According to the World Bank development indicators, less than 0.5 % of agricultural lands in Ethiopia were irrigated in the period 2001-2005. The livelihood of 85 % of the population depends on agriculture, which also constitutes approximately 40% of the GDP and 60% of export earnings (CIA, 2015).

Using a Ricardian approach of measuring the impacts of climate change, Deressa and Hassan (2009) show significant negative marginal impacts of increases in temperature and decreases in rainfall on crop revenue per hectare. Their projections of damages up to 2050 and 2100 calls into question the very survival of the Ethiopian agricultural sector. In the face of such serious impacts, it is natural to expect that farmers use migration as one coping strategy, especially as alternative means of insurance are limited. Agricultural adaptation measures, such as planting trees, have been shown to reduce damages to some extent (Di Falco et al., 2012), but may not be sufficient to compensate for the expected losses. Also, the most vulnerable households are the least likely to undertake adaptation measures (Di Falco et al., 2011). Although higher rainfall levels in the preceding season increase yield and income, and thus relax credit constraints that may limit farmers' use of productivity-enhancing inputs, the effect of rainfall variability as such is different. Alem et al. (2010) show that rainfall variability, a credible proxy for uninsured risk, decreases both the probability to apply fertilizer and the amount applied by farmers in their sample from the Ethiopian highlands. The risk induced by rainfall variability has also been shown to directly affect farmers' wellbeing (Alem and Colmer, 2016). The risk of a negative rainfall shock and its impact on consumption discourages households' adoption of a risky input such as fertilizer and can leave households in poverty traps (Dercon and Christiaensen, 2013). Poverty and market imperfections also reduce households' investments in soil quality (Shiferaw and Holden, 1999). The existing evidence thus underscores the importance of rainfall variability in Ethiopia and the fact that most vulnerable smallholder households do not have the means to adapt to climate change in the most effective manner. These households may thus be trapped in poverty, unless they have some means to cope with climate variability such as sending a member as a migrant.

3 Conceptual Framework

We view migration as a risk-coping strategy of the household, again following the new economics of migration (Stark and Bloom, 1985; Stark, 1993). A household bases its migration choice on the expected utility of consumption with migration compared to no migration. The impact of rainfall variability is an indirect effect, in that it affects agricultural production, and hence consumption, should the household not be able to smooth its consumption through other strategies, such as drawing down on assets, or searching for employment in the non-agricultural sector, for example. Drought is indeed the most commonly cited shock in rural Ethiopia and harvest failure is the most cited cause of hardship (Dercon and Krishnan, 2000). Using a subsample from the ERHS data from 1989 to 1997, Dercon (2004) finds that a 10% decline in rainfall reduces food consumption by about 5% and that the effect lingers on several years afterwards. In a subsequent analysis, Porter (2012) analyzes the complete ERHS survey data beyond 1997 and find that extreme rainfall realizations drive the results. Rainfall in the lowest quintile can reduce consumption by 10 to 20%. Alternative strategies, such as diversification from non-agricultural income, does not succeed in reducing the losses from particularly bad rainfall shocks, whereas idiosyncratic shocks can be insured through informal mechanisms.

The migration decision depends upon household characteristics (family size, highest education level in the household, asset holdings) and the costs of migration (in terms of distance to major destinations, or road access). Agricultural income is endogenous in the year of migration and we will use an instrumental variables approach to instrument it in the migration equation.

Kiremt

t-1 ——————————————— t

Ex ante	rainfall	Ex post
RCV_j	R_j	$SHOCK_j$

Figure: Timeline

Following Rose (2001), we separate rainfall variability as a determinant of *ex-ante* migration decisions and rainfall levels - and hence shocks - as a determinant of *ex-post* migration decisions. Prior to observing the current year's (season's) rainfall, household i in PA j may take an *ex-ante* decision to send a migrant as a function of household characteristics (F_{ij}), costs of migration from the PA (C_j) and rainfall variability based on past observations of the rainfall distribution. A relevant measure for rainfall variability is the rainfall coefficient of variation measured at the village level (RCV_j). This *ex-ante* decision can be expressed as

$$M_{ij,t-1}^{ante} = f(F_{ij,t-1}, C_{j,t-1}, RCV_{j,t-1}) \tag{1}$$

Ex-post, after observing the current year's (season's)[4] rainfall outcome and its impact on the harvest, and thus on agricultural income (Y^{AG}), the household may decide to send a member away, but this *ex-post* decision will be based on the actual rainfall level and the shock it represents compared to the expected (mean) rainfall:

$$M_{ij,t}^{post} = f(F_{ij,t}, Y_{ij,t}^{AG}, C_{j,t}, SHOCK_{j,t}) \tag{2}$$

Taken together, the final migration observed in household i in PA j in year t is a function of both rainfall variability and the rainfall shock:

$$M_{ijt} = f(F_{ij,t}, Y_{ij,t}^{AG}, C_{j,t}, RCV_{j,t-1}, SHOCK_{j,t}) \tag{3}$$

Note that the final specification includes controls for other coping strategies that are available to the household. After a rainfall shock, households may draw down on assets (Fafchamps et al., 1998; Hoddinott, 2006; Kazianga and Udry, 2006; Porter, 2012) or may increase their activities in the non-agricultural sector (Bezabih et al., 2010). In particular, the vector of household characteristics

[4] In Ethiopia, there are two main rainy seasons, *kiremt* or *meher*, which is the long rainy season from mid-June to mid-September, and *belg*, which is the short one from February to May.

F_{ij} controls for household assets, represented by land owning and livestock, and human capital, which increases employability in the non-agricultural sector. We also use membership in an iddir - an informal risk-sharing institution in Ethiopia - to control for access to informal insurance against shocks.

4 Data and Empirical Strategy

4.1 Data

We use data from the Ethiopia Rural Household Survey (ERHS), a longitudinal survey implemented by the department of Economics of Addis Ababa University, Ethiopia, in collaboration with the International Food Policy Research Institute (IFPRI), and the Centre for the Study of African Economies (CSAE) at the University of Oxford. Data were collected for the first time in 1989 from 6 villages that suffered drought in 1984. The survey was further expanded in 1994 to encompass 15 peasant associations (PA)[5] across the four major regions of Ethiopia (Tigray, Amhara, Oromia and Southern Nations and Nationalities and people's region), constituting 1477 households, and subsequent rounds took place in 1995, 1997, 1999, 2004 and 2009. The sample of villages and households were chosen randomly to represent the major agro-ecological zones of the country, excluding the nomadic population. The data thus give a representative sample of Ethiopia apart from nomadic pastoral lands.[6]

In order to investigate the role of migration as an adaption to weather variability, we use the 1999 and 2004 waves of the ERHS. Attrition in the panel has been low, at 1-2 percent of households per year (Dercon and Hoddinott, 2011). The ERHS documents detailed information on individual and household characteristics, assets, expenditures, consumption, health, agricultural production and use of agricultural inputs.

In addition to the ERHS panel data, annual rainfall data have been collected from the Ethiopian meteorology agency for the weather stations nearest to each village.[7] The rainfall data have been matched with the ERHS villages using the geo codes of the villages to compute our key weather variables.

[5]A peasant association is the lowest administrative unit in Ethiopia and normally consists of several villages.
[6]Refer to Dercon and Hoddinott (2011) for a detailed description of the ERHS panel data set.
[7]We thank Catherine Porter for sharing the rainfall data with us.

4.2 Empirical Strategy

We use a random effects probit framework to model the decision by households in rural Ethiopia to send at least one household member as a migrant in response to weather variability. Let the latent model of migration be specified as

$$m_{it}^* = x_{it}'\beta + \varepsilon_{it} \qquad i = 1, 2, ..., N; \qquad t = 1, ..., T \tag{4}$$

$$\varepsilon_{it} = c_i + u_{it} \tag{5}$$

where m_{it}^* is a latent dependent variable; m_{it} is the observed binary outcome variable defined as

$$m_{it} = \begin{cases} 1 & \text{if } m_{it}^* > 0; \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

x_{it} represents a vector of time-varying and time-invariant variables which influence m^*; β represents a vector of parameters to be estimated; and ε_{it} is a composite error term which can be decomposed into c_i, a term capturing unobserved individual (household in our case) heterogeneity, and $u_{it} \sim IN(0, \sigma_u^2)$, a random error term. The subscripts i and t refer to households and time periods respectively. One can marginalize the likelihood function by assuming that, conditional on the x_{it}, the unobserved individual heterogeneity term $c_i \sim IN(0, \sigma_c^2)$, is independent of the x_{it}s and u_{it}.[8]

Assuming that the distribution of the latent variable m^*, conditioned on c_i, is independent normal (Heckman, 1981), the vector of parameters, i.e., the βs can be estimated easily. Thus,

$$Pr(m_{it} = 1 | c_i, x_{it}) = Pr(\frac{u_{it}}{\sigma_u} > \frac{-x_{it}'\beta - c_i}{\sigma_u}) = \Phi(v_{it}) \tag{7}$$

where

$$v_{it} = -(x_{it}'\beta + c_i)/\sigma_u \tag{8}$$

[8] A straightforward implication of this assumption is that the equicorrelation between the composite error terms in two successive periods for household i is constant and given by: $\lambda = corr(\varepsilon_{it}, \varepsilon_{it-1}) = \frac{\sigma_c^2}{\sigma_c^2 + \sigma_u^2}$.

and Φ is the distribution function of the standard normal variatevariable. Consequently, the likelihood function to be maximized (which is marginalized with respect to c) is given by

$$\prod_i \{ \int_{-\infty}^{\infty} \prod_{t=1}^{T} [1 - \Phi(x'_{it}\beta^* + \sqrt{\frac{\lambda}{1-\lambda}} c^*)]^{1-m_{it}} \times [\Phi(x'_{it}\beta^* + \sqrt{\frac{\lambda}{1-\lambda}} c^*)]^{m_{it}} \phi(c^*) dc^* \}$$

where $\beta^* = \beta/\sigma_u$ and $c^* = c/\sigma_c$. A standard software can be used to estimate β^* and λ, which are normalized on σ_u.[9]

The time-varying and time-invariant variables captured in the vector x_{it} include weather variability (as measured by the coefficient of variation), income from agriculture, wealth (as measured by the value of livestock owned and the size of land), human capital, membership in informal risk-sharing institutions, and village-level variables such as access to a good road and to town. A detailed description and motivation of these variables is provided in the next section.

It is plausible to argue that some of the explanatory variables (e.g., income) would be endogenous. We attempt to take care of endogeneity of income using the level of rainfall in the previous production year as a credible instrumental variable (IV), and estimate a binary instrumental variables model of migration. We specifically estimate the instrumental variables probit model using the *ivprobit* command in Stata. This estimator identifies the parameters of a model with a binary dependent variable and an endogenous explanatory variable (or variables). As in the linear instrumental variables estimator, the instrumental variables probit model is estimated in a two-stage process. Consistent estimation is based on the assumption that the error terms of the two equations (in both the first and second-stage) are independently and identically distributed multivariate normal. If this assumption is not fulfilled, one could use *clustered standard errors* to control for the lack of independence (Maddala, 1983).

5 Explanatory variables

We discuss the *ex-ante* hypotheses on each explanatory variable used in the migration equation and in the agricultural income equation. The rainfall variability and shock measures are discussed separately in section 5.3.

[9]One other applicable binary choice panel data estimator is the fixed effects logit model (Cameron and Trivedi, 2009). However, because it is based on a within transformation (which also drops any time-invariant observable variables in x_{it}) and is based on variation in the dependent variable over time (which limits the number of observations to be used for estimation and consequently reduces our sample size significantly), we preferred not to use it.

5.1 The migration decision

Agricultural income

Migration depends first upon agricultural income (in logarithms). The standard hypothesis is that droughts decrease agricultural income and push households to migrate (Munshi, 2003). The higher the agricultural income of the household, the less likely it is to have to resort to migration to cope with climatic shocks. However, studies on Burkina Faso (Henry et al., 2004a, 2004b) and Ecuador (Gray, 2009) found the opposite result. A positive correlation is consistent with the so-called hump-shaped pattern of migration (Hatton and Williamson, 2002), which refers to the cost of migration that is too much for households to afford below a critical income threshold. The probability of migration by poor households may thus vary positively with agricultural income. The measure of agricultural income in the ERHS comprises total agricultural income, from both crop and livestock production. Income is given in Ethiopian birr, adjusted for spatial price differences using carefully constructed price deflators.[10]

Household assets

The more assets the household possesses, the less likely it is to have to rely upon migration as a risk coping strategy. For example, the landless have a higher propensity to migrate as a response to shocks, as demonstrated by Jayachandran (2006). Asset ownership is often proxied by the number of livestock units owned (Kazianga and Udry, 2006). Livestock sales can be used as one strategy to smooth consumption when there is an environmental shock (Hoddinott, 2006).[11] Rogg (2005) provides an in-depth study of the asset portfolio responses of the ERHS households to adverse shocks during the first four rounds of the survey, and also on portfolio responses to *ex ante* uncertainty. He finds that households in more risky environments hold significantly less livestock. He also shows that households use buffer-stock assets such as crop/food stocks and some types of livestock to smooth consumption when income fluctuates. In order to reduce endogeneity problems, we use the value of livestock in $t-1$ as a control variable for migration in t.

Household size

We control for household size before migration, which would enter as a factor of production in working the field to produce agricultural income. Household size also takes into account our assumption that the migration decision is part of a household-level optimization strategy. Larger

[10] In 1999, 1 ETB equaled approximately 0.17 USD.

[11] Whether livestock is used to smooth consumption depends on the particular context. For example, Kazianga and Udry (2006) find that livestock is not sensitive to idiosyncratic household shocks, based on a sample of households in Burkina Faso.

households are more likely to send more migrants away. Ideally, we would have preferred to use the dependency ratio, defined as the number of dependent persons (under 15 and above 65 years of age) over the number of working persons. The rationale is that a higher dependency ratio may be an obstacle to migration, as migration would result in fewer adults available to take care of the youngest and oldest. This control variable has not been retained, however, for two main reasons. First, the number of working persons over non-working persons is endogenous to migration, as the latter has been shown to reduce child and female work (see Acosta, 2011, for an application to El Salvador). Second, age data is incomplete on former members, so the variable would very likely be biased.

Education

Education is generally considered to have a positive influence on internal migration (Lucas, 1997; Taylor and Martin, 2001) and positive evidence of this is found in many studies (Henry et al., 2004a; Konseiga, 2006; Tsegai, 2007; Beegle et al., 2011). On the one hand, it should increase the employment possibilities of a member who migrates. On the other hand, it also increases the opportunities to find non-agricultural work within the same PA, thus decreasing the probability of sending a member away. The first effect seems to dominate in Beegle et al. (2011), which highlights a strong positive and non-linear effect of education on migration. The variable used here (human capital) measures the highest education level in the household, in the following categories: some primary education or adult literacy program, completed primary education, secondary education, some university education.

Membership in iddir

The literature suggests a range of mechanisms that households living in risky environments have developed to shield their consumption from risk, including social insurance arrangements, particularly important in the absence of formal insurance or credit markets. An iddir is a kind of mutual insurance association that pays for funerals. The variation is not that large in this variable; in 2004, for example, 80 % of the households were members of an iddir. Nevertheless, we use it to control for access to credit or support if the household were to suffer a reduction in its income.

Distance to town and good road

Accessibility is measured by the distance between the PA that the household resides in and the nearest town. We also use a measure of road accessibility from the PA. Following Dercon et al. (2009) we define road accessibility as a dummy variable equal to one if the PA has at least one road that is accessible to trucks and buses in both rainy and dry weather, and equal to zero otherwise.

The influence of distance to town and accessibility by road is a priori ambiguous. On the one hand, closer proximity to markets makes it easier to purchase inputs and sell crops, and it should also increase the possibilities of seeking alternative wage employment in the origin location as a diversification strategy. These factors all speak for a negative influence of the accessibility variables on the migration decision. On the other hand, proximity to a nearby village and road accessibility reduces the cost of migration and should thus positively influence migration, as in Henry et al. (2004a), for example. These last two variables are measured at the level of the PA, and do not vary across households in the same PA.

5.2 The agricultural income equation

Household agricultural income is a function of the household's number of laborers, proxied by the total number of household members before migration. This variable should be refined to only include working-age people, but, since the sample shows that people start working in the field as early as 6 years old, there is no clear cut-off for the definition of useful labor. The value of livestock holdings in the current year is included as a production factor for agricultural income. Following a Ricardian production factor approach (Mendelsohn and Dinar, 2009), we control for the size of the household's landholdings, measured in standardized units (ha).

5.3 Weather variables

Rainfall variability has been shown to be a relevant climate parameter for agricultural yields in other parts of Africa (Sultan et al., 2010). The household survey data is matched with data on rainfall over the period 1967-2004 from the weather station closest to the PA. The rainfall data used in the study thus vary only across PAs and over time. We use the rainfall in the 12 months preceding the survey to account for the impact of rainfall on agricultural income. The rainfall shock variable is defined as equal to one if the annual rainfall in the 12 months preceding the survey was below one standard deviation from the long-term mean of 30 years of rainfall data, representing a negative rainfall shock.[12] Apart from average rainfall based on past observations, and deviations from this rainfall level, another relevant measure is the variability of rainfall. We use the coefficient of variation to measure the riskiness in the household's environment. The coefficient of variation is defined as the standard deviation over the mean, multiplied by 100. We will thus use the coefficient of variation of the 30 year rainfall distribution as a measure of the riskiness of the household's

[12] Other definitions of extreme shocks above two standard deviations were also tested and the results were robust in terms of coefficients and significance.

environment with respect to rainfall. This should be the basis for a household's *ex ante* decision to send a member as a migrant, before the actual rainfall level and its impact on the harvest have been observed. Ex post, once the rainfall level of the particular year (harvest season) has been observed, it is the actual rainfall shock that will determine a migration decision. Because the survey does not enable us to separate the two types of decisions (*ex ante* and *ex post*), it is important to include both measures in the equation. A test of the hypothesis of a non-zero coefficient on any of the variables should test for its relevance in the final migration decision, which includes both *ex ante* and *ex post* considerations.

Table 1 shows the descriptive statistics of the variables used in the study.

Table 1: Descriptive statistics of variables over time

	[1999]		[2004]	
	Mean	SD	Mean	SD
Sent a migrant	0.02	0.15	0.09	0.28
Agricultural income (birr)	2014.38	2651.72	2410.73	3167.17
Value of livestock (birr)	1800.73	2087.54	2578.60	3388.25
Land size (ha)	1.20	1.02	1.61	2.10
Household size adjusted for migrants	6.79	3.05	5.88	2.59
Household human capital (cat. 0-3)	1.24	0.95	1.02	0.72
Member of at least one iddir (dummy)	0.72	0.45	0.80	0.40
Coefficient of variation of rainfall	28.35	13.45	28.35	13.45
Village experienced rainfall shock	0.20	0.40	0.12	0.32
Distance to nearest town (km)	8.55	5.91	8.55	5.91
Accessible road (dummy)	0.44	0.50	0.69	0.46
Annual rainfall	956.79	295.15	945.44	313.88
Observations	1347		1347	

Source: Authors' computation from ERHS 1999 and 2004.

6 Results

Table 2 shows random effects probit regression results and the corresponding marginal effects for the household model of migration presented in Equation [4]. The results show that household size and household education positively affect the decision to send a member as a migrant, while distance to the nearest town reduces the likelihood of sending a migrant. The results also show that more households sent a migrant in 2004 relative to 1999, which is the base year. We do not find any statistically significant effect of our key variables of interest: household income, weather variability, and rainfall shocks. The random effects probit treat all the right-side variables as exogenous. It is however plausible to expect that most of the household variables are endogenous. We use the level of rainfall in the main agricultural season as an instrument to take care of endogeneity of agricultural income. Other household variables, such as value of livestock, land size, household size and education are also likely to be endogenous. However, we do not find credible IVs to instrument them. Thus, we do not make causal inference between migration and these variables, but we control for them in the estimations.

Table 2: A Household Model of Migration: Random Effects Probit Regression Results

	[RE-PROB]		[ME]	
	[1]		Coeff.	SE
Agricultural income (log)	-0.023	0.031	-0.003	0.004
Value of livestock (log)	-0.014	0.020	-0.002	0.002
Land size	0.024	0.020	0.003	0.002
Household size adjusted for migrants	0.085***	0.017	0.010***	0.002
Household human capital	0.113**	0.058	0.013**	0.007
Member of at least one eddir (dummy)	0.251	0.153	0.029*	0.018
Coefficient of variation of rainfall	0.007	0.004	0.001	0.001
Village experienced rainfall shock	-0.050	0.128	-0.006	0.015
Distance to town in km	-0.020**	0.008	-0.002**	0.001
Accessible road (dummy)	-0.059	0.099	-0.007	0.011
Year 2004	0.632***	0.103	0.067***	0.010
Intercept	-2.619***	0.300		
Log-likelihood	-493.939			
Observations	2297			

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

The first-stage and second-stage regression results from the instrumental variables probit estimator are reported in Tables 3 and 4. We begin with the first-stage regression results. Table 3 shows that the first-stage relationship between rainfall and agricultural income is strongly positive: the level of annual rainfall is significantly related to agricultural income at the one percent significance level.

This relationship is robust to exclusion of the other variables[13] and the Wald test rejects the null hypothesis of no endogeneity (pvalue=0.001). In a country like Ethiopia where more than 95% of smallholder farmers are rain-dependent for their livelihood, positive rainfall typically leads to better agricultural production. The first-stage regression results also show that all the other correlates of agricultural income have the theoretically expected signs and are all statistically significant at the one percent level, except the rainfall shocks variable, which is significant at the ten percent level.

Table 3: A Household Model of Migration: IV Probit - First Stage Regression

	[First]	
	Coeff.	SE
Value of livestock (log)	0.185***	0.014
Land size	0.095***	0.021
Household size adjusted for migrants	0.090***	0.014
Household human capital	0.216***	0.044
Member of at least one eddir	0.499***	0.106
Coefficient of variation of rainfall	-0.013***	0.004
Village experienced rainfall shock	-0.189*	0.099
Distance to town in km	0.019***	0.007
Accessible road (dummy)	0.293***	0.083
Year 2004	0.743***	0.074
Level of rainfall	0.001***	0.000
Intercept	3.499***	0.272
Observations	2297	

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

Regression results from the second-stage of the instrumental variables probit model presented in Table 4 demonstrate the importance of controlling for endogeneity of agricultural income in the migration equation. Column [1] presents the parameter estimates and Column [2] presents the corresponding marginal effects. The log of agricultural income is now statistically significant at the one percent level in Column [1] and positively and strongly determines rural Ethiopian households' decision to send a member as a migrant. From the marginal effects reported in Column [2], we observe that a one percent increase in agricultural income leads to about an 11.5 percent increase in the probability of sending a member as a migrant. This is consistent with findings in earlier studies of migration (Henry et al., 2014a; Gray, 2009), where the liquidity constraints argument seems to be the dominant mechanism in explaining the effect of income on migration. Migration is costly and higher income provides more resources for households to cover the cost of migration. The value of livestock on the other hand is negatively correlated with the probability of sending a household member as a migrant and the effect is statistically significant at the one percent level. A one percent increase in the value of livestock is associated with a 2.5 percent decrease in the

[13] Results are available from the authors upon request.

probability of sending a migrant (Column [2]). Livestock are important as wealth and factors of production in a smallholder farming setups like rural Ethiopia. Consequently, other factors being constant, greater livestock wealth gives the household the opportunity to be productive in farming and get better access to other productivity-enhancing modern agricultural inputs such as chemical fertilizer (Alem and Broussard, 2016).[14]

Table 4: A Household Model of Migration: IV Probit - Second Stage Regression

	[1]		[2]	
	[IV-Prob]		[ME]	
	Coeff.	SE	Coeff.	SE
Agricultural income (log)	0.458***	0.458***	0.115**	0.055
Value of livestock (log)	-0.098***	0.021	-0.025**	0.011
Land size	-0.027	0.021	-0.007	0.007
Household size adjusted for migrants	0.012	0.028	0.003	0.006
Household human capital	-0.027	0.060	-0.007	0.016
Member of at least one eddir (dummy)	-0.090	0.146	-0.023	0.041
Coefficient of variation of rainfall	0.014***	0.003	0.003***	0.001
Village experienced rainfall shock	0.122	0.100	0.031	0.029
Distance to town in km	-0.024***	0.006	-0.006***	0.002
Accessible road (dummy)	-0.142*	0.074	-0.036	0.022
Year 2004	0.053	0.212	0.013	0.050
Intercept	-3.650***	0.235	-	-
athrho	-1.044**	0.409		
lnsigma	0.497***	0.015		
Log-likelihood	-4893.384			
Observations	2297			

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

We will now analyze how climate factors affect households' decisions to send a migrant. Instrumental variables probit regression results presented in Table 4 suggest that the decision to send a household member as a migrant is positively influenced by weather variability, as measured by the coefficient of variation of rainfall. A one unit increase in the coefficient of variation increases the probability of sending a migrant by about 0.3 percent. The effect is statistically significant at the one percent level. This provides strong and important evidence supporting our hypothesis that households in areas with highly variable weather are more likely to adapt through sending a migrant. This is an *ex-ante* effect of weather variability. Because climate change is expected to result in extreme weather events and the Sub-Saharan African region is going to experience even greater variability in rainfall (IPCC, 2014), our findings imply that there will be increased migration by household members in rural communities in the future. On the data studied here, no statistically significant evidence (probably due to a large standard error) is found that migration decisions are

[14] Due to the many restrictions in the land market in Ethiopia, livestock plays an important role in farm productivity in rural Ethiopia. It is an important wealth indicator and it can serve as collateral for credit.

driven by negative rainfall shocks over the short run (24 months); rather, such decisions are taken due to assessments based on the long-term risk of variability in rainfall as given by the coefficient of variation.

We finally note that distance to the nearest town negatively affects the decision to send a migrant. This may sound counterintuitive, as proximity to towns should make migration easier. However, it is also plausible that households close to towns have the option of participating in off-farm activities without the need to leave home. This last result thus yields support to the proximity to markets argument: better access to markets for inputs and outputs enables the household to be more productive in agriculture and also to find alternative employment in urban centers (Bezabih et al., 2010).

7 Conclusions

Climate change is predicted to impact society and ecosystems by resulting in extreme weather events, changing precipitation and declining agricultural productivity in large parts of the world (IPCC 2014). As a result of its dependence on climate variables, agriculture is more vulnerable than other sectors to the effects of climate change. Sub-Saharan Africa, whose agricultural sector is known for its low productivity, is one of the most vulnerable regions. This paper attempts to shed light on whether households in rural areas of Ethiopia use migration as a strategy to adapt to weather variability. We use Ethiopian Rural Household Survey panel data combined with village-level rainfall data to investigate both the *ex-ante* and *ex-post* impact of climate variables on households' likelihood to send a migrant. Compared to earlier studies, the key contributions of the paper are in using objective measures of rainfall variability and rainfall shocks, which are exogenous to households, and in teasing out the *ex-ante* and *ex-post* effects. We also control for endogeneity of income - an important determinant of migration - using a credible instrument.

Instrumental variables probit regressions suggest that households in rural Ethiopia adapt to weather variability by sending a migrant. Smallholder farm households that live in places with higher rainfall variability are likely to send a household member as a migrant. This effect is economically important and statistically significant at the one percent level. We also find suggestive evidence on the *ex-post* impacts of weather, proxied by the prevalence of negative rainfall shocks between one and two standard deviations above the long-run mean, in the year preceding migration. The variable positively affects the decision to send a migrant, but it is not statistically significant at the conventional levels, most probably due to large standard errors. We also find that income (instrumented by the level of rainfall) has a significant positive impact on the decision to migrate, while wealth (proxied by the value of livestock owned by the household) is negatively associated with the likelihood of engaging in migration. Regression results also show that living close to a town reduces the likelihood of sending a migrant.

Extensions to this analysis could study the role of irrigation, not included in our study because the measurement errors in the variable are large in the ERHS data.[15] Improving water access would be a useful policy objective, given the strong impact that we find from rainfall variability. Developing rainfall insurance products that could cushion the impact of rainfall variability also seems an important policy implication of the results, in line with previous research on the negative effects of rainfall variability on small holder farm households. Because several factors enter into the migration decision, it is also clear that some migration is unavoidable - and even desirable from a household viewpoint. Policy measures should also be directed toward supporting development in the urban sector of the country that will receive the out-migrants from the rural areas that are subject to high rainfall variability.

[15] Water harvesting by traditional means is often interpreted as irrigation in the survey.

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