Crop and income diversity as adaptation strategies to cope with climate change: insights from Uganda panel data.

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Abstract

Ugandan territory is a challenging environment for agriculture due to the frequency and severity of extreme climate events such as droughts, heat waves, floods and storms. These climate-related events are likely to harm agriculture production and food security. Therefore, people who depend on farming activities will require a variety of adaptation strategies to mitigate the negative effects of climate change and maintain the livelihoods of farming families. There is limited knowledge on how farmers are responding to the effects of a changing climate and how they have adjusted their farming practices to cope with the changes in climate. In this paper we explore to what extent farmers use crop and income diversity as self-protection measures against climatic shocks. To address sample selection and unobserved heterogeneity often associated with the adoption of adaptation strategies, we estimated a panel data switching endogenous regression model. Using three rounds of Uganda National Panel Survey (2009, 2010 and 2011), we found that the climate variability tends to significantly affect crop diversity decisions. When farmers experience severe environmental conditions, they increase the number of crop species to reduce the risk of crop loss and maintain the livelihoods of farming families. Policies aiming at providing farmers with better access to crop and varietal diversity can strengthen their capacity to adapt to climate change. Incentivising smallholders to grow diverse varieties and local cultivars is also critical to the success of in-situ *conservation.*

JEL Classification: Q12, Q16, Q54, O39,

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1. Introduction

A wide strand of literature has focused on studying the impact of *ex-ante* insurance and *ex-post* coping strategies in mitigating the adverse impact of climatic and market shocks on rural livelihood capacity. While a branch of these studies emphasised the role of migration by household (HH) or HH members (Bazzi et al., 2016; Bai & Jung, 2011; De Brauw, 2011) other branches concentrated on access to microcredit (Fenton et al., 2017), government and NGOs aids (Porter, 2012; Davis et al., 2010; Angelucci & De Giorgi, 2009), climate smart agriculture and technology adoption (Arslan et al., 2015; Dercon & Christiaensen, 2011; Howden et al., 2007).

Diversification of both household's nonfarm income sources and cultivated crops mix also came out as a valuable strategy to manage erratic irregularities of rainfall and temperature pattern as well as fluctuations of agricultural products' price (Asfaw et al., 2018; Di Falco & Chavas., 2009; Barrett et al., 2001). While diversification is a well-known mean to be insured against risk as in the portfolio theory (Schindler et al., 2010; Di Falco & Perrings, 2005), the individual degree of risk aversion inversely depends by the farmer' wealth that can sustain farmers in dealing with unexpected shocks by smoothing income variability (Niehof, 2004; Morduch, 1995). Risk aversion, conditional to the full set of an HH's endowment, is expected to increase as both idiosyncratic or covariate shocks are increasingly perceived to be random but likely to replay over years (Alpizar et al., 2011; Tanaka et al., 2010). In this context, diversifying may help farmers to reduce the livelihood stress due to a changing environment. Nevertheless, such "distressing" diversification could also play a role in locking farmers into income-spreading but low return activities since the risk aversion push them to pay an insurance premium in terms of foregone income from diversifying instead than specializing (Martin & Lorenzen, 2016). Whether this premium is positive depends by the effectiveness of the diversification strategy because, under certain agroclimatic conditions and infrastructural or liquidity constraints, this can provide better relative results than specialization (Coromaldi et al., 2015). Although diversification can be a suitable strategy for poor HH, it has been investigated that, due to an increasing access to human capital as education and labour or social capital (networking), well-endowed HH are those people more capable to adopt a successful diversification thanks to a larger set of available options (e.g., selection of non-agricultural wage activities by the more skilled household's members) (Reardon et al., 2000).

Crop diversification can play a fundamental role in the capacity of agriculture and food system to adapt and respond to climate change. Traditionally, crop diversity is used as a strategy for risk avoidance due to sharp fluctuations in crop yield or prices (Ellis, 2000; Di Falco and Chavas 2009; Bezabih and Sarr 2012). The farmers' income volatility is reduced by diversification if crop incomes are not perfectly correlated (Gollier 2001; Elton et al. 2009). Thus, in a dynamic context, crop diversity has been designated to enhance resilience to climate shocks through spreading the risk of yield failures and preserving the option value of crop diversity (Pascual et al., 2011). Moreover, the loss of crop diversity has negative impact on ecosystem services such as pollinating services and pest control and, indirectly, on food security and dietary diversification (Jones et al., 2014). However, the literature has also stressed as poorly endowed HHs can be locked-in in a diversified, but low-returns, set of activities (Asfaw et al., 2018).

According to Biodiversity International, crop varieties resistant to heat, droughts, floods and diseases can reduce the use of pesticides, lessen the need for irrigation stabilize the soils and reduce application of fertilizers. Above that, these kinds of shock response may promote forest conservation and eliminate the need to create more farmland for food production. Overall, it is necessary to mention that climate is likely to cause multiple stresses which can be dealt with by using a wide range of crop varieties and other shock responses (Meldrum et al, 2017). It is worth to say that a close analysis of crop variety as an adaptation strategy might be appropriate to face the issue of food security in the medium and long term. Specific adaptation strategies to climate change effects include changing the timing of planting and using heat and drought resistant varieties, practicing soil and water conservation techniques, fertilizer use, irrigation and diversification to non-farm activities. Environmental factors can influence crop portfolios and farmers will be forced to change their practices and find crops and varieties better adapted to new weather dynamics.

Rural HHs can react to potential climatic and market shocks also by diversifying their portfolio of income sources (Asfaw et al, 2018). The degree of diversification is related to the degree of risk aversion and to the vulnerability level, i.e. the asset endowment (Carney, 1998). Although farm income usually constitutes a high share of rural households’ income, off-farm diversification strategies may occur for several reasons and climate-driven insecurity may as well be included. Income diversification is likely to be the result of households’ attempt to diversify income sources not strongly related to local agricultural outcomes (Delgado et al., 1997). It appears that at low income levels, farmers are mostly focused on subsistence agriculture, while income diversification increases when the level of commercialisation is higher (Reardon et al., 1994). Diversification of on-farm and off-farm activities among smallholder farmers in Sub-Saharan Africa is highly related to risk mitigation strategies driven by, among others, harmful climatic shocks (Bradshaw et al., 2004). In fact, when a household can account for several income sources across time, this is usually an indicator of vulnerability to society, market, climatic or other environmental variables (Adger, 1999).

2. Country background

As a case study, Uganda seems to be suitable in order to implement an empirical investigation regarding coping strategies among rural households. Uganda's economy is considered among one of the poorest in the world: 20% percent of population spends not enough to meet their caloric requirements and are considered chronically poor, especially in rural areas where there is usually no formal education [UBOS, 2016]. In addition to an insecure social and economic context, Uganda is a challenging environment for agriculture due to the frequency and severity of extreme climate events, such as droughts, heat waves, floods and storms. The country is landlocked and set in the equatorial area of Africa, right below Saharan desert. It is characterised by two rainy seasons, from March to June and to August to November, and a high level of humidity. In spite of extreme events recently occurred, Uganda is very rich in biodiversity and it has relatively fertile soils. This Sub-Saharan country is not only expected to see a relatively large increase in the mean annual temperature (according to the Fourth Intergovernmental Panel on Climate Change Assessment Report, climate change is likely to increase average temperatures by 1.5 ºC in the next 20 years and 4.3 ºC by the 2080s), but the Uganda may also experience a rise in extreme precipitation and rainfall distribution is likely to become more irregular. As many of SSA countries, Uganda deeply relies on agricultural sector, which accounts for 20% of GDP and employs 70% of Ugandan labour force (USAID, 2012). Moreover, over 80% of Ugandan citizens lives in rural areas and depend on rain-fed agriculture. Thus, Uganda is a geographic region which climate change literature has highlighted as prone to be affected by extreme weather variability (Pearce et al., 1996; McCarthy, 2001). The impact of climate change in Uganda is manifold: variability in rainfall and regular severe droughts affect agricultural productivity; moreover, climatic events have deep impact on the increasing incidence of malaria and on receding water levels in lakes and rivers. The effects of climate-related events have harmful implications, making the affected communities even more vulnerable. These communities have limited capacity to adapts to the harsh consequences of climate change.

Despite considerable progress made by the Ugandan government in developing a governance system for climate change adaptation, culminated with the approval in April 2015 of the National Climate Change Policy, implementation still limits positive responses. Policies are mainly developed by central government agencies while local communities are excluded. Climate change adaptation becomes constrained due to discontinue communication between national, district and community levels. There are also limited technical capacity, political interference and absence of functional implementation structures across these levels (Ampaire et al., 2017). Therefore, in this context crop diversification could play a fundamental role in the capacity of agriculture and food system to adapt and respond to climatic shocks.

3. Data description

Two datasets were used in the analysis. Household longitudinal data are based on Uganda National Panel Survey (UNPS) program implemented by Uganda Bureau of Statistics, with financial and technical support of the Government of Netherlands, and the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project. The UNPS is a multi-topic panel household survey that commenced in 2009/10 and continued for the years 2010-11, 2011-12, and 2013-14.

Individuals grouped in 4373 households were included in the balanced panel built for the investigation. Each survey envisages two visits in order to capture agricultural outcomes associated with the two cropping seasons of the country.

These nationally representative household surveys include detailed information on household demographic characteristics such as education, household size, sex and age of the household head and other data on household shocks and assets.

The data on crop and total income, nonfarm income and other sources of income come from Smallholders Data Portrait provided by FAO (2018). The smallholder farmers' Data Portrait is a comprehensive, systematic and standardized data set on the profile of smallholder farmers across the world. At present it provides information for nineteen countries.

Agriculture modules are a core part of data collected because they contain information at plot level on agricultural production, farm technology, use of modern inputs and composition and productivity of crops. The LSMS-ISA survey data record geo-referenced household and enumeration area level Latitude and Longitude coordinates using handheld global positioning system (GPS) devices. This creates the possibility of linking household level data with geo-referenced climatic information to identify how weather variables affect the farmers' diversification strategies and their impact on food security measures.

Climatic data are collected by the Global Land Data Assimilation System (GLDAS) v2.1. GLDAS is a global gridded reanalysis dataset (Rodell et al., 2004a) with a spatial resolution of 0.25°*0.25° and 3-hourly temporal resolution. Climatic indicators considered are the following: mean temperature, total precipitation, the Standard Precipitation Index (SPI) and the Consecutive Dry Days (CDD). The SPI is and indicator of seasonal trends in precipitation; it is calculated on long-term precipitation and it is based on the probability of precipitation for any time scale (Edwards and McKee 1997). The present study includes two precipitation variables (and their square values), which count the number of months in which the SPI is greater (less) than 1 (-1), in order to compute the effects of droughts (floods). CDD is the annual count of days during which dryness at local level is present; while the former indicators are rainfall-related variables, the latter regards the state of temperature. In order to assess the impact of climate on the variable of interest, it is important to include both kinds of indicators (and their squared values) in the analysis.

Table 1 describes how the number of crops each household owns has changed through the years of investigation. According to the data, households' percentage with the same number of crops has been stable both moving from the first to the second wave and from the second to the third one. What is striking is the difference between the first transition and the second one on the increase, and particularly on the decrease, of the number of crops held by the households. In fact, it appears that 51% of rural households in 2011 experienced a reduction in their number of crops, in comparison with 2010. Although the table by far do not allow for any speculation, it is clear that certain occurrences at social, economic or environmental level have caused a shrinkage in households' agricultural assets.

4. Conceptual framework

The sustainable rural livelihood framework (SRL) provides a fundamental reference to analyse the strategic choices made by a farmer i to manage their welfare levels $W_{i,t}$ at a specific time t (Ellis, 2000). We adapt this framework by considering a rural HH who can be represented as a decision-making unit whose reaction to exogenous climatic and market shocks is correlated with a vector of idiosyncratic characteristics and the past, long or short-term experience with such shocks (Mertz et al., 2009). The farmer i observes the impact on W after an unexpected shock and try to cope to adjust fluctuations in his income, for example migrating or selling some asset (Morduch, 1995). Otherwise, the higher is the shock event repeated over a time span $t-\tau$, the higher the probability that farmer would adapt by increasing the level of diversification even if, as mentioned above, the capacity to diversify effectively also depends by the HH's wealth. So, both the capacity to cope *ex-post* and the *ex-ante* adaptation depend by the access to a vector $K_{i,t}$ of strategic assets. The reaction to exogenous shocks is heterogeneous because heterogeneous is the observable and unobservable mix of assets that compose $K_{i,t}$ (Suri, 2011). These can be classified as $K_{i,t}^N, K_{i,t}^P, K_{i,t}^H, K_{i,t}^F$ and $K_{i,t}^S$ which represent the natural, physical, human financial and social capital, respectively (Scoones, 1998).

While the SRL has been recently utilized to investigate the determinants of farmers' decisions in developing countries (Trædal &Vedeld, 2018; Nguyen et al., 2017; Martin &Lorenzen, 2016; Atela et al., 2015), we combine it with a simplified non-separable household (NSH) model (Wouterse & Taylor, 2008; De Janvry et al., 1991) to investigate the timing and the impact of diversification on the rural welfare ,conditional to weather and market shocks. The NSH model is useful to analyse farmers' strategies when crop and off-farm income sources diversification levels are affected by the same set of asset endowment in a variable and risky context (Asfaw et al., 2018). On the other hand, Gao and Mills (2018) suggest that the diversification strategy is effective when the variation in the HH's consumption is minimized after an adverse income shock (Porter, 2012). So, for example, while the level of income diversification can increase as the HH is endowed with an high human capital, an observed reduction in rainfall could push him to increase the number of crops cultivated to manage this risk; nevertheless, the effectiveness of such diversification could, in turn, depend by soil conditions (natural capital) and the availability of HH's member labour that could be, however, unavailable because employed in non-farming activities.

As a result, subject to exogenous climatic anomalies and price fluctuations, the HH's welfare can be represented as a random outcome function of income and crop diversification ($D_{i,t}^{Income}$ and $D_{i,t}^{Crop}$, respectively). These are set up to maximize the welfare, $W_{i,t}$, according to the HH's endowment $K_{i,t}$:

$$\begin{cases} D_{i,t}^{Income} = f\left(S_{i,t-\tau}^{C};\ S_{i,t}^{C};\ S_{it}^{M};\ K_{i,t}; v\right) \\ D_{i,t}^{Crop} = f\left(S_{i,t-\tau}^{C};\ S_{i,t}^{C};\ S_{it}^{M};\ K_{i,t}; u\right) \end{cases} \tag{1}$$

$$W_{it} = f\left[\left(D_{i,t}^{Income}, D_{i,t}^{Crop}\right);\ K_{i,t}; S_{i,t}^{C};\ S_{it}^{M}; z\right], \tag{2}$$

where $S_{i,t-\tau}^{C}$ represents, the past climatic shocks experienced by farmer i over a time span $t-\tau$. These frequencies are likely to impact on decision to adapt *ex-ante*. On the contrary, $S_{i,t}^{C}$ and $S_{i,t}^{M}$are the contemporaneous shocks that are relevant in explaining the implementation of *ex-post* coping strategies that should impact also on welfare outcome because applied to reduce the vulnerability. Finally, v and u are unobserved time variant and invariant drivers of income and crop diversification, while$z$ are unobserved time variant and invariant characteristics that impact on the income gap.

5. Empirical strategy

Our empirical strategy is set up to investigate determinants of livelihood strategies and impact on rural HH's welfare subject to climatic and market shocks in a context of heterogeneous and time-varying response. Farmers face differentiated conditions according to observable individual endowment of land, type of soil, education or access to agricultural input and infrastructure that we contained in the vector $K_{i,t}$ in Section 4. Nevertheless, farmers' decisions are also affected by unobservable characteristics such as attitude, beliefs, skills or risk aversion which are likely to drive the decision to adopt or not a combination of income and crop diversification strategies but are, as well, drivers of the farmers' welfare (Koutchadè et al., 2018).

Thus, self-selection and endogeneity are econometric challenges relevant in our type of investigation. Selection refers to the case where the decision to adopt a specific mix of diversification levels is observed only for a restricted, non-random sub-samples of population and imputable to systematic characteristics of these sub-samples. Endogeneity arises since decision to diversify is correlated with unobservable factors affecting the welfare outcome (Semykina, & Wooldridge, 2010).

In a context of panel data, as the one we investigate, the self-selection in a group of diversification strategies is expected to be time-variant because deriving from the unobserved heterogeneity that causes differentiated responses to random exogenous shocks (Dustmann & Rochina-Barrachina, 2007; Wooldridge, 2010). We adopt a panel multinomial endogenous switching regression (PMES) model that allows to both control for time-varying unobserved heterogeneity and the diversification strategies, which works as switching variable, to interact with observable HH's endowments and unobserved heterogeneity. The latter means that, since the welfare outcome among the adopters' group of different diversification levels is assumed systematic because of selection, the impact of livelihood decisions is estimated not just through an intercept shifters *à la* Heckman (1976) but for diverse covariates coefficients across groups (Maddala., 1986).

To estimate the PMES we follow a recent multistep-step procedure as in Murtazashvili and Wooldridge (2016) that combines the control function approach (Bourguignon et al., 2007) with an endogenous switching. This procedure has been recently empirically applied in Kassie et al., (2016). In a first step a multinomial logit model is estimated on a categorical selection equation representing all the combinations of different levels of crop and income diversification. A feature of the multinomial logit model is the independence of irrelevant alternative (IIA) assumption. Nevertheless, Bourguignon et al. (2007) demonstrated as the selection bias correction based on the multinomial logit model seems a reasonable alternative to multinomial normal models when the focus is on estimating an outcome over selected populations rather than on estimating the selection process itself. This seems robust even when the IIA hypothesis is violated.

Following, separated OLS for each group of diversification strategies are estimated in the welfare outcome equation including the Inverse Mills Ratio (IMR) from the first step as additional regressor that capture selection bias. Moreover, both the steps are corrected through the Chamberlain-Mundlak device (1978) that, by including the means of the time-varying covariates, controls for time invariant unobserved heterogeneity[1].

We categorize $D_{i,t}^{Income}$ in a binary variable that assumes value 0 in the farmer i relies only on on-farm income, while assumes value 1 if relies on additional income sources. $D_{i,t}^{Crop}$ assumes three values: 0 for no crop diversification, 1 for low crop diversification and 2 for high crop diversification. Then we build our multinomial treatment variable, $D_{i,t}^{j}$, to be estimated in the first step by allowing for all the potential combinations of $D_{i,t}^{Income}$ and $D_{i,t}^{Crop}$. $D_{i,t}^{j}$ goes from 0 to 5. At each period i adopts the strategy of diversification mix$j$ that maximizes the expected welfare (or minimize the gap from the permanent income) according to his endowment and the exogenous shocks with respect other diversification levels $k \neq j$. Consequently, the probability that a farmer i adopts a diversification mix level j, is equal to:

$$\mathrm{Prob}\left(j \middle| H_{i,t}, S_{i,t-\tau}^{C}, S_{i,t}^{M}, \bar{\mu}_i\right) = \frac{\exp\left(\alpha_j + H_{i,t}\beta_j + S_{ea,t-\tau}^{C}\gamma_j + S_{i,t}^{M}\delta_j + \bar{h}_i\Gamma^j\right)}{\sum_{k\neq j}\exp\left(\alpha_k + H_{i,t}\beta_k + S_{i,t-\tau}^{C}\gamma_k + S_{i,t}^{M}\delta_k + \bar{h}_i\Gamma^k\right)} \; for \; all \; j = 0,1,3,4,5, \qquad (3)$$

where $H_{i,t}$ is a matrix containing the asset endowments $K_{i,t}$at HH level and the contemporaneous shocks $S_{ea,t}^{C}$and $S_{ea,t}^{M}$ at enumeration area level; in the same manner,$S_{ea,t-\tau}^{C}$ represents the past observed shock at enumeration area level. These also function as selection instruments to have the model identified (Di Falco et al., 2011). Finally,$\bar{h}_i$ is a vector of Mundlak devices representing the mean time values of $H_{i,t}$, and $\beta_j, \gamma_j, \delta_j, \Gamma^j$ are unknown parameters to be estimated.

In the second step, the 5 welfare outcome equations$W_{i,t}^{j}$are estimated separately through an OLS and controlling for the endogeneity of the diversification level adopted. The 6 regimes result as follows:

$$\begin{cases} W_{i,t}^{0} = \alpha_{i,t}^{0} + H_{i,t}^{0}\Phi^0 + \bar{h}_i^0\Gamma^0 + \hat{\lambda}_{i,t}^{0}\Omega^0 + t * \hat{\lambda}_{i,t}^{0}\Psi^0 + \epsilon_{i,t}^{0} \\ \vdots \\ W_{i,t}^{5} = \alpha_{i,t}^{5} + H_{i,t}^{5}\Phi^5 + \bar{h}_i^5\Gamma^5 + \hat{\lambda}_{i,t}^{5}\Omega^5 + t * \hat{\lambda}_{i,t}^{5}\Psi^5 + \epsilon_{i,t}^{5} \end{cases} \qquad (4)$$

[1] While this could be done with a fixed effect estimator, with nonlinear models there is evidence of incidental parameters problem that would affect consistency of estimates (Wooldridge, 2005)

Where $\hat{\lambda}_{i,t}^{j}$ is the IMRs estimated from (3) using the Durbin and McFadden formula (Bourguoignon et al., 2007) that are also interacted with time dummies to control for time trend which could drive selection probability; Ω^{j} and Ψ^{j} are coefficients to be estimated and represent the covariance between selection and outcome equation, while $\epsilon_{i,t}^{j}$ are normally distributed error terms.

Expected actual and counterfactual outcomes

One of the main advantages of the PMES is the possibility to build counterfactual outcomes which assess the average treatment effects (ATE) of the adoption of a diversification practice with respect to the other diversification levels and is given by the structural difference of welfare between the actual adoption choice and a counterfactual scenario of adoption choice. The actual expected outcomes are:

$$\begin{cases} E\left[W_{i,t}^{1} | j=1\right] = \alpha_{i,t}^{1} + H_{i,t}^{1}\Phi^{1} + \bar{h}_{i}^{1}\Gamma^{1} + \hat{\lambda}_{i,t}^{1}\Omega^{1} + t * \hat{\lambda}_{i,t}^{1}\Psi^{1} \\ \vdots \\ E\left[W_{i,t}^{5} | j=5\right] = \alpha_{i,t}^{5} + H_{i,t}^{5}\Phi^{5} + \bar{h}_{i}^{5}\Gamma^{5} + \hat{\lambda}_{i,t}^{5}\Omega^{5} + t * \hat{\lambda}_{i,t}^{5}\Psi^{5} \end{cases} \quad (5)$$

The counterfactual outcomes are obtained by plugging into equation (5) the coefficients obtained from the estimation of $W_{i,t}^{0}$ in (3), as follow:

$$\begin{cases} E\left[W_{i,t}^{0} | j=1\right] = \alpha_{i,t}^{0} + H_{i,t}^{1}\Phi^{0} + \bar{h}_{i}^{1}\Gamma^{0} + \hat{\lambda}_{i,t}^{1}\Omega^{0} + t * \hat{\lambda}_{i,t}^{1}\Psi^{0} \\ \vdots \\ E\left[W_{i,t}^{0} | j=5\right] = \alpha_{i,t}^{0} + H_{i,t}^{5}\Phi^{0} + \bar{h}_{i}^{5}\Gamma^{0} + \hat{\lambda}_{i,t}^{5}\Omega^{0} + t * \hat{\lambda}_{i,t}^{5}\Psi^{0} \end{cases} \quad (6)$$

The zero-diversification mix is the base level category to estimate the ATE. The ATE is thus the welfare outcome that adopters would have if they decided to not adopt any level of income and crop diversification and is equal to:

$$E\left[W_{i,t}^{j} | j=J\right] - E\left[W_{i,t}^{0} | j=J\right] \quad (6)$$

6. Estimation results

In Table 3, we report the multinomial logit results of rural household decision to diversification.

Table 3 shows that factors influencing household decision to diversify crop and income portfolio are: sex of the household head, marital status of the household head, land size, the use of intercropping, number of hours worked, the use of improved seeds, the use of information services and climatic indicators such as the number of months in which SPI is less than -1 in the last five years. The likelihood to diversify income and crops increases as the head of the household is female. This is probably attributed to the fact that female-headed HHs have a higher degree of risk aversion (Covarrubias, 2015; Asfaw et al, 2018). Single HH heads are less likely to diversify their crop portfolio, as it is also revealed in previous studies (). Education does not represent a significant crop diversification determinant, on the other hand, we found that the more the members are educated the higher the probability of participation in off-farm work (Yunez-Naude and Taylor, 2001).

Another push factor inducing households to diversify is the availability of land. Holding more agricultural land rises household's probability to increase crop and income diversification because the risk aversion on vulnerable lands is higher (Di Falco & Chavas, 2006). As expected, intercropping practises increase the probability of crop diversification set (I_0C_1, I_0C_2 , I_1C_1 , I_1C_2), while the adoption of improved seeds constitutes a negative driver of crop diversification since these technologies outperform in intensive and monocropping cultures (Pascual & Perrings, 2007).

A nonlinear concave relationship can be found between diversification sets which include lower and higher crop diversification level and a count climatic indicator such as the number of months in which SPI is less than -1 in the last five years. When SPI is less than –1 indicates that drought events occurred. Thus, in the presence of climatic shocks such as droughts farmers rely on a rich set of local landraces as part of an agricultural risk minimization strategy (Coromaldi et al., 2015) but up to a certain level after which the crop diversification is not allowed due to the extreme weather conditions. On the contrary, floods are related to a value of SPI greater than 1. In our results, this climatic indicator does not affect the household’s decision to diversify.

The estimated coefficients of the outcome equations are reported in Table 4 and 5. As sensitivity analysis, we analyse the implications of the diversification decision on consumption per capita as well as on gross crop income. In Table 4, we do not report results for the inverse Mills ratios and the mean of time varying variables, however we noted that in some of the outcome equations the coefficients associated with these variables are significant, indicating the presence of sample selection in the diversification choice set. ...

7. Conclusions

The aim of this paper is to explore to what extent farmers use crop and income diversity as a self-protection measure against market and climatic shocks. Uganda LSMS ISA data and GLDAS dataset are employed in order to implement a two-steps analysis. After applying multinomial endogenous switching regression model, results point out that rural households who put in act a certain amount of crop diversification strategies might increase their own consumption, given the presence of negative climate-related shocks and market outbreaks. Moreover, it appears that gender may play a specific role; most specifically a female household head seems to positively affect diversification strategies, which is a potential key result to consider when elaborating a policy. Climatic indicators confirm results acknowledge in past literature, which in this context indicate a non-linear effect of climate on the probability to diversify. In sum, the outcome of the present paper suggests that policies aiming at providing farmers with better access to crop and varietal diversity and at boosting gender empowerment in rural communities can strengthen their capacity to adapt to climate change.

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Tables

Transition		
	From 2009 to 2010	**From 2010 to 2011**
HHs' percentage with the same number of crops	21.79	21.12
HHs' percentage which increase the number of crops	43.18	27.87
HHs' percentage which decrease the number of crops	35.03	51.00

Table 1 Crop transition from 2009 to 2010 and from 2010 to 2011

Variable	mean	p50	sd	min	max	N
Female household head (1=yes)	0.191	0	0.393	0	1	4453
Single household head (1=yes)	0.239	0	0.426	0	1	4450
Average level of education (years)	3.821	3.5	2.322	0	16	4444
Distance from the nearest market (Km)	32.850	31.48	19.178	0.621	116.23	4453
Crop area (Ha)	0.908	0.800	0.802	0	5.324	4449
Use of anti-erosion measures (1=yes)	0.279	0	0.448	0	1	4453
Use of intercropping (1=yes)	0.844	1	0.363	0	1	4453
Market shock (1=yes)	0.029	0	0.166	0	1	4453
Log Labour (person day)	5.299	5.371	0.789	0	9.849	4437
Use of improved seeds (1=yes)	0.274	0	0.446	0	1	4453
Use of chemical fertilisers (1=yes)	0.053	0	0.225	0	1	4453
Number of livestock units owned	1.842	0.4	11.008	0	575.26	4453
Use of information services (1=yes)	0.297	0	0.457	0	1	4453
Nr of months in which SPI>1 in the las 5 years	5.461	5	4.115	0	20	4453
Square of Nr of months in which SPI>1 in the las 5 years	46.746	25	60.203	0	400	4453
Nr of months in which SPI<-1 in the las 5 years	6.362	6	4.165	0	14	4453
Sqaure of Nr of months in which SPI<-1 in the las 5 years	57.810	36	55.595	0	196	4453
Log Consecutive Dry Days	7.068	7.306	1.002	-0.366	8.229	4401
Square of Log Consecutive Dry Days	50.958	53.379	11.551	0.134	67.711	4401
Year=2010	0.334	0	0.472	0	1	4453
Year=2011	0.333	0	0.471	0	1	4453

Table 2 Descriptive statistics

VARIABLES	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	I_0C_1		I_0C_2		I_1C_0		I_1C_1		I_1C_2	
Female household head (1=yes)	0.476**	0.490**	0.356	0.362	1.014***	1.046***	0.927***	0.941***	1.091***	1.134***
Single household head (1=yes)	-0.312	-0.331*	-0.757***	-0.758***	0.0009	-0.0359	0.0549	0.017	-0.222	-0.244
Level of education (years)	0.0137	-0.0582	-0.0353	-0.0408	0.0817***	-0.0485	0.0552*	-0.0348	0.0592*	-0.167**
Distance from the nearest market (Km)	-0.00616*	-0.0447	-0.00381	-0.156	0.00572*	-0.0824	0.00221	-0.0632	0.004	-0.086
Crop area (Ha)	0.540***	0.782***	1.057***	1.369***	0.410**	0.424**	0.677***	0.883***	1.148***	1.420***
Use of anti-erosion measures (1=yes)	-0.0678	-0.0539	0.261	0.275	-0.203	-0.205	-0.0133	-0.00732	0.301*	0.315*
Use of intercropping (1=yes)	2.733***	2.746***	3.350***	3.354***	0.119	0.133	2.382***	2.401***	2.924***	2.947***
Market shock (1=yes)	0.616	0.627	0.0439	0.0243	0.196	0.218	0.177	0.21	0.141	0.153
Labour	0.487***	0.489***	0.519***	0.362**	-0.133	0.0339	0.270***	0.424***	0.478***	0.386**
Use of improved seeds (1=yes)	-0.296*	-0.284*	-0.107	-0.102	-0.127	-0.128	-0.316**	-0.307**	-0.259	-0.231
Use of chemical fertilisers (1=yes)	-0.448	-0.422	0.033	0.0517	0.165	0.189	0.0151	0.0605	0.318	0.348
Total Livestock in TLU	-0.0248	0.00975	-0.00282	0.0514***	-0.000639	0.0054	-0.00436	0.00842	-0.0253**	-0.0231
Use of information services (1=yes)	0.18	0.202	0.323*	0.365**	0.397**	0.398**	0.542***	0.566***	0.507***	0.516***
Nr of months in which SPI>1 in the las 5 years	0.0121	0.0156	0.0537	0.0496	0.0255	0.0239	0.0217	0.024	0.0506	0.052
Square of Nr of months in which SPI>1 in the las 5 years	-0.00137	-0.00145	-0.00413	-0.00345	-0.00197	-0.00169	-0.000596	-0.000634	-0.000324	-0.000171
Nr of months in which SPI<-1 in the las 5 years	-0.179**	-0.183**	-0.181**	-0.182**	-0.201***	-0.194***	-0.0742	-0.0715	-0.0564	-0.0679
Sqaure of Nr of months in which SPI<-1 in the las 5 years	0.0135**	0.0135**	0.0155***	0.0152**	0.0156***	0.0151***	0.0079	0.00757	0.00713	0.00754
Consecutive Dry Days (logarithms)	-0.346	-0.329	0.624	0.633	0.0811	0.107	0.123	0.142	0.955	0.976
Square of Consecutive Dry Days (logarithms)	0.0209	0.019	-0.0937**	-0.0953**	0.00536	0.00274	-0.0179	-0.0199	-0.116**	-0.118**
Year=2011	-0.942***	-0.913***	-3.171***	-3.169***	-0.247	-0.226	-1.159***	-1.101***	-3.648***	-3.647***
Constant	-1.917*	-2.210*	-4.342***	-5.605***	-0.209	0.475	-2.474**	-2.045*	-5.551***	-6.452***
Mundlak		Yes		Yes		Yes		Yes		Yes
Observations	4373	4373	4373	4373	4373	4373	4373	4373	4373	4373

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Results from the first step - multinomial logit.

VARIABLES	(1) I_0C_0	(2) I_0C_1	(3) I_0C_2	(4) I_1C_0	(5) I_1C_1	(6) I_1C_2
Female household head	0.0459	0.104	0.266	-0.0793	0.0673	0.373**
Single household head	0.234	0.411***	0.247**	0.0164	0.223***	0.104
Level of education	0.0297	0.0335	0.0251	-0.044	0.00597	-0.00182
Average level of education	0.122	0.113**	0.0985	0.226***	0.174***	0.176***
Distance from the nearest market	-0.0151	-0.0409	0.0138	0.0289	0.0419*	0.0159
Crop area	0.201	0.19	0.354*	-0.235	0.0558	0.392**
Use of anti-erosion measures	0.06	0.0597	0.121*	-0.0829	-0.0772	0.0472
Use of intercropping	1.28	0.463	1.673**	-0.945	1.155*	1.224
Market shock	0.732*	0.0235	0.178	0.486	0.620***	0.381**
Labour	0.275	0.097	0.301*	-0.196	0.316**	0.26
Use of improved seeds	-0.0986	-0.0708	-0.152	0.296*	-0.265***	-0.108
Use of chemical fertilisers	-0.119	0.227	-0.153	-0.0146	-0.136	-0.176
Total Livestock in TLU	0.00237	-0.0104	-0.0389*	-0.0296	-0.00949	0.00659
Use of information services	-0.135	0.0796	0.262**	-0.181	0.12	0.0907
2010	-0.13	-0.282***	-0.13	0.000933	-0.117*	0.00274
2011	-0.364	-0.628***	-0.561*	-0.455	-0.0661	-0.446*
Constant	8.045***	8.831***	6.688***	10.23***	8.424***	8.301***
Observations	356	738	454	643	1223	895
R-squared	0.243	0.245	0.286	0.323	0.289	0.279

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4 :Results from the second step – OLS.

VARIABLES	(1) I0C0	(2) I0C1	(3) I0C2	(4) I1C0	(5) I1C1	(6) I1C2
Female household head	7.753*	-0.119	1.083	-1.813	3.301*	-1.893
	0.068	0.958	0.818	0.528	0.077	0.508
Single household head	0.973**	0.904***	0.664*	0.0942	0.295*	0.535**
	0.013	0.000	0.064	0.729	0.091	0.024
Level of education	-0.712	-0.062	0.440	1.194	-0.172	-0.453
	0.615	0.924	0.674	0.222	0.741	0.552
Average level of education	1.973	0.636	-0.124	-1.387	0.447	0.968
	0.335	0.484	0.937	0.321	0.544	0.379
Distance from the nearest market	0.0641	0.637**	0.196	-0.235	-0.252	0.875***
	0.890	0.015	0.646	0.507	0.226	0.002
Average distance from the nearest market	-0.0440	-0.628**	-0.183	0.244	0.260	-0.882***
	0.926	0.018	0.673	0.500	0.220	0.003
Crop area	-4.680	-17.60***	-8.9	-6.204*	6.897	-17.95***
	0.300	0.001	0.353	0.082	0.122	0.001
Use of anti-erosion measures	-7.230**	-11.01***	-6.781	-4.882**	2.407	-9.684***
	0.013	0.000	0.195	0.017	0.356	0.001
Use of intercropping	-16.79	-51.18***	-24.86	-15.51	19.13	-52.82***
	0.186	0.001	0.353	0.130	0.127	0.000
Average crop area	3.795*	8.760***	4.909	3.363**	-2.683	8.253***
	0.074	0.001	0.263	0.035	0.204	0.001
Market shock	10.13**	11.82***	6.481	2.493	-2.316	11.54***
	0.011	0.000	0.237	0.386	0.389	0.000
Labour	-0.480	-5.353***	-2.193	-1.256	2.972*	-5.961***
	0.772	0.004	0.508	0.350	0.051	0.001
Use of improved seeds	-1.147	1.780**	0.431	0.753	-1.642**	2.270**
	0.291	0.045	0.798	0.353	0.021	0.017
Use of chemical fertilisers	-2.842	-7.290***	-3.968	-2.671*	2.681	-7.063***
	0.129	0.001	0.293	0.064	0.137	0.001
Total Livestock in TLU	-0.317	-0.335	0.003	0.359	0.041	-0.498*
	0.554	0.157	0.993	0.346	0.833	0.071
Average Labour	-5.256*	-6.291***	-4.965	-3.790**	1.106	-4.549**
	0.063	0.003	0.152	0.049	0.538	0.041
Average of Total Livestock in TLU	0.262	0.381**	0.0708	-0.211	-0.0671	0.486**
	0.503	0.031	0.802	0.451	0.646	0.015
Use of information services	-1.193	-7.338***	-2.627	-0.922	3.713*	-8.822***
	0.666	0.004	0.556	0.681	0.070	0.000
2010	0.0599	-2.195**	-1.420	-1.655*	0.991	-1.893*
	0.966	0.031	0.407	0.088	0.219	0.072
2011	14.49	38.47***	23.41	19.08**	-11.98	36.10***
	0.189	0.001	0.250	0.017	0.221	0.002
Constant	52.98**	102.2***	66.60	50.77***	-18.56	95.08***
	0.035	0.000	0.155	0.005	0.418	0.000
Observations	360	743	456	613	1,209	896
R-squared	0.445	0.510	0.368	0.444	0.464	0.354
F	10.28	28.62	9.620	18.00	39.30	18.30

***p<0.01 , **p<0.05 , *p<0.1

Table 5: Sensitivity analysis on the second step – results.