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FARMERS' INVESTMENTS IN INNOVATIVE TECHNOLOGIES IN TIMES OF PRECIPITATION EXTREMES: A STATISTICAL ANALYSIS FOR RURAL TANZANIA

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Farmers' investments in innovative technologies in times of precipitation extremes: A statistical analysis for rural Tanzania

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Abstract

The paper shifts the focus from the exclusively devastating character of weather extremes on socio-economic outcomes to the possibility that positive side effects may occur. Positive side effects such as higher investments in improved agricultural technologies in years of weather extremes are crucial especially in rural developing areas to overcome the negative consequences of the shocks. For that purpose, out of all households that invest in improved seeds in rural Tanzania, we model the probability of high investments in improved seeds when a year of extreme high or low precipitation occurs. We apply a conditional dependence model for multivariate extreme values that so far does not find application in this context. Our appraisal of reflection on the current situation is based on recent data published by the World Bank's LSMS-ISA data between 2008 and 2013. Results suggest that extreme precipitation events and high investments in improved seeds with respect to overall investments are dependent events in rural Tanzania.

1. Introduction

The literature focuses often on the devastating character of weather extremes and their negative impacts on socio-economic outcomes. For instance, studies such as Lesk et al. (2016); Marmai et al. (2016) demonstrate that severe agricultural production losses are more likely in times of extreme weather events. But are there any positive side effects to the devastating effects of weather extremes? To answer this question, the paper analyzes how farmers in rural Tanzania invest in innovative agricultural technologies in years of extreme precipitation events. Precisely, we model the probability that farmers have higher investments than the majority of farmers in improved seeds when a year of extreme high or low precipitation occurs. The paper contributes to the discussion on weather extremes from a micro-economic perspective in rural developing areas in three ways. First, more investments in improved agricultural technologies are needed to overcome the negative effects of weather extremes. This paper is an attempt to explore the behaviour of pioneering farmers at the forefront of innovation investments in times of extreme weather events. Second, we apply a conditional dependence model for multivariate extreme values which was developed by Heffernan and Tawn (2004) and in addition account for temporal dependence (Keef et al., 2009). The paper introduces a modeling technique to the literature on weather extremes and development from a micro-economic perspective which is so far not known in the field. Third, the paper presents an understanding of the contemporary situation in rural Tanzania using survey and gauge estimates of precipitation data for georeferenced household locations from the World Bank LSMS-ISA for the period 2008 to 2013.

Nelson and Winter (1982) illustrate that both routines and stochastic events define the behavioural patterns of market actors. Thereby, they follow the idea of Simon (1955, 1959) by stating that market actors follow their routines as long as they are "satisficing", i.e. acceptable or satisfactory, to them. However, Nelson and Winter (1982) emphasize the importance of shocks in determining the market actors' decisions and decision outcomes. Stochastic events such as shocks and crisis conditions lead market actors to revise or radically change their routines because routines are not "satisficing" to them anymore. Because decision problems are too complex to understand comprehensively, market actors' rationality is bounded. They choose the alternative among all potential alternatives to solve the problem that is "satisficing" rather than optimal. The paper conveys this theory from the literature to the context of farmers in rural developing areas. We argue that farmers follow their routines but some farmers might show a different behaviour when a shock occurs and invest more in innovative technologies than the others because the outcomes of their routines are not "satisficing" to them anymore. If our argument is true, we should find a relationship between extreme events in weather and innovation investment.

In a recent review Haushofer and Fehr (2014) conclude that people in poverty, particularly in developing countries, are more likely to feel stressed as a result of shocks, meaning they are more likely to be risk-averse and investments in new technologies are therefore less likely. The papers under review typically study average population effects. We are interested only in effects seen in extreme contexts, i.e. the fraction of households above average investments in times of low and high precipitation extremes. In fact, on average the adoption of improved seeds and other agricultural innovations remains low in rural Tanzania. Most farmers retain seeds from the previous year's harvests. Relying on rain-fed and traditional farming practices (NBS, 2009, 2011a, 2014) they follow their routines to maintain their existence. Some farmers, however, might not follow routine behaviour patterns and have larger innovation investments than most farmers, when weather shocks occur. Indeed, most regions in Sub-Saharan Africa are exposed to pronounced wet and dry periods (Hellmuth et al., 2007). Extreme weather events are by nature unexpected and occur randomly causing heavy damages to the people's livelihoods. However, as farmers in Sub-Saharan Africa continue to be exposed to weather extremes (Kotir, 2011), they know that extreme weather events can occur. Studies such as Slegers (2008); Lema and Majule (2009) in Central Tanzania and Komba et al. (2012) in Eastern Tanzania find that farmers perceive the increased precipitation variability which negatively affects their production and so prospects for development. Similarly to Rogers (2003) we argue that the recognition of the devastating character of weather shocks as a need for an innovative solution to reduce the negative consequences can be the beginning of an innovation decision process. Recognizing the need stems from the frustration and dissatisfaction with the situation (Rogers, 2003), which may explain why some farmers take the risk to invest in new technologies in years of shock. For instance, Tang et al. (2016) find that farmers who experience frequent and severe droughts and whose production is therefore at greater risk adopt new irrigation technologies to reduce production risk in rural China.

The farmer's choice of traditional or innovative agricultural technologies depends on many factors, e.g. on the subjective evaluation of risk and vulnerability (Cooper et al., 2008), on the culture (Guerzoni and Jordan, 2016) but also on abilities and opportunities (Slegers, 2008). For instance, individuals evaluate information to reduce the uncertainty of the innovation's expected consequences before deciding to adopt an innovation. Therefore, the individual must be able to think hypothetically and plan ahead (Rogers, 2003). The ability to plan ahead may be especially important in times of shocks, which are situations of high uncertainty. Already the seminal work of Schumpeter (1912) suggests that even though shock situations are destructive, foresighted pioneering entrepreneurs emerge who look for radical new solutions and increase their innovation expenditure. Shocks may "bring to light inner powers and secrets" (Nietzsche, 1968a, p. 211). Individuals who face changes, challenges and extremes (Reinert and Reinert, 2015) can develop the strength to tackle them (Nietzsche, 1968b). Those actors who create can rescue themselves from suffering. Moreover, the motivation to create is the main driver for economic development (Sombart, 1930; Reinert and Reinert, 2015). Weather extremes remain and will remain highly destructive due to their insufficient predictability. Those who are aware of the risk of being exposed to extreme weather, can try to protect themselves from the damaging consequences of shocks (Taleb, 2010), which is essential to sustain livelihoods (Scoones, 1998).

Given that innovative expenditures remain mostly low in rural Tanzania, the paper investigates how far farmers spend more than the average of farmers in an innovative technology in years of weather shocks. Higher investments of farmers in innovative farming practices are not only important in ensuring agricultural productivity and livelihood protection but also development despite changing climate conditions. The focus is on improved seeds because they turn out be crucial in the adaption to critical climate conditions ensuring sufficient crop production and strengthening local markets, though their are not the only factor. The switch to crop varieties that are more resilient towards weather stress is one of the most frequently used adaptation strategies in Sub-Saharan Africa (Fisher et al., 2015). According to the FAO (2016) quality seeds of adapted and improved varieties are one of the cheapest yet fundamental technologies to raise agricultural productivity, secure food security and foster economic development. Improved seeds prove to be more tolerant to drought, flood and other weather extremes. Farmers who have higher investments in improved seeds are more likely to have access to a wider array of quality and improved seeds and take the opportunity to increase their adaptability towards weather shocks. A higher demand of improved seeds leads also to a growth of the seed market and local seed providers, which extends the access to more new varieties (FAO, 2016). An evaluation carried out by the WorldBank (2014) reveals that farmers in rural Tanzania are aware of the necessity and the profitability of investing in improved seeds instead of retaining them from previous harvests. Once the purchased improved seeds yield higher outcomes, farmers are more likely to continue to invest in the new technology and do not switch back to retain seeds from previous harvests.

The relevance of the paper to scholars and policy makers is twofold. First, to look at extreme weather events and the reactions of farmers is of particular interest because not only Tanzania but Sub-Saharan Africa as a whole experiences the occurrence of extreme weather events such as droughts and floods which are likely to occur more frequently and to be more severe in the future (Kotir, 2011). Second, so far studies examine the decision of adoption versus nonadoption of a new technology by farmers in rural Tanzania, see e.g. Nkonya et al. (1997); Isham (2002); Shiferaw et al. (2008). Already Feder et al. (1982) state that to only look at the initial yes/no decision of adoption instead of the extent or intensity of adoption may not give sufficient information to understand the behaviour of farmers. Thus, the focus on highly innovative farmers who invest much more than the average farmer in improved technologies provides an important additional perspective.

2. Data

To answer the research question we use the World Bank LSMS-ISA survey of Tanzania. Households were interviewed once in 2008/2009 and again in 2010/2011 and 2012/2013. We include observations of original households that remain in the same location or move in the analysis. If households split, we disregard the observations of the new household because in a few cases the new household reports the same plots as the original household when they stay close to the original household. In addition, we consider only households that cultivate their plots, i.e. do not rent out, give out or fallow their plots. Besides survey data, LSMS-ISA provides gauge estimates of precipitation data at a resolution of 0.1 decimal degrees for each survey year[1]. The precipitation data is uniquely identified by the georeferenced household location, i.e. the average of household GPS coordinates in the enumeration area, for further details see e.g. NBS (2011c).

Tanzania exhibits a tropical climate with regional differences because of its topography. Apart from the coastal area, the country consists mostly of highlands (McSweeney et al., 2012). Tanzania is characterized by two different precipitation patterns. On the coast the rain is unimodal from March to May. The climate on the coast is tropical, hot and humid. The mountains are semi-temperate and have bimodal rainfalls with one rainy period from November to December and another from February to May. The plateau regions are drier with seasonal variations of temperature and rainfall. Precipitation becomes more unpredictable and precipitation extremes increase. In fact, many areas of Tanzania encounter frequent and severe droughts. Droughts and floods are ranked among the top four hazards in Tanzania. Precipitation is assumed to further decrease in areas with unimodal precipitation and to further increase in areas with bimodal precipitation patterns (NAPA, 2007).

Besides precipitation, the variable of interest is improved seeds which is briefly discussed for Tanzania. Lyimo et al. (2014) state that improved seed varieties are conventionally varieties which have been ameliorated by plant breeding and perform better than unimproved varieties. Characteristics of improved seed may constitute higher productivity, tolerance to drought or other climate stresses, resistance to diseases among others (Sheahan and Barret, 2014). The data shows that around 81% (87%) of all purchased seeds (purchased improved maize seeds) are certified seeds, whereas around 9 % (6%) are quality declared seeds. No information is available for the rest of purchased seeds. The data does not provide more specific information on the type of improved seeds purchased. The supply side, however, provides some information. The private sector supplies most of the improved seed in Tanzania. These seeds are mostly hybrid seeds. The governmental agriculture seed agency produces and supplies the rest of the seeds which are open-pollinated seeds. Besides this, farmers produce quality declared seeds locally following the standards of the FAO (WorldBank, 2012).

Maize, paddy, beans, cassava, sweet potatoes and sorghum are the staple crops which dominate the agricultural sector in Tanzania with Maize being the major staple crop (NBS, 2011a). The survey data reveals that about 64 % of purchased improved seeds are maize seeds. Therefore, an analysis only for improved maize seeds accompanies the analysis for all purchased improved seeds. The paper looks at the amount spent on purchasing improved (maize) seeds in the long

[1] LSMS-ISA takes precipitation data from NOAA CPC, see `ftp://ftp.cpc.ncep.noaa.gov/fews/newalgo_est_dekad/`.

rainy season, e.g. from March to May 2008, and the corresponding 12-month total rainfall, e.g. from June 2007 to July 2008, for each plot of each household. Given that the long rainy season is at the end of the considered 12-month rainfall period, we use the data to work out whether the decision of farmers to spend extensively with regard to overall investments in an innovative technology is dependent on years of extremes in rainfall. We take observations from the long rainy season to get consistent data because all respondents of the survey report on their farming activities in the long rainy season whereas only some households report on their farming activities in the short rainy season (NBS, 2009, 2011a, 2014).

To get a comparable value of the expenditure of each household, we deflate the amount spent on improved seeds. In the case of maize, the survey provides price data of improved seeds for different villages, i.e. prices inside and outside the village, at planting time. We calculate median prices for each region separately for inside and outside village prices. Regional median prices serve as a proxy to compute the quantity of improved maize seeds purchased for each household by dividing the household-plot-specific amount spent on improved maize seeds by the price proxy. Even though more observations on outside village prices are available, the median and mean of both price proxies are similar. We use inside village prices to obtain the quantity purchased and conduct the analysis. However, we re-calculate the quantity using prices outside the village to evaluate the robustness of the analysis.

Prices for other seeds are not available but we use the National Tanzanian Panel Survey (NPS) price index or the FAO consumer price index for food (CPI) to deflate the expenditures of all improved seeds. Ideally, the index would cover the period from March to May 2008/2010/2012 which is the period of seed expenditure. The NPS price index is calculated for each survey year, i.e. October 2008/2010/2012 to September the following year. In contrast the CPI is available for each month. Thus, the CPI is more precise than the NPS price index in temporal aspects. Apart from this, there are several reasons why the NPS price index is the more accurate measure for the purpose of this paper. First, the NPS price index is measured based on food items which are purchased by at least 50 households in the country, whereas the CPI considers only urban market-prices of food items. Thus, the NPS price index reflects better the change in food prices for the rural population. Second, distinguishing between Zanzibar, rural and urban mainland Tanzania, the NPS price index adjusts not only for temporal but also for spatial price differences. Third, in each round the NPS price index uses updated weights for each good which display better the change in consumption compared to the CPI that is based on weights from 2007 (NBS, 2009).

Tanzania experiences a high inflation during the survey years due to a global food and fuel crisis (NBS, 2009). NPS and CPI change differently from 2008 to 2013. While the inflation rate

Table 1: *Overview of variables*

Variable	Description	Period
ValueSeed	Total expenditure of improved seeds	Mar-May 2008/10/12
VillagePrice	Price of improved maize seed per kg here in the village	At planting time
OutsideVillagePrice	Price of improved maize seed per kg outside the village	At planting time
NPS price index	National Tanzanian Panel Survey price index	Oct-Sept 2008/09(10/11, 12/13)
CPI	FAO consumer price index for food	Mar 2008/10/12
*Prec**	Gauge estimates of 12-month total rainfall at a resolution of 0.1 decimal degrees that are identified by the georeferenced household location[2]	Jul-Jun 2007/08(09/10, 11/12)
Constructed data		
*RealExpendSeed**	Real expenditure of improved seed standardized by administrative zone	Mar-May 2008/10/12
*QuantMaizeSeed**	Purchased quantity of improved maize seed standardized by administrative zone	Mar-May 2008/10/12

Expenditures and prices in T-Schilling, Precipitation measured in millimeters, *used in analysis

based on the NPS increases over time, for the CPI the inflation rate increases but then witnesses a sharp drop at the beginning of 2010 and rises again afterwards. The stark decline is mainly because of a higher food supply (ADB, 2011). The difference in change may be because the NPS price index does not include market prices. The NPS provides information on quantity purchased and amount spent from which measures for the household-specific value of each good are derived, see e.g. (NBS, 2009, p. 70) for details. Even though the CPI uses market prices of specific goods and for different brands of goods, and is more accurate in this respect than the NPS price index, it is questionable how far price changes of products in the cities affect the people in rural areas. We conduct the analysis using the NPS price index for rural Tanzania mainland and Zanzibar as the deflators. To check the robustness of the results, we re-do the analysis based on the CPI of March 2008/2010/2012 as the deflator.

Households, regions or administrative zones do not necessarily share the same characteristics. To deal with household-to-household, region-to-region, zone-to-zone variation, we can standardize observations on household, regional or zone level respectively. Standardization makes observations comparable across space and time and prevents extremes being missed when pooling data. However, standardization requires sufficient observations. The zone level is the most precise level with enough observations. Standardizing the household-plot-observations for each zone accounts for the fact that some zones have a higher potential for agricultural production and the use of innovative technologies and are better off than others in terms of economic conditions, infrastructure and wealth. In addition to this, the zones are confronted with different natural and climate conditions. To standardize the real expenditures of improved seed, the purchased quantity of improved maize seed and the total annual rainfall for each zone, we subtract the zone-specific mean from the observations of each variable separately and divide the difference by the zone-specific standard deviation. We class the administrative zones according to the classification of the Demographic and Health Survey (DHS) (NBS, 2011b). Table 2 (Annex) gives an overview of the zones and their composition of regions. We label the standardized variables as *RealExpendSeed*, *QuantMaizeSeed* and *Prec*, see Table 1 for a summary of all variables.

2.1. Descriptive Statistics

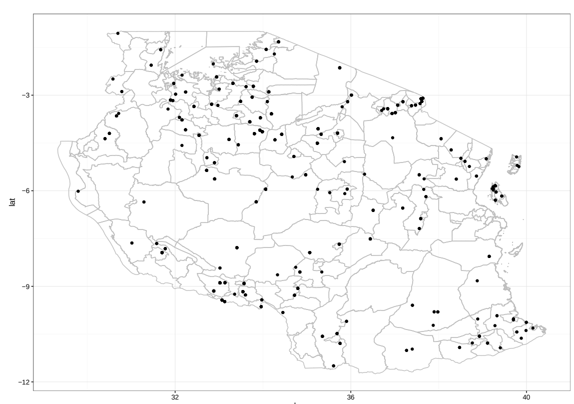


Figure 1: *Spatial distribution of purchased improved seeds in rural Tanzania in the long rainy seasons (March-May) 2008/10/12 grouped by households. The map of only purchased maize seeds shows a similiar distribution over rural Tanzania.*

Figure 1 shows the spatial distribution of purchased improved seeds in rural Tanzania in the long rainy seasons (March-May) 2008/10/12 grouped by households. The map only for purchased improved maize seeds looks similar. The purchase of improved (maize) seeds is quite scattered over Tanzania whereas they are mainly purchased in the Southern Highlands, the Northern, Western and Lake administrative zones. Most purchases are in the regions of Shinyanga and Mbeya which are located in the Western zone and Southern Highlands respectively, followed by Manyara in the Northern zone in the case of maize seeds. About 88 % of the observations are in the tropical-cool or tropical-warm subhumid climate zone. The other observations are mainly in the tropical-cool or tropical-warm semiarid zones. The two main regions are in the subhumid climate zone.

The behaviour of extreme values might be related to other criteria (Coles et al., 2001). First, in the case of the paper, higher investments in improved seeds might be because of a governmental subsidy programme (WorldBank, 2014) . Therefore, the programme is briefly discussed to evaluate how far it impacts the objective of the analysis of this paper. During the considered survey years the government provided three subsidy vouchers to farmers such that they only had to pay 50 % of the input costs for improved seeds and fertilizer, e.g. for 10 kg of improved maize seeds. The aim was to secure household and national food security by increasing maize and rice production, to promote the adoption of innovative technologies and to expand the input supply chains of improved seeds and fertilizer. The programme was nationwide but with a focus on high potential areas in terms of soils, lower weather risks etc. such as Southern Highlands (Mbeya and Iringa) and Northern Highlands (Kilimanjaro). To be selected, farmers had to have limited experience with improved agricultural technologies, cultivate less than 1 acre of land and be able to pay the other 50 % of the input costs among others. The programme was not meant to support farmers who experience extreme weather events but those that would make the best use out of the vouchers. The data shows that out of all households which purchased improved seeds in 2009 and 2011 only around 20 % of the households reported that they received a voucher. No data is available for 2007. The paper is interested in higher investments in improved seeds. Looking only at the households that invested more than the average in improved seeds, the percentage of households who got a voucher drops to around 13 %. For maize seeds, the percentage is around 15 % in both cases. Thus, the farming households who spent a lot are not necessarily affected by the subsidy voucher.

Second, the adoption of an agricultural innovation can be related to the plot size (Feder et al., 1982). In the paper expenditures could rise because of an increase in plot size. However, households with the highest values of *RealExpendSeed* or *QuantMaizeSeed* do not necessarily have the largest plots which is especially the case for *QuantMaizeSeed*. Most of the households that have among the highest *QuantMaizeSeed* have very small plots. The picture is mixed for *RealValueSeed*. Some of the households with the largest plots, also have the highest spending but there are also households with very small plots that have among the largest *RealValueSeed*.

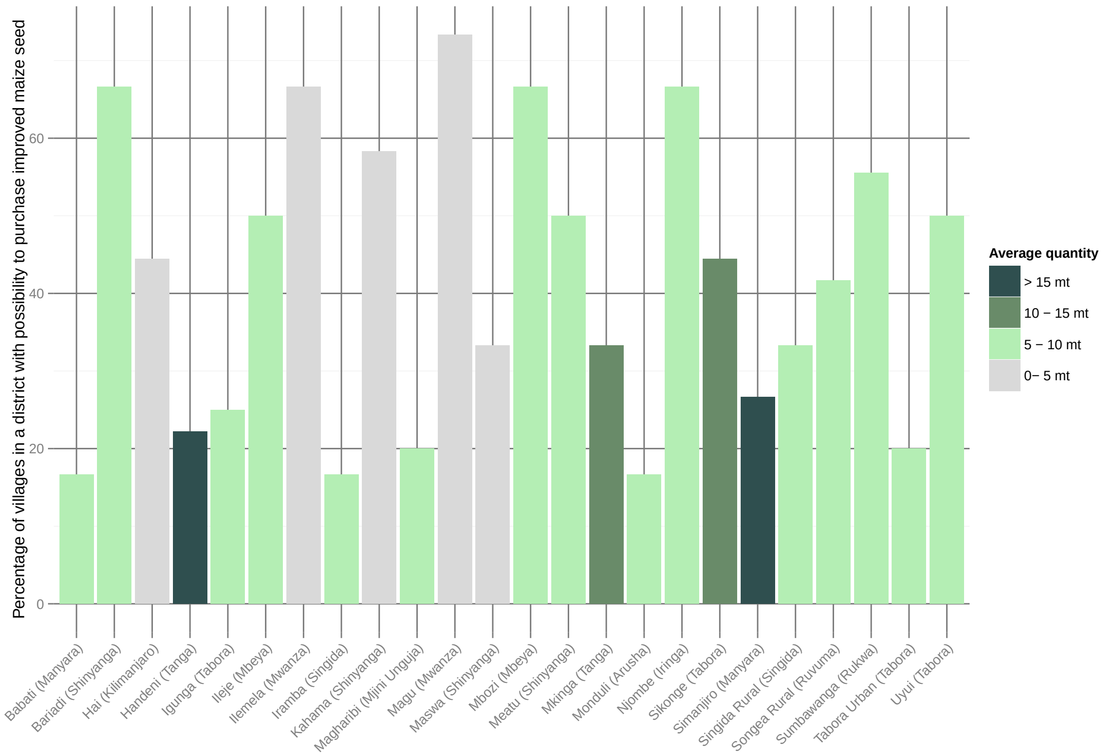
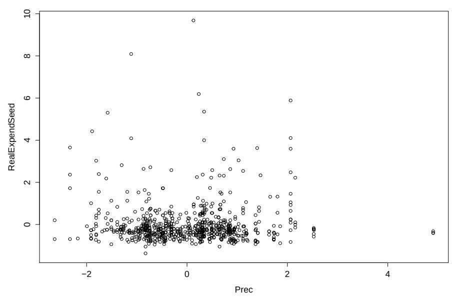
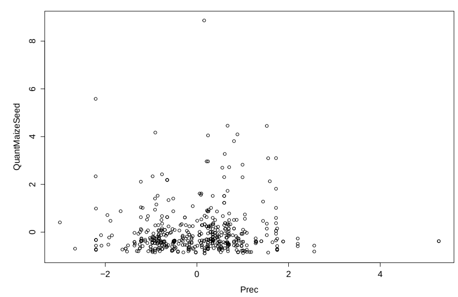


Figure 2: *In the districts where are the 50 households with the highest purchases located we plot the availability of improved maize seeds, i.e. the percentage of villages in the district with the possibility to purchase improved maize seeds. Besides the availability, the average of the purchased quantity in the district is displayed.*

Third, the accessibility and availability of improved agricultural technologies is crucial for the adoption (Komba et al., 2012). Following a report of the WorldBank (2012) the availability of improved seeds has increased from 2008 to 2012, whereby most of the improved seeds are improved maize seeds in Tanzania, e.g. about 85 % in 2010. While the availability of improved seeds has increased, the demand remains low (for instance in 2010/11 a percentage of 16.8 % was recorded). Only 3 % of the farmers state that availability is the reason why they do not use improved seeds. 69 % of the farmers declare costs as the main reason (WorldBank, 2012). The data provides information only on the availability of improved maize seeds but on the district level. Figure 2 plots the availability of improved maize seeds in districts with the 50 households where the highest purchases are made. Precisely, we show for each of these districts the percentages of villages in the district where it is possible to purchase improved maize seeds. Besides the availability, Figure 2 also displays the average quantity purchased in the district. Some districts, e.g. Monduli in the Arusha region and Njombe in the Iringa region, are in the same class of average quantity purchased but the availability is notably different. Moreover, Hadeni in the Tanga region and Simanjiro in the Manyara region are the districts with the highest quantity purchased on average but are not the districts with the highest availability. In contrast, in districts such as Magu in the Mwanza region and Kahama in the Shinyanga region the availability of improved seeds is comparatively high in the village but the quantity purchased remains low on average. Thus, a high availability of improved seeds in a district does not necessarily lead to high investments on average.



(a)



(b)

Figure 3: *Real expenditure of improved seeds using NPS price index as the deflator and precipitation (3a), purchased quantity of improved maize seeds based on inside village prices and precipitation (3b)*

Figure 3 illustrates that the purchase of improved seeds remains mainly low. Most observations of *RealExpendSeed* and *QuantMaizeSeed* are around zero for different values of *Prec* but there are some extreme visible values which are those of interest for the analysis, i.e. observations in the top right corner and in the top left corner of Figure 3. To define extreme positive (negative) events in *Prec*, we consider the values above (below) a threshold value. Thus, observations are located in the upper (lower) tail of the distribution (Coles et al., 2001). The distributions of the variables *RealExpendSeed* and *QuantMaizeSeed* are right-skewed. In theses cases the interest is only in observations in the the upper tail of the distribution. The focus of the analysis is to model the probability of high expenditure of improved seeds or higher purchased quantity of improved maize seed when extremely high or low precipitation occurs.

3. Method

We denote $X = (X_1, \dots, X_d)$ as a continuous vector variable with unknown distribution function $F(x)$. From a series of independent and identically distributed realizations we want to estimate the conditional distribution of $X_{-i}|X_i > x$ when x is large, where X_{-i} denotes the vector X excluding the i^{th} component. To obtain the conditional distribution requires marginal distribution functions F_{x_i} of X_i, with $i = 1, \ldots, d$. We stick to Heffernan and Tawn (2004) and adopt a semi-parametric model $\hat{F}_{x_i}$ for F_{x_i} which is based on the generalized Pareto distribution (GPD):

$$\hat{F}_{x_i} = \begin{cases} 1 - \{1 - \tilde{F}_{x_i}(u_{x_i})\}\{1 + \xi_i(x - u_{x_i})/\beta_i\}_+^{-1/\xi_i} & x > u_{x_i} \\ \tilde{F}_{x_i}(x) & x \leq u_{x_i} \end{cases}$$

where β_i and ξ_i are the scale and shape parameters of a GPD for the exceedances over the threshold u_{x_i} and $\tilde{F}_{x_i}$ is the empirical distribution of the component X_i. Because we focus on modeling the dependence structure of X we want standardized forms of the estimated marginal distributions $\hat{F}_{x_i}$ for each component. Keef et al. (2013) propose to transform to standardized Laplace distributions in order to avoid modeling difficulties with components that are negatively associated. We can then model the extremal dependence of components with Laplace marginal distributions, i.e. the distribution of $Y_{-i}|Y_i = y$ for y large. Let therefore normalizing functions $a_{|i}(x)$, $b_{|i}(x)$: $\mathbb{R} \rightarrow \mathbb{R}^{d-1}$ / $\forall$ fixed $z \in \mathbb{R}^{d-1}$. For any sequence of y_i values with $y_i \rightarrow \infty$, i.e. y_i becomes large, we obtain a limiting distribution $G_{|i}$:

$$lim_{y_i \rightarrow \infty}[Y_{-i} \leq a_{|i}(y_i) + b_{|i}(y_i)z_{|i}|Y_i = y_i] = G_{|i}(z_{|i}). \tag{1}$$

where G_i the i^{th} marginal distribution of $G_{|i}$, a non-degenerate distribution function with $lim_{z\rightarrow\infty}\{G_i(z)\}$=1 $\forall i$. We assume the limiting distribution $G_{|i}$ to hold $\forall$ $y_i > u_{Y_i}$, where u_{Y_i} is a sufficient high threshold. Alternatively, equation 1 can be expressed in terms of the standardized variable $Z_{|i}$:

$$lim_{y_i \rightarrow \infty}P(Z_{|i} \leq z_{|i}|Y_i = y_i) = G_{|i}(z_{|i}), \tag{2}$$

with $Z_{|i} = \frac{Y_{-i} - a_{|i}(y_i)}{b_{|i}(y_i)}$.

Given assumption 1, or correspondingly 2, conditionally on $Y_i > u_{Y_i}$, as $u_{Y_i} \rightarrow \infty$, the variables $Y_i - u_{Y_i}(> 0)$ and $Z_{|i}$ are independent in the limit and their limiting marginal distributions are exponential and $G_{|i}(z_{|i})$ respectively (Heffernan and Tawn, 2004).

Heffernan and Tawn (2004) suggest a semi-parametric model to estimate the normalizing functions $a_{|i}(y)$ and $b_{|i}(y)$ and the limit distribution $G_{|i}$ that describe the extremal dependence behaviour. The regression model

$$Y_{-i} = a_{|i}(y) + b_{|i}(y)Z_{|i} = a_{|i}y + y^{b_{|i}}Z_{|i} \tag{3}$$

provides parametrically estimates of $a_{|i}(y)$ and $b_{|i}(y)$, where $a_{|i}(y) = a_{|i}y$ and $b_{|i}(y) = y^{b_{|i}}$, with the restrictions $(a_{|i}, b_{|i}) \in [-1, 1]^{d-1} \times (-\infty, 1)^{d-1}$. We follow the modification of Keef et al.

(2013) and set further joint constraints on the parameters to ensure consistent inference in regard to the marginal distributions and parameter identification. If $0 < a_{j|i} \leq 1$ and $-1 \leq a_{j|i} < 0$, the variables (Y_i, Y_j) exhibit positive and negative dependence respectively, where $a_{j|i}$ is the element of $a_{|i}$ related to Y_j and large Y_i (Keef et al., 2013). The empirical distribution of replicates of the random variable $\hat{Z}_{|i}$ gives then a non-parametric estimate of $G_{|i}$.

3.1. Modeling multivariate temporal dependence

We extend the model of Heffernan and Tawn (2004) to account for multivariate temporal dependence following the procedure suggested by Keef et al. (2009). The conditional distribution is then:

$$\{Y_{j,t+r} : j \in \triangle, r \in A_j | Y_{i,t} = y_t\} \tag{4}$$

for $y_t > u_{Y_i}$, u_{Y_i} being a suitable high threshold and $A_j = \{-L_j, \ldots, L^j\}$ with $-L_j, L^j \geq 0$. The set A_j contains time lags with respect to the conditioning variable. The interest is then in the conditional distribution of each component of $Y_{-i,t}$ in the current and r lagged period to the conditioning variable $Y_{i,t}$. The vector $\{Y_{j,t+r} : j \in \triangle, r \in A_j\}$ is an extension of $Y_{-i,t}$ (Keef et al., 2009) and has Laplace marginal distributions.

The estimation of the dependence model follows the procedure which is described in Section 3 but for each time lag r the dependence model is estimated separately. Thus, we estimate the conditional distribution $Y_{j,t+r}|Y_{i,t}$ for each time lag $r \in \{-L_j, \ldots, L^j\}$ and $j \in \triangle$. The dependence parameters are then $a^{(r)}_{|i}$ and $b^{(r)}_{|i}$. To obtain the dependence parameter estimates we estimate the distribution of $Z^r_{|i}$. At time t, with $y_t > u_{Y_i}$, the (standardized) random variable $Z^r_{|i}$ is:

$$z_{j,t|i} = \frac{y_{j,t+r} - \hat{a}^{(r)}_{j|i}(y_t)}{\hat{b}^{(r)}_{j|i}(y_t)}.$$

We obtain then pseudo-samples from the conditional distribution for each time lag r separately, i.e. from the conditional distribution of equation (4) for each time lag. Based on the simulated observations we derive point estimates of the conditional probabilities for each time lag r (Keef et al., 2009):

$$P(Y_{j,t+r} > v_p | Y_{i,t} > v_p), \tag{5}$$

where v_p is the p^{th} quantile of $Y_{j,t+r}$ and $Y_{i,t}$ respectively, i.e. the threshold above which observations of $Y_{j,t+r}$ and $Y_{i,t}$ are taken to obtain the conditional probability. For the assessment of the uncertainty of the point estimates, we follow Heffernan and Tawn (2004) who propose a bootstrap procedure to get confidence intervals.

4. Empirical analysis

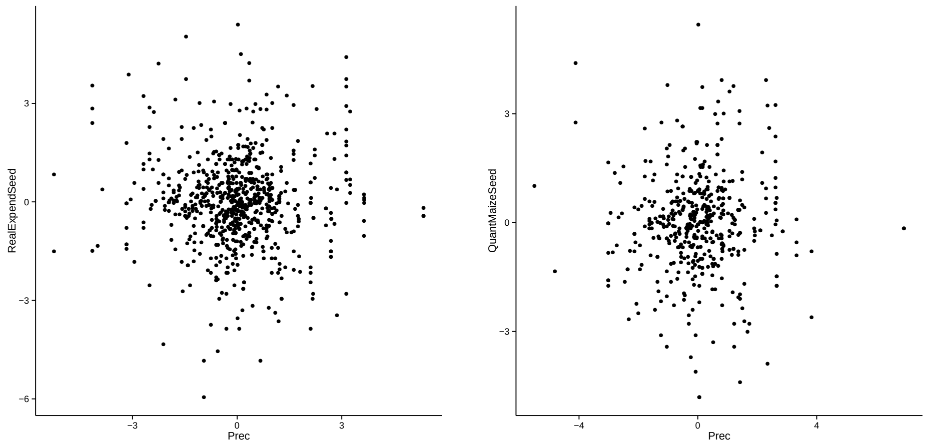
The model of Heffernan and Tawn (2004) explores the upper tail of the distribution which is suitable to extreme high precipitation, high real expenditure of improved seed and high quantity of purchased maize seeds, i.e. *Prec*, *RealExpendSeed* and *QuantMaizeSeed* respectively. To account for extreme low precipitation, we reflect the variable precipitation and call it *LowPrec*. In addition, we account for multivariate temporal dependence. Specifically, for *QuantMaizeSeed* (or *RealExpendSeed*) we consider a one-period lag to the conditioning variable *Prec* (or $LowPrec$). That is for instance the purchased quantity of improved maize seed from March to May (long rainy season) 2010 given extremes in total rainfall in the period from July 2008 to June 2009. We can only include *Prec* (or $LowPrec$) of 2008/09 and 2010/11 and the corresponding lags of *QuantMaizeSeed* (or *RealExpendSeed*) in the long rainy seasons of 2010 and 2012 due to limited data availability.

We define eight two-dimensional vectors $X = (X_1, X_2)$ with unknown distribution function $F(x)$, where X_1 is either *QuantMaizeSeed* or *RealExpendSeed* or a one-period lag of *QuantMaizeSeed* or *RealExpendSeed* and X_2 is either *Prec* or *LowPrec*. We model the extreme values in a bivariate context and analyze separately each two-dimensional vector such as for instance $X = (QuantMaizeSeed, Prec)$. For the sake of simplicity the procedure of fitting the dependence model is explained for the pair $X = (QuantMaizeSeed, Prec)$ but the results of the other pairs of variables are available on request.[3]

We model the GPD independently for each variable and transform X component-wise to have identical Laplace marginal distributions. To model the GPD requires a suitable threshold above which the GPD model is valid. Mean residual life plots serve to choose the threshold. The plots indicate that linearity is ensured for thresholds of the 60^{th} quantile and the 70^{th} quantile of *QuantMaizeSeed* and *Prec* respectively. Above these quantiles probability, quantile and return level plots demonstrate that the estimated distribution function is a reasonable estimate of the theoretical function. We then transform the variables in order to have standardized Laplace marginal distributions, see Figure 4 for *(RealExpend, Prec)* and *(QuantMaizeSeed, Prec)*.

The fitting of the marginal variables *QuantMaizeSeed* and *Prec* with identical Laplace distributions provides the basis to estimate the dependence structure of these variables. The focus is on

[3] The `R` packages `texmex` (Southworth et al., 2013), `evd` (Stephenson, 2015), `ggplot2` (Wickham, 2015) and `sp` (Pebesma et al., 2016) are used to conduct the analysis.



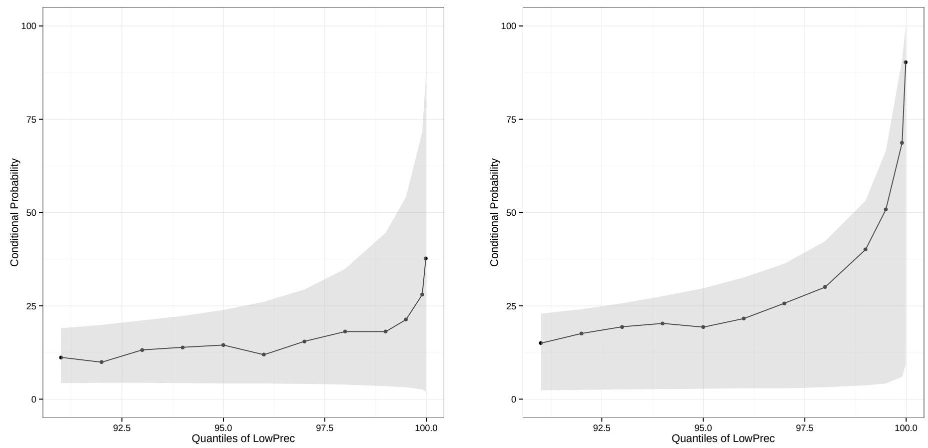
(a) **(b)**

Figure 4: *Real expenditure of improved seeds using NPS price index as the deflator and precipitation (4a), purchased quantity of improved maize seeds based inside village prices and precipitation (4b). All variables have Laplace marginal distributions.*

the conditional distribution of *QuantMaizeSeed* given extreme values of the variable *Prec* which requires a suitable high threshold u_{Y_i} over which the limiting distribution holds. To select u_{Y_i}, we assess the threshold stability of the estimated parameters $a_{|i}$ and $b_{|i}$ of the dependence model (3) using the 50 to 90 th quantiles of the conditioning variable *Prec* as possible thresholds. Estimates of the parameters change up to the 90 th quantile. We select, therefore, the 90th quantile as the suitable threshold. Parameter estimates are $\hat{a}_{j|i} = -0.0392$ and $\hat{b}_{j|i} = 0.8754$. The estimates can be sensitive to the initial value of the optimization procedure which is used for the estimation because ordering constraints are imposed on the values of the parameters (Southworth et al., 2013), see Section 3. Constrained dependence parameter estimates are in the maximum of the profile likelihood surface and thus, do not rely on the choice of the initial value. The estimate $\hat{a}_{j|i} = -0.0392$ indicates that the variables *QuantMaizeSeed* and *Prec* are negatively extremal dependent. We evaluate the uncertainty of the parameter estimates using the bootstrapping procedure explained by Heffernan and Tawn (2004).

We plot the standardized variable $Z_{|i}$ against the conditioning variable Y_i for values of Y_i over the threshold selected to fit model. Because the plot does not show any trend, we conclude that the model assumption of independence of $Z_{|i}$ and Y_i is not violated. In addition to this, the fitted quantiles of the conditional distribution and the observations on the original scale match, which demonstrates that the model is a good fit.

4.1. Extrapolation



(a) **(b)**

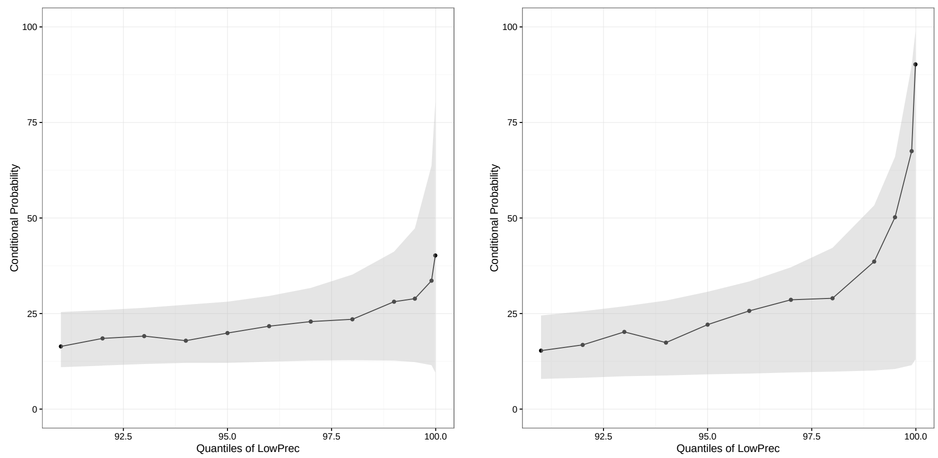
Figure 5: *Point estimates and 95 % confidence intervals of the probabilities of QuantMaizeSeed above its 90th quantile conditioned on LowPrec above its 91st to 99,99th quantile in the same period (a) and considering a one-period lag (b). To obtain QuantMaizeSeed the variable ValueSeed for maize is divided by the regional-specific median of the variable VillagePrice.*

Based on the estimates of the dependence model from the previous section and original data, we simulate 1000 observations from the joint distribution of *(QuantMaizeSeed, Prec)* conditional on $Prec > qu_{Prec}$, where qu_{Prec} is the 91st to 99,99th quantile of the conditioning variable *Prec*. The simulated observations are employed to calculate the conditional probabilities $P(QuantMaizeSeed > qu_{QuantMaizeSeed}|Prec > qu_{Prec})$, where $qu_{QuantMaizeSeed}$ is fixed to the 90th quantile of the variable *QuantMaizeSeed*. This is the probability of purchasing a high quantity of improved maize seed given rising extremes in high precipitation. Accordingly, we compute the probability of high *RealExpendSeed* given rising extremes in *Prec*, as well as the probabilities of *QuantMaizeSeed* and *RealExpendSeed* conditioned on increasing extremes in *LowPrec*. When accounting for multivariate temporal dependence, the conditional probability of interest is then the probability of having a high *QuantMaizeSeed* (or *RealExpendSeed*) one survey period after the occurrence of extremes in *Prec* (or *LowPrec*). We assess the uncertainty of the point estimates by using the 95 % confidence intervals of the conditional probabilities based on 10000 bootstrap samples[4].

[4]If we consider a one survey period lag of the pair *RealExpendSeed* and *Prec* (using NPS or CPI as the deflator) we create 5000 bootstrap samples because the system is computationally singular for higher numbers of bootstrap runs.

First, we display the probabilities to buy a high quantity of improved maize seeds conditioned on increasing extremes of low precipitation in the same period (Figure 5a) and considering a one-period lag (Figure 5b). To obtain the quantity of improved maize seeds we divide the variable *ValueSeed* for maize by the regional-specific median of *VillagePrice*. Both figures show the same behaviour of the conditional probabilities. The more extreme low precipitation becomes, the higher the probability of a high purchased quantity of improved maize seeds with respect to the overall purchased quantity. Looking at low precipitation extremes in the same period, conditional probabilities are around 15 % for lower thresholds of the conditioning variable and increase up to 39 % for higher thresholds but with a widening confidence interval. Accounting for a lag of *QuantMaizeSeed* with respect to the conditioning variable conditional probabilities are between 15 and 25 % for lower quantiles of low precipitation but rise sharply up to almost 90 % for higher quantiles with larger confidence intervals. Some farmers are very likely to purchase a higher quantity of improved maize seeds than the majority of farmers if precipitation becomes extremely low. The result is reasonable because low rainfall is perceived as the major climatic stress for maize cultivation in Tanzania (Lyimo et al., 2014) and maize yields are projected to further decrease countrywide because of droughts (NAPA, 2007). Thus, farmers have to react especially to low precipitation extremes. Besides this, the maize seeds available may be more resilient to droughts. An indication is the "Drought Tolerant Maize for Africa" project which has provided 160 drought-tolerant varieties between 2007 and 2013. Tanzania was one of the benefiting countries in Sub-Saharan Africa (Fisher et al., 2015). The result is even more pronounced if we consider a one-period lag between the low precipitation extreme and the decision to invest extensively with regard to overall investments in improved maize seeds which may indicate that farmers need time to adjust their routines after they experienced a weather shock. To check the robustness of the results, we compute the purchased quantity of improved maize seeds using price data outside the village and re-calculate conditional probabilities, see Figure 9 (Annex). Conditional probability curves are shaped alike for quantities based on inside and outside village prices. Only for high thresholds of extremes in low precipitation in the same period confidence interval bounds are zero providing no evidence of an association between extreme low precipitation and a high purchased quantity of improved maize seeds in the same period.

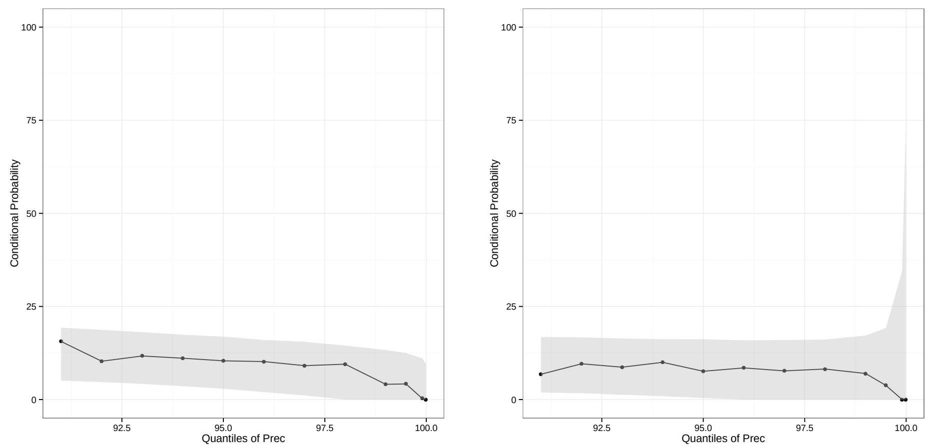
Second, we show the probabilities to have high real expenditures with respect to overall real expenditures of improved seeds given rising extremes in low precipitation in the same period (Figure 6a) and considering a one-period lag (Figure 6b). Real expenditures of improved seeds are calculated by deflating *ValueSeed* by the NPS price index. In both figures conditional probabilities evolve in a similar manner and increase steadily with higher thresholds of low precipitation



(a) **(b)**

Figure 6: *Point estimates and 95 % confidence intervals of the probabilities of RealExpendSeed above its 90th quantile conditioned on LowPrec above its 91st to 99,99th quantile in the same period (a) and considering a one-period lag (b). The variable RealExpendSeed is obtained using the NPS price index as the deflator.*

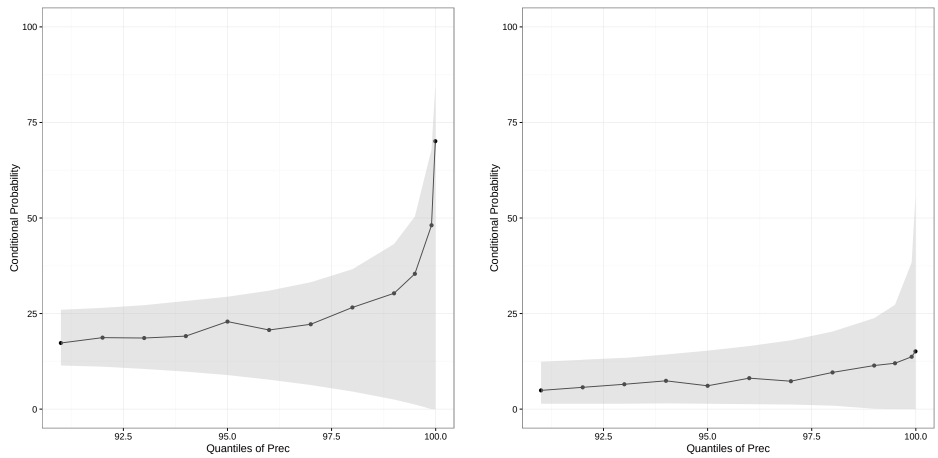
extremes. Conditional probabilities stay around 20 to 25 % and increase up to 38 % with enlarging confidence intervals given high extremes of *LowPrec* in the same period. If we consider a lag of *RealExpendSeed* with respect to *LowPrec* conditional probabilities vary around 15 to 25 % for lower quantiles of the conditioning variable and exhibit a remarkable increase of up to 91 % for higher quantiles of the conditioning variable but with wider confidence intervals. The results are in line with the findings shown in Figure 5. Some farmers have higher investments in an innovative technology if a low precipitation shock occurs, which becomes even more evident if the low precipitation shock is in the recent past. There are farmers who revise their routines after they have experienced a weather shock but they need time. We presume that they do so because they are no longer satisfied with their farm output. Extreme low precipitation destroys the farmers' harvest but some of the them decide to invest largely in innovative technologies to counterbalance the negative effects of low precipitation on their harvest. We examine the robustness of the results shown in Figure 6 by deflating the variable *RealExpendSeed* by the CPI. Figure 10 (Annex) illustrates that results are robust. Conditional probabilities of real expenditures of improved seeds based on the CPI or the NPS price index change in a similar manner. However, conditional probabilities are higher if the CPI is used instead of the NPS price index as the deflator. An explanation may be that the inflation rate based on the CPI decreases drastically in 2010 while it keeps on rising based on the NPS price index. If inflation decreases, prices are lower and the cost of living depending on these prices are lower, which might explain why the probability of having high expenditures of improved seeds are higher using the CPI as the deflator.



(a) **(b)**

Figure 7: *Point estimates and 95 % confidence intervals of the probabilities of QuantMaizeSeed above its 90^{th} quantile conditioned on Prec above its 91^{st} to $99{,}99^{th}$ quantile in the same period (a) and considering a one-period lag (b). The variable QuantMaizeSeed is based on price data inside the village.*

Third, Figure 7 plots the conditional probabilities of a high purchased quantity of improved maize seeds based on inside village prices and conditioned on high precipitation extremes. The more extreme high precipitation becomes, the more conditional probabilities decrease towards zero. In fact, lower confidence interval bounds and conditional probabilities are zero for thresholds of the conditioning variable above the 97.5^{th} quantile in the same period (Figure 7a) and above the 95^{th} quantile considering a one-period lag (Figure 7b). Above these quantiles we cannot assume an association of extreme high precipitation and a high purchased quantity. For thresholds below these quantiles conditional probabilities are around 10 %. The robustness check using quantities calculated with outside village prices supports these findings. Figure 11 (Annex) illustrates that conditional probabilities evolve in a similar manner. Contrary to times of low precipitation extremes, see Figure 5, the results indicate that farmers are less likely to have higher investments in improved maize seeds, the more extreme high precipitation becomes and refrain from high investments when high precipitation becomes very extreme. Depending on the type of precipitation extreme the conditional probabilities evolve considerably differently for increasing extremes of precipitation.



(a) **(b)**

Figure 8: *Point estimates and 95 % confidence intervals of the probabilities of RealExpendSeed above its 90th quantile conditioned on Prec above its 91st to 99,99th quantile in the same period (a) and considering a one-period lag (b). The variable RealExpendSeed is obtained using the NPS price index as the deflator.*

Fourth, we report the probabilities of *RealExpendSeed* conditioned on increasing extremes of *Prec* in Figure 8. Real expenditures of improved seeds are calculated by deflating *ValueSeed* by the NPS price index. Conditioned on high precipitation in the same period (Figure 8a) conditional probabilities increase steadily with higher quantiles of the conditioning variable. The probabilities vary around 20 to 35 % up to the 99,5th quantile and increase up to 49 % above this quantile but with wider confidence intervals. For thresholds above the 99,9th quantile of high precipitation lower confidence interval bounds are zero which provides no evidence of an association between extreme high precipitation and higher real expenditures of improved seeds. On the other hand, the probabilities are considerably lower if we take a one-period lag of *RealExpendSeed* to the conditioning variable into account, see Figure 8b. Conditional probabilities remain around 10 %. Above the 99,9 th quantile we do not find *RealExpendSeed* and *Prec* to be associated. In contrast to investments only in improved maize seed, higher investments in all kinds of improved seeds are more likely to occur with high precipitation extremes in the same period. For comparison see Figures 7a and 8a. However, if we look at high precipitation extremes in the previous period (Figure 8b), higher investments in all kind of improved seeds are less likely. The probability curve is then similar to the one for investments only in improved maize seeds, see Figure 7b. The robustness check in Figure 12 (Annex) analyzes *RealExpendSeed* deflated by the CPI. Conditional probability curves evolve in a similar manner with respect to Figure 8 and results are robust. As in the case of low precipitation, the probabilities based on the CPI are slightly higher than those based on the NPS price index.

5. Conclusion

Weather shocks lead drastically to the destruction of livelihoods and prospects of development in rural developing areas. However, in this paper we show that in times of precipitation extremes there are foresighted pioneering farmers who have much higher investments than the majority of farmers in an innovative technology. They invest more in a fundamental technology such as improved seeds to alleviate the negative consequences of extreme weather conditions, ensure their food security and improve their living conditions.

We provide systematic evidence of an association of years of extreme precipitation and high investments with respect to overall investments in improved seeds in rural Tanzania. More specifically, the results show the following: first, given that innovation investments remain largely low in rural Tanzania, a high investment in improved seeds is likely to be observed after considerably high or low precipitation extremes. Second, particularly with extreme events of very low precipitation, the probability that farmers invest more than others in improved seed technologies rises tremendously. The more extreme the low precipitation shock is, the more likely it is for high investments to be made. The finding is reasonable because reports such as ADB (2011) emphasize the severity and frequency of droughts in Tanzania. We assume that the destructive character of the frequent shock induces some farmers to change their behaviour and make larger investments in innovation. Third, we come to the conclusion that changing behaviour and adjusting routines takes time because larger investments are even more likely when we look at low precipitation extremes in the previous year.

The paper demonstrates that farmers can have the capacity and understanding in particularly harmful moments to make high investments with respect to overall investments in innovative technologies. Policy makers should strengthen the position and attempts of farmers by improving the access to innovative technologies and supporting the creation of innovative practices. Considering that changing climate is projected to create more frequent and severe precipitation anomalies, the attempts of pioneering farmers at the forefront of innovative investments have to be extended to the wider community. Therefore, we need to understand the determinants that explain the behaviour of farmers who decide to invest on a larger scale than the majority of farmers in innovative practices. To explain that is beyond the scope of this paper and is left for future research.

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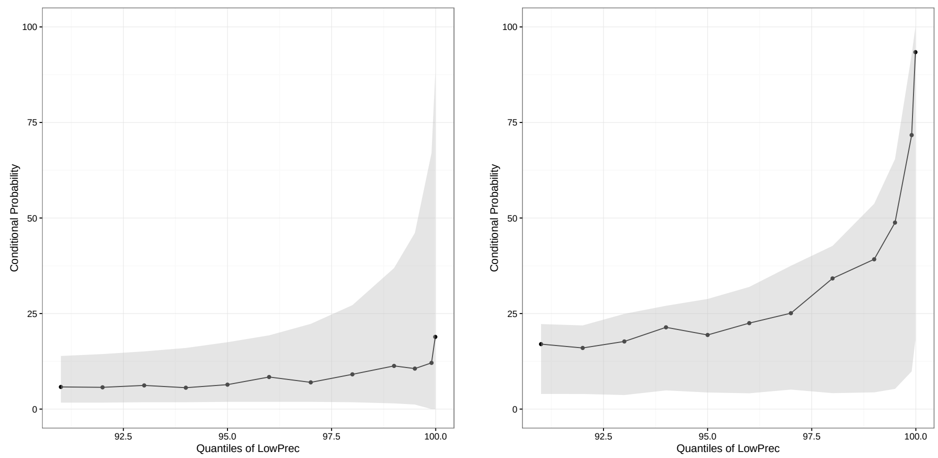
A. Annex

Table 2: *Overview of administrative zones*

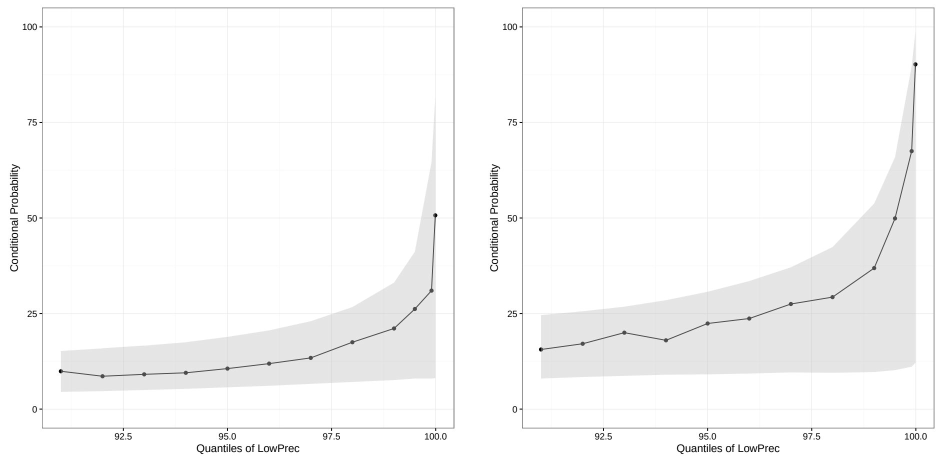
Administrative Zone	Regions
Western	Tabora, Shinyanga, Kigoma
Northern	Kilimanjaro, Tanga, Arusha, Manyara
Central	Dodoma, Singida
Southern Highlands	Mbeya, Iringa, Rukwa
Lake	Kagera, Mwanza, Mara
Eastern	Pwani, Morogoro
Southern	Lindi, Mtwara, Ruvuma
Zanzibar	Unguja North, Unguja South, Town West, Pemba North, Pemba South

Administrative zones are taken from DHS (NBS, 2011b). In the case of maize seeds, the zones Eastern and Zanzibar are combined to have enough observations to standardize. This is reasonable because both administrative zones are in the same agro-ecological zone and observations of quantity purchased of improved maize seeds and precipitation do not show large differences between both regions.



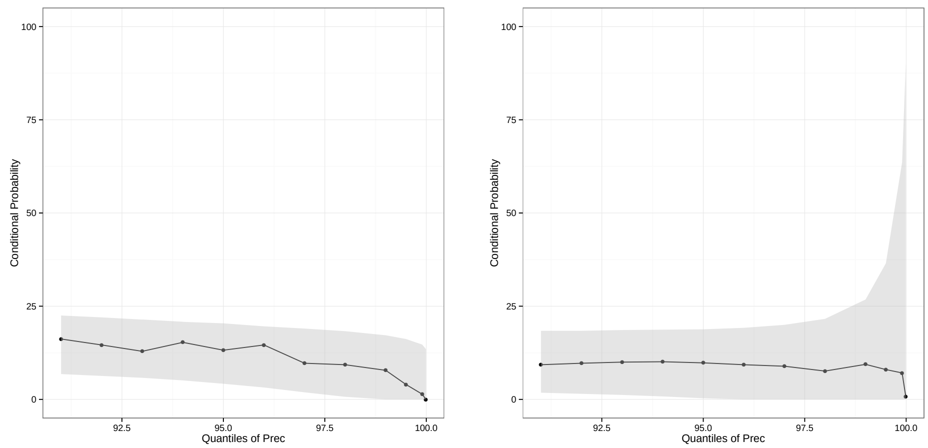
(a) **(b)**

Figure 9: *Point estimates and 95 % confidence intervals of the probabilities of QuantMaizeSeed above its 90th quantile conditioned on LowPrec above its 91st to 99,99th quantile in the same period (a) and considering a one-period lag (b). To obtain QuantMaizeSeed, the variable ValueSeed for maize is divided by the regional-specific median of OutsideVillagePrice. For high thresholds of LowPrec in the same period lower confidence interval bounds are zero showing no evidence of an association between extreme precipitation and a high purchased quantity of improved maize seeds. For lower thresholds of the conditioning variables conditional probabilities vary between 5 % and 15 %. If we consider a one-period lag to the conditioning variable conditional probabilities increase steadily up to 93 % but with wide confidence intervals.*



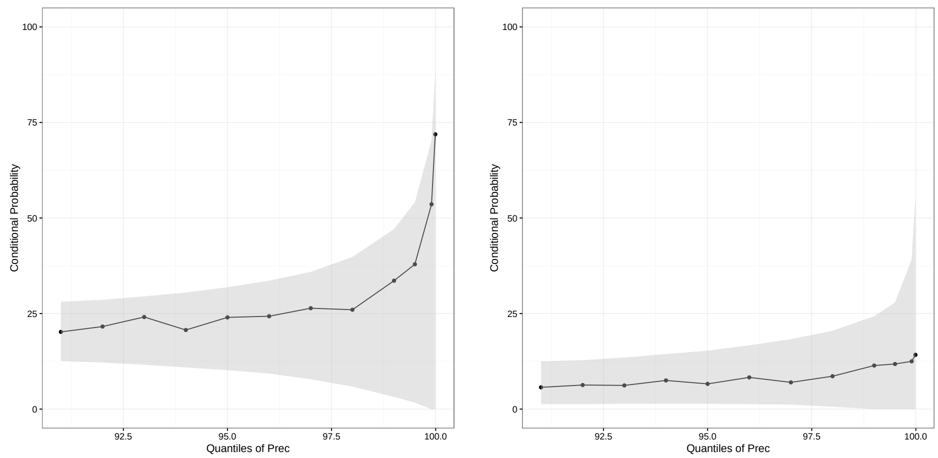
(a) **(b)**

Figure 10: *Point estimates and 95 % confidence intervals of the probabilities of RealExpendSeed above its 90th quantile conditioned on LowPrec above its 91st to 99,99th quantile in the same period (a) and considering a one-period lag (b). RealExpendSeed are calculated by deflating ValueSeed by the CPI, i.e. the FAO consumer price index for food items. In both cases conditional probabilities are below 25 % for lower thresholds of the conditioning variable but increase with widening confidence intervals up to 50 % and 90 % for higher thresholds of LowPrec in the same period and considering a one-period lag respectively.*



(a) **(b)**

Figure 11: *Point estimates and 95 % confidence intervals of the probabilities of QuantMaizeSeed above its 90^{th} quantile conditioned on Prec above its 91^{st} to $99{,}99^{th}$ quantile in the same period (a) and considering a one-period lag (b). The variable QuantMaizeSeed is based on price data outside the village. The conditional probabilities are below 15 % up to the 98^{th} quantile of the conditioning variable in the same period and up to the 96^{th} quantile of the conditioning variable considering a one-period lag. Above these quantiles confidence interval bounds are zero providing no evidence of an association between extreme high precipitation and a high purchased quantity of improved maize seeds.*



(a) **(b)**

Figure 12: *Point estimates and 95 % confidence intervals of the probabilities of RealExpendSeed above its 90^{th} quantile conditioned on Prec above its 91^{st} to $99{,}99^{th}$ quantile in the same period (a) and considering a one-period lag (b). RealExpendSeed are calculated by deflating ValueSeed by the CPI, i.e. the FAO consumer price index for food items. The probabilities are between 20 and 40 % for lower quantiles of Prec in the same period and reach 56 % for the $99{,}99^{th}$ quantile. If we take the $99{,}99^{th}$ quantile of the conditioning variable, the lower confidence interval bound is zero. Considering a one-period lag conditional probabilities remain below 12 % up to the 98^{th} quantile. Above this quantile the lower confidence interval bound is zero, i.e. RealExpendSeed and Prec seem not to be associated.*