Rainfall Variability and Farm Households' Food Insecurity in Burkina Faso: The Nonfarm Enterprises as Coping Strategy

M.R. Tankari;

IFPRI, , Senegal

Corresponding author email: mahamadoutankari@yahoo.fr

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This study explores the impact of rainfall variability on farm households' food insecurity and how participation in nonfarm enterprises may contribute to mitigate such effect. The ordinary least square and copula switching regressions are performed on the data of the 2014 Multi-sectoral Continuous Survey (EMC-BF). It appears that both short-term and long-term rainfall variability are important determinants of farm households' food insecurity level in Burkina Faso. An increase in the rainfall average significantly reduce the level of farm households' food insecurity. However, the effect of a short-term decrease in rainfall is only significant among the rural farm households indicating these latter dependences to rainfall for their livelihood compared to urban farm households. Furthermore, the study reveals nonfarm enterprises reduce farm households' food insecurity. Therefore, operating a nonfarm enterprise may be a strategy to cope with rainfall variability effects among farm households in Burkina Faso.

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1 INTRODUCTION

Like other Sahelian countries, Burkina Faso's agriculture is mainly rainfed, making it highly dependent upon rainfall amounts and distribution. Burkina Faso still faces the ongoing challenge of ensuring food demand of its population. Indeed, domestic food production is far lower than the national demand. Therefore, to meet the food needs of population,

massive quantities of food are imported to make up the deficit. However, the household food situation is far from satisfactory. Food insecurity affects, in general, more than one household in three and it is more widespread in the rural than in urban areas. In addition, malnutrition is endemic (SMART, 2014) and is a major concern for public health in Burkina Faso being the cause of over 54% of deaths of under 5 years children (PNDS, 2011).

The Burkinabe economy depends strongly on its agricultural sector that occupies more than 80 percent of the workforce and contributes to more than 40 percent of GDP. It is the main source of food and income with so-called traditional cereals (sorghum, millet, maize and to a lesser extent fonio) consumed by 90% of the population. However, this agriculture is handicapped by its low productivity and its exposition to a number of risks. Among the latter, the adverse climatic conditions are often considered to be the most severe. Over the last few decades, the Sahel region has indeed been hit by rising temperatures, reduction in average rainfall and higher climate variability reflected, in particular, in more frequent major droughts (Druyan, 2011; IPCC, 2013). Within this context, the living conditions of the fast-growing population are particularly precarious, especially for rural households. However, the diversification of income sources by households may be a good strategy to mitigate the effect of climate variability on food security. For Haggblade et al. (2009), diversification is a strategy that households put in place to deal with certain particularly climatic hazards in agricultural households.

Despite there are unfortunately very few studies focusing exclusively on Burkina Faso, or if they do, they only take into account a limited number of crops most studies concerning the Sahel or west Africa predict a downturn of yields due to climate change particularly among Millet, sorghum, maize, and rice which are the principal crops grown for domestic consumption. For instance, Sultan et al. (2013) forecast reductions in millet and sorghum yields in the Sahel of up to 41% for a 6° temperature increase and a 20% drop in rainfall. Thomas and Rosegrant (2015) calculate changes in Western African yields of −5.8% to +0.3% for groundnuts, −9.5% to

−15.9% for sorghum and +0.5 to −4.4% for rice. Therefore, noting the apparent consensus in agro-climate literature that Burkina future weather conditions could deteriorate and be characterized by both a drier climate and a higher frequency of severe droughts (Sylla et al., 2010; Mohino et al., 2011; Roudier et al., 2011; IPCC, 2013; Sultan 2013; Niang, 2014), the present study seeks to assess the effects of rainfall variability on farm households' food security and investigate how nonfarm enterprises may contribute to mitigate such effects.

However, this study must deal with measuring and assigning a degree of food insecurity to households which appeared to be a non-trivial task. For that, we rely on the set of manifest indicators of food insecurity and transforming them into an index of food insecurity. There are various approaches to estimate such a food insecurity index by using a set of food deprivation indicators. However, this paper uses the approach based the item response theory (IRT) model, which allows generating a food insecurity index (Faye et al., 2011; Nord, 2014). This later is regressed on rainfall variability indicators and other socioeconomic households' variables. The exploration of how nonfarm enterprises constitute a mitigation strategy is conducted by means of a copula switching regression model.

This study has many distinguishing features which bring contributions to the current literature on climate change and food security. First, by analyzing the effect of rainfall variability on food security, it provides evidence on how droughts which will become frequent with climate change will affect food security among farm households in Burkina. This is very important as while there is a great deal of uncertainty over the exact magnitudes of the global changes in temperature and precipitation, it is widely accepted that significant deviations of the variability of climate from its historical patterns are likely to occur (IPCC, 2014). In addition, the study highlights the role of nonfarm enterprises on mitigating the impact of climate variability which may be a strategy of resilience.

The study continues as follows: after this introduction (section 1), a literature review and theoretical framework will be presented (section 2). Next, the methodology will be detailed (section 3). After that, the data and a descriptive analysis of the data will be conducted (section 4). Subsequently, the results will be discussed (section 5). Finally, the study ends with a conclusion on the main findings (section 6).

2 LITTERATURE REVIEW AND THEORETICAL FRAMEWORK

Food security is generally defined as when all people at all times have physical and economic access to sufficient, safe, and nutritious food for a healthy and active life. Household food security is, therefore, a combination of availability of safe food and assured possibility for households to meet their dietary needs and food preferences in socially acceptable ways. Therefore, food security is influenced by many factors such as rising demand for food, higher input prices, soil degradation and increasing competition for land and water from non-food uses (Hertel, 2011).

According to Schmidhuber and Tubiello, (2007) climate change will affect all pillars of food security (access, availability, utilization and stability). The impact of climate change on food security is shaped by its drivers, which include biophysical systems, their cycles and management, socio-economic variables, and demographic, cultural and political variables. These drivers impact the four components of food security. Reduced rainfall, if not managed by adaptation strategies, will lead to low crop yields and reduce food availability. This, in turn, will cause increases in food prices, affecting its accessibility by decreasing of food affordability (Shisanya and Mafongoya, 2016). Regarding utilization, people might not be able to have a diversity of food nutrients as they will be rationing their consumption to prioritize calorie -rich but nutrient poor foods (Bloem et al., 2010).

Climate change, thus, without adaptation will deliver substantial negative effects, especially in the agricultural sector and therefore induces further detrimental effects on food security IPCC (2014). Adaptation involves lowering risks and vulnerability, searching opportunities, and building nations, regions, cities, and individuals capacities to cope with climate change (Tompkins et al., 2010). The main drivers of adaptation are crop diversification, changing crop varieties combined with enhanced water and soil conservation strategies. Nevertheless, smallholder and subsistence farmers are likely to suffer complex, localized impacts as they have limited adaptive capacity and are therefore likely to experience negative effects of climate change on yields (Aggarwal and Singh 2010).

A review of existing literature highlights that adaptation in agriculture significantly increases farm net revenues (Di Falco, 2014). However, Non-farm enterprises are an essential complement to adaptation strategies: in case of food shortages, they contribute to better resilience. Most studies agree that in most rural areas of developing countries, off farm earnings supplement

family income and are important to both low and high-income households (Barrett et al., 2005; Haggblade et al., 2007). For Mehta (2002), the main motivation for the creation of non-agricultural activities by households is linked to the fact that the development of the agricultural sector is hampered by the degradation of natural resources or the growth of urbanization. As a result, the expansion of non-agricultural potential activities, particularly those based on local resources, has been an important alternative option for solving underemployment and poverty problems and preserving household livelihoods.

Yet, for Davis (2006) rural nonfarm livelihoods in transition countries should be seen as part of a growth strategy rather than a temporary "shelter" or household survival. For example, a considerable number of rural households in sub-Saharan Africa do not limit labor allocation to agriculture, but also operate and work in nonfarm enterprises (Reardon et al., 2006). For the landless and the very poor, often employed as farm laborers, sustainable income gains at the household level are generally associated with additional wages earned from non-farm employment and self-employment opportunities. Particularly in rural areas, there is emerging evidence that diversification and secondary town development leads to faster poverty reduction and more inclusive growth patterns than metropolitization (Christiansen, 2013; Christiaensen, et al., 2013; Dorosh et Thurlow, 2013). For example, in Kwara state in Nigeria is was found that off-farm income improves household's level of calorie supply, dietary quality and micronutrient supply (Babatunde and Qaim 2010) while in Bangladesh, the impacts of off-farm income appeared to be uniformly positive across the food consumption expenditure distribution (Mishra et al., 2015).

Therefore, first we hypothesize that shifts in amount of rainfall may impinge food security among farm households. The impact pathway is agricultural production reduction under climate change as agriculture in Burkina Faso is predominately rainfed with limited irrigation coverage. Second, engaging in nonfarm enterprise may constitute a strategy of resilience to rainfall variability by decreasing farm households' food insecurity level.

3 METHODOLOGY

3.1 Measuring food security and Ordinary Least Square

The first step of the analysis is to estimate the food insecurity index. By definition, the food insecurity level of household is a latent trait. As mentioned above, it is inferred based on a set of observable indicators of deprivation. The strategy consists of summarizing the information from the different indicators into a single synthetic index. To infer a single indicator from the set of observed indicators of deprivation, the Items Responses Theory (IRT) approach is applied. IRT model describe a parametric relationship between item responses (the indicators) and the latent summarizing variable through a link function. Depending on the number of parameters used to model the responses to each item, the IRT models are one parameter IRT, two-parameter IRT, or three- or four-parameter IRT. All models posit the assumption that a single underlying latent trait is the primary causal determinant of the observed responses to each test's item. However, they differ with respect to the way in which the latent trait is presumed to cause the item response. In addition, two types of IRT models exist following the link function: the normal IRT model based on the cumulative normal probability distribution function, and the logistic model based on the logistic function. In this paper, we use the one parameter IRT models with a logistic link to estimate the fam households' food insecurity index in Burkina Faso.

Let y_{ij}^* be measuring the latent deprivation of individual $j(= 1, \dots, m)$ for the item i $(= 1, \dots, n)$; the general form of the one-parameter IRT model is as follows:

$$y_{ij}^* = \beta_i + \theta_j^* + \varepsilon_{ij} \qquad (1)$$

$$y_{ij} = \begin{cases} 1 \; if \; y_{ij}^* > 0 \\ 0 \; otherwise \end{cases} \qquad (2)$$

where θ_j^* is the latent score of deprivation for individual j, β_i is the difficulty of indicator or item i, and ε_{ij} is an error term. The parameter β_i represents the item i difficulty parameter (or the parameter of severity of item i). The parameter θ_j^* is the individual score of deprivation. According to the one-parameter IRT model, the probability of being deprived decreases with the difficulty parameter of the item, given θ_j^*, and increases with the individual deprivation score, given the difficulty parameter β_i. In addition, the probability of being deprived equals ½ when the individual deprivation score equals the item difficulty parameter. In what follows, we treat θ_j^* as random individual effects to use the standard maximum likelihood to estimate both the parameter β_i and the deprivation score θ_j^*. we also consider the error term ε_{ij} as logistically

distributed with zero-mean and fixed variance. Note that the one-parameter IRT model is known as the Rasch model if θ_j^* are treated as parameters instead of random variables and the error term has a logistic distribution. The Rasch model has a particular property that distinguishes it from other IRT models. In the Rasch model, the score computed as the unweighted sum of the responses to the items constitutes a sufficient statistic of the latent trait. In other words, the simple aggregation of the indicators respecting the Rasch model assumptions gives the food insecurity index.

To analyze how farm households' food security level is affected by rainfall variability, a reduced form of household welfare model is estimated econometrically. The food insecurity index was expressed as function of household characteristics and variables that indicate rainfall variability. The estimation is the ordinary least square regression in order to highlight the average effects of rainfall variability. The reduced-form equation estimated for the analysis is presented as follow:

$$\hat{\theta}_j = \beta_1\left(R_{pt} - \bar{R}_p\right) + \beta_2\bar{R}_p + \beta_3 X_j + \varepsilon_j \quad (1)$$

Where $\hat{\theta}_j$ is the estimated food insecurity index of farm household j. The variables of interest which are all in log, are the long-term average of rainfall, $\bar{R}_p$ and the deviations of rainfall from this long-term average during the current season rainfall, $R_{pt} - \bar{R}_p$ following Rabassa et al. (2014). The remaining terms are controls for farm households socioeconomic characteristics (X_j). However, we used the regional fixed-effect regression to eliminate unobserved time-invariant region level variables.

3.2 Estimating nonfarm enterprise effect with copula switching regression

The nonfarm enterprise operation decision as a function of rainfall variability and household socioeconomic characteristics and its implications in terms of an outcome of interest can be modeled in the setting of a two-stage framework (Zereyesus et al., 2017). In the first stage, we use a selection model for nonfarm enterprise operation where a representative farm household chooses to engage in nonfarm enterprise activities if they generate net benefits. We can therefore represent the net benefits derived from nonfarm enterprise operation by a latent variable D_j^*, which is not observed but can be expressed as a function of the observed characteristics and attributes, denoted as Z, in a latent variable model as follows:

$$D_j^* = \gamma_1\left(R_{pt} - \bar{R}_p\right) + \gamma_2\bar{R}_p + \gamma_3\boldsymbol{Z}_j + \varepsilon_j \text{ with } D_j = \begin{cases} 1 \; if \; D_j^* > 0 \\ 0 \; otherwise \end{cases} \quad (2)$$

In Eq. (2), D_j is a binary variable that equals 1 for households that engage in nonfarm enterprises and zero otherwise, γ denotes a vector of parameters to be estimated. Household j will choose to operate (D_j =1) nonfarm enterprise only if the perceived net benefits are positive $D_j^* > 0$. The error term ε_j with mean zero and variance σ_ε^2 captures measurement errors and factors unobserved to the researcher but known to the farmer. Variables in Z include factors that influence the decision to operate such as farm level, household characteristics and rainfall. Although the perceived net benefits of operation are unknown to the researcher, the characteristics of the farm household and the attributes of the nonfarm enterprise are observed during the survey period.

In the second stage, we model the effect of nonfarm enterprise on food insecurity. The simplest approach to examine the impact of engagement in nonfarm enterprise on farm households would be to include a binary variable which takes the value of one if the household operates a nonfarm enterprise and zero otherwise. and then use ordinary least squares regression to estimate the food insecurity equation. However, because the decision to engage in nonfarm enterprise may be based on individual self-selection, this approach would yield biased results. This is so because there may be unobserved heterogeneity which drives the decision to engage in and affects food insecurity level. Farmers that operated nonfarm enterprises may have systemically distinctive characteristics from farmers that did not and may have decided to engage based on expected benefits. Given that we dispose of cross-section data only and thus have no information on the counterfactual situation we employ the endogenous switching regression model developed by Lee (1982).

The endogenous switching regression approach as a generalization of Heckman's selection correction approach, accounts for selection on unobservable by treating selectivity as an omitted variable problem (Heckman 1979). In the switching regression approach, households are classified per their status as adopters and non-adopters to capture the differential responses of the two groups. Regimes are defined as follows:

Regime 0 (non-adopters): $\hat{\theta}_{NJ} = \beta_{1N}\left(R_{pt} - \bar{R}_p\right) + \beta_{2N}\bar{R}_p + \beta_{3N}X_{NJ} + u_{NJ}\ if\ D_j = 0$ (3a)

Regime 1 (adopters): $\hat{\theta}_{AJ} = \beta_{1A}\left(R_{pt} - \bar{R}_p\right) + \beta_{2A}\bar{R}_p + \beta_{3A}X_{AJ} + u_{AJ}\ if\ D_j = 1$ (3b)

In Eqs. (3a) and (3b), $\hat{\theta}_J$ is food insecurity index in regimes 0 and 1 and X_{NJ} and X_{AJ} are vectors of household socioeconomic characteristics; β_N and β_A are vectors of parameters and u_{NJ} and u_{AJ} are independently and identically distributed errors.

Although the variables in the vectors X in Eq. (3) and Z in Eq. (2) may overlap, it is important to note that accurate identification requires that at least one variable in Z does not appear in X. These variables are that directly affect the selection variable but not the outcome variable. Our selection instruments are time to practicable road and degree of involvement in cash crop. We establish the admissibility of these instruments by performing a simple falsification test (Wouterse, 2017); if a variable is a valid selection instrument, it will affect the operation decision but it will not affect the food insecurity index among farm households that did not operate.

The error terms u_{NJ} and u_{AJ} are assumed non-independent to ε_j otherwise the OLS estimation of each equation would lead to consistent estimators of the model parameters. To obtain consistent estimates it should be taken into account the dependence of the error terms. The classic hypothesis at this level for the estimation of the model is that the joint distribution of errors terms follows a normal distribution. We depart from that by adopting the Copula approach that generates a joint distribution based on marginal distributions (for details see Smith, 2003). To perform the estimations, it is necessary to postulate the marginal of different equations terms. Therefore, for the selection equation, the logistic distribution is assumed for the errors while for the errors of different regimes equations a normal distribution is assumed.

The copula method generates a joint distribution given marginal distributions. Let $F_{NJ}\ (u_{Nj})$, $F_{AJ}\ (u_{Aj})$ and $F_j\ (\varepsilon_j)$ be marginal cumulative density function of u_{NJ}, u_{AJ} and ε_j and let $F_N\ (u_{Nj}, \varepsilon_j)$ and $F_A\ (u_{Aj}, \varepsilon_j)$ be the bivariate joint cumulative distribution functions. The copula functions C_N and C_A couples the two marginal distributions to generate bivariate cumulative density function:

$F_N\left(u_{Nj}, \varepsilon_j\right) = C_N(F_{NJ}\ (u_{Nj}), F_j\ \left(\varepsilon_j\right);\ \theta_N)$ and

$F_A\left(u_{Aj}, \varepsilon_j\right) = C_N(F_{AJ}\ (u_{Aj}), F_j\ \left(\varepsilon_j\right);\ \theta_A)$.

Where θ_N and θ_A are parameter that govern the degree of dependence. The different combinations of two copulas among the Farlie–Gumbel–Morgenstern, placket, Ali–Mikhail–Haq, clayton, frank, gumbel and joe, have been estimated the best couple is the one that minimizes Akaike information criterion (AIC) or Bayesian information criterion (BIC) (Hasebe,

2013). For more information on different copulas properties see Hasebe (2013). The model is estimated using the maximum likelihood estimation.

Furthermore, the degree of dependence is measured in addition to dependence parameters θ_N and θ_A that governs degrees of dependence. θ_N and θ_A do not share universal meanings across copulas. In other words, the dependence parameter of one copula cannot be directly compared with the parameters of other copulas. Instead, it is common to report Kendall's τ as a measure of the degree of dependence. This measure can be expressed in terms of a copula. For pairs of continuous random variables (u_{NJ}, ε_j) and (u_{AJ}, ε_j) with marginal cumulative density functions $F_{NJ}(u_{Nj})$, $F_{AJ}(u_{Aj})$ and $F_j(\varepsilon_j)$ and joint distributions by copulas:

$$\tau_N = \iint C_N(F_{NJ}(u_{Nj}), F_j(\varepsilon_j);\ \theta_N) dC_N(F_{NJ}(u_{Nj}), F_j(\varepsilon_j);\ \theta_N) - 1$$

$$\tau_A = \iint C_A(F_{AJ}(u_{Aj}), F_j(\varepsilon_j);\ \theta_A) dC_A(F_{AJ}(u_{Aj}), F_j(\varepsilon_j);\ \theta_A) - 1$$

These measures provide information about the co-movement between the two errors terms in each regime over entire joint support.

After the estimation of the model switching regression model, the equations are used to measure an average treatment effect (ATE).

4 DATA SOURCES AND DESCRITPTIVE ANALYSIS

The methodology is implemented on the data of the 2014 Multi-sectoral Continuous Survey (EMC-BF) conducted by the National Institute of Statistics and Demography (INSD). This is a nationwide survey that took place in four passages. The EMC-BF sample design is a two-stage survey. This survey based on a sample of approximately 10060 households contains sections on agriculture and socioeconomic characteristics of households. However, the subsample for the analysis contained about 6243 observations which are only rural and urban farm households.

Table1: Summary statistics of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Have you been worried about not having enough food for lack of money or other resources? (Var1)	6,243	63.3%	0.482	0	1
You have not been able to eat healthy and nutritious food for lack of money or other resources? (Var2)	6,243	59.6%	0.491	0	1
Did you eat a little food for lack of money or other resources? (Var3)	6,243	70.2%	0.458	0	1
Did you have to skip a meal because you did not have enough money or other resources to eat? (Var4)	6,243	34.8%	0.476	0	1
Have you eaten less than you thought you should have eaten because of lack of money or others? (Var5)	6,243	46.3%	0.499	0	1
Your household ran out of food because there was not enough money or other resources? (Var6)	6,243	23.1%	0.422	0	1
You were hungry but you did not eat because there was not enough money or other resources to get food? (Var7)	6,243	25.3%	0.435	0	1
You spent an entire day without eating for lack of money or other resources? (Var8)	6,243	12.7%	0.333	0	1
Household Head Gender: Woman	6,243	0.115	0.319	0	1
Household Head Age	6,243	47.139	14.661	15	99
Monogamous Household Head	6,243	0.542	0.498	0	1
Polygamous Household Head	6,243	0.346	0.476	0	1
Free union Household Head	6,243	0.021	0.145	0	1
Household Head literacy	6,243	0.233	0.423	0	1
Household size	6,243	8.297	5.168	1	63
Land size	6,243	4.954	13.020	0.02	399.960
Animal for traction	6,243	0.546	0.498	0	1
Traction Unit	6,243	0.416	0.493	0	1
Time to Food Market 15-29 min	6,238	0.212	0.409	0	1
Time to Food Market 30-44 min	6,238	0.187	0.390	0	1
Time to Food Market 45-59 min	6,238	0.094	0.292	0	1
Time to Food Market 60mn et +	6,238	0.233	0.423	0	1
Rainfall average (in log)	6,243	6.658	0.152	6.179	6.923
Rainfall deviation	6,243	-0.006	0.262	-0.800	0.569
Non-farm enterprise	6,243	0.449	0.497	0	1
Cash crop share in Total production	6,243	0.223	0.282	0	1
Time to practicable road 15-29 mins	6,238	0.146	0.353	0	1
Time to practicable road 30-44 mins	6,238	0.126	0.332	0	1
Time to practicable road 45-59 mins	6,238	0.079	0.270	0	1
Time to practicable road 60mns et +	6,238	0.264	0.441	0	1

Source: Author calculations

The food security is captured by eight questions. According to that 63.3% of households reported that they have worried about not having enough food for lack of money or other resource. In addition, 59.6% of households have not been able to eat healthy and nutritious food for lack of

money or other resources. About 70.2% of households ate little food for lack of money or other resources. However, less than 35% of households had to skip a meal because they did not have enough money or other resources to eat. In plus, 46.3% of households have eaten less than they thought they should have eaten while 23.1% of households ran out of food because there was not enough money or other resources. Furthermore, 25.3% of households were hungry but did not eat because there was not enough money or other resources to get it. Finally, only 12.7% spent an entire day without eating for lack of money or other resources.

With respect to household's characteristics, only 11.5% of households' heads are women. The average age of households' heads is 47 years with a minimum of 15 years. Most of households' heads are monogamous with this type of marital status representing 54.2% of households. In plus, 4.6% of households are polygamous while only 2.1% are in free union. In term of literacy, most of households' heads are illiterate as only 23.3% are literate. The average households size is 8 members per households. The farm households are in general small producers with a land size of 5 ha. In addition, 54.6% of households own an animal of traction while 41.6% possess a traction unit. Then, 21.2% of households spent between 15 to 29 minutes (min) to reach a food market, 18.7% of households need 30 to 44 min to attain a food market while 9.4% spent 45 to 59 min to reach a food market. The households spending more than one hour to reach a food market are also numerous and their share is 23.3%. With respect to precipitation, the average rainfall in the different provinces is 780 mm. furthermore, nonfarm enterprise operation is also wide spread as 45% of households have a member that engaged in nonfarm enterprise of food processing or small trade. The share of cash crops in total agricultural production is in average 22.3%. Finally, 14.6% of households spent 15 to 29 min to reach a practicable road, 12.6% of households reach a practicable road after 30 to 44 min while 8% spent 45 to 49 min to reach a practicable road. However, the proportion of households that spent more than one hour to reach a practicable road is 26.4%.

5 FINDINGS

5.1 Food Security Measurement and Ordinary Least Square Regression Results

Table 3 reports the estimates of the IRT models. Across the columns are statistics corresponding to the one-parameter IRT specification. Estimates from Table 3 indicate that the item var8 is the most discriminating variable, followed by the item var6. The least discriminating item is var3. The item var5 displays a parameter close to zero, which suggests that this item is not a discriminating variable. These results mean that at a low level of food deprivation index, one should expect the item var8 have the lowest probability rate of affirmative response, the item var1, and the item var3 have the highest rate. The item var8 is clearly the most severe followed by the item var6.

Table 3: Estimates from the IRT models

	Coefficients	Std. Err.	Z-statistics
Discrim	3.228	0.052	62.35***
var3	-0.582	0.019	-30.08***
var1	-0.380	0.018	-20.89***
var2	-0.277	0.018	-15.55***
var5	0.082	0.017	4.71***
var4	0.412	0.018	22.32***
var7	0.731	0.020	35.98***
var6	0.815	0.021	38.96***
var8	1.318	0.026	51.27***

*p<0.10; **p<0.05; ***p<0.01. The "z-stat" column represents the Z-statistics of the null hypothesis significance test for each Coefficient, with the null hypothesis being that the coefficient value is zero

Table 4 displays the results of the ordinary regression of food security. The first column of the results presents the estimations of the sample of all farm households. In addition, estimations for urban and rural farm households are conducted separately. Important results are highlighted from these estimations. First, our variables of interest, the rainfall average and deviation from this rainfall average, are all negative at the significance level of 5% in the estimate on the sample of all farm households. In addition, these variables are also significant in the regression of rural households. However, in the regression of urban households only the average of rainfall is significant at 5%. These results indicate that both short-term and long-term rainfall variabilities are important determinants of farm households' food insecurity level. More precisely, an increase in the average rainfall significantly reduce the level of food insecurity of farm

households. This can be explained by the strong dependence of agriculture in Burkina to rainfall and the low level of irrigation in the country.

Table 4: Ordinary Least Square Regression of Food insecurity index

	All	Urban	Rural
Household Head Gender: Woman	0.020(0.045)	0.118(0.121)	-0.012(0.049)
Household Head Age	0.004(0.001)***	0.003(0.002)	0.005(0.001)***
Monogamous Household Head	-0.091(0.049)*	0.040(0.114)	-0.136(0.055)**
Polygamous Household Head	-0.077(0.049)	0.014(0.126)	-0.117(0.054)**
Free union Household Head	-0.143(0.092)	-0.115(0.291)	-0.192(0.098)**
Household Head literacy	-0.205(0.026)***	-0.309(0.061)***	-0.163(0.029)***
Household size	-0.010(0.003)***	-0.023(0.007)***	-0.008(0.003)***
Land size	-0.001(0.001)	0.001(0.002)	-0.003(0.001)**
Animal for traction	-0.169(0.033)***	-0.134(0.081)*	-0.179(0.036)***
Traction Unit	-0.063(0.032)**	0.017(0.085)	-0.090(0.034)***
Time to Food Market 15-29 min	0.104(0.031)***	0.224(0.074)***	0.066(0.034)*
Time to Food Market 30-44 min	0.062(0.033)*	0.082(0.077)	0.046(0.036)
Time to Food Market 45-59 min	0.123(0.041)***	0.054(0.116)	0.117(0.044)***
Time to Food Market 60min et +	0.117(0.033)***	0.064(0.094)	0.106(0.036)***
Rainfall average (in log)	-0.929(0.131)***	-0.786(0.307)**	-0.885(0.145)***
Rainfall deviation	-0.364(0.110)***	-0.417(0.270)	-0.296(0.121)**
Regional Fixed effects	*yes*	*Yes*	*yes*
Constant	6.320(0.905)***	4.962(2.113)**	6.094(1.003)***
R-squared	0.109	0.132	0.119

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This result call for the promotion of drought tolerant seed in Burkina in order to cope with the effect of rainfall variability. The negative effect of rainfall deviation reveals also that an increase of rainfall above average reduce significantly the level food insecurity for all the households. However, as the effect is only significant among the rural as revealed by the different regression on rural and urban, this indicates that rural farm households are more dependent of rainfall for their livelihood compared to urban farm households. In other words, only rainfall average changes may affect urban farm households. This indicates their stronger resilience to rainfall shock compared to rural farm households.

With respect to other variables important results are also highlighted. First, surprisingly the gender of household is not significant in all the regressions indicating that the food insecurity level of the farm households is independent of household head gender. In other words, the level of food insecurity of households headed by women is not significantly higher than that of households headed by man. In addition, the age of household head is significant at 1% in the regression including all the farm households. However, this effect is only significant among the

rural farm households' regression. In other words, being an old household, increases the level of food insecurity among rural farm households. This can be explained by the fact that in rural areas the main livelihood of households is agriculture and the main input is human force but older households have less active member which may impact negatively on their output. This result is also supported by the effect of households' size variable. The households size is significant and negative at 1% in all regressions indicating that the level of households' food insecurity decreases with households' size. This also reveals that the labor force is an important source of livelihood of farm households. Another important result is related to households' marital status which appear to be determinant in rural areas. In fact, being monogamous, polygamous or in free union reduce the level of households' food insecurity at 5% among rural farm households. In plus, the literacy of households' heads is significant and negative at 1%. In other words, the literacy of households' head reduces the food insecurity. This result reveals the importance of education in fighting food insecurity in Burkina Faso. Furthermore, the production assets also appear important in reducing food insecurity in farm households. The possession of animal of traction significantly reduces food insecurity particularly among rural households at 1% while the possession of traction unit is only significant among rural households, due to rural areas lack of modern transport. However, an important factor in agricultural production which is land size is only significant among rural households at 5% indicating also the dependence of rural households to land for their livelihood. Finally, another important finding is related to time spent to access to food market. It appears that access to food market is an important determinant of households' food security.

3.2 Nonfarm enterprises effect with copula switching regression

The second phase of the analysis has focused on the impact of nonfarm enterprises on farm households' food insecurity level. As mentioned above, the first step consisted of selection of the best copula in order to define the link between the selection error term and the errors terms in different regimes. The selection was based on the SIC and BIC. About 64 models have been estimated using the different combination of copulas. It appeared the couple of clayton copula in the two regime is the one that yield the minimum SIC and BIC. Therefore, it is that model with two clayton that has been estimated.

After the estimation of the model, a Wald test of independence has been conducted. Its test statistic is 89.344 with an associated p-value of zero. This indicates that the null hypothesis of independence between the selection equation errors term and the different regimes equations is not accepted. The results of the switching regression model are displayed in table 5. The last columns of the table show the strength of the dependence between the errors term of the selection equation and those of the different regimes.

Table 5: Copula Endogenous Switching regression model results.

Variables	Selection	Regime0	Regime1
Household Head Gender: Woman		-0.019(0.058)	0.119(0.070)*
Household Head Age		0.003(0.001)***	0.004(0.001)***
Monogamous Household Head		-0.070(0.064)	-0.118(0.076)
Polygamous Household Head		-0.090(0.064)	-0.085(0.076)
Free union Household Head		-0.180(0.117)	-0.197(0.123)
Household Head literacy		-0.207(0.036)***	-0.154(0.035)***
Household size	0.061(0.005)***	0.004(0.004)	0.007(0.004)
Land size		-0.002(0.002)	-0.001(0.001)
Animal for traction		-0.149(0.043)***	-0.135(0.047)***
Traction Unit		-0.070(0.042)*	-0.025(0.043)
Time to Food Market 15-29 min		0.038(0.045)	0.142(0.041)***
Time to Food Market 30-44 min		0.028(0.045)	0.049(0.044)
Time to Food Market 45-59 min		0.079(0.055)	0.072(0.059)
Time to Food Market 60mns et +		0.035(0.045)	0.105(0.046)**
Rainfall average (in log)	0.765(0.341)**	-0.730(0.192)***	-0.587(0.242)**
Rainfall deviation	0.800(0.279)***	-0.079(0.156)	-0.103(0.198)
Cash crop share in Total production	0.269(0.088)***		
Time to practicable road 15-29 min	-0.170(0.073)**		
Time to practicable road 30-44 min	-0.251(0.076)***		
Time to practicable road 45-59 min	-0.403(0.093)***		
Time to practicable road 60min et +	-0.253(0.069)***		
Regional Fixed Effects	*yes*	*yes*	*yes*
Constant	-6.212(2.356)***	5.038(1.327)***	3.018(1.715)*
Lnsigma		-0.146(0.014)***	0.149(0.038)***
Atheta		-0.185(0.157)	1.114(0.202)***
Tau		-0.294(0.033)	-0.604(0.048)

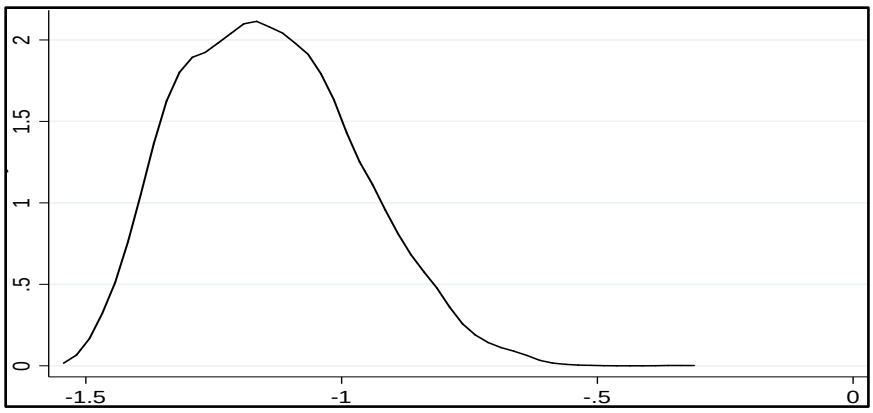
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The parameter *atheta* is significant and positive at 1% and greater than one in Regime1 indicating that the errors are positively dependent in regime 1. This result is also confirmed by the value of tau of Kendall of -0.604. However, in regime 0 the *atheta* parameter is non-significant its tau of Kendall is near to zero.

The equation of selection reveals important results. First, the excluded instruments including cash crop share in total production and time to practicable road are significant. The effect of cash crop share in total production is positive indicating that involvement in cash cropping increases the probability of nonfarm enterprise operation. This can be explained by the fact that cash is a source of liquidity that may allow households to invest in this activity. In addition, the time spent to access to practicable road is negatively related to engaging in nonfarm enterprise. Furthermore, it is found that the size of the household affects significantly and positively the probability of engaging in nonfarm enterprise. However, the average and deviation in rainfall increase the probability of engaging in nonfarm enterprise. This result reveals that rainfall is also important for nonfarm enterprise operation. Therefore, in order to allow farm households to engage in nonfarm enterprise other source of funding should be made available like microcredit or cash transfer.

Finally, the impact of engaging in nonfarm enterprise on food insecurity level is estimated. for each household, the level of food insecurity when it engages in this activity is compared to the one when the household doesn't not engage in. The density of this difference is displayed in figure 2. The figure reveals important finding. All the values of the distribution are negative. This indicates that each household observes a lower level of food insecurity when it engages in nonfarm enterprise compared to the situation when it doesn't not. Therefore, nonfarm enterprises appear to be a strategy with high potential in reducing farm household food insecurity in face of rainfall variability. For that, farm households should have opportunities to engage in nonfarm enterprises. In context of poverty like Burkina Faso farm households may need some funding to start these activities and microcredit development particularly in rural areas may be a good option to handle the funding shortage.

Figure 2: food insecurity index difference



Source: Author Computations

This line is line with the World Bank (2007) finding in Tanzania indicating that Nonfarm enterprises are an essential source of livelihood for a sizable proportion of Tanzania's rural population. Furthermore, Households that run a nonfarm enterprise have an income that is about 24 percent higher than that of those without, suggesting that access to informal employment in the rural nonfarm sector could provide a path out of poverty. Given a lack of social protection and insurance schemes, rural households need to manage shocks, deal with surplus household labor, and respond to seasonality. Operating an enterprise can present a strategy to cope with these kinds of uncertainties (Nagler and Naudé, 2017). Evidence shows that over time the contribution of these enterprises to household incomes and employment has increased rather than decreased, as some development economists in the 1960s and 70s expected (Lanjouw and Lanjouw, 2001; Start, 2001; Haggblade et al., 2010). In this regard, it is important to take this opportunity to make farm households more resilient to climate change that the world is preparing and whose negative impact on agricultural sector of Burkina Faso is well agreed.

6 CONCLUSION

The strong dependence of agriculture to rainfall in Burkina Faso necessitates to inquire how rainfall variability affect farm households' food insecurity. By using the data of the 2014 Multi-sectoral Continuous Survey (EMC-BF) conducted by the National Institute of Statistics and Demography (INSD), this study provided evidence on the impact of short and long terms rainfall variability on farm households food insecurity and how non-farm enterprises may contribute to mitigate the impact of rainfall variability.

The ordinary least square regression of the food insecurity index reveals that both short-term and long-term rainfall variability are important determinants of farm households' food insecurity level in Burkina Faso. More precisely, an increase in the rainfall average significantly reduces the level of food insecurity of farm households. A similar result is found for short term rainfall increase. However, this later effect is only significant among the rural indicating that rural farm households are more dependent of rainfall for their livelihood compared to urban farm households.

The implementation of the copula switching regression model reveals that nonfarm enterprises appear to be a strategy with high potential in reducing farm household food insecurity indicating that farm households should have opportunities to engage in nonfarm enterprises in face of rainfall variability. In this regard, it is important to take this opportunity to make farm households more resilient to climate change that the world is preparing and whose negative impact of agricultural sector of Burkina Faso is well agreed.

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