

Impact of climate-smart innovations on food security of farming household in Benin: A Case study of Drought tolerant maize (DTM) varieties

Tchègoun Michel ATCHIKPA^{1;5;*}, Chérif Sidy KANE², Justice A. TAMBO³, Tahirou Abdoulaye⁴, Jacob Afouda YABI⁵.

¹ Graduate Research Program (GRP) on Climate Change and Economics (CCEcon), at University of Cheikh Anta Diop of Dakar (Senegal) in WASCAL (West African Science Service Centre on Climate Change and Adapted Land Use: <https://www.wascal.org/>)

²University of Cheikh Anta Diop, Fac. Des Sciences Economiques et de Gestion, Senegal

³ Center for Agriculture and Biosciences International (CABI), Delémont, Switzerland

⁴International Institute of Tropical Agriculture (IITA), Socioeconomic Unit, Nigeria

⁵University of Parakou, Faculty of Agronomy, Benin.

* Corresponding authors: atchikpa.t@edu.wascal.org or michelatchikpa@gmail.com

Abstract:

This paper examines with a case study on Drought tolerant maize (DTM) varieties, the impact of climate-smart innovations adoption on food security, using country-wide cross-sectional data of about 518 maize farming households from 48 villages in Benin. We used respectively household food expenditure per capita, household food consumption scales (HFCS), household diet Diversity Score (HDDS) and household food insecurity experienced score (HFIES) as outcome indicators of food security of maize farming households in Benin. We used a mixed methods approach based on qualitative techniques for the data collection on the first hand. The quantitative techniques (Endogenous Switching Regression (ESR)) permits to identify the causal effects of adopting drought-tolerant maize varieties on the productivity and food security of maize farming in households in Benin using two instrumental variables. To control, such differences and allow a causal interpretation of the real effect of Drought tolerant maize varieties adoption, we have estimated the Average Treatment Effect (ATE). In the end, our analyses have indicated that adoption of Drought tolerant maize varieties adoption significantly increased respectively household food expenditure per capita by about 1.44%, the household food consumption scales (HFCS) by about 31.83%, the household diet Diversity Score (HDDS) by about 2.34% and decreased the household food insecurity experienced score (HFIES). These results showed that adoption supports severely food insecure households to reach moderate and acceptable food security status by empowering them to acquire cereals and tubers, pulses, vegetables, and fruits daily. Our findings point out that Drought tolerant maize varieties can play an essential role in farm performances in Benin and indirectly in food security.

Keywords: climate-smart innovations, Adoption and Impact, Drought tolerant maize (DTM), food security, Endogenous Switching Regression, Benin.

Résumé :

Cet article examine avec une étude de cas sur les variétés de maïs tolérantes à la sécheresse (DTM), l'impact de l'adoption d'innovations intelligentes face au climat sur la sécurité

alimentaire, en utilisant les données transversales à l'échelle nationale d'environ 518 ménages de producteurs de maïs de 48 villages du Bénin. Nous avons utilisé respectivement les dépenses alimentaires des ménages par habitant, les échelles de consommation alimentaire des ménages (HFCS), le Score de diversité du régime alimentaire des ménages (HDDS) et le Score de l'insécurité alimentaire des ménages (HFIES) comme indicateurs de résultat de la sécurité alimentaire des ménages de producteurs de maïs au Bénin. Nous avons utilisé une approche de méthodes mixtes basée sur des techniques qualitatives pour la collecte de données de première main. Les techniques quantitatives (Endogenous Switching Regression (ESR)) permettent d'identifier les effets causals de l'adoption de variétés de maïs tolérantes à la sécheresse sur la productivité et la sécurité alimentaire de la culture du maïs dans les ménages au Bénin en utilisant deux variables instrumentales. Pour contrôler ces différences et permettre une interprétation causale de l'effet réel de l'adoption de variétés de maïs tolérantes à la sécheresse, nous avons estimé l'effet de traitement moyen (ATE). Au final, nos analyses ont indiqué que l'adoption de variétés de maïs tolérantes à la sécheresse a augmenté de manière significative respectivement les dépenses alimentaires des ménages par habitant d'environ 1,44%, les échelles de consommation alimentaire des ménages (HFCS) d'environ 31,83%, le Score de diversité de l'alimentation des ménages (HDDS) d'environ 2,34% et a diminué le score d'insécurité alimentaire des ménages (HFIES). Ces résultats ont montré que l'adoption aide les ménages en situation d'insécurité alimentaire grave à atteindre un statut de sécurité alimentaire modéré et acceptable en leur permettant d'acquérir quotidiennement des céréales et des tubercules, des légumineuses, des légumes et des fruits. Nos résultats montrent que les variétés de maïs tolérantes à la sécheresse peuvent jouer un rôle essentiel dans les performances des exploitations au Bénin et indirectement dans la sécurité alimentaire.

Mots-clés : innovations intelligentes face au climat, adoption et impact, maïs tolérant à la sécheresse (DTM), sécurité alimentaire, régression de commutation endogène, Bénin.

Introduction

With the existence of very critical areas where hunger is rife, the food security status in the world is very worrying (FAO and PAM, 2009). Indeed, over 39 countries surveyed in 2006 with a high level of food insecurity in the world 25 of them come from Africa. According to Horton et al., (2009), the undertaking of micronutrient in consumption food than the required is one of the most significant health and socio-economic issues, but the treatment of which is underestimated. Rising food prices have severe consequences for inflation and the well-being of people around the world (Golay, 2010) and especially in developing countries. The strong disturbances in agricultural production due to climate change are the leading causes contributing to food insecurity (Kurukulasuriya and Mendelsohn, 2008). Furthermore, Hubert and Caron, (2009), through the EICASTD report, states that the impacts of climate change associated with growing demand for food and energy products can have serious consequences for the natural resources on which agriculture depends, security food will take a hit.

West Africa is identified as one of the most vulnerable regions to climate change (Yegbemey et al., 2014). Benin, like other Sub-Saharan countries, is vulnerable to climate change. Climate risks mainly identified on the territory of the Republic of Benin are drought, floods, sea level rise and coastal erosion. Also, it is noted that the rainfall decline, the reduction in the

length of the agricultural season, the persistence of negative anomalies, the rise in minimum and maximum temperatures, now characterize the climates of Benin and modify rainfall patterns and agricultural production systems (Ogouwalé 2006, Tidjani and Akponikpè, 2012).

The impacts of climate change are significant and are characterised by a degradation of natural resources, the displacement of populations, disruption of economic activities, mainly agricultural. In fact, agriculture is the primary activity with a contribution of 35% to the gross domestic product (GDP) and 75% of export revenue, the agriculture's sector in Benin which employs 70% of the active population (Bini, 2016). Agricultural products accounted for about 20.50 % of total export earnings between 2015 and 2016¹. However, the IPCC, (2014) predicts a decrease in agricultural yields in West Africa of around 20 to 50% in semi-arid sub-Saharan Africa by 2050, which could be between 5 and 20% Benign. This decline would not be uniform across the territory. According to Boko et al., (2012) can be expected to have a positive impact on different regions and cultures. The climatic variability and in particular the decrease of the precipitations from March to May poses a significant risk on the food security of the country. For Agbossou et al., (2012) and Gbêtondji and Porgo, (2014), cereal yield is sensitive to temperature in Benin. Thus, climate change is degrading the food and nutritional situation of the population in the face of food insecurity, particularly that of rural households.

In Benin, according to the AGVSA, (2014)², 1.1 million people were food insecure in 2013, coming from 11% of households with less than 1% severe food insecurity and 11% moderate food insecurity. These households have inadequate food consumption or cannot meet their minimum food needs without resorting to irreversible adaptation strategies (ACF (Action Contre la Faim), 2012; OECD, 2008; Paunov, 2013). Thus, the proposals for action related to the reduction of impacts and the adoption of pre-adoption strategies (Füssel and Klein, 2006). ACF, (2012) points out that these populations, already threatened by food insecurity, do not have much choice to cope with and adapt to climate change. They use negative coping strategies, further exacerbating their vulnerability, or weakening their resilience. For Burton, (1997), the consequences are mostly for the reduction of agricultural and economic risks through the diversification of activities. As for the ACF, (2012), adaptation approaches must take into account three levels of simultaneous intervention: the ex-ante approach, the ex-post approach and the mitigation measures. Indeed, it is commonly accepted that climate-smart innovations are crucial to meeting the challenges of adaptation to climate change to ensure food security and increase farmer's income (Campbell et al., 2014; Long et al., 2016).

The paper examines the adoption DTM varieties as climate-smart innovations and evaluate its impact of on food security and nutritional status of maize farming households in Benin. Indeed, according to Cooper et al., (2013) and Fisher et al., (2015) the drought-tolerant maize varieties are climate-smart innovations firstly because they are increasing yields even under moderate drought conditions, thus raising income for farmers. Secondly, the new varieties are enabled farmers to cope with more frequent droughts projected as a result of climate change.

¹ Retrieved from <http://perspective.usherbrooke.ca/bilan/servlet/BMIImportExportPays?codePays=BEN>

² Global Vulnerability and Food Security Report

In the literature, there are several studies related to climate change adaptation in agriculture, at the micro-level (i.e. farm level) and an impressive number of empirical studies³ (e.g. Campbell et al., 2014; Deressa et al., 2009; FAO, 2013; Gnangle et al., 2012; Long et al., 2016) identified and reported that the development, the promotion and the adoption of new crop varieties appropriate to our socio-economic realities would help not only to adapt to climate change but also to improve economics performances, food (and nutritional) security and reduce poverty (Fisher et al., 2015; Shiferaw et al., 2014; Tambo and Abdoulaye, 2012; Wossen et al., 2017). Some research has done on climate change adaptation strategies on the level of food security and nutritional status of rural populations. But most of these are broad (i.e. not on a specific case of climate change adaptation strategy such as drought-tolerant varieties) on adoption of climate change strategies (eg: Lobell et al., 2008; Di Falco et al., 2011; Gregory et al., 2005) but also more focused on Africa or in the best case on eastern Africa. Furthermore, the existing studies on DTM mostly focus on adoption and impacts on yield (Holden and Fisher, 2015; Kassie et al., 2017; Tambo and Abdoulaye, 2012; Wossen et al., 2017) and our paper adds to these studies by focusing on food and nutrition security.

With the aim of reducing poverty and ensure food security by increasing agriculture productivity while adapting to climate change since 2006, some research institutions like International Center for the Improvement of Maize and Wheat (CIMMYT) and the International Institute of Tropical Agriculture (IITA) with the collaboration of the National Research Institute of Agriculture of Benin (INRAB) and West Africa Agricultural Productivity Project in Benin (WAAPP) have developed and disseminated or promoted seven varieties⁴ of Drought Tolerant Maize in Benin (DTMA, 2009). However, thing surprising despite these multiple efforts is that not only generally empirical data on adoption of rates, on productivity and outcome indicators related to well-being are few in the literature, but there are practically no studies on the adoption of DTM varieties and better on their impact in Benin. Indeed, for this Drought Tolerant Maize for Africa (DTM) varieties developed and disseminated from 2006 to 2016, simultaneously in 13 countries including Angola, Benin, Ethiopia, Ghana, Kenya, Malawi, Mali, Mozambique, Nigeria, Tanzania, Uganda, Zambia and Zimbabwe, showed high adoption rate (85 percent of farmers that adopt DTM varieties) in Kenya and Zambia, but only 20 percent in Benin, 30 percent in Mali and 27 percent in Mozambique (CIMMYT-IITA, 2015). In the context of Benin, understanding the primary determinants of DTM varieties adoption, in addition to the expected returns from adoption, so as to design policies that could address the supply side constraints in West Africa is consequently essential.

With the aim to bring out the probable impacts of adoption of DT maize varieties at the household level in Benin this paper offers a comprehensive ex-post assessment. Especially, it seeks to address the following relevant questions: What is the impact of adoption of DT maize varieties on food security? Furthermore, this study empirically contributes to the current adoption literature by examining the food security effects using a rigorous approach accounting for both unobserved and observed variables of heterogeneity between non-

³ For more reading, check the review of (John K. M. Kuwornu, Al-Hassan, Etwire, & Osei-Owusu, 2013)

⁴ For the name of the varieties disseminated see: <http://dtma.cimmyt.org/index.php/varieties/dt-maize-varieties>

adopters and adopters. The rest of this paper is structured as following sections: section 2: data sources, section 3: the empirical framework, section 4: the results and discussion and section 5: Conclusion.

1. Data and methods

1.1. Data sources

The data used come from household survey data collected from the rural zone in Benin. From November 2017 to January 2018, the survey was carried out. The study adopted a multi-stage sampling procedure selecting the respondents. First, municipalities were randomly selected within each AEZ based on their number of agricultural households. Second, villages were randomly selected within selected municipalities. Finally, random farm households were selected within selected villages. Therefore, the municipalities were randomly selected within each AEZ (AEZ I: one municipality, AEZ II: one municipality, AEZ III: one municipality, AEZ IV: one municipality and AEZ V: two municipalities). The choice of municipalities and there the number per AEZ is linked to the high number of producers of maize and food and cash crops, and the predominant agricultural production systems are cash-based and food-based crops with maize, cotton, yam, sorghum, millet, ...etc. First of all, where the agro-ecological zone has more than three municipalities, the first three having the highest maize production in relation to the total area cropped. Above all, the municipalities were selected within each AEZ by means of Primary Sampling Units (PSUs).

In each selected municipality, villages were also randomly selected in the exploratory survey according to the level of drought or the rainfall perturbations they experienced, the diversification of the drought tolerant maize disseminated and adopted, the access to the village, and their response to climate change, especially in dry season. Also, the villages are villages where WAAPP has introduced the DTM varieties - IITA-INRAB. Indeed, the selection of these villages is justified by the fact that they were the villages in which the spread of improved and tolerant varieties of maize was made. This information was obtained from exploratory surveys conducted with some resource persons such as extension agents, seed production managers such as APRODIS (Association of Producers and Seeds Distributors) of each municipality. These officials and extension agents have seed distribution centres for drought-tolerant maize varieties in their respective municipalities. As a result, they have a wide range of village information on the adoption of improved and tolerant maize varieties. This is the reason why they have been associated with the study with the objective smooth out the possible varietal confusions, all the more so as producers re-label varieties in their own language. In each selected village, ten farming household's in an average of eight villages were surveyed in each municipality, it except Kétou (five villages), Kandi (nine villages) and Savè (nine villages) due to logistical and accessibility constraints. This sampling framework overall generated a total of 518 farming households.

1.2. Methods

The information collected in the survey were on the households socioeconomic characteristics , household income, expenditure of household on food and non-food items, information on adoption of improved maize varieties, outputs of maize, food security

indicators (*like households Dietary Diversity (HDD), Household Food Consumption Score (SCA), and Household Food Insecurity Access Scale (HFIAS)*) and anthropometric measure (for children under five years old and the women between fifteen and forty five years old). Indeed, in addition to the anthropometric measurement's materials (personal scale, height gauge, tricolour strip), it is important to note that each enumerator kept along the survey the seven specimens of DT maize cob disseminated in Benin⁵. Adoption of DTM varieties as treatment variable, was created using the following survey two questions: 1) During the last cropping season (2015/16), what is the name (in local or French language) of the maize seed or how can you describe the seed package, seed size and seed color of the variety, does your household have to grow? And 2) During the last agricultural season (2015/16), give the code of the varieties of maize that your household has grown? At the first question, enumerators were asked to see the seed bag, if available, or ask a more educated household member for the name of the variety with the goal to fill the second question. Based on the second question, we extracted a dummy variable that took one as value if the farmer had grown one of the DT maize varieties, and zero otherwise. About 60 % of farm households had used DT maize varieties in the survey season according to our survey. TZE Comp 3DT, EV DT 97, STR W; 2000 Syn EEW; Across 97 TZL Comp 1 were the most common DTM varieties identified in our survey. Across the different municipality of Benin, there was also significant variation in the use of DTM varieties.

In the literature, some authors have used as an indicator for the assessment of household food security to different shocks, per capita consumption or per capita income of the household (Abdoulaye and Wossen, 2018; Boarini and Johansson, 2006; Dercon, 2006; Droy et al., 2004; Wossen et al., 2017). According to Kakwani and Son, (2016) compared to per capita income, per capita consumption is more directly related to people's level of food security and more accurately reflects a household's actual standard of living. In fact, the use of per capita consumption, rather than income per capita, makes it possible to understand the response of rural households to climate hazards better. Based on this background and according to Bickel et al., (2000); Coates and Bilinsky, (2007); Hoddinott and Yohannes, (2002); Parry et al., (1999) and Yohannes, (2002), in our research, the main proxy used for household food security and nutritional status outcome indicators were per capita expenditure, *food* per capita expenditure, *households Dietary Diversity score (HDDS), Household Food Consumption Score (SCA), Household Food Insecurity Access Scale (HFIAS)* and our main productivity outcome indicator included grain yield of maize.

In fact, the SCA, the HDDs indicators capture quality and diversity (Ndiaye, 2014) and that HFIAS measures access (Bickel et al., 2000; Coates et al., 2007; FAO, 2016). These consumption scores are indicators of food accessibility and the quality of food consumption (FAO & PAM, 2009; INSAE, 2015). They are calculated from: a) the diversity of the diet (number of food groups consumed by a household during the seven days preceding the survey); b) the frequency of consumption (number of days during which a food group was

⁵ The name of the DTM varieties are available here: <http://dtma.cimmyt.org/index.php/varieties>

consumed during the seven days preceding the survey); c) The relative nutritional importance of different food groups. That is why, as part of our research, we used the three scores.

Firstly, following Bickel et al., (2000) and Coates et al., (2007), the score of food consumption that reported the level of household food security was computed. It is a dietary diversity score weighted (w_i) by frequency. The calculation is based on the frequency of consumption of the different food groups (grouped in 8) consumed by a household during the seven days preceding the research (FAO, 2016). According to N'diaye, (2014) that score is an acceptable proxy for measuring calorie intake and diet quality at the household level, indicating household safety status combined with other indicators of household food access. Given that, SCA is the sum of the Weighting of each food group multiple by the number of days of consumption in the last seven days (Coates et al., 2007; FAO and PAM, 2009)

Also, a second HDDS score has been calculated; it represents the dietary diversity of the number of foods or food groups consumed during a given reference period. This similar SCA score does not provide information on the frequency but a proxy for household access to a varied diet (N'diaye, 2014). Following (Bilinsky and Paula, (2006) and Kennedy, (2013), for the HDDs calculation, the food groups used for the SCA were grouped into seven groups by summing the frequencies. Thus, we have group 1: cereals and tubers; group 2: legumes; group3: vegetables; group 4: fruits; group 5: meat and fish; group 6: milk and group 7: oil. For each group, a binomial variable is created that takes two values: 1- yes: the household consumed food of this group; 0- no: he did not eat this food. Subsequently, all binomial variables are summed to create a new HDD variable; this new variable has a value between 0 and 7 (the number of food groups collected).

Finally, regarding, the HFIAS score computed, provides information on food insecurity (access) at the household level. Four types of indicators can be calculated to help understand the characteristics and changes in household food insecurity (access) in the surveyed population. These indicators provide summary information on the following: a) Conditions related to food insecurity (access) of the household; b) Areas related to household food insecurity (access); c) Scale score related to household food insecurity (access); d) Prevalence related to household food insecurity (access). The condition of household food insecurity (access) is an indicator that provides specific and disaggregated information on the behaviours and opinions of the households in the survey. Indeed, the HFIAS score is a continuous measure of the level of food insecurity (access) in the household in the last four weeks (last 30 days). First, the HFIAS score variable is calculated for each household by summing the codes for each question on the frequency of occurrence. The maximum score for the household is 27 (the household's response to all nine frequency of occurrence questions was "often," coded as 3); the minimum score is 0. The higher the score, the higher the household's food insecurity (access). The lower the score, the less the household experiences food insecurity (access).

The descriptive statistics of the main outcome indicators, variables of inputs used (soil fertility status, the use of chemical fertilizer, pesticides, and herbicides) and of some specific characteristics (gender, membership of different social groups, household size, age, education, land size...etc.) of household of maize producer based on adoption status is

presented in the table 1 as control variables. The risk-taking the behaviour of farmers for new improved maize varieties was also used as an additional control. This variable measured as a dummy variable (one if the respondent is willing to try any type of new variety, and zero otherwise), is linked to farmer's willingness to take the risk to adopt new varieties. In the same table 1, we presented the difference of the main control variables means between adopters and non-adopters. The Instruments variables used are the distance from home to the shop where they sell seeds to households and distance from home to the demonstration field. For our instrument variables, they were the statistically significant difference between the two groups (adopters and non-adopters). All of our instrument's variables were continuous variables.

We supposed that variables used in the regression model could affect farmer's decisions to adopt, their productivity and as well as their household's food security and nutritional status. For example, maize income has a positive and significant effect that influences food security. According to Sib et al., (2013), income stability and the reliability of income sources are positively influence food security. Similarly, age is a factor that influences adoption and household food security. The head of household whose age is very advanced may not reach food security. On the other hand, a young producer can better achieve this food security with other contributing factors. The influence of age remains significant but mitigated. Contact with an extension service and belonging to an organisation enhances adoption (Wossen et al. 2015) and contribute to the food security of a rural household. The size of the farm is a factor that influences a producer's decision to adopt and food security. The larger the size of the farm, the more income the farmer will have and meet the food needs of his household. It is, therefore, a significant but mitigating factor, as the case may be. Kassie et al. (2011) documented that there is a positive effect of a more abundant supply of family labour on adoption decisions. Education has a significant influence on household food security. According to Sib et al., (2013), educational attainment can be an essential constraint to human capital development. For PAM and INSAE (2014), the level of household food insecurity is related to the level of education of the household head. However, rural producers, given their ancestral know-how and other enabling factors such as extension services and membership in an organisation, can improve adoption decision and their food security without any formal education. In sum, education has a positive influence on food security and adoption decision in our research area.

Base on the producer theory, we assumed that maize producer adopts DT varieties based on expected benefits. Indeed, the rational producer always seeks to maximise his profit by reducing the costs of the inputs. In this particular case, a producer adopts DTM varieties if the output (gain) from adoption is superior to non-adoption.

Assuming that the cropping of DTM varieties net gain (compared with non-cropping) for a given producer is Y^* , then $Y^* > 0$ implicates that the benefit from adoption is superior to non-adoption. Evidently, it is not possible to observe Y^* . However, the gain from adoption (Y^*) can be stated as a function of an observable vector of covariates in a latent model presented further down:

$$Y^* = \alpha X_i + \omega_i \begin{pmatrix} A_i & \text{if } Y^* > 0 \\ 0, & \text{otherwise} \end{pmatrix} \quad (1)$$

Where A_i is a binary variable that equals 1 if a producer adopts the DTM varieties and zero otherwise; X_i is a vector of socio-economic and demographic characteristics as well as control and institutional variables at the farm level, and ω_i is a vector of parameters to estimate in the equation; ε_i is the error term of a specific household, assumed to be normally distributed. Isolating the causal effect of DTM varieties adoption on productivity and hence on household food security and nutritional status, in the above framework, is difficult due to endogeneity bias. According to Alene and Manyong, (2007) and Wooldridge, (2010, 2011) cited by (Abdoulaye et al., 2018), Audu and Aye, (2014); Bratti, (2009); Kassie et al., (2014); Manda et al., (2016), the causal effects of adoption on productivity requires controlling for both observable and unobservable sources of heterogeneity between adopters and non-adopters. To solve this issue, a model that accounts for both unobserved and observed sources of bias like ESR (Endogenous switching regression) has usually been employed (Lokshin and Sajaia, 2004, 2011; Malikov & Kumbhakar, 2014). This model required instrumental variables, and most of existing literature use awareness to innovation or technology and distance is quietly use. Following Shiferaw et al., (2014); Kassie et al., (2014); Alene and Manyong, (2007), access to information about DT maize varieties was used as an instrument. While following Asfaw et al., (2012); Di Falco et al., (2011) and Tambo and Wünscher, (2017) the distance from home to the shop where they sell seeds to households and distance from home to the demonstration field was used as an instrument. Indeed, we assume that distance variables and access to information on DTM varieties can affect adoption decision, but it cannot affect the welfare outcomes of non-adopter households.

Finally, following Lokshin and Sajaia (2004) and Woolbridge, (2002), the ESR approach was used to address the problem of endogeneity, we have simultaneously estimated the selection model (first stage) and then secondly the outcome model (second stage), using the full information maximum likelihood (FIML).

Based on the above conceptual framework, the outcome function conditional on adoption can be stated as an ESR model in the following way:

$$\text{Regime 1: } Y_{1i} = f(H; Z; X; \alpha_1) + \varepsilon_{1i} \quad \text{if } A_i = 1 \quad (2)$$

$$\text{Regime 2: } Y_{2i} = f(H; Z; X; \alpha_2) + \varepsilon_{2i} \quad \text{if } A_i = 0 \quad (3)$$

Where Y_{1i} and Y_{2i} represent the outcome indicators for adopters (maize yield and welfare indicators) and for non-adopters respectively; ε_i represents the error term of the outcome variable. The variables H, Z and X capture respectively the grown of DT maize varieties, the farm inputs and characteristics socio-economic/demographics with all others variables presented in Table 1. Finally, the variable A_i measures adoption status ($A_i = 1$, implies the producer is an adopter and $A_i = 0$ implies the producer is non-adopter). The error terms in the selection and the outcome equation (1), (2) and (3) are assumed to have a

tri-variate normal distribution with mean zero and covariance matrix (Φ) in the following way:

$$\Phi = \begin{bmatrix} \sigma_{\omega}^2 & \sigma_{1\omega} & \sigma_{2\omega} \\ \sigma_{\omega 1} & \sigma_1^2 & . \\ \sigma_{\omega 2} & . & \sigma_2^2 \end{bmatrix} \quad (4)$$

Di Falco et al., (2011) and Tesfaye and Tirivayi, (2018), documented that, since the error terms in the selection equation are correlated with those in the outcome equations, the means of the error terms in the outcome equations conditional on the sample selection are non-zero. For instance, if the estimated covariance turns to be significant, DTM varieties adoption outcome are correlated proving evidence of endogenous switching.

Table 1: Definition of the variable used in the model and descriptive statistics of maize farmers in Benin by DTM varieties adoption status.

<i>Variable Name and description</i>	<i>full sample</i>	<i>Adopters</i>	<i>non-Adopters</i>	<i>Mean Diff</i>
Household Per capita Food Expenditure (in thousands of Euro ⁶)	72.72	73.26	71.88	1.37
Household food consumption scores (1 "Poor" 2 "Limite" 3 "Acceptable")	2.67	2.75	2.55	0,20*
Household Dietary Diversity Score	6.23	6.27	5.70	0,57***
Food insecurity severity experienced by households	1.99	2.23	1.62	0,61***
Holding of any personal capital before started maize farming (1=Yes and 0 otherwise)	0.81	0.85	0.76	0.088***
Number of members of your household	11,19	11,31	11	0,31
Total area planted (in ha)	8,16	7,83	8,67	-0,84*
Household farm income in Euro	2231.68	2520.163	1787.645	732.51***
Ownership of land where maize is produced (1 = yes and 0 = no)	0.93243	0.96492	0.8823	0.08***
Experience in agriculture (in years)	24.22	24.14	24.35	-0.21
Emigration for agricultural purposes (0 = No, 1 = Yes)	0,05	0,04	0,05	-0,00
Experience of growing maize (years)	22,67	22,83	22,42	0,41
Average total area planted in all for your maize crop	4,16	3,87	4,62	-0,75*
Use fertilizers (0=No,1=Yes)	0,75	0,73	0,79	0,06**
Distance from the closest formal magazine where farm input is stored	7,72	8,48	6,55	1,93***
Membership in an association or producer's cooperative (0 = No, 1 = Yes)	0,39	0,36	0,43	-0,06*
Easy access to agricultural credits (0 = No, 1 = Yes)	0,43	0,35	0,33	0,02
Status of Ownership of livestock (0 = No, 1 = Yes)	0,87	0,84	0,91	-0,06**
Total farm member participating farm activities in the household	9,20	8,87	9,70	-0,84*

⁶ Note that during the survey period the official exchange rate was (1 Euro = 655. 95 FCFA).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and Standard errors in parentheses

Source: author's computation, result from survey

We estimated the endogenous switching regression models using the full information maximum likelihood estimation (Wooldridge, 2002; Lokshin and Sajaia, 2004). Afterward estimating the model's parameters, the conditional expectations or expected outcomes and the Average treatment effect on treated households (ATT) are computed as follows:

$$E(Y_{1i} | A_i = 1) = f(H; Z; X; r_1) + \lambda_{1i} \tau_{1S} \quad (5)$$

$$E(Y_{2i} | A_i = 0) = f(H; Z; X; r_2) + \lambda_{2i} \tau_{2S} \quad (6)$$

$$E(Y_{2i} | A_i = 1) = f(H; Z; X; r_2) + \lambda_{1i} \tau_{2S} \quad (7)$$

$$E(Y_{1i} | A_i = 0) = f(H; Z; X; r_1) + \lambda_{2i} \tau_{1S} \quad (8)$$

$$ATT = E(Y_{1i} | A_i = 1) - E(Y_{2i} | A_i = 1) \quad (9)$$

2. Results and discussion

Our main results are presented in this section (table 2 and table 3). In table 2 the second-stage estimations of the Endogenous Switching Regression (ESR) model by full information maximum likelihood (FIML) for household food consumption expenditure per capita and Household food consumption score (HFCS) are presented. The table 3 presented the second-stage estimations of the Endogenous Switching Regression (ESR) model by full information maximum likelihood (FIML) for Household Food insecurity severity experienced (HFIES) and Household food consumption score (HFCS) and Household Dietary Diversity Score (HDDS). For each outcome, the third column represents the selection equation which reports the determinants of adoption. In the first two rows of each outcome, the determinants of the concern outcome by adoption status (respectively for non-adopters and adopters) are shown.

2.1. Determinants of impacts on household food consumption expenditure per capita

The results (table 2) show that the household size, experience in agriculture, the quantity of maize consumed in the household, holding a bank account, amount of own financial capital, use fertilizers significantly affect food consumption expenditure per capita of both adopter and non-adopters always in the same direction either positively or negatively. In fact, that means, an increase or decline in one of this variable implies an increase or a decline in food consumption expenditure per capita. Some differences between what determines expenditure per capita and food consumption expenditure per capita among adopter and non-adopters were remarked, and this explains the use of the ESR model. For example, the access to agricultural credits, the experience in agriculture and the total maize farm size are significantly and positively correlated with food consumption expenditure per capita of DTM farmer's non-adopters, but the impacts are insignificant among adopters. In

opposition, the total amount of the household assets, the gender and the awareness of climate change are significantly and positively correlated food consumption expenditure per capita of only DTM farmer's adopters.

Table 2: Endogenous switching regression result of DTM adoption and food consumption expenditure per capita of households and Household food consumption score (HFCS).

VARIABLES	household Per capita Food consumption expenditure per year in (US Dollars)			Household food consumption score (HFCS)		
	Non-adopter	Adopter	selection	Non-adopter	Adopter	selection
Household's total assets amount	-0.00 (0.00)	0.00** (0.00)	-0.00 (0.00)	0.00*** (0.00)	0.00 (0.00)	-0.00 (0.00)
Gender	0.03 (0.16)	0.26** (0.11)	0.18 (0.33)	-0.19 (0.26)	-0.08 (0.13)	0.07 (0.34)
Access to agricultural credits	0.20* (0.11)	0.03 (0.05)	0.30 (0.19)	-0.18 (0.18)	-0.04 (0.07)	0.29 (0.20)
Awareness of climate change	-0.20 (0.15)	0.13*(0.07)	0.83*** (0.26)	-0.51** (0.23)	-0.19** (0.08)	0.83*** (0.26)
Participation in Migration	-0.21 (0.20)	-0.03 (0.13)	-0.33 (0.44)	-0.40 (0.32)	0.29* (0.16)	-0.12 (0.44)
Size of the household	-0.05*** (0.01)	-0.06*** (0.01)	0.04** (0.02)	0.04* (0.02)	-0.00 (0.01)	0.05** (0.02)
Number of children under 5 years old	-0.03 (0.05)	-0.03 (0.03)	0.07 (0.10)	0.02 (0.08)	0.05 (0.03)	0.09 (0.10)
Number of children dropped from school	-0.00 (0.02)	0.01 (0.01)	-0.04 (0.03)	-0.11*** (0.03)	-0.02** (0.01)	-0.04 (0.03)
Experience in agriculture	0.01** (0.01)	-0.00 (0.00)	-0.02 (0.01)	0.03*** (0.01)	-0.01* (0.00)	-0.02* (0.01)
Contact with extension services	-0.10 (0.10)	-0.06 (0.06)	-0.38** (0.19)	0.50*** (0.16)	0.08 (0.07)	-0.38* (0.20)
Quantity of maize consumed in the household	0.00*** (0.00)	0.00** (0.00)	0.00*** (0.00)	-0.00*** (0.00)	-0.00 (0.00)	0.00** (0.00)
Holding of a bank account	0.28** (0.12)	0.25*** (0.06)	0.26 (0.21)	-0.58*** (0.19)	-0.00 (0.07)	0.39* (0.21)
Amount of Own financial capital	0.00*** (0.00)	0.00*** (0.00)	0.00 (0.00)	-0.00*** (0.00)	-0.00 (0.00)	0.00 (0.00)
Use fertilizers	0.28** (0.12)	0.19*** (0.07)	-0.58** (0.24)	0.03 (0.19)	-0.03 (0.08)	-0.66*** (0.25)
Total maize farm size	0.03*** (0.01)	0.00 (0.01)	-0.09*** (0.02)	-0.02 (0.02)	-0.00 (0.01)	-0.10*** (0.03)
Possession of a side activity	0.11 (0.10)	0.01 (0.06)	0.02 (0.19)	0.32** (0.16)	0.01 (0.07)	-0.16 (0.19)
Existence of Health centre	-0.20 (0.13)	-0.12* (0.07)	-0.01 (0.26)	0.34* (0.20)	0.10 (0.08)	0.01 (0.27)
Year of Education	0.00 (0.01)	0.00 (0.01)	0.03* (0.02)	0.03* (0.02)	0.00 (0.01)	0.03 (0.02)
Participation in an informal education	0.07 (0.05)	0.03 (0.03)	0.05 (0.10)	0.07 (0.08)	-0.10*** (0.04)	0.03 (0.11)
Awareness of DTM varieties	0.24 (0.15)	0.01 (0.07)	0.86*** (0.24)	-0.05 (0.22)	0.15* (0.09)	0.78*** (0.24)
The distance of home to Demonstration fields			-0.43*** (0.06)			-0.47*** (0.05)
The distance of home to Farm inputs shop			0.07*** (0.01)			0.08*** (0.01)
Constant	11.08*** (0.32)	11.85*** (0.21)	0.08 (0.74)	4.01*** (0.51)	3.84*** (0.26)	0.53 (0.74)
Wald chi2		143.83***			92.52***	
Log-likelihood		-427.10008			-581.65748	
lns0, lns1		-0.636***, -0.878***			-0.151**, -0.690***	
r0, r1		0.004, 0.811**			-0.331**, 0.147	
0, 1		0.529, 0.415			0.859, .501	
0, 1		0.004, 0.670***			0-.319**, 0.146	

LR test of indep. eqns.

chi2(2) = 8.83 Prob > chi2 = 0.0121

chi2(2) = 4.37 Prob > chi2 = 0.1127

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: author's estimations

The selection bias is provided by the correlation coefficients between the error terms of the selection and outcome equations (0 and 1) at the bottom part of the table of equation outcomes result. In the food consumption expenditure per capita where (0) and (1) represent respectively, the correlation coefficients of non-adopter and adopters, only 1 is positive and statistically significant, telling that there is self-selection among adopters. So, farm households with higher than average household food consumption expenditure per capita for adopter are more likely to adopt DTM varieties. Finally, the significance of the likelihood ratio tests for independence of equations indicates that there is joint dependence between the selection and food consumption expenditure per capita equations for non-adopter and adopter.

2.1. Determinants of impact on Household food consumption score (HFCS)

The household food consumption score (HFCS) estimations result (table 2) from the Endogenous Switching Regression (ESR) model by full information maximum likelihood (FIML) shows that the awareness of climate change, the number of children, dropped from school, and the experience in agriculture are statistically significant and affect HFCS of both adopter and non-adopters from the results HFCS equations (Table 31). Indeed, the positive or negative correlation with one of the variable means respectively implies an increase or a decline in HFCS.

This results also, shows that the total amount of the household assets, the household size, the contact with extension services, the possession of a side activity, the existence of health centre, the year of education are statistically significant and positively affect only the DTM non-adopters' farmers, but the impacts are insignificant among adopter (Table 1). In the other hand, only the participation in migration for agriculture purposes and awareness of DTM varieties are statistically significant and positively affect only the DTM adopter's farmers while insignificant for the DTM non-adopters' farmers. At the bottom part of table 31 of the equation of the outcome result, the correlation coefficients between the error terms of the selection and HFCS outcome equations (0 and 1) are provided and represent respectively, the correlation coefficients of non-adopter and adopters. Only 0 is negative and statistically significant, telling that there is self-selection among non-adopters.

So, farm households with lower than average household food consumption score for non-adopters are less likely to adopt DTM varieties. Also, the non significance of the likelihood ratio tests for independence of equations indicates that there is not joint dependence between the selection and household food consumption score equations for non-adopter and adopter.

Table 3: Endogenous switching regression result of DTM adoption and Household Food insecurity severity experienced (HFIES) and Household Dietary Diversity Score (HDDS).

VARIABLES	Household Food insecurity severity experienced (HFIES)			Household Dietary Diversity Score (HDDS)		
	Non-adopter	Adopter	selection	Non-adopter	Adopter	selection
Household's total assets amount	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
Gender	-0.19 (0.40)	-0.61* (0.34)	0.11 (0.34)	-0.10 (0.07)	-0.13** (0.06)	0.11 (0.31)
Access to agricultural credits	0.27 (0.28)	0.19 (0.17)	0.26 (0.21)	-0.01 (0.05)	-0.10*** (0.03)	0.31*(0.18)
Awareness of climate change	-0.31 (0.36)	-0.03 (0.21)	0.80*** (0.26)	0.07 (0.06)	0.02 (0.04)	0.60** (0.26)
Participation in Migration	-0.34 (0.49)	-0.05 (0.41)	-0.09 (0.46)	0.12 (0.09)	-0.03 (0.07)	0.04 (0.39)
Size of the household	0.02 (0.03)	0.01 (0.02)	0.04** (0.02)	-0.00 (0.01)	-0.01** (0.00)	0.03** (0.02)
Number of children under 5 years old	0.08 (0.12)	-0.01 (0.09)	0.12 (0.10)	0.03 (0.02)	0.03** (0.02)	0.10 (0.09)
Number of children dropped from school	0.02 (0.04)	-0.01 (0.03)	-0.04 (0.03)	-0.01 (0.01)	-0.01 (0.00)	-0.02 (0.02)
Experience in agriculture	0.01 (0.02)	0.00 (0.01)	-0.02 (0.01)	0.00 (0.00)	0.01** (0.00)	-0.02** (0.01)
Contact with extension services	-0.27 (0.25)	-0.33* (0.18)	-0.39** (0.20)	-0.03 (0.04)	0.11*** (0.03)	-0.38** (0.18)
Quantity of maize consumed in the household	0.00 (0.00)	0.00 (0.00)	0.00** (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00** (0.00)
Holding of a bank account	0.15 (0.29)	0.02 (0.18)	0.37* (0.21)	0.10* (0.05)	0.07** (0.03)	0.27 (0.19)
Amount of Own financial capital	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Use fertilizers	-0.28 (0.29)	0.15 (0.20)	-0.63** (0.26)	0.24*** (0.05)	0.06 (0.04)	-0.72*** (0.24)
Total maize farm size	0.01 (0.03)	0.00 (0.02)	-0.09*** (0.03)	0.00 (0.01)	0.01 (0.00)	-0.09*** (0.02)
Possession of a side activity	0.37 (0.25)	0.30* (0.18)	-0.07 (0.19)	-0.05 (0.04)	-0.08** (0.03)	-0.14 (0.17)
Existence of Health centre	0.07 (0.31)	0.12 (0.20)	0.01 (0.27)	0.13** (0.06)	0.01 (0.04)	-0.31 (0.25)
Year of Education	-0.07*** (0.03)	0.02 (0.02)	0.03 (0.02)	0.01* (0.00)	0.00 (0.00)	0.04** (0.02)
Participation in an informal education	0.32** (0.13)	0.03 (0.10)	0.02 (0.11)	0.05** (0.02)	-0.03* (0.02)	0.03 (0.10)
Awareness of DTM varieties	-0.14 (0.35)	0.26 (0.23)	0.80*** (0.24)	0.12* (0.06)	-0.12*** (0.04)	0.68*** (0.21)
The distance of home to Demonstration fields			-0.47*** (0.05)			-0.33*** (0.09)
The distance of home to Farm inputs shop			0.08*** (0.01)			0.07*** (0.01)
Constant	2.15*** (0.80)	2.24*** (0.68)	0.28 (0.75)	1.57*** (0.14)	2.16*** (0.12)	-0.00 (0.72)
Wald chi2		21.78			179.88***	
Log-likelihood		-921.12135			-96.468296	
lns0, lns1		0.288***, 0.228***			-1.470***, -1.458***	
r0, r1		-0.397**, -0.186			0.114, -1.425**	
0, 1		1.334, 1.256			0.229, .232	
0, 1		-0.377**, -0.184			0.113, -0.890***	
LR test of indep. eqns.	chi2(2) =	4.86 Prob > chi2 = 0.0879		chi2(2) =	3.91 Prob > chi2 = 0.1416	

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: author's estimations

2.2. Determinants of the impact on Household Food insecurity severity experienced (HFIES)

In Table 3, the result from the Endogenous Switching Regression (ESR) model by full information maximum likelihood (FIML) of Household Food insecurity severity experienced (HFIES) shows that none of the variables introduces in the model has a simultaneous significantly impact on the household experience of food insecurity of both adopter and non-adopters. But, variables like gender, the contact with extension services, the possession of side activity, the year of education, the Participation in an informal education somehow impact the household Food insecurity severity experienced (HFIES) whether negatively or positively. Indeed, the positive or negative correlation or impact with one of the variable means respectively implies an increase or a decline in HFIES.

In addition, it has also shown some differences between what impact HFIES among adopter and non-adopters in table 32. For instance, the possession of a side activity and only that is significantly and positively correlated with household experience of food insecurity of DTM farmer's adopters, while the impacts are insignificant among non-adopters.

On the contrary, participation in an informal education is significantly and positively correlated household experience of food insecurity of only DTM farmer's adopters.

In the result of HFIES, β_0 and β_1 are negative, but only β_0 is statistically significant and negative, telling that there is self-selection among non-adopters. The same result in the table 32 states a significant correlation coefficient and also the significance of the likelihood ratio tests for independence of equations indicates that there is joint dependence between the selection and HFIES outcome for non-adopter and adopter.

2.3. Determinant of impact of Household Dietary Diversity Score (HDDS)

On the other hand, table 3 presented the second-stage estimations of the Endogenous Switching Regression (ESR) model by full information maximum likelihood (FIML) for household Dietary Diversity Score (HDDS). Generally, the results show that the gender, the access to agricultural credits, the household size, the number of children under 5 years old in the household, the experience in agriculture, the contact with extension services, the holding of a bank account, the use or application of fertilizers, the possession of a side activity, the

existence of Health centre, the number of year of Education, the participation in informal education and the awareness of DTM varieties are significantly correlated (or impacted) with household Dietary Diversity Score (HDDS) whether specially positively or negatively on adopter and non-adopters. In fact, the positive or negative correlation (or

impact) with one of the variable means respectively implies an increase or a decline in household Dietary Diversity Score (HDDS).

A deep analysis of the results in table 33 show that the holding of bank account and the Participation in an informal education significantly affect household Dietary Diversity Score (HDDS) of both adopter and non-adopters always in the same direction either positively or negatively. But, the awareness of DTM varieties which also significantly affect household Dietary Diversity Score (HDDS) of both adopter and non-adopters is impacted in a different direction (positively for non-adopters and negatively for adopters). The HDDS model estimations provides also that the number of children under 5 years' old in the household, the experience in agriculture and the contact with extension services are only statistically significant and positive impacted the HDDS of adopters while the use of fertilizers, the existence of health centre and the number of year of Education are only statistically significant and positive impact on the HDDS of non-adopters.

In the result of HDDS, 0 and 1 are negative, but the only 1 is negative and statistically significant, telling that there is self-selection among adopters. So, farm households with lower than average household Dietary Diversity Score (HDDS) for adopters are less likely to adopt DTM varieties. The same result in table 33 states a non-significance of the likelihood ratio tests for independence of equations indicates that there is independence between the selection and HDDS outcome for non-adopter and adopter.

2.4. Impact of Adoption of DTM varieties on household food security in Benin

An essential component of the objective of this thesis is to estimate the impact of DTM adoption on the food security status of the households. This involved the counterfactual analysis and the estimation of the average treatment effect on the impact of adoption of DTM varieties food security and the result shown in table 4. Indeed, the table 4 presents the average or mean of the impact of DTM adoption. This table shows that the DTM varieties adoption significantly increase food expenditure and food security while reducing food insecurity of the DTM adopters' households.

Indeed, that DTM varieties adoption significantly increased the household food consumption expenditure per capita of the DTM adopters' households base on the ATT by 11.68 compared to 11.51 for non-adopter's households representing about 1.44% increase in household food consumption expenditure per capita of the adopter's households. This positive impact on total household expenditure may come from DTM productivity or from the potential reduction of DTM production costs. This result are consistent with Shiferaw *et al.*, (2014) and Kassie *et al.*, (2014), who respectively found at the household level, that adoption of improved varieties increases food consumption expenditure up to 2.7% and 14, 44% points in Ethiopia and Tanzania. In fact, this result is consistent with Awotide *et al.*, (2016b) finding which concludes that DTMVs adoption increase per capita consumption expenditure significantly in Nigeria using a propensity score matching approach.

Similarly, the result of the ATT shows that adopting households significantly increased their household food consumption score (HFCS) by about 17.58%. Indeed, that DTM varieties adoption significantly increased the household food consumption score (HFCS) of the DTM adopters' households base on the ATT by 3.84 compared to 2.91 for non-adopter's households. This result is not consistent with Tambo and Wünscher, (2017) funding in Ghana, the adoption of innovations contribute significantly to increase of household income but not significantly translate into the nutritious diet, measured by household dietary diversity. But, this result is consistent with Mathenge *et al.*, (2014) and Smale, Moursi, and Birol, (2015) findings.

In addition, from the estimations of ATT for the HDDS, it was suggested that adoption of DTM varieties increase household dietary diversity. Specifically, a significant increase of 1.86 index points (about 2.34% of increasing of household dietary diversity) for adopters of the DTM adoption compares to 1.82 for non-adopter's households. This result is not consistent with Tambo and Wünscher, (2017) funding in Ghana which found that innovations contribute significantly to increase of household food security. Indeed, their study finds that positive impact of innovations on household income do not significantly translate into a nutritious diet, measured by household dietary diversity. But, this result is consistent with Mathenge *et al.*, (2014) and Smale, Moursi, and Birol, (2015) findings. In fact, according to that study, there is a powerful effect on the numbers of food groups consumed by household members and the adoption of hydride varieties of maize.

Table 2: Impact of DTM adoption on the food security in farming household in Benin

Outcomes	Adoption of DTM varieties		ATT	ATT in %	T-test
	Non-adopters	Adopters			
Household food consumption expenditure per capita	11.51	11.68	0.166	1.449	5.63***
Household food consumption score (HFCS)	2.91	3.848	0.929	31.83	17.58***
Household Food Insecurity Access Scale (HFIES)	4.14	2.26	-1.88	-45.46	18.06***
Household diet Diversity Score (HDDS)	1.82	1.86	0.042	2.34	3.47***

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

Source: author's computation, estimations results

Finally, the same of ATT in table 34 shows that DTM varieties adoption significantly reduced Household Food Insecurity experience score of the DTM adopters' households base on the ATT by 2.260285 compared to 4.144288 for non-adopter's households representing about 25.32% reduction in Household Food Insecurity experience of the adopter's households. This suggests that the harvested quantity of maize does indeed convert into nutritious diets.

Conclusion

By conducting our study on the impact of Drought tolerant maize (DTM) varieties adoption on household productivity, food security and Nutritional status in Benin, we contribute to the existing literature on smart climate innovations.

For this purpose, we have based our analysis on estimations of the Treatment Effect (ATT) method for adoption DTM varieties on productivity and household welfare indicators measured by total expenditure, consumption expenditure and food security and nutritional status. To control selection bias, we have applied econometric techniques on our data from a field survey of rural farm households in Benin.

We have, in this study, grouped the different varieties of DTM adopted by the producers into one and also, we have only adopters and non-adopters according to which one of the varieties was cultivated the past agricultural campaign. However, it will be interesting to assess the gap between the different categories of adoptive parents based on the experience in adoption (the number of years since the household began cultivating incessantly) adopting DTM varieties and better to estimate how the different specific varieties of DTM contribute to household welfare. We also have a relatively small sample size, so we recommend that future searches with a large sample size allow such an analysis.

As a result of our study, using both subjective and objective indicators of food security and nutritional status, we have been able to confirm many other studies, written or oral reports (farmers' perceptions), on the important role of smart climate innovations such as DTM varieties on the livelihoods of rural farm households. As a first result, we found that the adoption of DTM varieties not significantly improves the productivity of adopter households' but increases total household spending and their level of dietary diversity in general food and nutritional security. Furthermore, one of the exciting results of our study is that because of the adoption of DTM varieties, households reduce expenditures on food purchases and also that these households are the most likely to be food secure.

Overall, it is clear that our findings highlight that adoption potentially contributes, despite this current climate change context, to improve the livelihoods of rural households. Consequently, it would be beneficial to support existing adaptation strategies and to intensify the dissemination of DTM varieties to all AEZs in Benin. Indeed, information is crucial in the adoption of agricultural technologies and more particularly improved varieties of maize including DTM where the risk perceived by maize growers can be very high. Thus, a lack of information or under-reporting could lead to an undervaluation of expected earnings and downgrade potentially profitable technology. For this reason, public and / or private bodies involved in the extension of these varieties should be encouraged and supported.

Omitted the indicator of Household Food Insecurity Access, the significant contribution to all the other indicators of food security and household nutritional status in Benin of the adoption of DTM varieties, suggests the need to undertake additional actions to ensure that the positive effects on productivity translate into an increase in the share of maize harvests reserved for consumption likely to undergo agri-food processing for better household nutrition in the area of our study. Thus, it would be beneficial that beyond the availability dimension of food security, in our study area that policies to reduce food insecurity also focus on nutritional security.

Even though our study has shown that poor rural farmers with limited resources through the adoption of DTM varieties that generate benefits on household welfare, the adoption of innovation being a dynamic process, we envision that future research involving panel data to study the long-term effects of innovations led by farmers. Finally, it would also be interesting to extend this research on the impact of DTM varieties on the schooling of children in the same study area also on the nutritional status of children and women in the same household in Benin using anthropometric measurement.

References

- Abdoulaye, T., Wossen, T., & Awotide, B. (2018). Impacts of improved maize varieties in Nigeria: ex-post assessment of productivity and welfare outcomes. *Food Security*, 10(2), 369–379. <https://doi.org/10.1007/s12571-018-0772-9>
- ACF (Action Contre la Faim). (2012). *Enhancing Climate Resilience and Food & Nutrition Security*.
- Agbossou, E., Toukon, C., Akponikpe, P. B. I., & Afouda, A. (2012). Climate Variability and Implications for Maize Production in Benin : a Stochastic Rainfall Analysis. *African Crop Science Journal*, 20(s2), 493–503.
- Alene, A. D., & Manyong, V. M. (2007). The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: An endogenous switching regression analysis. *Empirical Economics*, 32(1), 141–159. <https://doi.org/10.1007/s00181-006-0076-3>
- Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy*, 37(3), 283–295. <https://doi.org/10.1016/j.foodpol.2012.02.013>
- Audu, V. I., & Aye, G. C. (2014). The effects of improved maize technology on household welfare in Buruku, Benue State, Nigeria. *Cogent Economics and Finance*, 2(1), 1–10. <https://doi.org/10.1080/23322039.2014.960592>
- Awotide, B. A., Awoyemi, T. T., Omonona, B. T., & Diagne, A. (2016). Impact of improved agricultural technology adoption on sustainable rice productivity and rural farmers' welfare in Nigeria. *Inclusive Growth in Africa: Policies, Practice, and Lessons Learnt*, 216–237. <https://doi.org/10.4324/9781315562179>
- Below, T. B., Mutabazi, K. D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., & Tscherning, K. (2012). Can farmers' adaptation to climate change be explained by socio-economic household-level variables? *Global Environmental Change*, 22(1), 223–235. <https://doi.org/10.1016/j.gloenvcha.2011.11.012>
- Bickel, G., Nord, M., Price, C., Hamilton, W., & Cook, J. (2000). Guide to Measuring Household Food Security Revised 2000. *Agriculture*, 1–76.
- Bilinsky, A., & Paula, S. (2006). *Score de Diversité alimentaire des Ménages (SDAM) pour la mesure de l'accès alimentaire des ménages : Guide d'indicateurs VERSION 2*. 14.
- Bini, V. (2016). Food security and food sovereignty in West Africa. *African Geographical Review*, 6812(May), 1–15. <https://doi.org/10.1080/19376812.2016.1140586>
- Boarini, P. R., & Johansson, Å. (2006). Les indicateurs alternatifs du bien-être. *Cahiers Statistiques de l'OCDE*, 1(Septembre), 8.
- Boko, M., Kosmowski, F., & Vissin, E. (2012). Les Enjeux du Changement Climatique au

- Brandt, P., Kvaki, M., Butterbach-Bahl, K., & Rufino, M. C. (2017). How to target climate-smart agriculture? Concept and application of the consensus-driven decision support framework “targetCSA.” *Agricultural Systems*, 151, 234–245. <https://doi.org/10.1016/j.agsy.2015.12.011>
- Bratti, M. (2009). *Selection endogenous dummy ordered probit, and selection endogenous dummy dynamic ordered probit models*.
- Burton, I. (1997). Vulnerability and adaptive response in the context of climate and climate change. *Climatic Change*, 36(1–2), 185–196. <https://doi.org/10.1023/a:1005334926618>
- Campbell, B. M., Thornton, P., Zougmore, R., van Asten, P., & Lipper, L. (2014). Sustainable intensification: What is its role in climate smart agriculture? *Current Opinion in Environmental Sustainability*, 8, 39–43. <https://doi.org/10.1016/j.cosust.2014.07.002>
- CIMMYT-IITA. (2015). *Maïs résistant à la sécheresse*. 4(1), 1–4.
- Coates, J., & Bilinsky, P. (2007). *Echelle de l' Accès déterminant l' Insécurité alimentaire des Ménages (HFIAS) pour la Mesure de l' Accès alimentaire des Ménages : Guide d' Indicateurs VERSION 3*. 1–17.
- Cooper, P., Cappiello, S., Vermeulen, S., & Campbell, B. (2013). *Large-scale implementation of adaptation and mitigation actions in agriculture*.
- Dembélé, N. N. (2001). Sécurité alimentaire en Afrique Sub-saharienne: Quelle Stratégie de Réalisation? In *Ageconsearch.Umn.Edu*.
- Dercon, S. (2006). La vulnérabilité: une perspective microéconomique. *Revue d'économie Du Développement*.
- Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, 19(2), 248–255. <https://doi.org/10.1016/j.gloenvcha.2009.01.002>
- Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 825–842. <https://doi.org/10.1093/ajae/aar006>
- Droy, I., Ced, I. R. D., & Bordeaux, U. De. (2004). ENTRE CYCLONES ET MARCHES MONDIAUX : LA VULNERABILITE DES MENAGES RURAUX DE LA COTE EST DE La problématique de la Côte Est de Madagascar Les données disponibles : des enquêtes ménages en panel. *Ged.U-Bordeaux4.Fr*, 1–18.
- DTMA, P. (2009). *Definitions of common terms used in the DTMA Project*.
- Everts, E. (2003). Identifying a particular family humor style: A sociolinguistic discourse analysis. *Humor*, 16(4), 369–412. <https://doi.org/10.1515/humr.2003.021>
- FAO. (2013). *Evaluation de la Sécurité Alimentaire des ménages ruraux dans les zones Sahélienne et soudanienne du Tchad*.
- FAO, & PAM. (2009). *Etat de l'insécurité alimentaire dans le monde 2009 : Crises économiques, répercussions et enseignement*.

- Fieldsend, A. (2013). Facilitating Innovation In Agriculture: Lessons From A European Perspective. *Agricultural Economics and Rural Development*, (2), 177–190.
- Fisher, M., Abate, T., Lunduka, R. W., Asnake, W., Alemayehu, Y., & Madulu, R. B. (2015). Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. *Climatic Change*, 133(2), 283–299. <https://doi.org/10.1007/s10584-015-1459-2>
- Food and Agriculture Organisation. (2016). *Voices of the Hungry Technical Report* (Vol. 2016).
- Füssel, H. M., & Klein, R. J. T. (2006, April). Climate change vulnerability assessments: An evolution of conceptual thinking. *Climatic Change*, Vol. 75, pp. 301–329. <https://doi.org/10.1007/s10584-006-0329-3>
- Gbêtondji, M. A. N., & Porgo, M. (2014). *Effect of climate change on cereal yield: evidence from Benin and Burkina Faso*. 1–16.
- Gnangle, P., Egah, J., Baco, M., Gbemavo, C., Kakai, R., & Sokpon, N. (2012). Perceptions locales du changement climatique et mesures d'adaptation dans la gestion des parcs à karité au Nord-Bénin. *International Journal of Biological and Chemical Sciences*, 6(1), 136–149. <https://doi.org/10.4314/ijbcs.v6i1.13>
- Golay, C. (2010). Crise et sécurité alimentaires : vers un nouvel ordre alimentaire mondial ? *Revue Annuelle de Politique de Développement – Genève*, (1), 229–248. <https://doi.org/10.4000/poldev.133>
- Gonfa, L. (2015). *Farmers' willingness to pay for improved forage seed in LIVES Districts of west Shewa Zone, Ethiopia*.
- Halpin, B. (2017). SADI: Sequence analysis tools for stata. *Stata Journal*, 17(3), 546–572. <https://doi.org/The Stata Journal>
- Hoddinott, J., & Yohannes, Y. (2002). *Dietary Diversity as a Household Food Security Indicator*. 136(May), 4.
- Holden, S. T., & Fisher, M. (2015). Subsidies promote use of drought tolerant maize varieties despite variable yield performance under smallholder environments in Malawi. *Food Security*, 7(6), 1225–1238. <https://doi.org/10.1007/s12571-015-0511-4>
- Hu, M., Fu, X., Cui, Y., Xu, S., Xu, Y., Dong, Q., & Sun, L. (2015). Expression of KAP1 in epithelial ovarian cancer and its correlation with drug-resistance. In *International Journal of Clinical and Experimental Medicine* (Vol. 8). <https://doi.org/10.1596/978-0-8213-8077-2>
- Hubert, B., & Caron, P. (2009). Imaginer l'avenir pour agir aujourd'hui, en alliant prospective et recherche : l'exemple de la prospective Agrimonde. *Natures Sciences Sociétés*, 17(4), 417–423. <https://doi.org/10.1051/nss/2009060>
- INSAE. (2015). *Enquête Modulaire Intégrée sur les Conditions de Vie des ménages 2ème Edition (EMICoV-Suivi 2015): Note sur la pauvreté au Bénin en 2015*.
- IPCC. (2014). *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.
- John K. M. Kuwornu, Al-Hassan, R. M., Etwire, P. M., & Osei-Owusu, Y. (2013). Adaptation Strategies of Smallholder Farmers to Climate Change and Variability : Evidence from

- Northern Ghana. *Information Management and Business Review*, 5(5), 233–239.
- Kakwani, N., & Son, H. H. (2016). Measuring Food Insecurity: Global Estimates. *Social Welfare Functions and Development*, 253–294. https://doi.org/10.1057/978-1-137-58325-3_9
- Kassie, G. T., Abdulai, A., Greene, W. H., Shiferaw, B., Abate, T., Tarekegne, A., & Sutcliffe, C. (2017). Modeling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in Rural Zimbabwe. *World Development*, 94, 465–477. <https://doi.org/10.1016/j.worlddev.2017.02.008>
- Kassie, M., Jaleta, M., & Mattei, A. (2014). Evaluating the impact of improved maize varieties on food security in Rural Tanzania: Evidence from a continuous treatment approach. *Food Security*, 6(2), 217–230. <https://doi.org/10.1007/s12571-014-0332-x>
- Kurukulasuriya, P., & Mendelsohn, R. (2008). How Will Climate Change Shift Agro-Ecological Zones and Impact African Agriculture? *Policy Research Working Paper 4717*, (September).
- Lokonon, B. O. K., Savadogo, K., Mbaye, A. A., & others. (2015). Assessing the impacts of climate shocks on farm performance and adaptation responses in the Niger basin of Benin. *African Journal of Agricultural and Resource Economics Volume*, 10(3), 234–249.
- Long, T. B., Blok, V., & Coninx, I. (2016). Barriers to the adoption and diffusion of technological innovations for climate-smart agriculture in Europe: Evidence from the Netherlands, France, Switzerland and Italy. *Journal of Cleaner Production*, 112, 9–21. <https://doi.org/10.1016/j.jclepro.2015.06.044>
- Malikov, E., & Kumbhakar, S. C. (2014). A generalized panel data switching regression model. *Economics Letters*, 124(3), 353–357. <https://doi.org/10.1016/j.econlet.2014.06.022>
- Manda, J., Gardebroek, C., Khonje, M. G., Alene, A. D., Mutenje, M., & Kassie, M. (2016). Determinants of child nutritional status in the eastern province of Zambia: the role of improved maize varieties. *Food Security*, 8(1), 239–253. <https://doi.org/10.1007/s12571-015-0541-y>
- Mathenge, M. K., Smale, M., & Olwande, J. (2014). The impacts of hybrid maize seed on the welfare of farming households in Kenya. *Food Policy*, 44, 262–271. <https://doi.org/10.1016/j.foodpol.2013.09.013>
- Munz, E. D. (2017). Psychotherapie in der Psychiatrie. In *Nervenheilkunde* (No. 10). <https://doi.org/10.1007/s13398-014-0173-7.2>
- Ndiaye, M. (2014). Indicateurs de la sécurité alimentaire. In *Programme Alimentaire Mondial , Bureau Régional pour l’Afrique de l’Ouest, Dakar: Intégrer les programmes de nutrition et de sécurité alimentaire en situation d’urgence et pour le renforcement de la résilience, Atelier Régional de Formation: 10-12 Juin 20.*
- Nyasimi, M., Kimeli, P., Sayula, G., Radeny, M., Kinyangi, J., & Mungai, C. (2017). Adoption and Dissemination Pathways for Climate-Smart Agriculture Technologies and Practices for Climate-Resilient Livelihoods in Lushoto, Northeast Tanzania. *Climate*, 5(3), 63. <https://doi.org/10.3390/cli5030063>

- OECD. (2008). OECD Reviews of Innovation Policy: China 2008. *OECD Reviews of Innovation Policy*, (June), 395–423. <https://doi.org/10.1787/9789264039827-en>
- Ofuoku, A. U. (2011). Rural Farmers' Perception of Climate Change in Central Agricultural Zone of Delta State, Nigeria. *Indonesian Journal of Agricultural Science*, 12(2), 63. <https://doi.org/10.21082/ijas.v12n2.2011.63-69>
- Parry, M., Rosenzweig, C., Iglesias, A., Fischer, G., & Livermore, M. (1999). Climate change and world food security: A new assessment. *Global Environmental Change*, 9(SUPPL.), S51–S67. [https://doi.org/10.1016/S0959-3780\(99\)00018-7](https://doi.org/10.1016/S0959-3780(99)00018-7)
- Paunov, C. (2013). Innovation and Inclusive Development. *OECD Publishing*, 67. <https://doi.org/10.1787/5k4dd1rvsnjj-en>
- Peterson, J. E. (2014). Christopher M. Davidson. After the Sheikhs: The Coming Collapse of the Gulf Monarchies. In *Asian Affairs* (Vol. 45). <https://doi.org/10.1080/03068374.2014.874687>
- Shiferaw, B, Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia Bekele Shiferawa,† , Menale Kassie b , Moti Jaleta c , Chilot Yirga d - Tìm v i Google. *Elsevier*, 44, 272–284.
- Shiferaw, Bekele, Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44, 272–284. <https://doi.org/10.1016/j.foodpol.2013.09.012>
- Shiferaw, Bekele, Tesfaye, K., Kassie, M., Abate, T., Prasanna, B. M., & Menkir, A. (2014). Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather and Climate Extremes*, 3, 67–79. <https://doi.org/10.1016/j.wace.2014.04.004>
- Smale, M., Moursi, M., & Birol, E. (2015). How does adopting hybrid maize affect dietary diversity on family farms? Micro-evidence from Zambia. *Food Policy*, 52, 44–53. <https://doi.org/10.1016/j.foodpol.2015.03.001>
- Smit, B., McNabb, D., & Smithers, J. (1996). Agricultural adaptation to climatic variation. *Climatic Change*, 33(1), 7–29. <https://doi.org/10.1007/BF00140511>
- Smithers, J., & Blay-Palmer, A. (2001). Technology innovation as a strategy for climate adaptation in agriculture. *Applied Geography*, 21(2), 175–197. [https://doi.org/10.1016/S0143-6228\(01\)00004-2](https://doi.org/10.1016/S0143-6228(01)00004-2)
- Tambo, Justice A., & Wünscher, T. (2017). Farmer-led innovations and rural household welfare: Evidence from Ghana. *Journal of Rural Studies*, 55, 263–274. <https://doi.org/10.1016/j.jrurstud.2017.08.018>
- Tambo, Justice Akpene, & Abdoulaye, T. (2012). Climate change and agricultural technology adoption: The case of drought tolerant maize in rural Nigeria. *Mitigation and Adaptation Strategies for Global Change*, 17(3), 277–292. <https://doi.org/10.1007/s11027-011-9325-7>
- Technical, N., Project, A., Development, E., Ave, C., & Washington, N. W. (2005). *Measuring Household Food Insecurity Workshop II Report October 19, 2005*.
- Tesfaye, W., & Tirivayi, N. (2018). The impacts of postharvest storage innovations on food

- security and welfare in Ethiopia. In *Food Policy* (Vol. 75).
<https://doi.org/10.1016/j.foodpol.2018.01.004>
- Tidjani, M. A., & Akponikpè, P. B. I. (2012). Evaluation des stratégies paysannes d'adaptation aux changements climatiques : cas de la production du maïs au nord-Bénin. *African Crop Science Journal*, 20(Suppl. 2), 425–441.
- Wooldridge, J. M. J. (2011). Front matter. In *Neurology Secrets* (2nd ed.).
<https://doi.org/10.1016/B978-0-323-05712-7.00031-3>
- Wossen, T., Abdoulaye, T., Alene, A., Feleke, S., Menkir, A., & Manyong, V. (2017). Measuring the impacts of adaptation strategies to drought stress: The case of drought tolerant maize varieties. *Journal of Environmental Management*, 203, 106–113.
<https://doi.org/10.1016/j.jenvman.2017.06.058>
- Yegbemey, R. N., Yabi, J. A., Tovignan, S. D., Gantoli, G., & Haroll Kokoye, S. E. (2013). Farmers' decisions to adapt to climate change under various property rights: A case study of maize farming in northern Benin (West Africa). *Land Use Policy*, 34, 168–175.
<https://doi.org/10.1016/j.landusepol.2013.03.001>
- Yohannes, Y. (2002). *NUTRITION TECHNICAL Dietary Diversity as a Household Food Security Indicator* John Hoddinott.
- Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2017). Agricultural technology adoption and child nutrition enhancement: improved maize varieties in rural Ethiopia. *Agricultural Economics (United Kingdom)*, 48(5), 573–586.
<https://doi.org/10.1111/agec.12358>
- Zongo, B., Diarra, A., Barbier, B., Zorom, M., Yacouba, H., & Dogot, T. (2015). Farmers' Practices and Willingness To Adopt Supplemental Irrigation in Burkina Faso. *International Journal of Food and Agricultural Economics*, 3(1), 101–117.

This paper was presented at the Conference on Climate Change and Food Security in West Africa co-organized by Université Cheikh Anta Diop de Dakar (UCAD) and Center for Development Research (ZEF), University of Bonn, on 17-18 November 2019 in Dakar, Senegal.