Impact of the adoption of sustainable land management technologies on allocative inefficiency of smallholder farmers: Evidence from North-East Benin

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ABSTRACT

Declining soil fertility is one of the major agricultural problems in Republic of Benin. It leads to low yields and high production costs of crops. To improve soil fertility and alleviate its consequences, ISFMT are continuously promoted in the country. This paper makes an empirical contribution in addressing the paucity of evidence regarding the heterogeneous effect of ISFMT adoption on Allocative Inefficiency (AI) of maize farms. A correlated random coefficient model assuming a factor-structure for the unobserved covariates combined with instrumental variables (IV) was specified. The multinomial endogenous treatment and mixed discrete-continuous outcome were jointly estimated using the Generalized Structural Equation Model (GSEM) package. The model is estimated for a sample of 431 maize producers located in 19 villages in north-East of Republic of Benin with four ISFMT (Mucuna pruriens (MP), Crop Residue (CR), Cattle Manure (CM), and Pigeon Pea (PP)), The results consistently suggest that adopting any of the four ISFMT, significantly decreases the AI scores of the maize farms. On average, the largest decrease of maize farm AI stems from adopting *PP*, followed by CM and CR. Moreover, we find that the effects of adopting ISFMT vary depending on the gender of farmer, the use of mineral fertilizer and whether the maize farm is located in cotton area of the north of Republic of Benin. To reduce the AI of maize farm, policy makers should put more emphasis in ISFMT promotion for wider adoption by Beninese maize farmers

JEL classification : H21 ; Q16 ; Q18 ; O33 ; Q12 ; Q15

KEY WORDS: Maize producers, ISFMT, heterogeneous impact, Allocative Efficiency, correlated random coefficient model, Republic of Benin

1. INTRODUCTION

Sustainability has been a widely discussed and topical concept in the scientific community in recent years, since the Rio de Janeiro Earth Summit in 1992. At the heart of these debates, the issue of the preservation of natural resources in the image of the soil, which as a base and support for food production, is seriously threatened. Indeed, land pressure as a consequence of demographic pressure generates an abusive and irrational exploitation of natural resources (PSI/GDT). This results in soil degradation which has been widely addressed in soil socio-economics (Adjolohoun et al., 2013; Avakoudjo et al., 2013). This results in a decline in soil fertility (Azontondé et al., 2009) marked by the decline in soil nutrients such as nitrogen, phosphorus and potassium which regress (Azocli et al., 2015; Kombienou et al., 2015a).

Faced with this land degradation, several strategies or technologies have been developed through the joint action of farmers as well as through research. We have Sustainable Land Management Technologies (SLMT). These technologies are recognized around the world as an instrument for combating land degradation and, in turn, a mechanism for increasing land productivity (Martey et al., 2021) guaranteeing improved incomes (Martey et al., 2021) and a way to ensure food (Nkomoki et al., 2018; Sileshi et al., 2019) and nutrition (Kim et al., 2019; Manda et al., 2016; Zeng et al., 2017) of households. Although it should not be a panacea, they represent a way out for many producers faced with this problem. However, in view of this, these SLMT are poorly adopted (Mugwe et al., 2009; Ngwira et al., 2014; Vidogbéna et al., 2016).

While several studies have highlighted the role of certain key factors in explaining this low adoption rate (Etsay et al., 2019; Nigussie et al., 2017), others have highlighted economic parameters such as profitability of these technologies as an important aspect of their adoption (Giger et al., 2018; Tanto and Laekemariam, 2019). However, the poor combination of production factors could also be an obstacle to their adoption. Thus, in a recent study on mineral fertilizer, Legesse et al., (2019) showed that technical inefficiency reduces profitability, which discourages adoption. Also, results from a study in Zambia showed that the use of ISFMT improves the technical efficiency of hybrid maize production among smallholder farmers (Tchale et al., 2005). These studies have the merit of highlighting the role of efficiency in the literature on the adoption of ISFMT. This is all the more so as the agricultural policies that have developed and popularized these technologies ultimately expect an increase in yields and therefore producers who maximize their production. However, Nisrane et al., (2011) estimated the average level of agricultural efficiency of smallholder farmers in Ethiopia at 0.46 between 1994 and 2009, indicating that an average farmer produces less than half of the value of production produced by the most efficient farmer using the same technology and the same inputs. These results indicate that it is indeed possible to increase agricultural production at a certain level of input use. It is therefore imperative to provide empirical evidence on the effectiveness of the use of these technologies.

This article adds to the existing literature on technology efficiency impact analysis in the following ways. First, we investigate (for the first time, to our knowledge) the economic efficiency of adopting multiple ISFMT. Most studies have focused on technical (Issahaku and Abdulai, 2020a; Ndlovu et al., 2014; Selejio et al., 2018) and environmental (Abdulai and Abdulai, 2016; Issahaku and Abdulai, 2020) efficiency. Only the study conducted in Zimbabwe by Musara et al., (2012) mentioned the economic efficiency of mineral fertilizer. Generally, recent work on efficiency has paid little attention to SLMT (Gebregziabher et al., 2012; Sherlund et al., 2002). Second, we contribute to the literature on the impact of the adoption of SLMT by the analytical approach employed in this study, in addition to the use of the control function to control for possible selection bias and endogeneity bias. These two biases are those commonly encountered in adoption studies. Issahaku and Abdulai, (2020) used the stochastic production frontier corrected for selectivity bias to account for the potential bias of both observed and unobserved factors. However, this approach is limited because it does not take into account the truncated nature of our independent variable (efficiency score) which is more appropriately expressed as a nonlinear corner solution. Moreover, given the categorical nature of our dependent variable, the pioneering work of Deb and Trivedi (2006) provided the basis for estimating these general linearized models based on two treatments. In this extension Mújica-Mota et al., (2020) proposed another model based on the work of Deb and Trivedi, (2006) but with three treatments in their equation. This work is a first since it is based on 5 treatments. Third, we contribute to the limited empirical evidence on the effectiveness impacts of gender in ISFMT adoption.

The rest of the paper is organized as follows. Section 2 presents the background. Section 3 relates the theoretical and empirical framework. Section 4 presents the econometric framework for a control function model and an estimate of average treatment effects. Next comes a presentation of the empirical specifications of our estimation model. In Section 5, we discuss our estimation results and discussion. The last section concludes and draws the main findings and policy implications.

2. BACKGROUND

Benin's agricultural productive sector is characterized by the predominance of small farms and by its vulnerability to climate variability and extreme weather events. This sector suffers from the still low level of productivity and production of agricultural, pastoral and fisheries priority agricultural sectors (PSDSA, 2017). Incomes and productivity are low and the labor force is only partially valued, which makes agricultural products very uncompetitive. Most farmers make very little use of improved inputs and engage in mining practices that accentuate the degradation of natural resources. Crop production is affected by the characterized degradation of cultivated areas (Amonmide et al., 2019; Kombienou et al., 2015). This has as a corollary the decline in soil fertility which negatively influences the yields of food crops, mainly maize, which fell from 1422 kg.ha^{-1} in 2011 to 1281 kg.ha^{-1} in 2015, with an average of 1347 kg.ha^{-1} over the same period, in particular because of bad weather conditions. In Benin, sustainable land management is advocated for smallholder farmers to combat declining soil fertility. SLMT typically incorporate practices of integrated soil fertility management (ISFM), conservation agriculture (CA), soil and water conservation (SWC), agroforestry (AF) and the integrated agriculture and livestock (IAE). There is a compendium on the subject which details the specificities of each family of SLM. If it is not easy to situate in time the endogenous technologies which have been practiced for several centuries by the populations in order to deal with the problems of declining soil fertility, it is more or less easy to situate in time the beginning of the use of new soil fertility management technologies (Adégbola et al., 2002). Studies of SLM technologies in the social sciences have focused exclusively on the socio-economic determinants and rate of adoption of SLMT (Adebiyi et al., 2019; Adekambi et al., 2021; Riemer, 2018), on the economic impact and profitability of SLM technologies (Adégbola and Adékambi, 2006; Adjiba et al., 2019; Tovihoudji et al., 2021) and on peasant perception, research and popularization of SLMT (Egah et al., 2014). These studies help to understand the factors that motivate or demotivate the adoption of these SLM technologies and their impact on the well-being of producers. However, adoption can only be explained by these factors. The allocation of these resources for obtaining maximum output (TE) or the combination of these inputs in order to minimize costs with the aim of obtaining maximum output (Allocative Efficiency = EA) is not suggested in the Beninese literature on the SLM, however, is an important element that can enhance the low adoption rates obtained. However, as reported elsewhere, SLM technologies have the capacity to improve the efficiency of producers (Legesse et al., 2019b; Selejio et al., 2018; Tchale et al., 2005). In Benin, there is no empirical evidence that has produced confirmation of these results obtained elsewhere. This study focuses on 4 selected technologies, the maize of which is the supply of complementary nutrients compared to a technology taken individually. Pigeon pea and Mucuna pruriens as a cover crop enhance biomass and enrich the soil with organic plant matter and fight soil erosion. The cow house is a strong means of supplying organic matter of animal origin to the soil. Finally, the management of harvest residues makes it possible to preserve agro-biodiversity at soil level in order to allow the microbiological activity essential for soil fertilization. Do the producers effectively combine the different inputs necessary for their implementation?

3. THEORITHICAL FRAMEWORK

3.1 Modeling the heterogeneous effect of ISFMT adoption on allocative inefficiency

The theoretical framework underlying this study combines both the production theory and the latent variable model. The production theory provides the analytical framework for maize farms' AI analysis and for making assumptions about the behavior of these farms when their environment changes (Debertin, 1986). Furthermore, evaluation of ISFM practices adoption effects on maize farms AI scores is grounded in this study on the latent variable (index function) models. They provide a framework for combining economic theory and "structural econometric analysis" in causal treatment effects evaluation (Heckman and Vytlacil, 2007, pp. 4782–4783). Accordingly, the AI outcome is modelled in terms of its determinants as specified by production theory. In addition, the framework models both the adoption of ISFMT and its dependence with the AI outcome as produced by the variables common to the two equations.

To outline the latent variable models, we assume that each maize farm seeks to minimize their level of AI. We are interested in assessing the causal impact of the adoption of ISFMT on AI of maize farms. The set of ISFMT studied is T $\{t = 0, \cdots, 4\}$, with $t = 0$ corresponding to the status of non-adoption. Following Carneiro et al., (2003) and Heckman et al. (2007, P.4792), we define for each maize farm, a score AI associated with and without adoption of ISFMT t as Y_t and Y_0, respectively. The Y_t and Y_0 are outcomes realized after adoption or no adoption of the ISFMT t by the maize farm. The outcomes Y_t may be discrete, continuous or mixed discrete-continuous random variables (Heckman et al. 2007, P.4792). Furthermore, let $A_t = 1$ denotes the adoption of an ISFMT t; $A_0 = 0 \ for \ t \neq 0$ denotes the non-adoption of an ISFMT t. The measured AI score, Y_t associated with adoption of an ISFMT t can be written as follows:

$$Y_t = Y_0 + (Y_1 - Y_0)t_1 + (Y_2 - Y_0)t_2 + (Y_3 - Y_0)t_3 + (Y_4 - Y_0)t_4 \qquad (1)$$

where the subscripts indicate the adoption and non-adoption status of ISFMT t (MP =4, CR =3, CM =2, PP =1 and non-adoption=0), and we omit the individual subscripts to simplify notation. The equation (1) is an example of Potential outcomes Model, where a maize farm is observed to have one of five of potential outcomes, depending on which ISFMT is adopted. This model can be used to estimate structural econometric models (Aakvik et al., 2002). In this study we consider a generalized Roy model which is a variant of the Potential outcomes Model (Heckman et al. 2007, P.4811). Following Carneiro et al., (2003) and Heckman and Vytlacil (2007; P: 4811), we model the potential farms AI scores conditioning to variables X as follows:

$$Y_0 = X_0\beta_0 + U_0 \tag{2}$$

$$Y_t = X_t\beta_t + U_t \tag{3}$$

where in each potential outcome of adoption and non-adoption of a ISFMT t; $X_{(0,t)}$ is the observed characteristics of various farms and farmers, such as the management practices of farmer including managerial characteristics such as adoption status of ISFMT t (Solis et al., 2007), socio-economic and demographic characteristics and the characteristics of the maize production environment; $\beta_{(0,t)}$ are coefficients to be estimated and $U_{(0,t)}$ is the stochastic term which captures the unobserved characteristics. It fulfilled the condition $E\left[U_{(0,t)}|X_i\right] = 0$. The application of the "structural" approach in this study derives $X_{(0,t)}\beta_{(0,t)}$ from the production theory. The expected score of AI resulting from adoption and non-adoption of a ISFMT t are not observed when the farmer becomes aware of the ISFMT. However, to link the "potential outcomes framework to the literature on structural econometrics, we assume that they can be inferred by a latent variable A_t^*. Furthermore, assume that the maize farms are profit-maximizers. Accordingly, A_t^* represents the expected net differential profit $\left(E(\pi_t - \pi_0)\right)$, deriving from the adoption or non-adoption decisions of an ISFMT t (Adegbola, 2010; Dimara and Skuras, 2003). The adoption decisions process is expressed as follows:

$$A_t^* = \mathrm{\mu_A(t, 0, X, Z)} - V_t, \tag{4}$$

with

$$A_t = \begin{cases} t & if \quad A_t^* > 0 \\ 0 & if \quad A_t^* \leq 0 \end{cases}$$

Since there are five mutually exclusive ISFMT including the non-adoption, $\sum_{t=0}^{4} A_t = 1$ (Carneiro et al., 2003). The observed (by the econometrician) variables X and Z affect the adoption of the ISFMT. The covariates X are common with the outcome equations (2) and (3), while one or more variables Z are excluded from the latter; $\mathrm{\mu_A(t, 0, X, Z)}$ is the deterministic component and V_t is an i.i.d. error term indicating unobserved heterogeneity in the propensity for treatment. $\left(U_{(0,t)}, V_t\right)$ is unobserved. The random variable V_t may be a function of $U_{(0,t)}$. A_t^* is interpretable as the net gain from adoption decision (because individuals adopt an ISFM technology if $A_t^* > 0$). The latent variable model presented in Eq. (4) underlies the large majority of discrete choice models uncounted in the econometric literature (Maddala, 1983; McFadden, 1981). Following Amemiya, (1985, p. 286), Cameron and Trivedi, (2005, p. 496), the probability that a maize farm adopts an ISFMT t is a function of the independent variables and parameters and written as follows:

$$P_t = Pr(A_t^* = t) = F_t(X\delta_t), \quad t = 0, \cdots, 4. \tag{5}$$

where $F_t(\cdot)$ is the cumulative distribution function of the error term V_t in Eq. (4). Different functional specifications for F_t correspond to specific models, notably multinomial logit; nested logit, multinomial probit, ordered, sequential, and multivariate models (Cameron and Trivedi, 2005, p. 496).

The individual level causal effect of adoption on maize farm scores AI, is the differential AI scores between the adoption and non-adoption decisions of the ISFMT t and is given by $\Delta_t =$

$Y_t - Y_0 \;\; \boldsymbol{t \neq 0}$ (Carneiro et al., 2003; Heckman and Vytlacil, 2007, p. 4793). However, at a given time, we observe any farmer in one of the five possible adoption status. We do not know the AI score of the farm in other status and hence cannot directly estimate the individual level treatment effects (Heckman, 2007; p. 4814). Therefore, the population level effects parameters are mostly evaluated. Both Average Treatment Effect (ATE) and conditional Average Treatment Effect ($ATE|$ x) have been the focus of many economic impact evaluation studies. The former estimates for a farmer selected in the population, its mean gain for moving from non-adoption status of ISFMT $t = 0$, to adoption of ISFMT t status. The latter is evaluated for subpopulation with given observed characteristics $X_i = x$. Both parameters are respectively expressed as follows:

$$ATE(t, 0) = E[AE, A_t = 1] - E[AE, A_0 = 0] \quad (6)$$

$$ATE(t, 0 \mid \mathrm{x}) = E\,[AE \mid x, A_t = 1] - E\,[AE \mid x, A_0 = 0] \quad (7)$$

The Average Treatment Effect on Treated ($ATE1$ or ATT) and conditional Average Treatment Effect on treated ($ATE1|$ x) are also widely estimated. The latter estimates how those individuals with observed characteristics $X_i = x$ that are currently adopted the ISFMT benefit from them on average (Cornelissen et al., 2016, p. 9).

To define the causal effects in terms of economically interpretable parameters, following Heckman (2007, p. 4784) we relate the treatment effect model in Eq. (1) to structural econometric model as follows:

$$Y_t = \delta + X\gamma + A_t\tilde{X}\lambda + A_t\bar{\eta}_t + e_t, \quad (8)$$

where Y_t is the predicted farm-specific AI scores, δ is the constant of the model, X is the vector of explanatory variables that have potential influence on Y_t; $\gamma = \beta_0$, $\lambda = \beta_t - \beta_0$, $\eta_t = U_t - U_0$, and $\varepsilon_t = U_0$; $\bar{\eta}_t = E[\eta_t]$ is the mean of η_t; $\widetilde{\eta_t} = \eta_t - E[\eta_t]$ is the deviation of η_t from its mean; $e_t = A_t\widetilde{\eta_t} + \varepsilon_t$ is a composite error term comprising the interaction term of deviation from ATE, $\widetilde{\eta_t}$ with A_t and the error term ε_t; $\widetilde{X_t} = X - \bar{X}$ is demeaned explanatory variables; Y_t is a mixed discrete-continuous random variable (Carneiro et al., 2003). The first coefficient on the adoption binary dummy A_t, is the Average Treatment Effect conditional on $X = x$, $ATE(X) = \tilde{X}\lambda$. It estimates the average gain of an ISFMT adoption for a farmer with characteristics X, randomly selected. By demeaning the covariates X before interacting them with A_t we ensure that $\bar{\eta}_t$ is the average treatment effect at means of X. With this linear specification it is also the unconditional ATE. The second coefficient on the adoption binary dummy A_t, $\bar{\eta}_t$ the mean of $\eta_t = U_{ti} - U_{0i}$, is referred to as the idiosyncratic gain for a particular ISFMT adoption (Heckman, 1997). It constitutes the unobserved heterogeneity which implies that the effect of ISFMT adoption may vary across maize farmers even after controlling for observable heterogeneity using covariates X. The sum of the two coefficients on the adoption binary dummy A_t gives the individual adoption effect Δ_i on individual farm AI scores associated with adoption of ISFMT.

To outline the heterogeneous response model, in more formal terms, let's assume that both unobserved components in the error term e_t are linearly related to the error term V_t in the ISFMT adoption equation, Eq. (4). From this assumption two important sub-cases of the heterogeneous response model are derived. First, we hypothesize that A_t is statistically independent of $\widetilde{\eta_t}$ that's to say $(U_t - U_0)$, given X and hence are uncorrelated as would occur when treatment is randomized across farmers. But A_t is related to ε_t only. This means that farmers who are more likely due to unobserved characteristics adopt ISFMT differ in their pre-treatment characteristics from farms who are less likely to adopt. These characteristics may include the farmer's motivation, level of knowledge and innate managerial and technical abilities in understanding and using the ISFMT (Abdulai and Huffman, 2014). We conclude that, after controlling for the observables X, adoption of ISFMT by farmers is not based on the idiosyncratic gains associated with them (Cornelissen; et al. 2016). Second, we suppose that the error term e_t in Eq. (8) depends linearly on the unobservable V_t in Eq. (4). The adoption individual level causal effect Δ_t varies even after accounting for X. This case arises because as discussed earlier, farmers adopt the ISFMT on the basis of partial or full knowledge of their idiosyncratic gains resulting from adoption. In consequence $\widetilde{\eta_t}$ and A_t are positively correlated, even conditional on X, resulting in $E[A_t\widetilde{\eta_t}|A_t = 1] > E[A_t\widetilde{\eta_t}|A_t = 0]$. This implies that, in addition to respond differently to adoption of ISFMT, farmers with the same X are influenced by their knowledge of their idiosyncratic gains. This phenomenon is distinct from that of selection bias. Eq. (8) is referred as the "CRC*" or "*heterogeneous treatment effect" or "essential heterogeneity" model. This is the model specified in this paper to analyze the heterogeneous effect of adoption of ISFMT on maize farm AI. Several econometric models were developed to handle the issue of interaction of treatment effect with unobserved heterogeneity.

4. STUDY AREA

The study was carried out in the ProSOL project intervention area located in the north-east of Republic of Benin. The area comprises seven counties which form part of the Agricultural Development Hub (ADH) 2. The study was conducted in Kandi, Gogounou and Bembérèké town. The ADH two is subdivided in three homogenous Agricultural Development Sub-Hubs (ADSH) (Adégbola et al. 2018). It lies between latitudes N 10°00' et N 11°20'; and longitudes E 1°20' et E 4°00'. Rainfall distribution in the ADH 2 is unimodal pattern, allowing for one cropping season lasting from July to September and a dry season from October to April. This results in a growing period ranging from 180 to 200 days. The average annual rainfall is 1 005 mm. Temperatures range from a minimum of 22.4 °C, to a maximum of 34.7 °C, with an annual average of 28.45 °C. The predominant soil types are ferralitic and ferruginous soils. Raw and little evolved mineral soils are also encountered in the area. The soils have good physical properties, poor chemical characteristics and therefore of low fertility (Amonmide et al., 2019). About 80% of these soils have a level of fertility below the average (Adégbola et al, 2018). Due to continuous cropping without adequate replenishment, the soils in this area undergo a very strong chemical degradation. This includes deficiencies in organic matter, phosphorus, nitrogen, cation exchange capacity and exchangeable bases. The ADH 2 location has a high (low) population density of an average of 36 about inhabitants per km2. Population pressure has resulted in increased land-use intensity and has shorten the duration of natural fallows. The main economic activity undertaken in ADH 2 is rainfed subsistence agriculture. The dominant land-use systems are cash crops, annual staple food and livestock. The main cash crop is cotton (*Gossypium sp*) followed by the cashew nuts (*Anacardium occidentale*). ADH 2 is ranked the first cotton producer area in Benin in 2016 with 73% of national cotton production. The most important staple food crops are: sorghum (*Sorghum bicolor*) with 52% of national production in 2016; yam (*Discoprea esculenta*) with 26% of national production in 2016; rice (*Oryza* *sativa*) with 24% of national production in 2016 and maize (*Zea mays*): 23% of national production in 2016. They are cultivated from season to season mostly intercropped with cowpea (*Phaseolus vulgaris*) and groundnut (*Arachis hypogaea*). Livestock production is a major enterprise especially dairy cattle. Other livestock in the area include sheep and goats. There is a high proportion of use of animal traction by farmers. The ADH 2 recorded the second highest value of the presence index of agricultural services, estimated at 0.50 % Farmers in the hub have an average access to agricultural services.

5. A latent factor model for ISFMT adoption effect

Drawing from the theoretical framework described in the previous section, maize farms adopt ISFMT t on the basis of partial or full knowledge of derived idiosyncratic net gains. This article therefore chose the CRC model to analyze the heterogeneous effect of adoption of ISFMT on scores AI of maize (Aakvik et al., 2005). Furthermore, we use a model of four latent factors (l) to address the estimates bias issue often uncounted in empirical analysis due to moderate/severe contamination or association of selected IV with outcomes independent of adoption of ISFMT (Aakvik et al., 2002; Banerjee and Basu, 2021; Carneiro et al., 2003). The latent factor models have the potential to identify treatment effects even in the absence of instrumental variables. However, Banerjee and Basu, (2021) argue that a latent factor model combined with the IV approach is more robust than the latter. It reduces substantially the bias in estimating the causal effects of endogenous treatments. We apply in this paper a latent factor (l) model combined with Instrumental variables (IV) (Banerjee and Basu, 2021; Mújica-Mota et al., 2020). To build the latent factor model, and following Aakvik et al., (2002), Carneiro et al., (2003) and Banerjee and Basu, (2021)**,** we assume the factor structure of the errors V_t and e_t in Eq. (4) and Eq. (8), respectively to be written as follows:

$$V_t = \delta_t l_t + \epsilon_t \tag{8}$$

$$e_t = \lambda_t l_t + u_t \tag{9}$$

where l_t are the latent factors (scalar), ϵ_t and u_t are stochastic error terms; l_t ϵ_t and u_t have mean zero, for every $t \neq t'$, they are mutually independent, and are independent of the exogenous variables in the both selection and outcome equations. The parameters to be estimated δ_t and λ_t are the factors loading for the selection and outcome equations, respectively.

A two-stage approach was used to estimate the parameters. In the first stage, the stochastic cost frontier was specified to estimate the AE scores. The model returns AI scores of farms, bounded between 0 and 1. Then in the second stage, both the predicted AI scores function and the adoption of ISFMT model are jointly estimated to analyze the effects of adoption. Following Debb and Trivedi (2006) and Mújica-Mota et al., (2020), the system of Eqs. (5) and (8) was specified as a joint distribution of endogenous treatment and outcome using a latent factor structure. In this framework, a CRC model for a multinomial choice of ISFMT and a mixed discrete-continuous outcome is specified (Carneiro et al., 2003). Let $A_t = [A_{1,}A_2, A_3, A_4]$ be four binary dummy variables that equal 1 for adopters of ISFMT t and 0 otherwise. In addition, we assume that the distribution function of V_t, F_t in Eq. (5) is a Weibul (or Type I extreme value) probability distribution. Thus, following Deb and Trivedi, (2006b) the probability of adoption can be written as a mixed multinomial logit (MMNL) structure as follows:

$$Pr(A_t|\mathrm{x},\mathrm{z},\mathrm{l}_t)=\frac{exp(\,x\beta_t+z\alpha_t+\delta_t l_t)}{1+\sum_{k=0}^{4} exp(x\beta_k+\,z\alpha_k+l_k)}.\, j=0,\cdots,4. \tag{10}$$

where x and z are defined as in the Eq. (4), β, α and δ are parameters to be estimated; l_t are latent factors representing the unobserved covariates (unobserved heterogeneity) such as farmers motivation, level of knowledge and innate managerial and technical abilities in understanding and using the ISFMT (Abdulai and Huffman, 2014). They are included in both treatment and outcome equations to allow for unobserved influencing adoption of ISFMT to affect their impact on AI scores (Banerjee and Basu, 2021; Deb and Trivedi, 2006b; Nkegbe et al., 2018). Thus, we can distinguish the selection on unobservable from that on observables. In addition, they allow for the control of unobserved covariates in the same manner as is done with observed confounders and therefore solve for the endogeneity issue (Banerjee and Basu, 2021**.** The factor loadings are interpreted in much the same way as coefficients on observed covariates can (Deb and Trivedi, 2006b). In addition to the latent factors, we include identifying exclusion restriction z. To fulfil the rank condition, four were chosen (Wooldridge, 2002). The four following available instruments access to information (Asfaw et al., 2012; Khonje et al., 2015; Tufa et al., 2019); contact with project (Hörner and Wollni, 2022; Pender and Gebremedhin, 2007); contact with extension agents (Owusu and Abdulai, 2019; Sileshi et al., 2019) and distance to market (Kalinda et al., 2017; Wale, 2022) were selected based on the literature.

In the second stage, the CRC model is specified. More specifically, this consisted in interacting the latent factors l_t, with the adoption A_t dummies (Mújica-Mota et al., 2020). Consequently, the model of AI scores is specified following Eq. (7). Furthermore, since the AI scores are bounded between 0 and 1, the two-limit Tobit (TLT) regression model is specified as in Eq. (7) (Mamam et al., 2018; Musa et al., 2015; Okello et al., 2019; Sapkota and Joshi, 2021) :

$$\ln AE^* = X\beta+\sum_{t=1}^{4} A_t X(\beta_t-\beta_0)+\boldsymbol{A_1}\sum_{t=1,k=1}^{\mathbf{4}}\lambda_{tk}l_t+\boldsymbol{A_2}\sum_{t=1,k=1}^{\mathbf{4}}\lambda_{tk}l_t+ \boldsymbol{A_3}\sum_{t=1,k=1}^{\mathbf{4}}\lambda_{tk}l_t+\boldsymbol{A_4}\sum_{t=1,k=1}^{\mathbf{4}}\lambda_{tk}l_t+\sum_{t=1}^{4}\lambda_t\, l_t+u_t \tag{11}$$

where $\ln AE^*$ is a latent variable representing the natural logarithm of AI scores of maize farms; X is a set of exogenous covariates common to both two equations with associated parameter vector β; A_t are four binary dummy variables as defined earlier; four latent factors l_t, each for the binary dummy variables; 24 interaction terms of the latent factors l_t with the adoption dummies A_t; The latent factors are included in Eq. 11 to control for the endogeneity of each binary dummy variables A_t**;** $(\beta_t-\beta_0)$ are coefficients to be estimated. They denote the adoption effects of each of the four ISFMT t relative to their non-adoption; λ_t and λ_{tk} are factor loadings to be estimated, which are assumed to be different from zero if they control for endogeneity of A_t (Mújica-Mota et al., 2020), u_t is the same error term as in Eq.12. Denoting $\ln AE$ as the observed variables, the TLT model is specified as follows:

$$\ln AE=\begin{cases} 1 \;\; if\;\ln AE^*\geq 1\\ \ln AE^* \;\; if\;\; 0<\ln AE^*<1\\ 0\;\; if\;\ln AE^*\leq 0\end{cases} \tag{12}$$

For identification of the parameters in model estimation, a set of restrictions are imposed. First, the number of outcomes must be ≥ 4 (Banerjee and Basu, 2021). Second, we impose $\lambda_{tt'}=0$ $\forall\, t\neq t'$, i.e. each adoption decision of ISFMT is affected by a unique latent factor. Third, one requires that one of the factor loadings λ_{tt} in Equations (10) or (11) be normalized to a constant value. We set the factor loadings in Equation (10), $\lambda_{tt} = 1 \ \forall t$. This implies that the scale of effects of unobserved factor is normalized and equal to 1 in the adoption equation (Aakvik et al., 2002; Banerjee and Basu, 2021; Deb and Trivedi, 2006b, 2006a).

The variance of the latent variable **was set at one** in both equations.

We use the GSEM software package in STATA 14 to jointly estimate the Eq. (11) and Eq. (12) by maximising the (simulated) likelihood of the sample of data **with multiple values of $\boldsymbol{l_t}$ sampled from k using Halton sequences (Bhat 2001, Debb and Trivedi 2006)**.

In our study, 200 simulation draws were generated. Deb and Trivedi, (2006) suggest using a greater number of simulations draws than the square root of the number of observations. As the sample was composed of 4236 observations, the number of simulations draws obtained was more than sufficient.

In order to validly estimate this model, the instruments must satisfy the condition

$$E(\boldsymbol{\varepsilon}|SCU, LNU, z_{SC}, z_{LN}, z_{IC}) = E(\boldsymbol{\varepsilon}|z_{SCi}, z_{LNi}, z_{ICi}) = \mathbf{0}$$

A Wald test for H_0: λ_{11}=0, λ_{12}=0, λ_{21} = 0, λ_{22} = 0 is a test of the null of exogeneity of treatment effects (i.e. no selection by returns).

From the model consistent parameters estimates we can formulate several interesting ISFMT adoption effects parameters by comparing ISFMT t to ISFMT t'. First, following Cornelissen et al., (2016, p. 5), Deb and Trivedi, (2006) and Heckman (2007; p. 4802), we consistently estimate the unconditional $ATE(t, t')$ and conditional $\left(ATE(x)\right)$ to x, average treatment effects, respectively as follows:

$$ATE(t, t') = E[AE, A_t = 1] - E[AE, A_{t'} = 0] \tag{14}$$

This corresponds to the four coefficients of the binary dummy variables A_t in Eq. (11).

$$ATE(t, t' \mid \mathrm{x}) = E[AE \mid x, A_t = 1] - E[AE \mid x, A_{t'} = 0] \tag{15}$$

The hypothetical individuals we consider have the average characteristics of the entire sample. Both parameters are the effects of assigning a maize farm to an ISFMT adoption status – taking someone from the overall population (14) or a subpopulation conditional on x (15) – and determining the mean gain of the move from base state $A_{t'} = 0$. To find ATE we average $ATE(t, t' \mid \mathrm{x})$ for the full sample. We apply the generalized regression adjustment (GRA) model to consistently estimate the average treatment effect (ATE) (Drukker, 2016). A consistent GRA estimator for the ATE uses Maximum Simulated log likelihood estimators for parameters based on the GSEM model, which accounts for the endogenous sample-selection problem. The command margins is used to consistently estimate the means of each predicted potential outcomes. Then, we apply nlcom to consistently calculate the differences in the predicted potential outcomes means. margins accounts for the two-step estimation problem using the standard method discussed by Wooldridge (2010, chaps. 12 and 13) and Cameron and Trivedi (2005, chap. 6.6).

Then, we estimate the total marginal effects of the adoption of ISFMT t, following Bartus, (2005) using two-steps procedure. The first step was to estimate separately the marginal effects of the binary dummy variable A_t and each interaction term with the variable A_t, using discrete changes in the expected outcomes. The total marginal effect is computed in the second step by doing the sum of the marginal effects time their respective derivative with respect to the binary dummy variable A_t. Marginal effects are evaluated at sample means of covariates and by averaging over the simulated distribution of the latent variables.

6. DATA SOURCE, SAMPLING PROCEDURE AND DESCRIPTIVE STATISTICS

The data were obtained from surveys carried out between April and May 2021 in 19 villages located in ADH 2 in Benin where land degradation is severe. Selected villages were either involved in SLM adoption. Yamane, (1967) sample size determination formula was used to calculate the minimum sample size of the participating producer households in the ProSOL project. A random sample of 431 maize producers was surveyed which contained 287 participant and 144 non-participant smallholder producers in the ProSOL project intervention area and 1550 plots. Detailed plot-level data were collected on cost of input used in ISFMT, labor input and crop output for the 2020 cropping season. The estimation model consists of two dependent variables: adoption and AI. The adoption variable indicated whether the farmer adopted or rejected at least one ISFM technology.

Descriptive statistics demonstrate that AI score is 18% for non-adopter while is 17% for PP, 20% for CM, 19% for CR 16% for MP adopter. There are no significant differences between non-adopters and adopters of the 4 technologies for AI scores, level of formal education, number of agricultural workers, distance to market and farm income. The sample of PP and CM adopters is not homogeneous with non-adopters in the cotton zone with more PP producers in the cotton zone (85% > 73%) and fewer CM producers than non-adopters (53% < 73%). PP adopters use less fertilizer than non-adopters (20% < 54%), have less access to information (0.63% < 0.77%) and extension agents (15% < 36%) but have more access to formal credit (43% > 24%) and access to projects (88% > 57%), compared to non-adopters. MP adopters practice more intercropping (12% > 4%), have more access to projects (88% > 57%) but less access to extension agents (13% < 36%) compared to non-adopters. The proportion of men who adopted CR is below the non-adopting men (55% < 70%). Also, CR adopters have the least space allocated to production (7.74 ha < 11.03 ha), the least access to projects (43% < 57%), the least experienced in SLM (4. 6 years < 5.7 years) compared to the non-adopter. CM adopters belong more to a group (56% > 42%), have more access to projects (85% > 57%) but are younger (40 years < 44 years) and less access to extension agents (19 % < 36%) compared to non-adopters. Only CR (99% > 88%) and MP (100% > 88%) adopters perceive their land as fertile compared to non-adopters.

Table 2: Descriptive statistics of AI model

Inefficiency model	Non adoption	PP		CM		CR		MP	
	Mean (sd)	Mean (sd)	Test	Mean (sd)	Test	Mean (sd)	Test	Mean (sd)	Test
AI score	0.176 (0.089)	0.169(0.080)	0.010	0.197(0.082)	-0.020	0.189(0.111)	-0.012	0.159 (0.058	0.020
Gender of farmer (1=male, 0=female)	0.704(0.457)	0.732(0.449)	-0.059	0.735(0.447)	-0.062	0.547(0.501)	0.155***	0.562(0.512)	0.119
Age of farmer (Years)	43.715(10.248)	44.707(9.397)	-1.12	40.323(7.301)	3.653**	44.205(11.325)	-0.621	45.437(10.770)	-1.815
Farmer experience in ISFMP use (year)	5.726(6.024)	6.488(4.302)	-1.064	4.852(3.173)	0.728	4.589(4.630)	1.126*	5.375(6.820)	0.155
Education level of farmer (1=Yes, 0=No)	0.176(0.381)	0.220(0.419)	-0.042	0.235(0.430)	-0.058	0.164(0.373)	0.019	0.125(0.341)	0.058
Use of formal credit for ISFMP (1=Yes, 0=No)	0.236(0.426)	0.425(0.501)	-0.153**	0.354(0.486)	-0.074	0.342(0.477)	-0.068	0.312(0.478)	-0.027
Farmland size (hectare)	11.025(12.485)	12.844(11.749)	-2.369	13.25(13.047)	-2.753	7.743(9.611)	3.606**	8.968(8.452)	1.807
Northern cotton area (1=cotton zone, 0=non-cotton zone)	0.734(0.442)	0.854(0.358)	-0.120*	0.529(0.506)	0.233***	0.794(0.406)	-0.059	0.875(0.341)	-0.135
Member of an agricultural association (1=Yes, 0=No)	0.423(0.494)	0.439(0.502)	-0.0005	0.558(0.503)	-0.130*	0.438(0.499)	0.0001	0.437(0.512)	0.001
Family labor available (adult equivalent)	6.456(3.850)	7.049(5.657)	-0.630	6.882(4.005)	-0.439	6.136(3.367)	0.410	6.062(3.315)	0.431
Crop association (intercropping) (1=Yes, 0=No)	0.041(0.199)	0.049(0.218)	0.002	0.058(0.238)	-0.008	0.068(0.254)	-0.021	0.125(0.341)	-0.076*
Use of inorganic fertilizer (1=Yes, 0=No)	0.539(0.499)	0.195(0.401)	0.345***	0.529(0.506)	-0.023	0.561(0.499)	-0.064	0.5(0.516)	0.008
Instrumental variables									
Access to information (1=Yes, 0=No)	0.767(0.423)	0.634(0.488)	0.145**	0.794(0.410)	-.030	0.794(0.406)	-0.034	0.875(0.341)	-0.113
Contact with project (1=Yes, 0=No)	0.573(0.495)	0.878(0.331)	-0.283***	0.852(0.359)	-0.250***	0.493(0.503)	0.154**	0.875(0.341)	-0.262**
Contact with extension agent (1=Yes, 0=No)	0.363(0.481)	0.146(0.358)	0.189***	0.176(0.386)	0.153**	0.356(0.482)	-0.046	0.125(0.341)	0.200*
Distance from market	15.776(10.088)	17.078(10.502)	-1.045	16.767(10.317)	-0.689	16.143(10.373)	-0.013	18.25(9.497)	-2.199

*sd : standard deviation

Table 3: Descriptive statistics of the variables in the five equations (non-adoption and four SLM adoption).

Adoption GDT	Non adoption	PP		CM		CR		MP pruriens	
	Mean(sd)	Mean(sd)	Test	Mean(sd)	Test	Mean(sd)	Test	Mean(sd)	Test
AI score	0.704(0.457)	0.732(0.449)	-0.059	0.735(0.447)	-0.062	0.547(0.501)	0.155***	0.562(0.512)	0.119
Gender of farmer (1=male, 0=female)	43.715(10.248)	44.707(9.397)	-1.12	40.323(7.301)	3.653**	44.205(11.325)	-0.621	45.437(10.770)	-1.815
Age of farmer (Years)	5.726(6.024)	6.488(4.302)	-1.064	4.852(3.173)	0.728	4.589(4.630)	1.126*	5.375(6.820)	0.155
Farmer experience in ISFMP use (year)	0.176(0.381)	0.220(0.419)	-0.042	0.235(0.430)	-0.058	0.164(0.373)	0.019	0.125(0.341)	0.058
Education level of farmer (1=Yes, 0=No)	0.236(0.426)	0.425(0.501)	-0.153**	0.354(0.486)	-0.074	0.342(0.477)	-0.068	0.312(0.478)	-0.027
Use of formal credit for ISFMP (1=Yes, 0=No)	11.025 (12.485)	12.844(11.749)	-2.369	13.25(13.047)	-2.753	7.743(9.611)	3.606**	8.968(8.452)	1.807
Farmland size (hectare)	0.734(0.442)	0.854(0.358)	-0.120*	0.529(0.506)	0.233***	0.794(0.406)	-0.059	0.875(0.341)	-0.135
Northern cotton area (1=cotton zone, 0=non-cotton zone)	0.423(0.494)	0.439(0.502)	-0.0005	0.558(0.503)	-0.130*	0.438(0.499)	0.0001	0.437(0.512)	0.001
Member of an agricultural association (1=Yes, 0=No)	6.456(3.850)	7.049(5.657)	-0.630	6.882(4.005)	-0.439	6.136(3.367)	0.410	6.062(3.315)	0.431
Family labor available (adult equivalent)	0.041(0.199)	0.049(0.218)	0.002	0.058(0.238)	-0.008	0.068(0.254)	-0.021	0.125(0.341)	-0.076*
Crop association (intercropping) (1=Yes, 0=No)	0.539(0.499)	0.195(0.401)	0.345***	0.529(0.506)	-0.023	0.561(0.499)	-0.064	0.5(0.516)	0.008
Total income (FCFA)	311817.5 (171096.8)	339670.6 (138245.4)	- 22696.13	346874.5 (144190.9)	- 30116.83	317555 (139709.2)	1900.316	336844.8 (108513.7)	- 18394.14
Soil fertility level (1=Fertile, 0=Less fertile)	0.880(.325)	.902(.300)	.002	.882(.327)	.024	0.986(.117)	-.098***	1(0)	-.098*
Access to information (1=Yes, 0=No)	0.767(0.423)	0.634(0.488)	0.145**	0.794(0.410)	-.030	0.794(0.406)	-0.034	0.875(0.341)	-0.113
Contact with project (1=Yes, 0=No)	0.573(0.495)	0.878(0.331)	- 0.283***	0.852(0.359)	- 0.250***	0.493(0.503)	0.154**	0.875(0.341)	-0.262**
Contact with extension agent (1=Yes, 0=No)	0.363(0.481)	0.146(0.358)	0.189***	0.176(0.386)	0.153**	0.356(0.482)	-0.046	0.125(0.341)	0.200*
Distance from market	15.776(10.088)	17.078(10.502)	-1.045	16.767(10.317)	-0.689	16.143(10.373)	-0.013	18.25(9.497)	-2.199

*sd : standard deviation

Table 4: Farm AI indices by SLM

AI range	Non adoption	PP		CM		CR		MP	
	Freq(perc)	Freq(perc)	T test	Freq(perc)	T test	Freq(perc)	T test	Freq(perc)	T test
0.00-0.10	51(19.10)	7(17.07)	1.917	2(5.88)	8.593*	7(9.59	10.43*	3(18.75)	1.399
0.11-0.20	134(50.19)	22(53.66)		18(52.94)		41(56.16		10(62.50)	
0.21-0.30	55(20.60)	7(17.07)		12(35.29)		15(20.55		2(12.50)	
0.31-0.40	21(7.87)	5(12.20)		1 (2.94)		9(12.33		1(6.25)	
0.41-0.50	4(1.50)	-		1 (2.94)		-		-	
0.51-0.60	2(0.75)	-		-		-		-	
0.61-0.70	- -	-		-		-		-	
0.71-0.80	- -	-		-		-		-	
0.81-0.90	- -	-		-		1(1.37)		-	
Summary statistics									
Mean	0.176	0.169		0.197		0.189		0.159	
Minimum	0.049	0.056		0.079		0.066		0.066	
Maximum	0.558	0.344		0.498		0.829		0.304	

Freq: Frequency (number of observations)

Perc : pourcentage (%)

7. EMPIRICAL RESULTS

In this section we present the results from the jointly estimated correlated coefficient model. After some preliminary remarks regarding the goodness-of-fit, we present in Table 5 the results of the factors affecting the AI scores. This was followed by an analysis of the effect of ISFMT adoption on AI (Table 6). In this study, we have used S = 186 simulations draws based on Halton draws.

8.1. **Goodness-of-fit of the correlated random coefficients model estimations**

We apply in this study, the GSEM to correct for the three problems of selection, endogeneity biases and censoring (Nkegbe et al., 2018**.** Furthermore, the goodness-of-fit measures of the correlated random coefficients model estimations are presented in Table 5. The Wald tests statistic (Wald chi2) results indicate that the null hypothesis that all slope coefficients are zero is rejected at the 1% significance level. Accordingly, the variables in each of the four adoption equations and the impact model of AI contribute significantly as a group to explain the decisions to adopt or not the ISFMT and the AI scores of maize farms, respectively. In other respects, following Mújica-Mota et al., (2020); we perform the Hausman test z statistic where the null hypothesis is that the four factors loading λ_t are jointly equal to zero (joint exogeneity of the four adoption binary dummy variables A_t). We reject the null hypothesis in the four cases (p < .01). We conclude that endogeneity of A_t is indeed an issue in the correlated coefficient model of the AI. IVs to be valid, they have to determine the probability of adopting the four ISFMT (relevance condition), and be correlated with the outcome Y only through their association with the four binary dummy adoption variables A_t (conditional independence condition). The Wald F test statistic (with 2 degrees of freedom) rejects at a significance level of 1%, the null hypothesis that the instruments are irrelevant to identify the AI scores equation.

8.2. Correlated random coefficient model estimates of factors affecting allocative inefficiency

The coefficients and standard errors for the main variables that determine the maize farms AI as reported by the CRC model estimate are depicted in Table 5. The analysis disaggregated the explanatory variables into two different groups: 15 non- interacted explicative variables, four latent factors l_t for ISFMT (Table 5) and three Adoption binary dummy variables interacted with farmers characteristics along with 24 interaction terms of the latent factors l_t with the adoption dummies A_t (Table 6). The 15 non- interacted terms are the independent variables that explained the variation in AI among the maize farms. Moreover, the coefficients of most of the variables included in the model have the expected negative signs. A negative coefficient for an independent variable implies decrease in cost inefficiency and vice-versa (Mutoko et al., 2015).

Table 5. Factors affecting farm AI of maize farms (CRC models)

Parameters	**Estimate**	**Robust S. Error**
Constant	0.193	0.013***
Adoption of ISFMT		
GDT2 (PP)	-0.406	0.094***
GDT3 (CM)	-0.674	0.129***
GDT4 (CR)	-0.447	0.072***

GDT5 (MP)	-0.315	0.139***
Farmers and farms characteristics		
Gender of farmer	-0.70	0.063
Age of farmer	-0.384	0.272*
Farmer experience in ISFMP use	-0.105	0.078**
Education level of farmer	-0.073	0.014***
Use of formal credit for ISFM	-0.218	0.083***
Farmland size	-0.483	0.205***
Northern cotton area	-0.317	0.059***
Member of an agricultural association	-0.210	0.107***
Family labor available	0.426	0.338*
Crop association (intercropping)	-0.179	0.053***
Use of inorganic fertilizer	-0.296	0.018***
Var (e.Y_SE)	0.128	0.007
Latent factors		
λL2	-0.139	0.085**
λL3	-0.154	0.038***
λL4	-0.042	0.009***
λL5	-0.145	0.058***
Log pseudo likelihood	171.83	
Wald chi2		
N simulations	186	
N observations	431	
Instrument strength: Wald F test statistic (2 degrees of freedom)	GDTT2 eq: 7,13***; GDTT3 eq: 0,62*** GDTT4 eq: 3,82***; GDTT5 eq: 0,904***	
Wald test for joint significance of coefficients of the interacted terms: (all interaction terms=0)	Chi2 (11) =2847.05***	
Hausman test z statistic of H0: no endogeneity	GDTT2 eq: -2,74***; GDTT3 eq: 2,96*** GDTT4 eq: -16,04***; GDTT5 eq: -9,73***	
z statistic: H0: (variance of over- dispersion term)	3,64***	

Note: Significance: *** p<0.01, ** p<0.05, * p<0.1.

Results of correlated random coefficients model in Table 5, show that, on average, the adoption of the four ISFMT is negatively and statistically (P<0.01) associated with the AI scores. This result implies that maize farms who adopt these ISFMT were more likely to achieve lower AI. Furthermore, the four factor loadings (λ_{lt}), are all negative and statistically significant at the 1% critical level. This result suggests that the unobserved factors that increase the probability of adopting ISFMT also lead to lower farm AI, relative to that of the randomly assigned in adoption status (Deb and Trivedi, 2006b). For instance, the negative factor loading, related to the MP adoption (factor loading (λ_{l5}),) (Table 5) suggest that lower AI on farms with the MP (compared to randomly drawn farms) in part stems from a self-selection of “better” farms from the non-adoption status towards adopting MP status. We conclude that significant favorable selection on unobservable into the ISFMT adoption status exists. However maize farms adopt efficient ISFMT.

The results show that apart from the dummy adoption variables (At), 10 out of the 11 non- interacted explanatory variables have the expected negative signs and statistically related to AI (Table 5). First, education level of farmer, use of formal credit for ISFMT, Farmland size, Living and farming in cotton area, Member of an agricultural association, Crop association and Use of inorganic fertilizer are those variables that are highly statistically significant in determining the rice farmers' allocative inefficiency. The coefficient of education level of farmer is negative and significant, suggesting a high decrease in AI of maize farms as the education level of the farmer increases. Kolawole and Ojo, (2007) have found similar results in Nigeria in small scale food crop production. The use of formal credit for ISFMT decrease AI because of negative and significant of coefficient at 1% critical level. This result is in line with those found by recent studies (Abdulai and Abdulai, 2016; Ntabakirabose, 2017). The results indicated that a unit increase in the access to credit owned by a household head decreased AI. With access to credit, farmer's ability is improved to purchase the otherwise unaffordable farm inputs timely. The coefficient of farmland size was negative and significant at 1% critical level. This suggests that maize farm AI is likely to decline as farm size increases. This result is in accordance with the notion of "efficiency economy of scale" that states that larger farms have efficiency advantage over smaller ones. Similar finding is reported by other authors for cultivated area of rice and maize farms in Ghana, Northern Uganda, Chitwan district in Nepal, Mirzapur district in India respectively (Amewu and Onumah, 2015; Okello et al., 2019; Paudel and Matsuoka, 2009). Estimated coefficients for Northern cotton area locational dummy is negative and significant at 1% critical level. This implies that there is location relationship in maize production in the study area. More specifically, maize farmers in Northern cotton area have about 32%, less AI than their counterparts in other locations. This result is mainly attributed to distortions introduced by cotton policies (subsidies for inputs, guaranteed purchase of cotton fiber, access to credit, frequent extension contacts, etc.). Implication of these policies is taxes imposed on production of other crops in other hubs. This result is similar to the findings of Okello et al., (2019) who showed that AE is positively and significantly affected by location of the farmer. In contrast, Zavale et al., (2005) found that farm households located in the northern and central agro-ecological of Mozambique were more cost inefficient than the ones located in the southern. Membership in agricultural association is negatively and significantly related to AI, at the 1% critical level. This indicates that membership in farmers' group lowers the AI of the maize farm. Membership in farmers' group constitutes a social network in which farmers have better access to information about the proper use of ISFMT along with their adoption. Moreover, they acquire and improve their managerial skills including allocative efficiency achievement. Similar results were also reported by some other authors (Gideon et al., 2010; Obeng and Adu, 2014). Crop association is negatively and significantly related to allocative inefficiency, at the 1% critical level. This indicates that crop associations lower the AI of the maize farm. This result is in line with Nursalam et al., (2021) who found that crop association decrease AI. The use of inorganic fertilizer is negatively and significantly associated with AI at 1% statistical critical level. This result implies that the use of inorganic fertilizers decreases the AI. In addition, it suggests that the ISFMT might be complementary inputs of inorganic fertilizers. This finding supports the findings by Ahmed et al., (2017). Second, the years of farmer experience in ISFMP use is statistically and significantly associated with their maize farm AE at 5% critical. Estimated coefficients for the years of farmer experience in

ISFMP use is negative and significant at 5% critical level. Soil fertility training attained by farmer lead to productive ability, to acquire and process useful financial information increases with time, which decreased AI. No study have learned about this specific factor before but many studies revealed positive action of experience in agriculture of AI other there (Mutoko et al., 2015b). The finding indicates that most experienced farmers in ISFMP use achieve various cost-saving strategies over now more than 5 years in contact with ProSOL. They applied it in maize production under ISFMP as mentioned by Mutoko et al., (2015) who found that soil fertility management decreased AI. Third, age of household farmer and family labour availability are statistically significant in determining the maize farmers' AI at 10% critical level. Age of farmer is negatively and significantly ($P<0.10$) associated with maize farm AI. This result suggests that young maize farmers are more likely to realize high farm AI than old farmers. This result is on contrast with the young farmers' willingness of taking risk in using new improved technologies (Donkoh et al., 2019). Similar result is reported by Awotide and Bamire, (2010) in rice farming in Nigeria. The coefficient of family labour availability is positive and significant at 10% critical statistic level. This result indicates that the AI of maize farm increases with increasing family labour availability. This implies that smaller households would use more efficiently the family available labor than their larger counterparts. Some other authors found comparable result in their studies (Aliyu and Shelleng, 2019; Nwachukwu and Onyenweaku, 2009; Okello et al., 2019). In contrast, some other authors reported in their studies a significant and negative relationship of family labour availability with AI (Okello et al., 2019; Paudel and Matsuoka, 2009; Zavale et al., 2005). Fourth, the coefficient for gender dummy was negatively associated with the farm AI. The negative coefficient suggests that female farmers are more likely to achieve higher maize farm AI than male farmers. Some others studies found similar results (Amewu and Onumah, 2015; Zavale et al., 2005). This is in contrast with the hypothesis that female farmers are more allocative efficient than their male counterparts. However, it is not found to be statistically significant.

8.3. **Effect of the adoption of ISFMT on AI of maize farms**

Drawing from the high significance of the four factor loadings (λ_{lt}), the simultaneous equations model of adoption of ISFMT and AI of maize farms is correctly specified**.** Accordingly, the estimated marginal effect identifies the average treatment effect as in the case of randomly assigned treatment (Deb and Trivedi, 2006b). Table 6 presents results of three parameters effects of ISFMT adoption on AI, and associated standard errors. In Table 6, the results including both interaction terms of adoption binary dummy variables with characteristics and latent factors, respectively are presented. Furthermore, for each of the four ISFMT, three to five out of six interaction terms of the latent factors with the adoption dummies variables are statistically significant at 10% critical level at least. We conclude that the CRC coefficients model is well specified. In addition, the Wald test for joint significance of coefficients of the interacted terms of adoption dummy variables with three characteristics of the farm, its farm and living location (gender, use of inorganic fertilizer and cotton area): (all interaction terms=0) is statistically significant ($Prob<0.000$) thus, confirming the heterogeneity of the effect of adoption of ISFMT on AI. The implication is that there are significant interactions between the covariates and the adoption of ISFMT.

As shown in Table 6, for the three parameters, the effect of adoption of an ISFMT on maize farms AI was negative and statistically significant at 1% critical level for all four technologies. This implies that adoption of ISFMT decreases the AI of maize farms. Specifically, compared to the non-adoption farms of the ISFMT, the highest causal effect of maize farm AI was realized with CM, estimated to -0.703, -0.674 and -0.562, respectively for the ATE(X), ATE and marginal effects parameters. In contrast, the lowest causal effects are achieved with MP which were estimated to be -0. 224, -0.315 and -0.338, respectively for Marginal effects ATE and ATE (X) parameters. The causal effects of PP and CR adoption on AI are fairly similar.

Table 6: Correlated random coefficient model estimates: Adoption effects of ISFMT on AI scores of maize farms (standard errors in parentheses)

Parameters	ISFMT			
	GDT2 (PP)	GDT3 (CM)	GDT4 (CR)	GDT5 (MP)
Mean ATE	-0.406*** (0.094)	-0.674*** (0.129)	-0.447*** (0.072)	-0.315*** (0.139)
Mean ATE (X)	-0.422*** (0.097)	-0.703*** (0.103)	-0.478*** (0.174)	-0.338*** (0.085)
Marginal effects	-0.328*** (0.106)	-0.562*** (0.084)	-0.436*** (0.169)	-0.224*** (0.166)
Interaction terms A_t # characteristics				
GDT #sex	0.041* (0.023)	-0.094*** (0.025)	-0,114 (0,108)	0.316*** (0.008)
GDT #zone	-0.028** (0.007)	-0.107* (0.082)	-0.075** (0.033)	-0.179 (0.142)
GDT #Q engrais	-0.204* (0.141)	-0.075 (0.069)	-0.082** (0.035)	-0.008*** (0.002)
Wald test for joint significance of coefficients of the interacted terms: (all interaction terms=0)	Chi2 (11)=2847.05***			
Interaction terms A_t # latent factors L_t				
$\lambda_{At\,\#L2L3}$	-0.151 (0,184)	-0.005*** (0,018)	0.073 (0,086)	-0.073* (0,057)
$\lambda_{At\,\#L2L4}$	0,018 (0,009)	-0.184*** (0,036)	-0.018*** (0,005)	0.109 (0,128)
$\lambda_{At\,\#L2L5}$	-0.079** (0,035)	0.022 (0,018)	-0.005 (0,004)	-0.031 (0,026)
$\lambda_{At\,\#L3L4}$	-0.051*** (0,008)	-0.294* (0,202)	-0.408 (0,381)	-0.126** (0,075)
$\lambda_{At\,\#L3L5}$	0.022 (0,017)	-0.041* (0,029)	-0.127*** (0,036)	-0.194*** (0,042)
$\lambda_{At\,\#L4L5}$	-0.105* (0,012)	-0.039*** (0,012)	-0.149*** (0,018)	-0.108* (0,087)

***P < 0.01, **P < 0.05, *P < 0.1. Robust standard errors are in parenthesis

The results depict in Table 5 show that the effect of adoption of ISFMT on AI differs substantially across maize farms in the sample. The effects of adopting PP and MP on AI were 4.1% and 31.6%, respectively significantly higher for maize farms of men compared to those of female. In contrast, the effect of adopting CM on AI was 9.4% smaller for men farms compared to those of female. Results indicated negative significant differential living area effects for the adoption of PP, CM and CR. The highest significant differential living area effect of -0.107 units was recorded for CM adoption. This implies that the AI adoption effect of CM for farms in cotton area was 0.107 lower as compared to that of farms located in other areas. MP adopters in cotton area recorded a farm AI 0.179 lower compared to farms in other areas. However, this difference in adoption effect across area is not statistically significant. In the same vein, except for CM, adoption of ISFMT significantly lower the AI of farms using inorganic fertilizer compared to those that do not. Maize farms that combine CM with inorganic fertilizer record AI of 0.204 unit lower than farms that do not. These results collectively suggest that different groups of farms react differently to the incentives on ISFMT provided by projects, NGOs and public extension services working on fertility management in the study area. The implication of these findings is that the adoption effect of ISFMT on AI was highly heterogeneous across gender, living areas and use of inorganic fertilizer. In consequence caution is required in the design and implementation of agricultural policies geared towards enhancing adoption of ISFMT.

8. CONCLUSION AND POLICY IMPLICATIONS

We showed in the theoretical framework that farmers adopt the ISFMT on the basis of knowledge of the idiosyncratic gains derived from their adoption. The idiosyncratic gain is referred to as the unobserved heterogeneity**.** It implies that the effect of ISFMT adoption may vary across maize farmers even after controlling for observable heterogeneity using covariates. This phenomenon is distinct from that of selection bias. We address it by specifying a correlated random coefficients model for analyzing the heterogeneous adoption effect of the four ISFMT (MP, CR, CM, and PP), on the AI scores of maize farms which is a mixed discrete-continuous outcome. Furthermore, to substantially reduce the bias in estimating the causal effects of endogenous adoption treatments, we assume a factor-structure for the unobserved covariates combined with instrumental variables. We use the Generalized Structural Equation Model package to jointly estimate the multinomial endogenous treatment choice and mixed discrete-continuous outcome. In this regard, our theoretical framework and estimation strategy depart from the literature relating to impact evaluation of new agricultural technologies adoption. Major conclusions drawn from these analyses and their respective policy implications are discussed below.

The estimated adoption effect of ISFMT on AI scores of maize farms is heterogeneous both in terms of both observed and unobserved variables. Indeed, the four factor loadings are all negative and statistically highly significant. This implies the existence of selection on unobserved covariates into the ISFMT adoption status. In addition, the effect of adopting ISFMT varies depending of the gender of farmer, whether his maize farm is located in northern cotton area or not and the level use of inorganic fertilizer on the maize farm. We conclude that the specified correlated random coefficients model fits well the heterogeneous adopting effect of ISFMT on AI scores of maize farms. Furthermore, in line with our expectations, the results consistently suggest that adopting any of the four ISFMT, significantly decreases the AI scores of the maize farms. On average, the largest decrease ATE(X) on maize farm AI scores magnitudes (0.703) stem from adopting PP, followed by CM and CR that recorded fairly similar AI scores effects. The lowest decrease ATE(X) of 0.338 is achieved with MP. We also find that, different groups of farms react differently to the incentives on ISFMT provided by projects, NGOs and public extension services working on fertility management in the study area. The effects of adopting CM and MP on AI were 4.1% and 31.6%, respectively significantly higher for maize farms of men compared to those of female. In contrast, the effect of adopting PP on AI was 9.4% lower for men farms compared to those of female. In the same vein, except for PP, adoption of ISFMT significantly lower the AI of farms using inorganic fertilizer compared to those that do not. Maize farms that combine the CM with inorganic fertilizer record AI of 0.204 unit lower than farms that do not. As in most determinants of AI studies we find that the AI scores of maize farms are a function of farmer and farm-level characteristics. Specifically, the education level of farmer, use of formal credit for ISFMT, farmland size, farm located in cotton area, member of an agricultural association, crop intercropping, use of inorganic fertilizer, and gender of farmers were significantly associated with the decrease of AI scores of maize farms. On the other hand, the family labour availability increases the AI scores of maize farms.

Our findings have important policy implications for agricultural policy and future research in Republic of Benin. First, given the positive adoption effect of ISFMT on AI reduction, it is important for policymakers to identify ways to promote ISFMT for wider adoption by Beninese maize farmers. In this regard, as ISFMT are knowledge-intensive, removal of barriers to knowledge and creating awareness would greatly help in encouraging adoption. Promotion needs to be carefully targeted to heterogeneous conditions, both in terms of agroecological environments as well as farms and farmers' characteristics including resources available at the farm level. It is also important to address issues related to the use of ISFMT such as access to land and credit. Moreover, our results suggest that adopting ISFMT in combination with mineral fertilizer reduces significantly maize farms AI farmers than adopting ISFM alone. From a policy perspective, increasing farmers' accessibility to factor inputs is key to enhancing mineral fertilizer adoption. This study is based on cross-section data datasets. Hence, our estimates do not capture the adoption dynamics and long run effect of ISFMT on maize farms allocative inefficiency. Therefore, future research should focus on adoption dynamics and AI impact of ISFMT using nationally representative repeated agronomic observations and socioeconomic panel datasets. This would allow to account for previous input use and management decisions, and thus help to overcome potential limitations associated with cross sectional data.

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