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Complementary impact of social capital on the adoption of productivity enhancing technologies: Evidence from Senegal

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Abstract

When a new technology is introduced to farmers, not only do individual and household factors such as risk attitudes, wealth and resource endowments affect a farm household's likelihood of technology adoption but probably more importantly, social capital structures also appear to matter. In this paper, we use the multinomial endogenous switching regression model and empirical data from a nationally representative farm household survey in Senegal to identify the causal effects of social capital on the profitability of adopting two productivity-enhancing technologies – fertilizer and improved seeds. We find a positive and significant treatment effect of social capital on total crop and household income when coupled to the adoption of productivity enhancing technologies. This suggests the need to support farmer-based organizations and improve information channels related to input and output market information, credit and insurance.

Keywords: adoption, social capital, productivity enhancing technology, multinomial endogenous switching

1. Introduction

The agricultural sector continues to be the primary source of livelihood for between 10 to 25% of urban households in sub-Saharan Africa (OECD/FAO, 2016). Despite the immense importance of the sector, agricultural productivity in sub-Saharan Africa has been observed to be lower, compared to other developing regions. Some researchers (Foster and Rosenzweig, 2010; Dercon and Christiaensen, 2011; Suri, 2011; Bizimungu and Kabunga, 2016; Ketema *et al.*, 2016; Bold *et al.*, 2017) have attributed this to the lower than expected adoption of modern agricultural technologies in terms of improved seeds, farming practices, inputs and agricultural machinery.

Adoption of existing and new technologies is a crucial element in poverty reduction, food security and this is particularly important for adapting to climate change. Furthermore, agricultural development interventions built on productivity enhancing technologies such as quality fertilizers, better seeds, improved livestock, and micro-irrigation etc. have been observed to improve household welfare outcomes. For instance, a case study by Graf *et al.*, (2015), shows that potentially gains from adopting productivity enhancing technologies increases the incomes of smallholder farmers between 80-140%. In parallel, there is evidence that many barriers to adoption of new valuable technology exists and a large body of theoretical and empirical literature have tried to answer the adoption puzzle. Factors such as knowledge gaps (Duflo *et al.*, 2006; Matuschke and Qaim, 2008; Kabunga *et al.*, 2012; Ekbom *et al.*, 2013), risk and uncertainties (Knight *et al.*, 2003; Gillespie *et al.*, 2004; Yang *et al.*, 2005; Liu, 2013), liquidity or credit constraints (Foster and Rosenzweig, 2010; Andersson and D'Souza, 2014; Lambrecht *et al.*, 2014; Grabowski *et al.*, 2016), and behavioural biases (Choi *et al.*, 2011; and Duflo *et al.*, 2011) have been observed to hamper the adoption of technologies by farmers.

Probably the single most important factor influencing technology adoption, access to information about a new technology is a key factor determining adoption decisions of farmers and this is the first step-stage of the adoption decision-making process as outlined by the innovation-diffusion model, developed by Rogers (2003). In the agricultural technology adoption and dissemination literature, information has been observed to play a vital role in the adoption and dissemination of several profitable technologies (Simtowe *et al.*, 2012; Ali and Rahut, 2013; Arslan *et al.*, 2014; Grabowski *et al.*, 2014; Lambrecht *et al.*, 2014; Bizimungu and Kabunga, 2016; Donkor *et al.*, 2016). However, the dissemination of information has been observed to be particularly slow when new technologies are propagated by extension services (Noltze *et al.*, 2012; Kabunga *et al.*, 2012). Secondly, information access gap exists for most farmers in developing countries. For instance, in India, Tripp and Pal, (2000) shows that, only 12% of pearl millet farmers in the state of Rajasthan obtained information from government extension services with the rest of the farmers having to rely on other sources such as peers. Social capital¹ which simply describes the ties (bonding and bridging), networks and linkages between individuals, groups and communities serves as a very important source used by farmers in filling such information gaps (Birol *et al.*, 2015). In most developing countries, farmer's social networks are by far the most important source of social capital. Several empirical studies have proven that the dissemination of technologies takes place along social network lines as it provides networks, relationships and linkages that enable farmers to cooperate, coordinate,

¹ In the context of this study, social capital refers to membership of a farmer-based organization.

share information and resources, and act collectively. This is because social capital is recognized as a factor that may influence technology adoption through its effect on household resources and access to information about new technologies. Horizontal transmission of knowledge about a technology through “autochthonous knowledge” transmission channels occurs through a farmer’s peers or neighbours. This is important for the diffusion process of a new technology and at the same time fostering increased usage (Foster and Rosenzweig, 1995; Admassie and Ayele, 2010; Conley and Udry, 2010; Birol *et al.*, 2015; Songsermsawas *et al.*, 2016).

Analogously, a new strand of literature on technology adoption have focused on social networks and learning. These suggests that social interactions offer opportunities for the exchange of information, evaluation of information, and influence of behaviours of individuals, and these are particularly important in the context of new technologies adoption by farmers (see Burton *et al.*, 2003; Kohler *et al.*, 2001, 2007). For example, Conley and Udry (2010) found evidence that pineapple farmers in Ghana adjust their inputs to align with those of their information neighbours who were surprisingly successful in previous periods. In India, Munshi (2004) shows that wheat farmers tend to react to past acreage decisions taken by their village neighbours. Similarly, in Ethiopia Krishnan and Patnam (2014) find that while the initial impact of extension agents was high for technology adoption, the effect wore off after some time, in contrast to farmers learning from neighbours. In North-West India, Feder and Slade (1984) observed that social networks among farm households served as a source of information externality by which farmers learn from peers, friends, neighbours, or experts through active or passive learning. The aforementioned authors found that the likelihood of fertilizer usage was higher in villages where fertilizer adoption and social capital were higher.

Simultaneously, farmer’s technological knowledge might not only be limited regarding the information on available technologies, but farmers might further be fundamentally uncertain regarding the true properties of available technology they know. This leads farmers to develop or form subjective technological beliefs, i.e. simple mental models of how inputs might be transformed into outputs applying a specific technology. These technological beliefs are updated via observation, communication and learning (Jackson, 2008; Acemoglu and Ozdaglar, 2011). Given limited mental capacities, farmers apply a naive Non-Bayesian belief updating mechanism, where they simply update their technological belief based on technological beliefs communicated by their relevant peer groups (Golub and Jackson, 2010). Accordingly, belief updating and hence technology adoption depends on communication network structures among farmers (Jackson, 2008; Golub and Jackson, 2010).

Furthermore, many empirical studies on technology adoption (see Morris *et al.*, 1999; Doss and Morris, 2001; Bala *et al.*, 2006; Erenstein *et al.*, 2007; Admassie and Ayele, 2010; Asfaw and Shiferaw, 2010; Ali and Rahut, 2013), have observed that adopters of agricultural technologies have better access to knowledge via contacts with extension agent than non-adopters. Contrary to this, Birol *et al.*, (2015) finds that in Rajasthan, India, common pool sources of information that are comparatively non-exclusionary such as media and non-religious associations have no significant effect on adoption. In India, Magnan *et al.*, (2015) also shows that where networks are sparse, social networks limits the ability to drive widespread and rapid adoption of laser land levelling technology. In the nutshell, farmers actively seek information from their neighbours or learn passively from others within their social structures

during social interactions and this influences technology adoption. In summary, these empirical studies suggest that farmers do not act unilaterally; instead, they collaborate, consult and negotiate with others. Entrenched in these exchanges is a flow of knowledge, ideas and information that shapes the decision of farmers.

In the adoption literature, most of the work on social capital have centred on the determinants of adoption of particular technologies. In this regards, social capital is included as an explanatory variable in structural models to identify the probability of adoption given access to social capital structures (see Di Falco and Bulte, 2013; Wossen *et al.*, 2015; Husen *et al.*, 2017). The direct impact of social capital on adoption outcomes is hardly studied. A few exceptions are the work done by Davis *et al.*, (2012), Abebaw and Haile (2013), Verhofstadt and Maertens (2015), Ma and Abdulai (2016) and Wossen *et al.*, (2017) which shows positive and heterogeneous impacts of social capital. Nevertheless, social capital forms are not easily accessible or uniformly distributed across locations, which could bring about differentials in access to social learning, technology adoption and hence associated benefits.

This paper contributes to the literature on social networks and technology adoption by examining the causal effects of social capital on the profitability of adopting fertilizer and improved seeds among farm households in Senegal. A unique approach of this paper is that, analyse the causal impact of social capital and the adoption of productivity enhancing technologies in a multinomial framework, hence we do not simply divide farm households into members and non-members of farmer-based organizations as done in previous studies. We considered the adoption of fertilizers and improved high yielding seed varieties, individually or jointly, complemented by being a member of a farmer-based organization (FBO) or not. These two productivity-enhancing technologies are interesting to study because they have different information intensities. Having different intensity of information allows us to analyse the complementary role of social capital via information flows that could be related to use. We hence examine the impact of adopting these technologies individually and in combination coupled with access to social capital in the form of membership to a farmer-based organization. We employed a multinomial endogenous switching regression that accounts for selectivity bias to determine the welfare impacts of adopting fertilizers, improved high yielding seed varieties and membership of farmer-based organization in a multinomial framework. The rest of the paper is organized as follows. In Section 2, the conceptual framework, econometric specification, and the survey data used is described. In Section 3, we present the empirical results and discussions and finally, Section 4 offers conclusion and policy implications.

2. *Conceptual Framework and Econometric Specification*

Adoption of new technologies and membership of farmer-based organizations could result in positive outcomes, however, estimation of such outcomes in observational studies such as ours is unfrivolous because of the difficulty of observing the counterfactual outcomes. In cases where experimental data is available through randomized control trials for instance, information on the counterfactual situation would normally be provided, and as such, the problem of causal inference can easily be resolved (Miguel and Kremer, 2004). Furthermore, in a multiple adoption setting, farm households' simultaneous use of the productivity enhancing technologies; fertilizer and improve seeds, and membership of a farmer-based organization

(FBO) leads to eight² (2^3) possible combinations of decisions (*herein* adoption packages) that farm households could choose from (see Table 1). Farm households' decisions to adopt these combinations of decisions may not be random. Farm households may endogenously self-select adoption or non-adoption, or membership and non-membership of farmer-based organizations so decisions are likely to be influenced systematically both by observed and unobservable characteristics that may be correlated with our outcomes of interest, herein total crop and household income.

Such unobservable characteristics may include for example the innate managerial and technical abilities of farmers in understanding and using agricultural technologies or the types of social networks formed by farmers that are not captured, such as the kind of neighbours the farmer communicates with and whether such neighbours have adopted the technology. Inability to therefore capture these unobservable characteristics may lead to selection bias. To disentangle the pure effects of adoption, we model the farmers' choice of combinations of decisions and the impacts of these decisions in a multinomial endogenous switching regression framework. This approach is a selection-bias correction methodology based on the multinomial logit selection model developed by Bourguignon *et al.*, (2007). This approach allows us to firstly, obtain both consistent and efficient estimates of the selection process and a reasonable correction for the outcome equations, even when the axiom of the independence of irrelevant alternatives (IIA) is violated. Secondly, it allows us to evaluate both individual and combined decisions, while capturing the interactions between choices. Estimation of the multinomial endogenous switching regression occurs simultaneously in two steps. In the first stage, farm households' choice of individual and combined decisions are modelled using a multinomial logit selection model, while recognizing the inter-relationships among them. The respective parameters are also estimated and then used to calculate the selection-bias correction (or selectivity) terms.

In the second stage, the selection-bias correction terms together with the probability of each adoption package been chosen are incorporated as covariates to estimate the impacts of individual and combined packages on total crop and household income using ordinary least squares (OLS). Hence following the approaches of Di Falco and Veronesi (2013); Kassie *et al.*, (2015); and Teklewold *et al.*, (2017) we describe the empirical econometric approach used in the study below.

Table 1: Adoption packages available to farm households

Package (<i>j</i>)	Description	Frequency
ADP0	Non-adoption of fertilizer, improved seeds and non-member of FBO	2,378
ADP1	Fertilizer adoption	974
ADP2	Improved seeds adoption	478
ADP3	Membership of FBO	107
ADP4	Fertilizer and improved seeds adoption	782
ADP5	Fertilizer adoption and membership of FBO	137
ADP6	Fertilizer, improved seeds adoption and membership of FBO	421
ADP7	Improved seeds adoption and membership of FBO	35

² Due to fewer observations' adoption package ADP7 (i.e. improved seeds adoption and membership of farmer-based organization) was dropped from the analysis.

Stage I: Multinomial Adoption Selection Model

Farm households are assumed to maximize their expected revenues by using a combination of productivity enhancing technologies and being members of farmer-based organization. Let U_{ij}^* be the latent variable that captures the expected net revenues from adopting a particular package j ($j=1, \dots, M$) with respect to adopting any other package k . We specify the latent variable as

$$U_{ij}^* = X_i \alpha + \varepsilon_{ij} \tag{1}$$

with

$$U_i \begin{cases} 1 \text{ iff } U_{i1}^* > \max_{k \neq 1}(U_{ik}^*) \text{ or } \varepsilon_{i1} < 0, \\ \vdots \\ M \text{ iff } U_{iM}^* > \max_{k \neq M}(U_{ik}^*) \text{ or } \varepsilon_{iM} < 0, \end{cases}$$

that is, farm household i will choose package j if it provides expected net revenues greater than any other package $k \neq j$, that is, if $\varepsilon_{ij} = \max_{k \neq j}(U_{ik}^*) < 0$.

Equation [1] includes a deterministic component ($X_i \alpha$), and an idiosyncratic unobserved stochastic component ε_{ij} . The deterministic component is a latent variable determined by observed household characteristics such as household size, age, gender, education of household head, asset ownership, land size, soil fertility and climatic characteristics (e.g. mean rainfall and agro-ecology). While the unobserved stochastic component captures all the variables that are relevant to the farm household’s decision maker but are unknown to the researcher such as skills or motivation.

It is assumed that the covariate vector X_i is uncorrelated with the idiosyncratic unobserved stochastic component ε_{ij} , that is, $E(\varepsilon_{ij} | X_i) = 0$. Under the assumption that ε_{ij} is identically and independently Gumbel distributed, the probability of the i th farm household with characteristics X choosing the j th package can therefore be specified by a multinomial logit model (McFadden, 1974) specified as:

$$P_{ij} = P(\varepsilon_{ij} < 0 | X_i) = \frac{\exp(X_i \alpha_j)}{\sum_{k=1}^M \exp(X_i \alpha_k)} \tag{2}$$

The parameter estimates of the latent variable model can be estimated by maximum likelihood estimation. In our specification, the base category, non-adoption of productivity enhancing technologies and non-membership of a farmer-based organization (ADP0), is denoted as $j = 1$. In the remaining packages ($j = 2, \dots, 8$), at least one is applied by farm households.

Stage II: Multinomial Endogenous Switching Regression Model

In the second stage, we estimate a multinomial endogenous switching regression model to investigate the impact of each package on total crop and household income by applying the Bourguignon *et al.*, (2007) selection bias correction model. Our model implies that farm households face a total of M regimes (one regime per package, where $j = 1$ is the reference or base category. The production function to evaluate the total crop and household income implications of each package j is given as:

$$\begin{array}{ll} \text{Regime 1: } Q_{i1} = Z_i\beta_1 + \mu_{i1} \text{ if } A_i = 1 & [3a] \\ \vdots & \vdots \\ \text{Regime M: } Q_{iM} = Z_i\beta_M + \mu_{iM} \text{ if } A_i = M & [3m] \end{array}$$

where Q_{ij} is the outcome variable of farm household i in regime j , ($j = 1, \dots, M$), and Z_i represents a vector of inputs (e.g., fertilizer, seed, land, credit, machinery and labour), and farm household head and household's characteristics, asset ownership, soil fertility and climatic characteristics. μ_{ij} represents the unobserved stochastic component, which verifies $E(\mu_{ij} | Z_i, X_i) = 0$ and $V(\mu_{ij} | Z_i, X_i) = \sigma_j^2$.

For each sample observation, Q_{ij} is observed if and only if one among the M dependent regimes is observed. When estimating an ordinary least squares (OLS) model, the total crop income or household income equations, [3a] – [3m] are estimated separately. However, if the error terms of the selection model (equation 1) ε_{ij} are correlated with the error terms μ_{ij} of the outcome model [3a] – [3m], then the expected values of μ_{ij} conditional on the sample selection are nonzero i.e., $\text{corr}(\varepsilon_{ij}, \mu_{ij}) \neq 0$, and the OLS estimates will be biased and inconsistent.

To correct for the potential inconsistency, we employ the multinomial endogenous switching regression model by Bourguignon *et al.*, (2007), which takes into account the correlation between the error terms ε_{ij} from the multinomial logit model estimated in the first stage and the error terms μ_{ij} from each outcome equation. Just like the standard endogenous switching regression model, Bourguignon *et al.*, (2007) model addresses selection bias issue resulting from unobservable factors as a missing variable problem. The model by Bourguignon *et al.*, (2007) allows for the estimation of selection correction terms from equation [1], which can then be plugged into equations [3a] – [3m] to obtain selection bias-corrected outcome models. Bourguignon *et al.*, (2007), show that under the assumption of Normalized Dubin–McFadden linearity, consistent estimates of β_j in the outcome equations [3a] – [3m] can be obtained by estimating the following selection bias-corrected outcome equations:

$$\begin{array}{ll} \text{Regime 1: } Q_{i1} = Z_i\beta_1 + \sigma_1 \left[\rho_1 m(P_{i1}) + \sum_j \rho_j m(P_{ij}) \frac{P_{ij}}{P_{ij} - 1} \right] + v_{i1} \text{ if } A_i = 1 & [4a] \\ \vdots & \vdots \\ \text{Regime M: } Q_{iM} = Z_i\beta_M + \sigma_M \left[\rho_M m(P_{iM}) + \sum_j \rho_j m(P_{ij}) \frac{P_{ij}}{P_{ij} - 1} \right] + v_{iM} \text{ if } A_i = M & [4m] \end{array}$$

where P_{ij} represents the probability that farm household i chooses package j as defined in equation [2], ρ_j is the correlation between ε_{ij} , and μ_{ij} , and $m(P_{ij}) = \int J(v - \log P_j) g(v) dv$ with $J(\cdot)$ being the inverse transformation for the normal distribution function, $g(\cdot)$ the unconditional density for the Gumbel distribution, and $v_{ij} = \mu_{ij} + \log P_j$. This implies that the number of selection correction (bias) terms in each equation is equal to the number of multinomial logit choices M .

The specified model allows us to identify not only the direction of the bias related to the allocation of farm households in a specific package, but also which choice among any two alternative packages this bias stems from. For example, a positive bias correction coefficient related to alternative j selection equation in the alternative k outcome (e.g. total crop income) equation highlights higher incomes of farm households who chose alternative k compared to farm households taken at random, due to the allocation of farm households with worse unobserved skills out of alternative k into the alternative j . In the nutshell, for each package-based outcome estimation, a negative (positive) selectivity coefficient related to any of the alternative adoption package indicates lower outcomes (incomes) than those of randomly chosen farm households on account of the allocation of farm households with better (worse) unobserved characteristics out of the given package and into the respective alternative package.

While the variables X_i in equation [1] and Z_i in equation [4a] – [4m] are allowed to overlap, proper identification requires at least one variable in X_i that does not appear in Z_i . Therefore, the selection equation [1] is estimated based on all explanatory variables specified in the outcome equations plus at least one or more instruments. Following Di Falco and Veronesi (2013), we establish the admissibility of the selected instruments by performing a simple falsification test: the selected or valid instrument (s) is required to significantly influence a farm household's choice of package but have no significant effect on outcomes (i.e. total crop and household income). In this study, we employ perception about the quality of subsidized fertilizer and seeds, and insurance needs as identifying instrument. These are expected to influence the adoption of packages but not total crop and household incomes.

In addition, to overcome the possible correlation of crop-invariant unobserved heterogeneity with observed covariates, we employed the approach of Mundlak (1978) and Wooldridge (2010) which has been also used by Di Falco (2014), Kassie *et al.*, (2015) and Teklewold *et al.*, (2017)³. The approach allows us to exploit crop-level information to deal with the issue of farm household's unobservable characteristics such as their skills. Furthermore, crop-level information can potentially control for farm specific effects. In this approach, unobserved heterogeneities are parameterized by including the mean value of crop-varying variables \bar{Y}_i such as average fertiliser, labour, land and seed as additional covariates, which are inserted in the outcome equations [4a] – [4m]. This approach relies on the assumption that the unobservable characteristics v_i are a linear function of the averages of the crop-variant explanatory variables \bar{Y}_i ; that is $v_i = \hat{Z}_i \pi + \psi_i$ with $\psi_i \sim N(0, \sigma^2_\psi)$ and $E(\psi_i | \hat{Z}_i) = 0 \bar{Y}_i$, where π is the corresponding vector of coefficients, and ψ_i is a normal error term uncorrelated with \bar{Y}_i . According to

³ The listed studies employed plot-variant variables to control for unobserved heterogeneity. In the case of our study, we are unable to use plot-variant variables to control for unobserved heterogeneity due to the lack of such data. However, we use an alternative approach by using crop-variant variables since household produce multiple crops and we have data for each crop commodity.

Teklewold *et al.*, (2013), a Wald test of the null hypothesis that the vector π are jointly equal to zero is required to indicate the relevance of crop-specific heterogeneity.

As shown by Antle (1983) the error terms in equations [4a] – [4m] are likely to exhibit heteroscedasticity, hence following Bourguignon *et al.*, (2007), we bootstrapped the standard errors with 1000 replications in equations [4a] – [4m] to account for heteroscedasticity in the second stage.

2.1 Estimation of the treatment and counterfactual effects

The challenge of impact evaluation using observational data is to estimate the counterfactual outcome, which is the outcome of interest when adopters of a particular package could have gained had they not adopted the package in question. Di Falco (2014), argues that in the absence of a self-selection problem, it would be appropriate to assign to farm households that adopted a counterfactual outcome of interest equal to the average outcome of interest of non-adopters with the same observable characteristics. However, unobserved heterogeneity in the propensity to choose a package also affects the outcome of interest and creates a selection bias in the outcome of interest equation (i.e. [4a] – [4m]) that cannot be ignored. The Multinomial Endogenous Switching Regression framework however can be used to examine average treatment effects (ATT) by comparing expected outcomes of adopters with and without adoption. Following Bourguignon *et al.*, (2007), we first derive the conditional expected outcome of interest (total crop and household income) of farm households that adopted, which in our study means $j = 2 \dots \dots M$ ($j = 1$ is the reference category “non-adoption”) from equation [4a] – [4m], as

$$E(Q_{i2}|A_i = 2) = Z_i\beta_2 + \sigma_2 \left[\rho_2 m(P_{i2}) + \sum_{k \neq 2}^M \rho_k m(P_{ik}) \frac{P_{ik}}{P_{ik} - 1} \right] \quad [5a]$$

$$E(Q_{iM}|A_i = M) = Z_i\beta_M + \sigma_M \left[\rho_M m(P_{iM}) + \sum_{k=1 \dots M-1}^M \rho_k m(P_{ik}) \frac{P_{ik}}{P_{ik} - 1} \right] \quad [5m]$$

Then, we obtain the expected outcome of interest of farm households that adopted package j in the counterfactual hypothetical case that they did not adopt ($j = 1$) as

$$E(Q_{i1}|A_i = 2) = Z_i\beta_1 + \sigma_1 \left[\rho_1 m(P_{i2}) + \rho_2 m(P_{i1}) \frac{P_{i1}}{(P_{i1} - 1)} + \sum_{k \neq 2}^M \rho_k m(P_{ik}) \frac{P_{ik}}{P_{ik} - 1} \right] \quad [6a]$$

$$E(Q_{i1}|A_i = M) = Z_i\beta_1 + \sigma_1 \left[\rho_1 m(P_{iM}) + \sum_{k=2 \dots M}^M \rho_k m(P_{i,k-1}) \frac{P_{i,k-1}}{P_{i,k-1} - 1} \right] \quad [6m]$$

Equations [5a] – [5m] represent the actual expected outcomes of interest (total crop and household income) actually observed in the sample for adopting farm households, while equations [6a] – [6m] are their respective counterfactual expected outcomes of interest. The use

of these conditional expectations allows us to calculate the treatment effects (TT), which is the difference between equations [5a] and [6a] or [5m] and [6m] as an example.

2.2 *Method for addressing potential endogeneity*

An issue that needs to be addressed in estimating equation [1] is the potential endogeneity problem that may arise with variables such as nonfarm work participation, extension and credit access (see Abdulai and Huffman, 2015; Ma and Abdulai, 2016). Nonfarm work participation for instance potentially produces two effects related to labour loss and income with respect to adopting productivity enhancing technologies. For example, nonfarm work participation is potentially endogenous to the adoption of fertilizer and improved seeds, because adoption of these technologies is labour-intensive. In particular, farm households may have to decide between allocating labour to nonfarm work and to agronomic activities when adopting the two productivity-enhancing technologies. Especially during the farming season when labour is in high demand for farm work or harvest, farm households may choose to allocate more labour to farm activities, resulting in less time being allocated to nonfarm work. At the same time, farm households actively engaged in nonfarm work may not be able to adopt such practices. Furthermore, income earned from nonfarm work may be used to purchase inputs or invested in the two productivity-enhancing technologies.

Agricultural extension agents normally disseminate new technologies to farmers, leading to the adoption of the technologies. Furthermore, farm households adopting these productivity-enhancing technologies may potentially attract more visits by extension staff than non-adopters. At the same time, agricultural extension agents may also encourage them to join farmer-based organizations. As shown in several empirical studies, farmer-based organizations normally help their members to obtain credit from financial institutions, thus making access to credit a potentially endogenous variable. Thus, extension contact and access to credit variables may be jointly determined with the decision of choosing to adopt the two productivity-enhancing technologies or the choice of belonging to a farmer-based organization.

Thus, nonfarm work participation, extension and credit access variables may be jointly determined with the decision of choosing to adopt the two productivity-enhancing technologies and belonging to a farmer-based organization, which are the key components in our “package”. Hence, given the dichotomous nature of the dependent variables, we follow previously studies (see Abdulai and Huffman, 2015; and Ma and Abdulai, 2016), and control for potential endogeneity of the variables using the control function approach⁴ (Wooldridge, 2015). The approach involves the specification of the potential endogenous variable (i.e. nonfarm work participation, extension access, and credit access) as a function of explanatory variables influencing adoption of packages, together with a set of instruments in a first-stage logit regression (i.e. a separate logit estimation for nonfarm work participation, extension and credit access). That is, the specification used is

$$S_i = X_{ij}\tau + G_{ij}\gamma + \epsilon_{ij} \quad [7]$$

where S_i is vector of the observed potential endogenous variables such as nonfarm work participation, extension and credit access, X is as described previously in equation [1], G_{ij} is a

⁴ We do not provide the results for the control for potential endogeneity but they are available upon request.

vector of instruments that is correlated with the given endogenous variable but uncorrelated with the error term, ε_{ij} in equation [1], and is therefore excluded in estimating equation [1], and ε_{ij} is the error term. To ensure identification in the estimation of the adoption specification, some of the variables included in the first-stage estimation in equation [7] are excluded from the selection equation in [1]. For the purpose of our study, distance to major city is included as instruments to control for nonfarm work participation. The need for support and type of support are used as instruments to control for extension access and location is used as instruments to control for credit access. Another important consideration is that the instrumental variables used here (distance to major city, need for support, type of support and location) are required not to be correlated with the instruments (i.e. perception about the quality of subsidized fertilizer and seeds, and insurance needs) used for the Multinomial Endogenous Switching Regression model identification. Finally, both the observed factors and the “generalized residuals” predicted from equation [7] are used in estimating equation [1]. As suggested by Wooldridge (2015), the approach leads to robust, regression-based Hausman test for endogeneity of the suspected variables.

2.3 The empirical specification

The specification of our empirical model is based on economic theory and empirical adoption and impact studies of technology adoption (Feder, 1980; Feder *et al.*, 1981; Adesina and Zinnah, 1993; Baidu-Forson, 1999; Doss, 2003; Duflo *et al.*, 2008, 2011; Adhikari *et al.*, 2009; Admassie and Ayele, 2010; Asfaw and Shiferaw, 2010; Simtowe *et al.*, 2010; Sharma *et al.*, 2011; Simtowe *et al.*, 2011; Suri, 2011; Dandedjrohoun *et al.*, 2012; Simtowe *et al.*, 2012; Awotide *et al.*, 2013; Bonou *et al.*, 2013; Arslan *et al.*, 2014; Donkor *et al.*, 2016) and membership of farmer-based organizations (Foster and Rosenzweig, 1995; Isham, 2002; Padmaja *et al.*, 2006; Ali *et al.*, 2007; Katungi, 2007; Munasib and Jordan, 2011; Van Rijn *et al.*, 2012; Ramirez, 2013; Ntume *et al.*, 2015; Hansen and Roll, 2016; Tessema *et al.*, 2016; Hunecke *et al.*, 2017; Husen *et al.*, 2017; Wossen *et al.*, 2017; Olawuyi and Mushunje, 2019; Yahaya *et al.*, 2019). Following this literature, we have summarized variables that are hypothesized to affect adoption decisions, total crop and total household income.

These are grouped into five main groups; farm household and asset characteristics, access to services and institutions, farm and biophysical characteristics, environmental risks, and location variables. In addition, mean labour, land holding, fertilizer and seed quantities used were included as control for unobserved heterogeneity. Table 2 presents the definition of the variables used in the analysis. We also present the mean differences in the characteristics of farm households across the seven packages in Table 3.

2.4 Survey data

The data used in the study comes from a farm household survey as part of the larger Senegalese “Projet d’appui aux politiques agricoles (PAPA)” or the Agricultural Policy Support Project. The farm household survey was conducted between April and May 2017. The survey covered all the 14 administrative regions of Senegal and all the departments with the exception of the departments of Dakar, Pikine and Guédiawaye due to the lack of agricultural activity. The General Census of Population and Housing, Agriculture and Livestock conducted in 2013 show that about 755,532 households practice agriculture, with about 61% (458,797) of the farming

households practicing rainfed agriculture. The survey was targeted towards cereals, horticultural crops, and fruit and vegetable producers. The survey design was a two-stage, nationally based random survey that included rural census districts as the primary units and farm households as the secondary units. The method consisted of first dividing the statistical population (i.e. agricultural households) in the primary units so that each of them is unambiguously related to a well-defined primary unit. Then samples were drawn in two stages. In the first stage, a sample of rural census districts was drawn and in the second stage, a sample of agricultural households was selected at the level of each primary unit. In rural census districts where rainfed agriculture was practice and localized crops were grown such as Senegal River Valley and Niayes Market Gardening Zone, a stratification of the rural census districts was done before agricultural households were selected.

The agricultural survey was geared towards estimating the levels of agricultural production of family farms. The survey provided information on the physical characteristics of cultivated plots (geo location, area) and major investments made at their level, agricultural equipment ownership, agricultural risks and adaptation strategies, etc. The data collected include information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit, inputs use and cost, family and hired labour, sales volumes and processing activities. Others included household consumption, access to amenities, non-farm and livestock revenue, remittance, agricultural insurance, perceptions about subsidies related to fertilizer, seeds and agricultural equipment, and membership of farmer-based organizations.

3. Empirical Results

Because we are primarily interested in the drivers and effects of the adoption packages on total crop and household income, we do not discuss the econometric estimates of total crop income and household income model. These estimation results are however provided in the appendix (Table A1 and A2). We however provide a brief discussion of the selectivity correction terms (adp0 to adp6) in Table A1 and A2. As started earlier, the selectivity correction terms capture selectivity effects arising from unobserved factors. The results show that the selectivity correction terms are significant in the total crop income equations (Table A1) for fertilizer adoption only (ADP1), fertilizer and improved seeds only (ADP4) and, fertilizer, improved seeds adoption and membership of farmer-based organizations (ADP6). In the total household income equations (Table A2), we see this also for the adoption packages ADP0, ADP1, ADP2, ADP4 and ADP6. This indicates the presence of sample selectivity effects and using OLS would have produced biased and inconsistent estimates. Thus, accounting for selectivity effects using the Multinomial Endogenous Switching Regression model was appropriate.

Table 2: Variable definition and measurement

Name	Variable description
<i>Outcome variables</i>	
Total crop income	Log ⁵ of crop income in CFA
Total household income	Log of total household income in CFA
<i>Farm household and asset characteristics</i>	
Age	Age of household head in years
Gender	=1 if household is male-headed
Education	=1 if household head has formal education
HH size	Number of people residing in the household
Total labour	Total labour used by household
Lighting fuel ^a	=1 if source of lighting fuel is electricity
Risk attitude	=1 if risk averse
Nonfarm work	=1 if household participates in nonfarm work
Plough	=1 if household owns a plough
<i>Access to services and institutions</i>	
Extension access	=1 if accessed extension service
Credit access	=1 if access to credit
Market information	=1 if accessed market information
Fertilizer subsidy	=1 if access to fertilizer subsidies
Seed subsidy	=1 if access to seed subsidies
<i>Farm and biophysical characteristics</i>	
Land holding	Total land area farmed by household (ha)
SQI ⁶	Soil quality index
Rainfall	Mean annual rainfall in mm (2010 – 2017)
AEZ BasinAra	=1 if agro-ecological zone is Bassin Arachide
AEZ RiverVall	=1 if agro-ecological zone is River Valley
AEZ Casamance	=1 if agro-ecological zone is Casamance
AEZ CentEast	=1 if agro-ecological zone is Center East
<i>Environmental risks</i>	
Std. Rainfall	Standard deviation of rainfall in mm (2010 – 2017)
Risk count	Number of production risks faced by household
Loss count	Number of risk related losses experienced by household
<i>Location variables</i>	
Road	Log of distance to the nearest road (km)
Market	Log of distance to the nearest market (km)
<i>Mundlak fixed effects variables</i>	
Mean labour	Mean labour allocation across all crops grown
Mean land holding	Mean land (ha) allocation across all crops grown
Mean fertilizer quantity	Mean fertilizer (kg) use across all crops grown
Mean seed quantity	Mean seed (kg) use across all crops grown
<i>Instrumental variables</i>	
Fertilizer quality	=1 if perceived subsidized fertilizer quality is good
Seed quality	=1 if perceived subsidized seed quality is good
Insurance needs	=1 if farmer has specific insurance needs
Support needs	=1 if farmer has support needs
Type support needs	=1 if training on good farming practices is needed
Location	=1 if farm household is located in highly populous region
Distance to major city	Distance to major city in km

^a Source of lighting fuel is used as a proxy variable for household wealth

⁵ The logarithm of variables used in the analysis were to the base 10.

⁶ For soil quality, we computed a soil quality index using publicly available data from International Soil Reference and Information Centre (ISRIC – World Soil Information). We describe the computation of this index in appendix A2

3.1 *Factors driving the adoption of packages*

In Table 4, we present the parameter estimates of the multinomial logit model that permits us to identify factors that drives farm households' adoption of the various packages. We find that the multinomial logit model fits the data well, the Wald test is highly significant, hence rejecting the null hypothesis that all the regression coefficients are jointly equal to zero. Furthermore, the test for joint significance of instruments across the different packages are highly significant. The results from the control-function specification indicate that the correction for endogeneity in the model was necessary. We find the coefficient of the extension access, credit access and nonfarm work participation residual terms to be statistically significant in three packages, implying the presence of endogeneity of these variables.

Results show that the adoption of fertilizer (*package ADP1*) is largely driven by farm household and asset characteristics, and farm and biophysical characteristics. The relative probability of adopting fertilizer is strongly positive and statistically significant for education level of household head, household size and wealth. Participation in nonfarm work has a negative and statistically significant effect on the probability of fertilizer adoption. We also find that relative probability of adopting fertilizer is strongly positive and statistically significant for subsidized fertilizer access, land holding, farming in the River Valley, Casamance and Center East agro-ecological zones. On the other hand, soil quality, risk count, perception about the quality of subsidized fertilizer and seeds as well as insurance needs is strongly negative and statistically significant for fertilizer adoption. Similarly, we observe that the relative probability of improved seeds adoption (*package ADP2*) is strongly positive and statistically significant for household size, subsidized seed access, land holdings, Bassin Arachide and Center East agro-ecological zones. Risk attitude, market information access, subsidized fertilizer access, and perception about the quality of subsidized seeds is strongly negative and statistically significant for improved seeds adoption.

The relative probability of membership of farmer-based organizations (*package ADP3*) adoption is positive and statistically significant for household size, subsidized fertilizer access, and insurance needs. We also find that the relative probability of fertilizer and improved seeds adoption (*package ADP4*) is strongly positive and statistically significant for age and education level of the household head, household size, extension access, subsidized fertilizer and seeds access, land holding, River Valley agro-ecological zone and insurance needs. On the other hand, risk attitude, soil quality, Bassin Arachide, Casamance and Center East agro-ecological zones, distance to nearest market, risk count and the perception about the quality of subsidized fertilizer and seeds is negative and statistically significant for fertilizer and improved seeds adoption. The probability of fertilizer adoption and membership of farmer-based organizations (*package ADP5*) is positively driven by the education level of the household head, household size, subsidized fertilizer access, River Valley agro-ecological zone and insurance needs. Soil quality and the number of production risks experienced by a household is negative and statistically significant for fertilizer adoption and being a member of a farmer-based organization.

We find that the probability of adopting fertilizer, improved seeds and being a member of a farmer-based organization (*package ADP6*) is positive and statistically significant for education level of the household head, household size, nonfarm work participation, extension access,

subsidized fertilizer and seeds access, land holding, River Valley agro-ecological zone, number of risk related losses experienced and insurance needs. We also find that relative probability of adopting fertilizer, improved seeds and being a member of a farmer-based organization is negative and statistically significant for risk attitude, soil quality, Bassin Arachide, Casamance and Center East agro-ecological zones, the number of production risks experienced and perception about the quality of subsidized seeds.

In summary, we find that the relative probability to adopt the six packages is largely driven by the education level of the household head, household size, subsidized fertilizer and seeds access, land holding, soil quality, agro-ecological zones, number of risk related losses experienced, perception about the quality of subsidized seeds and insurance needs.

3.2 *Economic implications of packages on total crop income*

The economic implications of adopting each package on farm households' total crop and total household income measured here by the average treatment effects (ATT) is shown in Table 5 and 6 respectively. Unlike the simple mean presented in Table 3, the ATT estimates account for selection bias resulting from both observable and unobservable characteristics. Controlling for the effects of several covariates and the selection bias stemming from both unobserved and observed factors on total crop and household income, the adoption of the various packages is associated with significant incomes. Results show that the adoption of packages, whether in isolation or in combination, provides higher total crop income compared with non-adoption (Table 5). Though not significant, farm households that are only members of farmer-based organizations and do not adopt any of the productivity enhancing technologies seems to earn higher crop incomes compared to the counterfactual case of not being members. On the contrary, the opposite was observed for total household incomes with total household incomes being higher in the counterfactual case of non-membership of FBOs. The effect is not however statistically significant.

It is also interesting to note that despite empirical evidence of positive impacts of social capital, the result obtained here shows that relying solely on social capital without the adoption of productivity enhancing technologies does not bring a positive effect to farm household's total incomes. On the contrary adopting fertilizer and being a member of a farmer-based organization increases total crop and household incomes by about 65% and 27% respectively compared to a counterfactual case where farm households do not adopt fertilizer and are non-members of farmer-based organizations. The result here is congruent to other empirical findings (see Fischer and Qaim, 2012; Verhofstadt and Maertens, 2015; Ma and Abdulai, 2016; and Wossen *et al.*, 2017). We also find that the adoption of fertilizer, improved seeds and membership of a farmer-based organization produces the highest impact on total crop and household incomes. Hence, farm households employing this package gain about 198% higher total crop incomes and 61% higher total household incomes compared to a counterfactual case they do not adopt. The finding here is yet again congruent to what has already been reported in the empirical literature. Productivity enhancing technologies used in combination produces higher returns (see Harou *et al.*, 2017; Ragasa and Chapoto, 2017; and Teklewold *et al.*, 2017). Furthermore, we find statistical evidence of the impact of the productivity enhancing technologies when implemented in isolation.

Table 3: Descriptive Statistics by Adoption Package

Variable	ADP0		ADP1		ADP2		ADP3		ADP4		ADP5		ADP6		Pooled	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Crop income (log)	5.15	0.54	5.56	0.50	5.38	0.48	5.20	0.45	5.59	0.53	5.53	0.54	5.66	0.54	5.37	0.57
Total household income (log)	5.40	0.54	5.70	0.49	5.58	0.46	5.40	0.47	5.72	0.52	5.69	0.52	5.79	0.52	5.56	0.54
Age	53.21	13.44	52.47	13.35	53.47	13.87	48.90	11.65	53.56	13.17	50.88	11.77	52.78	12.35	52.98	13.28
Gender	0.91	0.28	0.95	0.23	0.92	0.26	0.81	0.39	0.93	0.25	0.93	0.25	0.93	0.26	0.92	0.27
Education	0.33	0.47	0.40	0.49	0.32	0.47	0.41	0.49	0.43	0.50	0.55	0.50	0.45	0.50	0.38	0.48
HH size	9.08	4.80	10.33	5.66	10.10	5.28	10.00	4.99	10.17	5.59	11.35	6.00	10.47	5.40	9.76	5.26
Lighting fuel	0.31	0.46	0.37	0.48	0.33	0.47	0.30	0.46	0.38	0.49	0.40	0.49	0.37	0.48	0.34	0.47
Risk attitude	0.48	0.50	0.45	0.50	0.47	0.50	0.54	0.50	0.42	0.49	0.46	0.50	0.42	0.49	0.46	0.50
Nonfarm work	0.27	0.44	0.26	0.44	0.25	0.43	0.38	0.49	0.24	0.43	0.31	0.46	0.26	0.44	0.26	0.44
Plough ownership	0.33	0.47	0.24	0.43	0.45	0.50	0.15	0.36	0.18	0.39	0.13	0.33	0.13	0.34	0.28	0.45
Extension access	0.06	0.25	0.11	0.32	0.07	0.25	0.29	0.46	0.27	0.44	0.32	0.47	0.52	0.50	0.15	0.36
Credit access	0.01	0.09	0.03	0.18	0.02	0.15	0.06	0.25	0.09	0.29	0.17	0.38	0.17	0.38	0.05	0.21
Market information	0.51	0.50	0.50	0.50	0.45	0.50	0.46	0.50	0.52	0.50	0.51	0.50	0.55	0.50	0.50	0.50
Seed subsidy	0.25	0.43	0.39	0.49	0.66	0.47	0.25	0.44	0.56	0.50	0.46	0.50	0.44	0.50	0.38	0.49
Fertilizer subsidy	0.11	0.31	0.56	0.50	0.18	0.38	0.18	0.38	0.67	0.47	0.68	0.47	0.72	0.45	0.35	0.48
Land holding	4.46	4.67	6.94	10.87	7.70	14.68	3.75	4.44	5.67	8.21	5.04	4.89	4.87	6.85	5.45	8.27
Total hired labour	0.13	1.05	0.24	1.08	0.11	0.59	0.08	0.57	0.24	0.93	0.31	0.99	0.37	1.17	0.19	1.01
SQI	0.41	0.09	0.36	0.10	0.42	0.10	0.36	0.07	0.36	0.09	0.35	0.10	0.34	0.10	0.38	0.10
Std rainfall	111.10	24.48	109.97	23.73	110.89	23.66	110.41	24.66	107.63	24.17	110.17	24.26	104.42	25.09	109.7	24.33
Rainfall	685.30	299.22	675.75	311.12	689.09	305.02	639.52	308.93	616.59	308.27	671.82	308.79	614.36	329.05	666.5	307.5
AEZ BasinAra	0.47	0.50	0.44	0.50	0.68	0.47	0.19	0.39	0.34	0.47	0.30	0.46	0.11	0.31	0.43	0.49
AEZ RiverVall	0.05	0.21	0.10	0.30	0.04	0.19	0.09	0.29	0.31	0.46	0.26	0.44	0.41	0.49	0.13	0.34
AEZ Casamance	0.23	0.42	0.32	0.47	0.11	0.31	0.53	0.50	0.12	0.32	0.22	0.42	0.09	0.28	0.21	0.41
AEZ CentEast	0.10	0.30	0.07	0.26	0.10	0.30	0.16	0.37	0.08	0.26	0.13	0.34	0.05	0.22	0.09	0.29
Loss count	1.71	1.06	1.64	1.00	1.87	1.22	2.01	1.16	1.64	0.99	1.51	1.10	1.81	1.17	1.71	1.07
Road	3.54	0.89	3.62	0.84	3.41	0.85	3.23	0.95	3.65	0.87	3.58	0.96	3.92	0.83	3.59	0.88
Market	3.97	0.47	3.99	0.44	3.89	0.41	3.93	0.51	3.92	0.49	3.95	0.41	3.98	0.39	3.96	0.46
Risk count	2.07	1.37	1.98	1.60	2.39	1.52	2.48	1.82	1.45	1.63	1.54	1.68	1.16	1.70	1.90	1.55
Fertilizer quality	0.05	0.22	0.16	0.37	0.08	0.27	0.03	0.16	0.21	0.41	0.20	0.40	0.19	0.40	0.11	0.32
Seed quality	0.16	0.37	0.20	0.40	0.34	0.48	0.16	0.37	0.25	0.43	0.28	0.45	0.11	0.32	0.20	0.40
Insurance needs	0.30	0.46	0.44	0.50	0.33	0.47	0.54	0.50	0.49	0.50	0.62	0.49	0.56	0.50	0.39	0.49
Mean labour	1.79	1.34	2.24	1.85	2.08	1.59	1.99	1.41	2.15	1.60	2.54	2.02	2.27	1.69	2.02	1.57
Mean land	0.10	0.11	0.15	0.15	0.16	0.14	0.08	0.11	0.12	0.16	0.11	0.13	0.07	0.13	0.12	0.14
Mean fertilizer	0.00	0.00	14.40	66.96	0.00	0.00	0.00	0.00	16.89	41.99	13.48	19.96	34.94	143.88	8.51	54.12
Mean seed	3.14	3.64	6.03	5.57	4.99	5.02	2.95	3.58	6.30	6.81	5.51	5.97	7.06	8.42	4.72	5.51
Type of support	0.43	0.49	0.57	0.50	0.46	0.50	0.66	0.48	0.62	0.49	0.63	0.48	0.67	0.47	0.51	0.50
Support needs	0.69	0.46	0.78	0.42	0.71	0.46	0.87	0.33	0.83	0.38	0.84	0.37	0.89	0.32	0.75	0.43
Location	0.21	0.41	0.11	0.31	0.25	0.43	0.04	0.19	0.06	0.24	0.03	0.17	0.03	0.17	0.15	0.36
Distance to city	46.62	35.06	46.09	35.04	39.99	26.33	42.19	27.21	65.68	46.12	61.79	46.89	92.58	47.66	52.90	40.21
N	2,313		972		477		97		782		137		420		5,198	

The adoption of improved seeds in isolation significantly increases total crop income by about 8% and total household incomes by about 2% compared to a counterfactual case where farm households do not adopt. The observed effect is however not statistically significant. These findings are in agreement to other studies involving improved seed (see Boughton and Frahan, 1994; Morris *et al.*, 1999; Adekambi *et al.*, 2009; Adhikari *et al.*, 2009; Krishna *et al.*, 2009; Asfaw and Shiferaw, 2010; Suri, 2011; Simtowe *et al.*, 2012; Bonou *et al.*, 2013; Wiredu *et al.*, 2014; Mensah and Brümmer, 2015; Manda *et al.*, 2016; Owusu, 2016). In parallel, the adoption of inorganic fertilizer in isolation increases total crop and household incomes by about 50% and 34% respectively compared to a counterfactual case where farm households do not adopt it. The results here are in agreement to several other studies that have evaluated the impact of fertilizer use (Heisey and Mwangi, 1996; Yanggen *et al.*, 1998; Duflo *et al.*, 2008; Marennya and Barrett, 2009; Xu *et al.*, 2009; Duflo *et al.*, 2011; Matsumoto and Yamano, 2011; Beaman *et al.*, 2013; Chapoto and Ragasa, 2013; Minten *et al.*, 2013; Ricker-Gilbert *et al.*, 2013; Sheahan *et al.*, 2013; Tully *et al.*, 2015; Savini *et al.*, 2016; Koussoubé and Nauges, 2017; Liverpool-Tasie, 2017; Takeshima *et al.*, 2017). The results also show that the treatment effect of fertilizer adoption in isolation is statistically different from improve seeds adoption (t -statistic = 10.26 for total crop income and t -statistic = 7.51 for total household income). This implies that farm households that adopt fertilizer only earn higher total crop and total household incomes compared to those who adopt improve seeds only.

Table 4: Parameter estimates of adoption of packages – multinomial logit selection model

Variable	ADP1		ADP2		ADP3		ADP4		ADP5		ADP6	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	-0.005	0.003	-0.001	0.004	-0.032***	0.011	0.007*	0.004	-0.005	0.007	0.002	0.006
Gender	0.141	0.200	-0.017	0.216	-1.059***	0.393	0.368	0.240	0.236	0.638	0.403	0.291
Education	0.323***	0.099	-0.033	0.124	0.141	0.281	0.373***	0.119	0.894***	0.215	0.539***	0.162
HH size	0.036***	0.009	0.023*	0.012	0.047**	0.022	0.040***	0.010	0.078***	0.017	0.080***	0.013
Lighting fuel	0.388***	0.103	0.085	0.132	0.264	0.312	-0.004	0.117	0.130	0.232	-0.267	0.163
Risk attitude	-0.107	0.115	-0.304**	0.154	0.138	0.482	-0.510***	0.144	-0.252	0.287	-0.657***	0.196
Nonfarm work	-1.429***	0.452	0.312	0.630	-1.111	1.902	0.261	0.594	0.411	1.145	1.936**	0.806
Plough ownership	-0.109	0.115	0.193	0.123	-0.130	0.404	-0.219	0.135	-0.450	0.338	-0.228	0.207
Extension access	0.654	0.478	0.616	0.644	1.634	1.059	1.552***	0.415	0.303	0.617	1.773***	0.517
Credit access	-0.928	1.969	1.869	2.848	-2.833	9.758	2.287	1.929	1.450	1.961	-0.655	1.935
Market information	-0.012	0.090	-0.242**	0.113	-0.238	0.250	0.078	0.103	-0.004	0.199	0.135	0.139
Seed subsidy	-0.132	0.163	1.974***	0.172	-0.201	0.693	1.048***	0.170	-0.144	0.356	0.673***	0.214
Fertilizer subsidy	2.685***	0.151	-0.527**	0.212	0.812*	0.416	2.618***	0.164	3.161***	0.290	3.109***	0.208
Land holding	0.046***	0.009	0.042***	0.010	-0.027	0.055	0.045***	0.010	0.026	0.017	0.059***	0.010
SQI	-4.520***	0.623	-0.770	0.732	-2.738	2.165	-5.342***	0.684	-7.283***	1.332	-9.596***	1.021
Std rainfall	-0.001	0.002	0.000	0.002	-0.003	0.005	-0.001	0.002	0.002	0.004	-0.003	0.003
AEZ BasinAra	0.175	0.203	0.555**	0.237	0.012	4.882	-0.889***	0.215	-0.647	0.440	-2.941***	0.306
AEZ RiverVall	0.971***	0.271	0.615	0.401	1.465	4.925	1.525***	0.239	2.043***	0.503	1.009***	0.303
AEZ Casamance	0.626***	0.221	-0.188	0.287	1.934	4.946	-1.356***	0.236	-0.511	0.528	-3.668***	0.370
AEZ CentEast	0.511**	0.259	0.598**	0.286	1.582	4.906	-0.691**	0.295	0.324	0.541	-2.662***	0.426
Loss count	-0.073	0.054	0.062	0.062	0.114	0.175	0.069	0.061	-0.081	0.142	0.187***	0.071
Road	0.048	0.057	-0.099	0.069	-0.225	0.163	0.002	0.066	0.004	0.146	0.075	0.104
Market	0.038	0.106	-0.117	0.128	-0.441	0.298	-0.358***	0.121	-0.245	0.230	-0.060	0.168
Risk count	-0.115***	0.042	0.025	0.044	0.024	0.114	-0.299***	0.051	-0.262***	0.100	-0.219***	0.060
Fertilizer quality	-0.440**	0.191	0.098	0.282	-1.389	4.805	-0.413**	0.207	-0.546	0.335	-0.075	0.245
Seed quality	-0.329*	0.181	-0.548***	0.170	1.071	0.756	-0.443**	0.177	0.287	0.330	-0.874***	0.263
Insurance needs	0.419***	0.098	0.124	0.126	0.901***	0.283	0.413***	0.115	0.972***	0.221	0.680***	0.155
Resid ext	-0.044	0.200	-0.361	0.269	0.060	0.381	-0.217	0.181	0.574**	0.256	0.204	0.233
Resid credit	0.569	0.541	-0.354	0.820	1.243	2.003	-0.260	0.561	0.316	0.550	1.048*	0.553
Resid nonfarm	0.788***	0.232	-0.274	0.338	0.685	1.074	-0.080	0.310	-0.040	0.594	-0.919**	0.425
Constant	-0.559	0.644	-1.971**	0.793	0.697	5.282	0.516	0.722	-1.638	1.302	-0.120	0.888
Joint sig Instruments (χ^2)	34.58***		13.66***		10.99**		29.48***		28.04***		39.31***	
Wald test, χ^2 (180)	2669.39***											
Log likelihood	-5830.68											
N	967		475		79		781		136		418	

Reported standard errors are the bootstrapped standard errors. ***, **, * represent 1%, 5%, and 10% significance level, respectively. ADP1- Fertilizer adoption only; ADP2 - Improved seeds adoption only; ADP3 - Membership of FBO only; ADP4 - Fertilizer and improved seeds adoption only; ADP5 - Fertilizer adoption and membership of FBO only; and ADP6 - Fertilizer, improved seeds adoption and membership of FBO.

We also find that farm households that adopted fertilizer and are members of farmer-based organizations (ADP5) gain high total crop and household incomes that is statistically different (t -statistic = 5.96 for total crop income and t -statistic = 6.30 for total household income) from farm households that are members of farmer-based organizations only (ADP3). However, we find that total crop and household incomes of farm households that adopted fertilizer and are members of farmer-based organizations (ADP5) are not statistically different (t -statistic = 1.14 for total crop income and t -statistic = 0.54 for total household income) from farm households that adopted fertilizer only (ADP1). Furthermore, we also find that total crop and household incomes of farm households that adopted the two productivity-enhancing technologies in addition to being members of farmer-based organizations (ADP6) are statistically different (t -statistic = 3.08 for total crop income and t -statistic = 3.58 for total household income) from farm households that adopted fertilizer and improve seeds only (ADP4). With the former earning higher total crop and household incomes compared to the latter. This finding suggests that farmer-based organizations can play a significant role in increasing the incomes of smallholders when it complements the adoption of productivity enhancing technologies.

Table 5: Total crop income treatment effects by package

Package	Actual total crop income	Counterfactual crop income - If households did		
		not adopt	ATT	Change (%)
ADP1	5.562(0.010)	5.386(0.015)	0.176***(0.018)	49.88
ADP2	5.380(0.013)	5.346(0.020)	0.034(0.024)	8.12
ADP3	5.196(0.045)	5.182(0.041)	0.013(0.061)	3.09
ADP4	5.595(0.013)	5.309(0.019)	0.286***(0.023)	93.17
ADP5	5.527(0.033)	5.309(0.042)	0.217***(0.054)	64.95
ADP6	5.662(0.018)	5.187(0.024)	0.475***(0.031)	198.45

Note: Figures in parenthesis are standard errors. ***represent 1% significance level. ADP1 - Fertilizer adoption only; ADP2 - Improved seeds adoption only; ADP3 - Membership of FBO only; ADP4 - Fertilizer and improved seeds adoption only; ADP5 - Fertilizer adoption and membership of FBO only; and ADP6 - Fertilizer, improved seeds adoption and membership of FBO. The change expressed in percentage in terms of treatment effect was computed using the formula $100(10^{ATT} - 1)$.

Social capital conditions the adoption of agricultural technologies through access and the dissemination of information which can go a long way to improve a farmers' ability to apply technologies, reduce uncertainty about technology attributes, and create certain expectations about returns. Also as shown in the study of Conley and Udry (2010), farmers adjust their inputs to align with those of their information neighbours who are successful in previous periods, hence social capital play an important role in the use of productivity enhancing technologies. Since fertilizer and improved seeds are both knowledge intensive technologies, their use is not only a function of implementation within a farm's plot but also knowhow related to optimal timing of fertilizer application and frequency, timing of planting, proper depth of sowing etc. The adoption of these knowhow practices related to productivity-enhancing technologies can benefit farmers by allowing for higher yields, quality of products and saving resources. We hence argue that the higher welfare we see in this study could be social capital likely preconditioning farmers to use these technologies properly or optimally. At the same time, farm households that are members of farmer-based organizations can have access to higher prices and marketing channels through collective actions, which can bring additional benefits such as higher sale prices, the reduction of transaction costs, and relaxation of supply side constraints.

All these in the nutshell could translate to higher welfare outcomes as we observe from the findings.

Table 6: Total household income treatment effects by adoption package

Package	Actual total household income	Counterfactual household income - If households did not adopt	ATT	Change (%)
ADP1	5.704(0.010)	5.576(0.013)	0.128***(0.016)	34.26
ADP2	5.580(0.012)	5.569(0.018)	0.010(0.022)	2.44
ADP3	5.358(0.042)	5.434(0.034)	-0.076(0.054)	-16.12
ADP4	5.719(0.012)	5.579(0.015)	0.140***(0.019)	38.02
ADP5	5.688(0.033)	5.586(0.033)	0.102**(0.046)	26.53
ADP6	5.795(0.018)	5.589(0.019)	0.206***(0.026)	60.83

Note: Figures in parenthesis are standard errors. ***represent 1% significance level. ADP1 - Fertilizer adoption only; ADP2 - Improved seeds adoption only; ADP3 - Membership of FBO only; ADP4 - Fertilizer and improved seeds adoption only; ADP5 - Fertilizer adoption and membership of FBO only; and ADP6 - Fertilizer, improved seeds adoption and membership of FBO. The change expressed in percentage in terms of treatment effect was computed using the formula $100(10^{ATT} - 1)$.

4. Conclusion and policy implications

In sub-Saharan Africa where, poor smallholders prevail and agricultural productivity is low, the adoption of productivity enhancing, technologies offer opportunities to increase farm incomes. However, one of the barriers to the adoption of such profitable technologies are information asymmetries and knowledge gaps that exists about the use of such technologies. Furthermore, social capital in the form of membership of farmer-based organizations such as cooperatives creates an environment where farmers can access and learn about new technologies in addition to other benefits such as a reduction in transaction cost, risk hedging and higher prices for commodities. In this paper, we examined the complementary impact of social capital on the adoption of two productivity enhancing agricultural technologies among farm households in Senegal. This paper therefore contributes to the analysis of the impact of productivity-enhancing technologies and social capital in smallholder agriculture by evaluating their impact on total crop and household incomes. Using data from a nationally representative farm household survey in Senegal, we employed a multinomial endogenous switching regression model that accounts for selectivity bias due to observable and unobservable factors to estimate the causal effects of adoption of productivity enhancing agricultural technologies and membership of farmer-based organizations on incomes.

The findings from this study shows that factors that drives farm household's decision to adopt productivity enhancing technologies and belonging to farmer-based organizations include, education level of the household head, household size, subsidized fertilizer and seeds access, land holding, soil quality, agro-ecological zones, number of risk related losses experienced, perception about the quality of subsidized seeds and insurance needs. The findings from this study suggests that the adoption of the productivity enhancing technologies complemented by social capital can play a significant role in increasing the incomes of farm households in Senegal. The empirical results showed a positive and significant relationship between adoption of the productivity enhancing technologies and total crop and household incomes. Though not having a statistically significant impact alone, social capital complemented with the adoption

of the two productivity-enhancing technologies in combination significantly increases total crop and household incomes. In particular, we find that farm household incomes from adopting fertilizer and being a member of farmer-based organizations is statistically significant and different from farm households that are only members of farmer-based organizations and who do not adopt fertilizer. Furthermore, we observe that farm households that are members of a farmer-based organization in addition to adopting fertilizer and improved seeds, increase total crop and household incomes by 198% and 61% respectively. We find that total incomes of farm households that adopted the two productivity-enhancing technologies in addition to being members of farmer-based organizations are statistically significant and different from farm households that adopted fertilizer and improve seeds only. This in the nutshell implies that social capital has a positive effect on farm household's welfare outcomes. These results can be used to target policies aimed at increasing adoption rates of productivity enhancing technologies. Furthermore, the significant role of social capital suggests the need for supporting farmer-based organizations and improving information channels related to input and output market information, credit and insurance. Because access to subsidies plays an important role in the adoption of these productivity enhancing technologies, establishing and strengthening local institutions, service providers, and extension systems in the administration, delivery and use of these technologies is important in accelerating and sustaining the adoption of profitable technologies.

Despite having a relatively larger sample for the study, the results should be considered with some caveats. First, more and better panel data with long-time dimension would have enabled us to capture more robust evidence and dynamic effects of social capital and productivity-enhancing technologies on household welfare outcomes. Future research should not only focus on social capital impacts on adoption and outcomes but should also account for the heterogeneous effect of social capital via different dimensions and structures of social capital. Furthermore, the impact of social capital could be decomposed into different information effects such as market information for prices, inputs access etc. and information effects related to technical knowhow. In this paper, we were not able to investigate the mechanism or the source of the observed treatment effects. Hence, future research can be devoted to investigating the underlying mechanism of social capital effects on household welfare.

APPENDIX A1

Table A1: Estimates of Log of Total Crop Income Equations by Multinomial Endogenous Switching Regression Model

Variable	ADP0		ADP1		ADP2		ADP3		ADP4		ADP5		ADP6	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	0.001	0.001	0.001	0.001	0.001	0.002	0.000	0.009	-0.003	0.002	0.002	0.004	0.001	0.002
Gender	0.145***	0.043	0.080	0.093	0.112	0.103	0.018	0.310	0.324***	0.073	0.253	0.252	0.299*	0.085
Education	-0.012	0.025	-0.078*	0.045	0.056	0.057	-0.180	0.215	0.045	0.043	-0.256	0.186	0.065	0.063
HH size	-0.002	0.003	-0.000	0.004	-0.003	0.006	0.026	0.024	0.006	0.005	0.007	0.013	0.005	0.008
Lighting fuel	-0.052*	0.027	-0.039	0.043	-0.093*	0.050	0.021	0.239	0.049	0.050	0.119	0.135	0.012	0.069
Risk attitude	-0.060**	0.025	-0.022	0.039	0.028	0.046	-0.061	0.202	0.011	0.040	-0.159	0.119	-0.006	0.055
Nonfarm work	-0.019	0.024	-0.005	0.038	-0.163***	0.052	0.147	0.177	-0.002	0.044	-0.114	0.119	0.040	0.061
Plough ownership	0.067***	0.024	0.062	0.042	0.084	0.051	0.094	0.242	0.102*	0.059	-0.037	0.177	-0.101	0.074
Extension access	0.115*	0.065	-0.030	0.088	-0.019	0.112	0.481	0.363	-0.178**	0.087	0.115	0.253	-0.049	0.181
Credit access	0.046	0.151	-0.019	0.117	0.065	0.219	0.443	0.642	-0.058	0.096	0.001	0.336	-0.049	0.151
Market information	-0.017	0.020	-0.004	0.033	0.005	0.049	0.026	0.157	-0.019	0.037	-0.016	0.115	0.003	0.049
Seed subsidy	0.112	0.103	0.260**	0.114	0.038	0.175	-0.213	0.766	0.006	0.102	0.252	0.328	0.226*	0.100
Fertilizer subsidy	-0.019	0.111	-0.234*	0.122	0.251	0.197	0.255	0.971	0.064	0.092	-0.174	0.335	-0.043	0.108
Land holding	-0.003	0.004	-0.003	0.003	0.001	0.003	-0.043	0.058	0.008	0.005	0.029	0.032	0.019*	0.010
Total hired labour	0.001	0.012	-0.006	0.017	-0.024	0.056	0.079	0.531	0.049**	0.023	0.046	0.066	0.065*	0.023
SQI	-0.543**	0.216	-0.204	0.308	-0.528	0.426	-1.245	1.786	-0.762**	0.303	-0.950	0.948	0.857	0.597
Rainfall	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AEZ BasinAra	0.242***	0.057	-0.132	0.125	-0.056	0.132	-0.085	0.602	0.215	0.151	-0.103	0.511	-0.079	0.335
AEZ RiverVall	0.232**	0.102	0.090	0.127	-0.282	0.202	-0.142	0.731	0.189*	0.109	-0.337	0.466	0.193	0.162
AEZ Casamance	0.192***	0.070	-0.242*	0.144	-0.129	0.168	-0.016	0.592	-0.036	0.165	-0.432	0.494	-0.269	0.312
AEZ CentEast	0.470***	0.055	-0.121	0.121	0.035	0.154	0.029	0.690	0.171	0.131	-0.073	0.486	-0.274	0.264

Reported standard errors are the bootstrapped standard errors. ***, **, * represent 1%, 5%, and 10% significance level, respectively. ADP1- Fertilizer adoption only; ADP2 - Improved seeds adoption only; ADP3 - Membership of FBO only; ADP4 - Fertilizer and improved seeds adoption only; ADP5 - Fertilizer adoption and membership of FBO only; and ADP6 - Fertilizer, improved seeds adoption and membership of FBO.

Table A1: Estimates of Log of Total Crop Income Equations by Multinomial Endogenous Switching Regression Model (continued)

Variable	ADP0		ADP1		ADP2		ADP3		ADP4		ADP5		ADP6	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Loss count	0.006	0.013	0.034	0.022	0.025	0.024	0.097	0.133	-0.010	0.024	0.045	0.066	-0.019	0.045
Road	-0.029**	0.015	-0.043*	0.024	0.028	0.031	0.016	0.141	-0.062**	0.027	0.016	0.078	0.013	0.037
Market	0.049*	0.025	0.057	0.044	0.028	0.054	0.212	0.200	0.220***	0.052	0.114	0.162	0.223**	0.084
Mean labour	0.021**	0.009	-0.008	0.010	0.030**	0.015	-0.029	0.069	0.005	0.012	-0.017	0.035	-0.013	0.020
Mean land	2.043***	0.282	1.279***	0.204	1.060***	0.240	2.586	2.377	0.602***	0.200	-0.404	1.523	0.754**	0.359
Mean fertilizer	-	-	0.001	0.002	-	-	-	-	0.003*	0.002	0.009*	0.005	0.000	0.001
Mean seed	0.033***	0.006	0.023***	0.003	0.017***	0.006	0.043	0.034	0.016***	0.004	0.006	0.016	0.012**	0.003
adp0	-0.203	0.138	-0.228	0.318	-0.630	0.433	-1.672	2.243	-0.784**	0.371	-0.056	1.356	-0.038	0.471
adp1	-0.312	0.292	-0.382***	0.104	-0.481	0.553	-1.016	2.138	0.043	0.435	-0.014	1.109	0.023	0.477
adp2	0.103	0.401	0.225	0.417	-0.200	0.193	-1.514	3.159	-0.190	0.386	0.709	1.273	0.369	0.508
adp3	-0.288	0.508	0.412	0.878	-1.342	1.047	0.163	0.476	-1.276	0.908	-0.692	2.084	-1.444*	0.764
adp4	-0.243	0.450	0.801*	0.424	0.234	0.599	-1.017	3.238	-0.126	0.124	0.551	1.361	0.016	0.520
adp5	-0.189	0.671	-1.461**	0.641	-0.755	1.287	-2.244	3.289	-0.898	0.640	-0.048	0.381	0.325	0.706
adp6	-0.516	0.517	-0.801*	0.464	-0.211	0.742	1.491	3.298	-1.129**	0.542	0.282	1.460	-0.034	0.246
Constant	4.487***	0.227	5.634***	0.454	4.647***	0.553	2.331	2.102	4.108***	0.365	5.347**	1.613	3.820**	0.603
Joint significance of crop varying covariates	348.84***		185.08***		56.38***		7.80*		52.22***		4.22		19.92***	
N	2,260		967		475		79		781		136		418	

Note: adp0 to adp6 refers to the correction term described in equation [4a]. Reported standard errors are the bootstrapped standard errors. ***, **, * represent 1%, 5%, and 10% significance level, respectively. ADP1- Fertilizer adoption only; ADP2 - Improved seeds adoption only; ADP3 - Membership of FBO only; ADP4 - Fertilizer and improved seeds adoption only; ADP5 - Fertilizer adoption and membership of FBO only; and ADP6 - Fertilizer, improved seeds adoption and membership of FBO.

Table A2: Estimates of Log of Total Household Income Equations by Multinomial Endogenous Switching Regression Model

Variable	ADP0		ADP1		ADP2		ADP3		ADP4		ADP5		ADP6	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	0.001	0.001	0.002	0.001	0.001	0.002	0.003	0.006	-0.003*	0.002	-0.001	0.005	0.001	0.002
Gender	0.077*	0.046	0.127	0.091	0.134	0.119	0.308	0.258	0.233**	0.078	0.252	0.220	0.180*	0.092
Education	-0.022	0.026	-0.077*	0.046	0.008	0.050	0.085	0.155	0.023	0.040	-0.244	0.156	0.048	0.057
HH size	0.009***	0.003	0.002	0.004	-0.002	0.006	0.036	0.022	0.008*	0.005	0.006	0.013	0.010	0.008
Lighting fuel	0.010	0.029	-0.010	0.042	-0.027	0.055	-0.052	0.178	0.062	0.046	0.129	0.130	0.022	0.061
Risk attitude	-0.018	0.026	-0.030	0.039	0.078*	0.047	-0.032	0.158	-0.005	0.035	-0.095	0.112	-0.024	0.050
Nonfarm work	0.440***	0.027	0.249***	0.035	0.221***	0.048	0.367**	0.144	0.195**	0.041	0.192*	0.115	0.210***	0.056
Plough ownership	0.079***	0.027	0.088**	0.043	0.134**	0.053	-0.016	0.225	0.101*	0.051	-0.032	0.158	-0.078	0.072
Extension access	0.265***	0.071	0.009	0.093	0.006	0.120	0.410	0.341	-0.097	0.080	0.062	0.232	-0.124	0.165
Credit access	0.156	0.128	-0.099	0.121	-0.002	0.179	1.056**	0.530	-0.044	0.086	-0.207	0.304	-0.093	0.149
Market information	-0.003	0.022	-0.001	0.033	-0.009	0.050	0.105	0.133	0.017	0.033	-0.066	0.104	-0.026	0.044
Seed subsidy	0.015	0.106	0.188	0.127	-0.080	0.178	0.106	0.583	0.080	0.100	0.126	0.299	0.189**	0.089
Fertilizer subsidy	0.002	0.112	-0.283**	0.113	0.268	0.189	0.650	0.638	-0.005	0.085	-0.345	0.328	-0.033	0.110
Land holding	0.002	0.004	-0.003	0.003	0.001	0.004	-0.012	0.024	0.009	0.005	0.031	0.028	0.016*	0.009
Total hired labour	0.002	0.013	-0.010	0.016	-0.051	0.054	0.124	0.434	0.048**	0.021	0.036	0.060	0.101***	0.021
SQI	-0.384*	0.223	0.259	0.267	-0.220	0.423	-0.547	1.331	-0.490*	0.282	-0.379	0.895	1.007*	0.550
Rainfall	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000
AEZ BasinAra	-0.075	0.059	-0.095	0.124	-0.305**	0.147	-0.278	0.457	0.159	0.137	-0.032	0.426	-0.017	0.330
AEZ RiverVall	0.080	0.099	0.160	0.128	-0.281	0.200	0.126	0.564	0.231**	0.101	-0.426	0.364	0.161	0.148
AEZ Casamance	-0.159**	0.080	-0.184	0.148	-0.333*	0.183	-0.558	0.486	0.025	0.147	-0.308	0.424	-0.149	0.308
AEZ CentEast	0.130**	0.059	-0.081	0.118	-0.309*	0.160	-0.074	0.526	0.155	0.120	0.147	0.410	-0.224	0.255

Reported standard errors are the bootstrapped standard errors. ***, **, * represent 1%, 5%, and 10% significance level, respectively. ADP1- Fertilizer adoption only; ADP2 - Improved seeds adoption only; ADP3 - Membership of FBO only; ADP4 - Fertilizer and improved seeds adoption only; ADP5 - Fertilizer adoption and membership of FBO only; and ADP6 - Fertilizer, improved seeds adoption and membership of FBO.

Table A2: Estimates of Log of Total Household Income Equations by Multinomial Endogenous Switching Regression Model (continued)

Variable	ADP0		ADP1		ADP2		ADP3		ADP4		ADP5		ADP6	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Loss count	-0.012	0.013	0.032	0.020	0.027	0.025	-0.003	0.097	0.000	0.021	0.055	0.064	-0.009	0.044
Road	-0.011	0.015	-0.024	0.023	0.029	0.030	0.072	0.099	-0.060**	0.025	0.014	0.069	-0.008	0.032
Market	0.042	0.027	0.015	0.047	0.021	0.054	0.111	0.132	0.209***	0.047	0.111	0.140	0.235***	0.083
Mean labour	0.014	0.010	-0.012	0.010	0.029**	0.014	-0.065	0.057	0.019*	0.011	-0.012	0.033	-0.038**	0.018
Mean land	1.364***	0.250	1.181***	0.166	0.901***	0.234	1.930	1.280	0.470**	0.202	-0.283	1.276	0.794**	0.351
Mean fertilizer	-	-	0.001	0.002	-	-	-	-	0.003**	0.001	0.009**	0.004	0.000	0.001
Mean seed	0.023***	0.005	0.021***	0.003	0.015***	0.006	0.034	0.026	0.014***	0.003	-0.002	0.015	0.008**	0.003
adp0	0.143	0.135	-0.153	0.305	-0.349	0.459	0.464	2.206	-0.799**	0.325	0.717	1.303	0.107	0.424
adp1	-0.016	0.301	-0.348***	0.115	-0.227	0.611	-0.317	1.574	-0.035	0.418	0.206	1.084	0.336	0.527
adp2	0.016	0.390	-0.125	0.418	-0.240	0.179	0.674	2.557	-0.132	0.361	0.968	1.236	0.847*	0.473
adp3	-0.251	0.662	0.678	0.869	-2.313**	0.996	-0.039	0.445	0.415	0.718	0.614	1.921	-0.575	0.992
adp4	-0.006	0.452	0.749	0.480	0.097	0.551	2.685	2.193	-0.119	0.114	0.550	1.222	0.407	0.462
adp5	1.288*	0.744	-1.940***	0.630	-0.753	1.209	3.648	2.982	-1.222**	0.590	-0.111	0.336	0.077	0.665
adp6	0.638	0.521	-0.751*	0.436	0.512	0.734	1.871	2.298	-0.942**	0.469	0.494	1.262	-0.029	0.241
Constant	4.899***	0.237	5.514***	0.500	5.147***	0.570	5.168*	2.202	4.157***	0.317	6.045***	1.345	4.309***	0.549
Joint significance of crop varying covariates	183.77***		178.73***		39.97***		12.68***		47.81***		5.64		17.06***	
N	2,313		972		477		97		782		137		420	

Note: adp0 to adp6 refers to the correction term described in equation [4a]. Reported standard errors are the bootstrapped standard errors. ***, **, * represent 1%, 5%, and 10% significance level, respectively. ADP1- Fertilizer adoption only; ADP2 - Improved seeds adoption only; ADP3 - Membership of FBO only; ADP4 - Fertilizer and improved seeds adoption only; ADP5 - Fertilizer adoption and membership of FBO only; and ADP6 - Fertilizer, improved seeds adoption and membership of FBO.

Table A3: Parameter Estimates: Test on the Validity of the Selection Instruments used to identify the Multinomial Endogenous Switching Regression model

	Selection for non-adopters		Log of total crop income of non-adopters		Log of total household income of non-	
	Coef.	Std.	Coef.	Std.	Coef.	Std.
Constant	0.559	0.623	4.758***	0.142	5.032***	0.142
Age	0.005	0.004	0.001*	0.001	0.001	0.001
Gender	-0.141	0.194	0.199***	0.036	0.091**	0.035
Education	-0.323***	0.101	-0.020	0.022	-0.054**	0.021
HH size	-0.036***	0.009	0.007***	0.002	0.012***	0.002
Lighting fuel	-0.388***	0.104	-0.055**	0.023	0.014	0.023
Risk attitude	0.107	0.118	-0.093***	0.021	-0.044**	0.021
Nonfarm work	1.429***	0.464	-0.043*	0.024	0.404***	0.024
Plough	0.109	0.115	0.060**	0.023	0.089***	0.023
Extension	-0.654	0.486	0.175***	0.041	0.238***	0.041
Credit access	0.928	1.921	-0.157	0.111	-0.040	0.109
Market	0.012	0.089	-0.018	0.020	-0.015	0.020
Seed subsidy	0.132	0.156	0.027	0.039	0.058	0.039
Fertilizer	-2.685***	0.151	0.078*	0.046	0.014	0.044
Land holding	-0.046***	0.009	0.042***	0.002	0.035***	0.002
SQI	4.520***	0.593	-0.877***	0.141	-0.472***	0.139
Std rainfall	0.001	0.002	-0.000	0.000	-0.000	0.000
AEZ BasinAra	-0.175	0.194	0.238***	0.033	0.016	0.033
AEZ RiverVall	-0.971***	0.273	0.175***	0.055	0.067	0.053
AEZ	-0.626***	0.221	0.119***	0.041	-0.114***	0.041
AEZ CentEast	-0.511**	0.248	0.353***	0.044	0.123***	0.044
Loss count	0.073	0.056	0.001	0.012	-0.018	0.012
Road	-0.048	0.062	-0.021*	0.012	-0.012	0.012
Market	-0.038	0.103	0.044*	0.022	0.037	0.022
Risk count	0.115***	0.042	-0.001	0.010	0.011	0.010
Fertilizer	0.440**	0.193	-0.022	0.063	-0.079	0.060
Seed quality	0.329*	0.178	-0.006	0.044	-0.033	0.043
Insurance	-0.419***	0.101	0.027	0.022	-0.020	0.022
Resid ext	0.044	0.201				
Resid credit	-0.569	0.521				
Resid nonfarm	-0.788***	0.236				

Note: ***, **, * represent 1%, 5%, and 10% significance level, respectively.

APPENDIX A2

Soil Quality Index (SQI) Calculations

In computing the soil quality index for the study, we used the “Soil nutrient maps of Sub-Saharan Africa⁷” raster file at 250 m resolution provided by the International Soil Reference and Information Centre (ISRIC). Nutrients covered in this data include; total nitrogen (N), total phosphorus (P), extractable phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na), aluminium (Al), boron (B), copper (Cu), iron (Fe), manganese (Mn) and zinc (Zn) in (ppm). For the estimation approaches for the nutrients data, curious readers are referred to Hengl *et al.*, (2017). Additionally, we used soil physical and biochemical properties data⁸ provided by ISRIC for the computation of the index. We also used free spatial data from DIVA-GIS⁹ in the form of shapefiles for administrative regions of our study country. Using the free and open source geographic information system, software called QGIS (previously known as Quantum GIS) and the geographic coordinate data of farm households, we calculate the soil parameters for each farm household. The Soil Quality Index (SQI) was calculated following the approaches described in Zheng *et al.*, (2005); Mukherjee and Lal (2014); and Zhang *et al.*, (2015). First, we used principal component analysis (PCA) to identify a minimum data set (MDS) to reduce the indicator load in the estimation of the index and avoid data redundancy. During the principal component analysis, only the ‘highly weighted’ variables were retained in the MDS. After selection of parameters for the MDS, all selected observations were transformed using linear scoring functions (less is better, more is better and optimum) based on the recommendations in the empirical literature (Amacher *et al.*, 2007; Mukherjee and Lal, 2014). Thereafter, the weighted additive SQI was computed using the formula below:

$$\text{SQI} = \sum \text{Weight} * \text{Individual soil parameter score}$$

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⁷ https://data.isric.org/geonetwork/srv/eng/catalog_search#/search?resultType=details&sortBy=relevance&any=Soil%20nutrient%20maps%20of%20Sub-Saharan%20Africa%20at%20250%20m%20resolution&from=1&to=20

⁸ https://github.com/ISRICWorldSoil/SoilGrids250m/blob/master/grids/models/META_GEOTIFF_1B.csv

⁹ <https://www.diva-gis.org/>

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