Research Paper

Welfare impacts of conservation agriculture adoption on smallholder maize farmers in South Africa

Oluwaseun Samuel Oduniyi[1,2] , Clarietta Chagwiza[3] and Tara Wade[4]

[1]Department of Agricultural and Applied Economics, Texas Tech University, Lubbock, Texas, USA; [2]Department of
Agriculture and Animal Health, University of South Africa, Pretoria, South Africa; [3]Department of Agricultural
Economics, Extension and Rural Development, University of Pretoria, Pretoria, South Africa and [4]Food and
Resource Economics Department, University of Florida, Gainesville, FL, USA

Abstract

Climate change and soil degradation are the issues depleting the soil's ability to promote good
yield. One of the ways to combat this is the practice of conservation agriculture (CA). This
study was carried out to explore and investigate the impact of CA. Multinomial endogenous
switching regression model and cross-sectional data were used to investigate the determinants
and the impact of the adoption of CA on the income of smallholder maize farmers in
Mpumalanga Province, South Africa. Three categories of CA (minimum tillage, crop diversi-
fication and a combination of both minimum tillage and crop diversification) were consid-
ered. The empirical results revealed that regardless of the choices of CA practices adopted
by the maize farmers, the income realized was higher for adopters than for non-adopters
of CA practices. The average treatment effect for the adopters of both minimum tillage and
crop diversification was the highest, showing an increase in income by 60.31% (R15575.99/
$996.57USD) compared to the non-adopters. The policy implication for these results is
that there is a need to promote the adoption of CA practices, particularly a combination of
both minimum tillage and crop diversification, given their significant impact on farmer
income, an important welfare outcome that has significant implications on food security
and poverty alleviation.

Introduction

The agricultural sector plays a crucial role in the economies of many developing countries as a
source of income and foreign exchange earnings (Kuntashula *et al.*, 2014). However, as high-
lighted by von Loeper *et al.* (2016), agriculture, which constitutes a third of the planet's sur-
face, has resulted in environmental and ecosystem degradation, such as soil erosion and
biodiversity loss. These have negative implications on crop yields and are exacerbated by
droughts and floods. Abdulai and Huffman (2014) pointed out that these lower yields often
lead to severe food shortages and welfare losses, particularly among smallholder farming
households in Sub-Saharan Africa.

Mango *et al.* (2017) further indicated that very few farmers in Sub-Saharan Africa employ
soil conservation farming practices, trapping farmers in a vicious circle of poverty and hunger
due to soil degradation. With the global imperatives of attaining sustainable development goals
(SDGs), such as ending poverty in all its forms (SDG 1) and zero hunger (SDG 2), the pro-
motion and adoption of good agricultural practices are paramount to achieving these goals,
especially in developing countries.

Conservation agriculture (CA) is considered an ideal system for sustainable, climate-smart
agriculture through which smallholder farmers can improve soil health and the environment,
attain higher levels of crop yields and food security, and achieve higher net income returns
(Mango *et al.*, 2017; Swanepoel *et al.*, 2018; Lehman, 2019; GrainSA, 2021). Although CA
includes crop diversification (CD), minimum tillage (MT) and soil cover, this study focuses
only on CD and MT. Specific features in South Africa, including low rainfall, limited agricul-
tural land area and a larger proportion of smallholder farmers, necessitate the implementation
of CA (Lehman, 2019).

The findings on the impact of CA on welfare outcomes from previous studies are quite
mixed, showing a positive impact, negative impact or no impact at all. As such, the findings
cannot be generalized across different locations, owing to other influential factors at play.
For instance, Abdulai and Huffman (2014) suggest that factors, such as variations in wealth,
size of landholdings and differences in soil conditions, make it difficult to generalize the adop-
tion patterns of new agricultural technologies in Sub-Saharan Africa. Moreover, there are lim-
ited studies on the assessment of the impact of adopting CA on smallholder farmers' income
or net returns; this study aims to fill this research gap.

The research seeks to achieve this by addressing two research questions: (1) What are the factors influencing the farmer's choice of CA practices? and (2) Have the practices of CA improved the income of smallholder (small-scale) farmers in the Mpumalanga Province of South Africa? Addressing these research questions can inform policy on which strategies to promote, given the effects on the income of smallholder farmers. As a result, financial and extension resources can be efficiently channeled toward the promotion of the strategies that are the most economically and environmentally beneficial.

The rest of the paper proceeds as follows. Section 'Impact of CA and related technologies adoption on welfare parameters' provides a brief review of the literature on the impact of CA on income and other welfare parameters such as food security. Section 'Materials and methods' presents the methodological approach adopted in the paper. The empirical results are presented and discussed in the "Results and discussion" section. The paper ends with some conclusions and policy recommendations in the "Conclusions and policy implications" section.

Impact of CA and related technologies adoption on welfare parameters

For any given technology or intervention, it is always imperative to assess the impact it has on the welfare of the supposed beneficiaries in order to inform policy. For instance, in this case, it is important to understand the effects of engaging in CA on the welfare of smallholder farmers. To achieve this, a number of previous empirical studies are reviewed to understand the impact of the adoption of CA and other related technologies on a number of outcome variables, including yields, income, employment creation and food security.

Osewe et al. (2020) studied the impact of MT on the welfare of smallholder farmers in Southern Tanzania. They focused on the effects of MT adoption on households' per capita net crop income and labor demand. Their findings revealed positive and significant impacts of MT adoption on smallholder households' per capita net crop income. The authors further reported a significant reduction in total household labor demands that allow family members to engage in other off-farm income-generating activities.

Similarly, Abdulai and Huffman (2014) examined the factors that influence the adoption of soil and water conservation technology, as well as the impact of adoption on yields and net returns among rice farmers in northern Ghana. Their results showed that farmers who adopted these technologies had significantly higher rice yields and net returns compared to the non-adopters. In China, Yang et al. (2021) assessed the determinants of the adoption of five mutually exclusive soil conservation practices (SCPs) and their impact on rice yield and chemical fertilizer use. The results showed significantly higher rice yield and decreased chemical fertilizer usage among farmers that adopted SCPs as a package.

Another study by Mango et al. (2017) used a sample of 1623 households in Zimbabwe, Malawi and Mozambique (Africa) to determine the impact of CA adoption on food security among smallholder farmers. The results showed no significant impact of CA adoption on the Food Consumption Score of farmers in Zimbabwe and Malawi. Contrasting results were reported in Mozambique, where CA was found to significantly improve the Food Consumption Score for farmers who adopted the technology.

Kuntashula et al. (2014) studied the impact of MT and crop rotation on maize yields and incomes for farmers adopting these strategies in Zambia. Their findings revealed that while both strategies improved maize productivity, only MT significantly improved gross income.

Another critical implication of CA is its influence on employment creation particularly in the rural areas where employment opportunities are limited. Hence, it is important to understand how the adoption of CA influences employment within farming households. Several studies present contradicting but interesting discussions on this issue. As mentioned earlier in this section, Osewe et al. (2020) found that the adoption of MT in Southern Tanzania had a significant reduction in labor demand thereby affording the household members more time for other non-farm income opportunities. In a similar vein, Johansen et al. (2012) highlight that CA reduce labor demands when planting is mechanized, and herbicides are applied to control weeds.

Contrary to Osewe et al. (2020), other authors (Montt and Luu, 2018) looked at how CA influences labor requirements in Ethiopia, Kenya, Malawi, Mozambique and Tanzania. Their findings showed that CA increases farms' labor input requirements, especially during the harvesting and threshing stages. However, they realized that these labor requirements are fulfilled by household labor (unpaid work) and not hired labor, shifting the farming workload toward women (as compared to men) and children. This has policy implications on gender dynamics given the alterations in the agriculture landscape owing to CA adoption. Wekesah et al. (2019) also pointed out that CA increases workloads, income, household food security, employment opportunities and health risks for women.

As alluded to earlier, the reviewed studies display mixed results on the impact of technology adoption on various welfare parameters, depending on specific circumstances in different study sites. Hence, a 'blanket approach' in promoting adoption of high-yielding technologies among smallholder farmers will not yield favorable results. Thus, extra caution needs to be taken not to generalize findings across different sites.

Materials and methods

Study area

The study was conducted in the Gert Sibande District Municipality in Mpumalanga Province of the Republic of South Africa. Gert Sibande District is a Category C municipality and is the largest of the three districts in the province, measuring 31,841 km^2 in area, which covers almost half (40%) of Mpumalanga Province's total land mass of 76,495 km^2. The district, which accounts for about 6.5% of South Africa's land surface, consists of seven local municipalities: Govan Mbeki, Chief Albert Luthuli, Msukaligwa, Dipaleseng, Mkhondo, Lekwa and Dr Pixley ka Isaka Seme. Figure 1 shows the district and its local municipalities. The major towns are Amersfoort, Amsterdam, Balfour, Bethal, Breyten, Carolina, Charl Cilliers, Chrissiesmeer, Davel, Ekulindeni, Embalenhle, Empuluzi, Ermelo, Evander, Greylingstad, Grootvlei, Kinross, Leandra, Lothair, Morgenzon, Perdekop, Secunda, Standerton, Trichardt, Volksrust, Wakkerstroom, eManzana and eMkhondo (Piet Retief).

This area was chosen because of its high concentration of subsistence farmers which accounted for about 2000 farmers (Mngqawa et al., 2016). The area between Carolina, Bethal and Ermelo produces the most sheep and wool in South Africa, which indicates the region's significance to agriculture in South Africa. Also, the area is known for its high maize production.
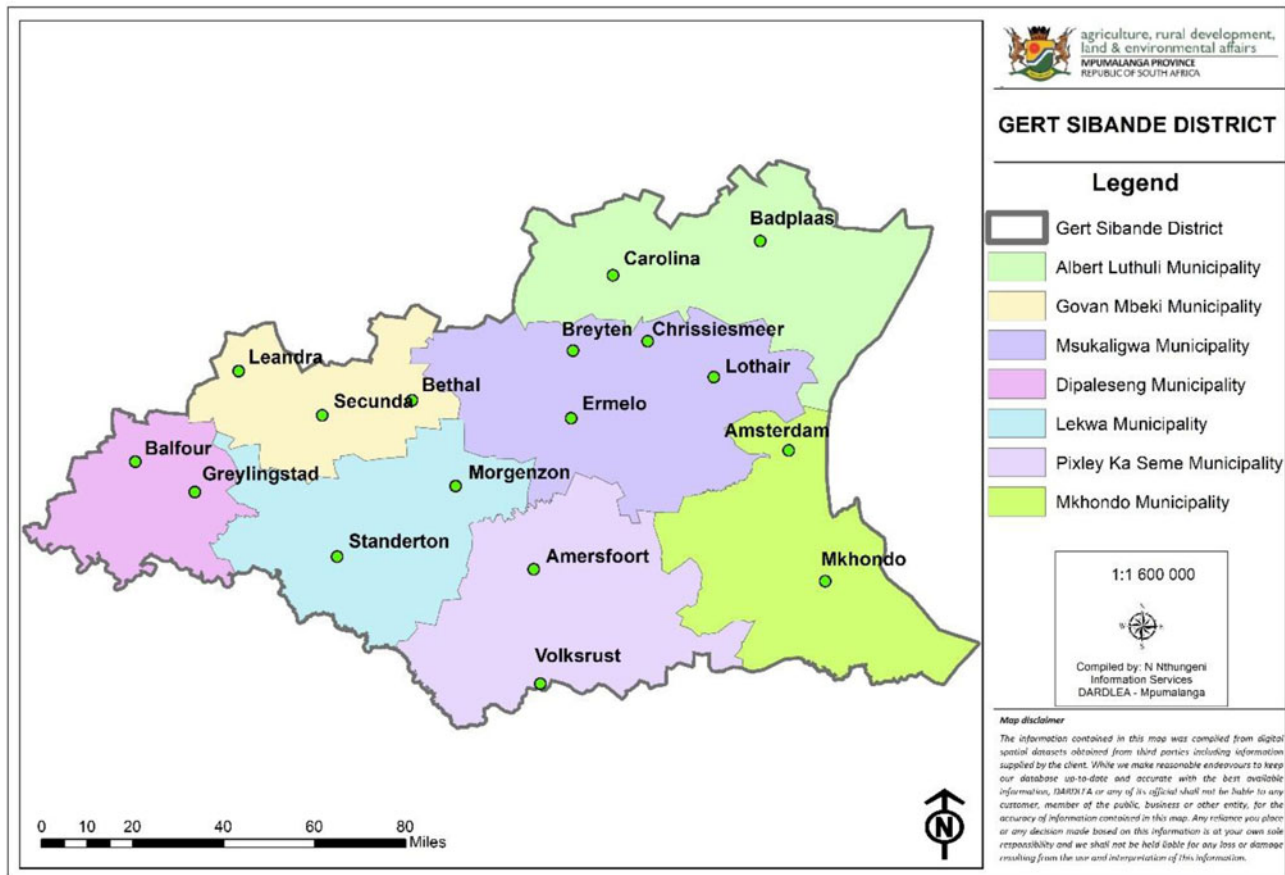
Fig. 1. Map of Gert Sibande District, Mpumalanga Province of South Africa.

Despite its size, in 2018, Gert Sibande District contributed only 2.06% to the GDP of South Africa, or 27.68% to the Mpumalanga Province's total GDP of R 363 billion, ranking it the lowest relative to all the regional economies in the Mpumalanga Province (SA Stat, 2018). The district was part of the mapping area where CA adoption was introduced, and it is one of the top three maize producing regions in South Africa, accounting for 23.5% of the total maize production in South Africa (Greyling and Pardey, 2019). The major economic sectors are mining, agriculture, energy and manufacturing.

Sampling technique and data collection

Farm-level cross-sectional survey data were collected between December 2019 and August 2020 from smallholder maize farmers in the Gert Sibande District of Mpumalanga Province, South Africa, using a semi-structured survey questionnaire validated by two agricultural economists. A test of reliability was performed on the questionnaire to establish its use. The questionnaire contained logic flow questions aimed at farmers' socio-economic characteristics, farm-based characteristics, CA adoption and knowledge about CA. The survey was conducted through 40 min face-to-face interviews with the help of four trained enumerators who received training on CA and related information. The questionnaire was translated into local languages that the farmers can understand for better interpretation and accuracy. Consent from the farmers and approval from the ethical department of the University of South Africa was obtained before the

commencement of the questionnaire administration, dated 19 February 2020. A representative sample size (250 maize farmers) was determined from the population of 710 smallholder maize farmers, using Slovin's formula, given in Equation (1), after which a total number of 250 questionnaires were administered to the maize farmers in the district, using a proportionate random sampling technique. Following Oduniyi (2018), this was achieved by adopting a quantitative model, as presented below:

$$n = \frac{N}{1 + N(e)^2} \tag{1}$$

where n is the sample size; N equals the total population of maize farmers in the seven local municipalities across the district; e equals maximum variability or margin of error, estimated at 5% (0.05); 1 equals the probability of the event occurring, and 250 equals the number of respondents sampled or sample size. Table 1 shows the distribution of sample size collected according to each municipality or stratum. The data collected were analyzed using STATA 15.

A conceptual framework and empirical/estimation techniques

A smallholder farmer's decision to adopt CA practices is a behavioral response, where farmers choose or adopt components of the CA practices that increase their utility or expected profit subject to constraints. The constraints are where the polychotomous adoption decision depends on several factors, such as socio-economic

Municipalities	Frequency	Percent
Govan Mbeki	42	16.8
Albert Luthuli	33	13.2
Mkhondo	60	24.0
Msukaligwa	34	13.6
Lekwa	32	12.8
Pixley Ka Seme	19	7.6
Dipaleseng	30	12.0
Total	250	100.0

Source: Author's computation (2021).

characteristics, available CA information and the benefits of CA. The adoption of any of the components of CA is modeled within the random utility framework (Ali and Abdulai, 2010; Kassie *et al.*, 2018). A farmer may decide to adopt either a single CA practice or a combination of CA practices, such as MT variety, CD or a combination of minimum tillage and crop diversification (MTCD) if the expected profit from adoption is higher than the expected profit from non-adoption. See Table 2, which explains the different CA choices.

Thus, the adoption of CA practices is based on individual choices and may be correlated with unobservable characteristics that could also affect farmers' income. However, a simple comparison of income groups may lead to an inaccurate result. To account for both endogeneity and sample selection, a MESR (multinomial endogenous switching regression) framework was used. More specifically, following Dubin and McFadden (1984), we apply a selective corrected MESR treatment effect approach and use the method by Bourguignon *et al.* (2007) to correct for selection bias.

According to Kumar *et al.* (2019), MESR has the advantage of evaluating both individual and alternative combinations of practices. MESR also captures both self-selection bias and the interactions between choices of alternative practices (Wu and Babcock, 1998; Mansur *et al.*, 2008) as well as unobserved heterogeneity associated with economic evaluations of the non-random adoption of CA practices. The model involves two stages. In the first stage, the maize farmers' choice of combination of CA practices was modeled using a multinomial logit selection model while identifying the interrelations among the CA choices. In the

second stage, the impacts of each choice of CA practices on the outcome variable were estimated using ordinary least squares (OLS) with a selectivity correction term from the first stage. Similarly, for identification, a variable named the number of extension visits was used as an instrumental variable.

Multinomial logit (adoption) selection model

Following Kumar *et al.* (2019) and Danso-Abbeam and Baiyegunhi (2018), it is assumed that smallholder maize farmer i aims to maximize his/her net returns, π_i, by comparing the positive return from different choices of CA practices, k, $(k = 1,2,3,4)$ over any alternative practice, m, which is given as

$$\pi_{ik} > \pi_{im} \; m \neq k, \; \text{or equivalently} \; \Delta\pi_{im} = \pi_{ik} - \pi_{im} > 0 \; m \neq k.$$
$$\pi_{ik}^* = X_i\beta_k + \varepsilon_{ik}$$

where π_{ik}^* is a latent variable defining the expected net benefits a maize farmer derives from the adoption of CA choices k, which is determined by both observed and unobserved characteristics. X_i represents a vector of observed exogenous or covariates variables, and ε_{ik} is an error term accounting for unobserved characteristics.

Assuming J is the index that signifies maize farmers' choices of CA practices k, such that

$$J = \begin{cases} 1 & if \; \pi_{i1}^* > 0 \max(\pi_{im}) \; or \; \eta_{i1} < 0 \\ & \quad for \; all \; m \neq k \\ K & if \; \pi_{ik}^* > 0 \max(\pi_{im}^*) \; or \; \eta_{iK} < 0 \end{cases} \quad (3)$$

In Equation (2) above, the index function suggests that maize farmers will adopt CA practice k, if they derive or expect a greater benefit or net returns from other CA practices m.

$$\text{Thus,} \; \eta_{ik} = \max(\pi_{ik}^* - \pi_{im}^*) > 0, \; m \neq k$$

Assuming that the error term (ε) is identical, and Gumbel is distributed independently, then the probability that maize farmer i with characteristics X_i will adopt CA practice k can be expressed by the use of a multinomial logit model (McFadden, 1973).

$$P_{ik} = \Pr(\eta_{ik} < 0/Z_i) = \frac{\exp(Z_i\beta_k)}{\sum_{m=1}^{K} \exp(Z_i\beta_m)} \quad (4)$$

Table 2. Adoption of conservation agricultural (CA) strategies and sample distribution

Choice (*j*)	Combination	Minimum tillage (MT)		Crop diversification (CD)		Sample observation	Frequency (%)
		Adoption MT_1	No-adoption MT_0	Adoption CD_1	No-adoption CD_0		
1	MT_0CD_0		✓		✓	118	47.20
2	MT_1CD_0	✓			✓	31	12.40
3	MT_0CD_1		✓	✓		55	22.00
4	MT_1CD_1	✓		✓		46	18.40
	Total					250	100.00

Source: Author's computation (2021).

The parameters of the latent variable model are then estimated with a maximum likelihood function.

Multinomial endogenous switching regression (MESR)

The use of MESR was explored in the second stage where the relationship between the outcome variables and a set of exogenous variables is assessed for the adopted CA practices. The model estimated the parameters of the impacts of CA choice sets k (MT_0CD_0 = non-adopters as reference category; MT_1CD_0 = adopters of MT practices; MT_0CD_1 = adopters of crop rotation practices; MT_1CD_1 = adopters of both MT practices and crop rotation practices) on the outcome variables. The outcome equation for each possible regime j is given as

$$\begin{cases} regime\ 1: & Y_{i1} = \beta_1 X_i + \varepsilon_{i1} & if\ j = 1 \\ & \vdots \\ regime\ k: & Y_{ik} = \beta_k X_i + \varepsilon_{ik} & if\ j = k \end{cases} \quad (5)$$

where Y_{ik} represents the outcome variable of the ith maize farmer associated with the selected regime k, X_i represents a vector of explanatory variables or exogenous covariates, β is the vector of parameters, and ε_{ik} and ε_{i1} are random disturbance terms. Y_{ik} is observed if, and only if, CA practice k is adopted, which occurs when $\pi_{ik}^* > \max_{m \neq k} (\pi_{im}^*)$. However, if the ε_k and ε_1 are not independent, OLS estimates obtained from Equation (4) will be biased. Thus, consistent estimation of X_i requires the inclusion of the selection bias correction terms of the alternative CA practices m in Equation (4). It is assumed that the linear assumption of the DM (Dubin and McFadden, 1984) is given as

$$(\delta_{ik}/\varepsilon_{i1} \ldots \varepsilon_{iK}) = \sigma_k \sum_{m \neq k}^{K} r_k (\varepsilon_{im} - E(\varepsilon_{im})) \quad (6)$$

With this assumption, the MESR in the equation above can be expressed as

$$\begin{matrix} regime\ 1: & Y_{i1} = \beta_1 X_i + \sigma_1 \lambda_1 + \varphi_{i1} & if\ j = 1 \\ regime\ k: & Y_{ik} = \beta_k X_i + \sigma_k \lambda_k + \varphi_{ki} & if\ j = k \end{matrix} \quad (7)$$

where σ_k is the covariance between the error terms δ in Equation (1) and ε in Equation (4); φ's are the error terms with an expected value of zero, and λ_k is the Inverse Mills ratio computed from the MESR estimate in Equation (2).

$$\lambda_k = \sum_{m \neq k}^{K} \rho_k \left[\frac{\widehat{P}_{im} \ln(\widehat{P}_{im})}{1 - \widehat{P}_{im}} + \ln(\widehat{P}_{ik}) \right] \quad (8)$$

where ρ_k defines the correlation coefficient of the three error terms, ε, δ and φ. However, the heteroscedasticity problem, which could arise from the generated regressor λ_k, was accounted for by the use of bootstrap errors.

Conditional expectations and estimation of average treatment effects

MESR was used to compute the treatment effect. This framework can compute both the average treatment effect on the treated (ATT) and on the untreated (ATU). This was done by comparing the expected outcome value of the treated (each choice of CA adopted) and the untreated (non-adopters) in actual and

counterfactual scenarios. Following Di Falco and Veronesi (2013), the ATT in the actual and counterfactual situation can be expressed as

Adopters with adoption (actual expectations observed in the sample):

$$\begin{cases} E(Y_{i2}/j = 2) = \beta_2 X_{2i} + \sigma_2 \lambda_2 \\ \qquad\qquad \vdots \\ E(Y_{ik}/j = k) = \beta_k X_{ki} + \sigma_k \lambda_k \end{cases} \quad (9a)$$

$$\begin{cases} E(Y_{i1}/j = 1) = \beta_1 X_{1i} + \sigma_1 \lambda_1 \\ \qquad\qquad \vdots \\ E(Y_{i1}/j = 3) = \beta_3 X_{3i} + \sigma_3 \lambda_3 \end{cases} \quad (9b)$$

Adopters, had they decided not to adopt (counterfactual expected outcomes):

$$\begin{cases} E(Y_{i1}/j = 2) = \beta_1 X_{2i} + \sigma_1 \lambda_2 \\ \qquad\qquad \vdots \\ E(Y_{i1}/j = k) = \beta_1 X_{ki} + \sigma_1 \lambda_k \end{cases} \quad (10a)$$

$$\begin{cases} E(Y_{i2}/j = 1) = \beta_2 X_{1i} + \sigma_2 \lambda_1 \\ \qquad\qquad \vdots \\ E(Y_{i2}/j = 3) = \beta_2 X_{i3} + \sigma_2 \lambda_3 \end{cases} \quad (10b)$$

Equations (8a) and (8b) represent the real expectations observed in the sample. Similarly, Equations (9a) and (9b) represent the counterfactual expected outcome. In order to compute the average treatment effect on the treated (ATT), the difference between Equations (8a) and (9a) was calculated. This could be expressed as

$$\begin{aligned} ATT &= E[Y_{i2}/j = 2] - E[Y_{i1}/j = 2] \\ &= X_{2i}(\beta_2 - \beta_1) + \lambda_2(\sigma_2 - \sigma_1) \end{aligned} \quad (11)$$

Correspondingly, the average treatment effect on the untreated (ATU) is the difference between Equations (8b) and (9b), given as

$$\begin{aligned} ATU &= E[Y_{i1}/j = 1] - E[Y_{i2}/j = 1] \\ &= X_{1i}(\beta_2 - \beta_1) + \lambda_1(\sigma_2 - \sigma_1) \end{aligned} \quad (12)$$

Results and discussion

Summary of the descriptive statistics

Table 3 shows the data measurement and the expected sign. The summary statistics are presented in Tables 4 and 5 in which the mean income of the non-adopter (MT_0CD_0) is R9674.29 ($618.95) per farm hectare of maize cultivated and the average income for all the farmers together is R16867.18 ($1079.15) per farm hectare of maize cultivated. The mean age of the smallholder maize farmers in the study area is about 48 years, the average farm experience is 11 years, the average farm size is 123 hectares and the years spent in school is 10 years. Note that farm size is not the total cultivated land for maize production, as farmers do not cultivate the whole farmland perhaps due to a lack of resources, that is, not the whole farmland is cultivated. Most of the farmers are male (52.4%), with 83.65% having access to extension services and 80.8% having access to agricultural inputs. Of

Table 3. Variables description and expected sign

Variables	Description and variable measurement	Expected sign
Age	Number of years (continuous)	+
Gender	Dummy, 1 if household head is a male and 0 if otherwise	−
Access to extension service	Dummy, 1 if yes, 0 if otherwise	+
Access to agricultural input (fertilizer)	Dummy, 1 if yes, 0 if otherwise	−
Years of farming	Number of years (continuous)	+
Farm size	Size in hectares (continuous)	+
Years spent in school	Number of years (continuous)	+
Access to credit facilities	Dummy, 1 if yes, 0 if otherwise	+
Member of cooperative	Dummy, 1 if yes, 0 if otherwise	+
Instrumental variable		
Number of extension visits	Categorical, (1 = once, 2 = twice, 3 = three times or more)/month	+
Outcome variable		
Income	The income per farm output (R)	

Source: Author's computation (2021).

the total sample, 47.2% of farmers have access to credit facilities and 80.4% are cooperative members.

Factors influencing the adoption of CA

The result of the multinomial logit estimate is presented in Table 6. As stated by Danso-Abbeam and Baiyegunhi (2018), the explanation of coefficient parameters does not provide a better interpretation of the magnitudes in probability models. However, providing the values of the marginal effect specifies the direction of the influence of the covariates on the dependent variables and reveals the magnitude of the effect on the predicted probability. Thus, the study provides the marginal effect values alongside the multinomial estimates. The results show that the estimated coefficients differ significantly across the different choices of adoption of CA practices.

The gender of the household head significantly affects the adoption of CA practices. Across the three options of CA practices, decisions of the male household head farmer are positive and statistically significant in influencing the adoption of MT ($P < 0.01$), CD ($P < 0.01$) and both MTCD ($P < 0.1$), respectively. Male-headed households are more likely than female-headed households to adopt CA practices across the three choices of CA practices. This is not surprising as male-headed households have a higher tendency to take chances in adopting innovations compared to female-headed households. In Africa, and mostly in rural areas, the involvement of male farmers is felt more in agricultural farming, which provides male farmers more opportunities and the predisposition to try innovations than their

female counterparts. This result is consistent with many studies on gender differences in agriculture. For example, Belay *et al.* (2017) and Marie *et al.* (2020) reported that male-headed households are more likely to have access to innovations than are female-headed households. Male farmers are in a better position to practice diverse adaptation strategies than their female counterparts. Similarly, Gebre *et al.* (2019) pronounced that intensity of the adoption of improved maize varieties (an example of innovation) is lower for female-headed households compared to male-headed households where decisions are made jointly. However, Yang *et al.* (2021) and Oduniyi (2021) were of a contrary opinion and reported that female-headed households are more likely to adopt the combination of the three SCPs.

Access to extension services was found to have a significant and negative impact on the decision to adopt MT (MT_1CD_0). In other words, farmers who do not have access to extension services are more likely to adopt MT out of the three CA practices. Although it is expected that access to information by the extension officer is crucial in increasing the adoption rate, this was not the case in this study. The plausible explanation could be those extension officers were unable to deliver quality and accurate information needed by the farmers in order to adopt CA practices. Many times, the extension officers failed to comprehend farmers' problems and priorities, leading to poor adoption of the recommended innovations. Masere (2015) reported that most of the technologies disseminated by the extension officer are the 'one-size-fit-all' approach to different farmer groups with different needs and problems. Besides, MT has been widely practiced in the past, which serves more as a traditional method for the farmers. Hence, in the absence of no or lack of accurate information, it is easier for farmers to continue with what they know. Contrary to this result, Akhter and Rahut (2013) and Abdulai and Huffman (2014) found that the impact of agricultural extension services plays a significant role in the adoption of improved agricultural technologies and SCPs, respectively.

There was a positive relationship between being a member of a farmer cooperative group and the adoption of MT (MT_1CD_0) and CD (MT_0CD_1). This suggests that farmers who belong to a cooperative group (farmers' group, social network) are more likely to have access to information that informed their decision to adopt two options of CA practices. This is not surprising as farmers may share information or experiences about successful production practices and adaptations to existing practices during their meetings. This result is supported by Wossen *et al.* (2017), showing that cooperative membership has a positive and statistically significant effect on technology adoption and household welfare. Similarly, this result is consistent with Bandiera and Rasul (2006), who avowed that social capital and farmers' groups are essential factors influencing the adoption of SCPs.

The impact of the adoption of CA on farmers' net returns

The impact of CA adoption on the farmers' net returns from maize production is explained in this section. Table A1 (see Appendix) shows the first stage of the selectivity corrected MESR method after which the estimated average net returns (income) from the adoption of CA practices are calculated for both the ATT and ATU (counterfactual) effects (see Table 7). Remarkably, in all three choices of CA practices, ATT and ATU effects are positive, suggesting that regardless of the choices of CA practices adopted by the maize farmers, the income realized is higher for adopters than for non-adopters of CA practices.

Table 4. Summary statistics of the variables used in the analysis

Variables	MT$_0$CD$_0$ (N = 118)		MT$_1$CD$_0$ (N = 31)		MT$_0$CD$_1$ (N = 55)		MT$_1$CD$_1$ (N = 46)		Pool (N = 250)	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Income per hectares (Rand)	9674.29	7357.08	25,064.52	16,701.17	20,184.84	15,428.32	25,827.46	31,787.93	16,867.18	18,531.69
Age of the farmer (years)	46.19	12.73	52.45	11.57	49.84	12.08	49.15	12.81	48.31	12.59
Gender[a] (male-headed farmer)	0.36	0.48	0.77	0.43	0.67	0.47	0.59	0.50	0.52	0.50
Access to extension service[a]	0.83	0.38	0.71	0.46	0.89	0.32	0.87	0.34	0.84	0.37
Access to agriculture input[a]	0.82	0.38	0.87	0.34	0.84	0.37	0.70	0.47	0.81	0.40
Experience in farming (years)	10.39	6.51	13.58	7.07	10.71	7.09	10.24	6.64	10.83	6.77
Farm size (hectares)	81.86	211.22	193.65	226.78	198.62	340.81	91.00	144.95	123.09	242.94
Years spent in school	9.79	4.68	9.81	5.04	11.22	4.88	10.67	5.04	10.27	4.84
Access to credit facilities[a]	0.48	0.50	0.58	0.50	0.49	0.51	0.37	0.49	0.47	0.50
Member of cooperative[a]	0.75	0.43	0.94	0.25	0.89	0.32	0.74	0.44	0.80	0.40
Number of extension visits (monthly)										
1 visit	0.21	0.41	0.32	0.48	0.15	0.36	0.15	0.36	0.20	0.40
2 visits	0.37	0.49	0.19	0.40	0.33	0.47	0.22	0.42	0.31	0.46
3 and above visits	0.42	0.50	0.48	0.51	0.53	0.50	0.63	0.49	0.49	0.50

Source: Author's computation (2021).
[a]Denotes dummy variables.

Table 5. Summary statistics of the variables used in the analysis

Variables	Frequency (%)
Gender	
Male	131 (52.4)
Female	119 (47.6)
Access to extension service	
Yes	209 (83.6)
No	41 (16.4)
Access to agriculture input	
Yes	202 (80.8)
No	48 (19.2)
Access to credit facilities	
Yes	118 (47.2)
No	132 (52.8)
Member of cooperative	
Yes	201 (80.4)
No	49 (19.6)

Source: Author's computation (2021).
Denotes dummy variables.

For example, the average treatment effect on the treated MT_1CD_1 adopters increases by 60.31% (R15575.99/\$996.88USD) compared to the non-adopters. Farmers who adopted MT_1CD_0 and MT_0CD_1 had a 50.32% (R12612.33/\$806.11USD) and 46.01% (R9287.83/\$593.62USD) increase in their income, respectively, compared with the non-adopters. This result is supported by Yang *et al.* (2018) and Varma (2019), whose studies found a positive relationship between agricultural technology adoption and yield.

Furthermore, the counterfactual effect measured what would have happened to the adopters in the absence of the CA practices. In all the counterfactual (ATU) cases, the smallholder maize farmers who adopted CA practices would have had lower incomes had they not adopted any of the CA practices (see Table 7). For example, for farmers who did not adopt any CA practices (MT_0CD_0), their income would have increased by R5722.09 (\$366.19USD) had they adopted MT_1CD_0. Farmers who adopted MT_0CD_1 and MT_1CD_1 increased their income by R6731.26 (\$430.90USD) and R13403.85 (\$858.05USD), respectively. Consequently, the results obtained from both the ATT and ATU situations indicate that farmers obtained a significantly higher income by adopting MT_1CD_0, MT_0CD_1 and MT_1CD_1 compared to non-adopters.

Conclusions and policy implications

A better understanding of the impact of CA on smallholder farm income and the factors that affect the adoption of these practices is imperative to improving food security in the developing world, as well as improving farm income and reducing agriculture's negative effect on the environment. Cross-sectional survey data from 250 smallholder maize farmers were used to investigate the impact of the adoption of three CA strategies on the income of smallholder farmers in the Gert Sibande District Municipality in Mpumalanga Province, South Africa: MT, CD and both. A MESR model was employed to determine the impact of adopting conservation agricultural practices on the income of smallholder maize farmers.

We find that adopting CA practices significantly increases the income of smallholder farmers in the region, ranging from a low of 37.17% (or R5722/\$366.29USD) for MT only to a high of 58.08% (or R13404/\$855.87USD) for a combination of both MT and CD, relative to not adopting either practice. Further, we

Table 6. Multinomial logit estimates of adoption of conservative agriculture (CA) practices

Variables	Minimum tillage (MT$_1$CD$_0$)			Crop diversification (MT$_0$CD$_1$)			Minimum tillage and crop diversification (MT$_1$CD$_1$)		
	Coef.	Std. Err.	*dy/dx*	Coef.	Std. Err.	*dy/dx*	Coef.	Std. Err.	*dy/dx*
Age	0.035	0.022	0.002	0.022	0.018	0.002	0.020	0.018	0.002
Gender	1.347***	0.507	0.083	0.983***	0.369	0.109	0.741*	0.383	0.048
Access to extension service	−2.724***	1.081	−0.120	−0.860	0.861	−0.042	−1.122	0.959	−0.087
Access to agriculture input	−0.112	0.722	0.001	−0.127	0.540	−0.001	−0.433	0.504	−0.060
Years of farming	0.034	0.035	0.003	−0.008	0.033	−0.002	−0.005	0.032	−0.001
Farm size	0.001	0.001	0.000	0.001	0.001	0.000	0.0002	0.001	−0.000
Years spent in school	0.055	0.052	0.003	0.057	0.041	0.007	0.040	0.041	0.003
Access to credit facilities	−0.194	0.567	−0.005	−0.375	0.456	−0.051	−0.223	0.488	−0.015
Member of cooperative	1.911**	0.915	0.139	1.095*	0.609	0.135	0.304	0.533	−0.036
Instrumental variable									
Number of extension visits	0.788	0.532	0.049	0.396	0.378	0.024	0.638	0.432	0.068
Constant	−5.879	1.606		−3.788	1.137		−2.943	1.109	

Source: Author's computation (2021).
Note: *, ** and *** denote statistical significance at 1, 5 and 10% levels, respectively.
Base group farmers are those who didn't adopt any CA practices (MT$_0$CD$_0$).

Table 7. Average expected income from maize cultivation/farming (Rand)

Choice of adopted CA strategies		Adopters of CA strategies	Non-adopters of any CA strategies	Treatment effect: ATT/ATU	% Change in Income
MT_1CD_0	Adopters	25,064.52	12,452.19	ATT = 12,612.33***	50.32
	Non-adopters	15,396.38	9674.29	ATU = 5722.09***	37.17
MT_0CD_1	Adopters	20,184.84	10,897.01	ATT = 9287.83***	46.01
	Non-adopters	16,405.55	9674.29	ATU = 6731.26***	41.03
MT_1CD_1	Adopters	25,827.46	10,251.47	ATT = 15,575.99***	60.31
	Non-adopters	23,078.14	9674.29	ATU = 13,403.85***	58.08

Source: Author's computation (2021).
Note: *, ** and *** denote statistical significance at 1, 5 and 10% levels, respectively.
Sample size is 250, and 500 simulation draws were used. The baseline category is non-adoption of CA practices.

find that male farmers are significantly more likely to adopt all three CA strategies and that those who are members of cooperatives are significantly more likely to adopt MT or CD but not both on maize fields. The effect of cooperative membership is not surprising since we know that farmers are more likely to use the information they receive from other farmers and social networks (Prokopy *et al.*, 2008). Conversely, maize farmers who had access to extension services were significantly less likely to adopt MT (though at the 10% level) and while not significantly different from zero, was negatively correlated with the use of CD as well.

These findings are promising for CA adoption in Sub-Saharan Africa and other arid regions where soil and water conservation are imperative to increase agricultural productivity and where agriculture is a primary means to both food and income security. We provide empirical evidence that combining practices increase income at much higher rates than single CA practice adoption. If the environmental benefits from simultaneous adoption are greater than single practice adoption, the total benefits (private and social) may far outweigh the costs. With only 18% of the sample adopting both practices, there is potential to increase farm income and environmental benefits through simultaneous CA adoption.

We know that farmers who adopt one CA practice are more likely to adopt additional practices than those who do not adopt any practices (Upadhyay *et al.*, 2003). Policies that try to improve farm income while also improving environmental benefits could first target the 34% of farmers who adopt single practices before attempting to convince those who have not yet adopted any practices. These campaigns could provide subsidies to use both practices simultaneously and to disseminate information and training through cooperatives and other farmers via the training of trainers approach. Many farmers may choose not to use CD and MT simultaneously because they are unaware of the best crop mix to use to reduce fertilizer and other input costs, improve weed management and receive target market prices. Subsidies could help pay for new technology and farm equipment, supplement income in seasons when the non-maize crop does not offer high enough prices (in the case of CD) and ease the risk of trying new CA practices.

Paying farmers in developing countries to adopt CA practices that are shown to provide them with financial benefits will be difficult where money could be spent on basic infrastructure, health, social welfare and education. Research shows that farmers are reluctant to try new practices, even if they are more profitable than the current practices (Baumgart-Getz *et al.*, 2012).

Additional subsidy incentives are required to convince many farmers to switch practices. This may be the case for the 34% of farmers who are already using one CA practice and those in the 47% who do not use any of the two CA practices. More effort is needed to promote the adoption of CA strategies among non-adopters given their impact on income, a welfare parameter that has direct implications on food security and poverty reduction.

Our findings related to extension officers are concerning. The study shows that extension can play an important role in education, problem-solving, identifying resources and disseminating information in general. Extension agents are familiar with local issues and are better able to reach territories that other government agents cannot. They could play an important role in the success of any new CA policy. There may be an opportunity for extension agents to leverage involvement in cooperatives to work more closely with farmers and help them navigate programs or policies designed to increase conservation acres and practices in the region.

Conflict of interest. None.

References

Abdulai A and Huffman W (2014) The adoption and impact of soil and water conservation technology: an endogenous switching regression application. *Land Economics* **90**, 26–43.

Akhter A and Rahut DB (2013) Impact of agricultural extension services on technology adoption and crop yield: empirical evidence from Pakistan. *Asian Journal of Agriculture and Rural Development* **3**, 1–14.

Ali A and Abdulai A (2010) The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of Agricultural Economics* **61**, 175–192.

Bandiera O and Rasul I (2006) Social networks and technology adoption in northern Mozambique. *Economic Journal* **116**, 869–902.

Baumgart-Getz A, Prokopy LS and Floress K (2012) Why farmers adopt best management practice in the United States: a meta-analysis of the adoption literature. *Journal of Environmental Management* **96**, 17–25.

Belay A, Recha JW, Woldeamanuel T and Morton JF (2017) Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. *Agriculture & Food Security* **6**, 24.

Bourguignon F, Ferreira F and Walton M (2007) Equity, efficiency, and inequality traps: a research agenda. *Journal of Economic Inequality* **5**, 235–256.

Danso-Abbeam G and Baiyegunhi LJS (2018) Welfare impact of pesticides management practices among smallholder cocoa farmers in Ghana. *Technology in Society* **54**, 10–19.

Di Falco S and Veronesi M (2013) How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economy* **89**, 743–766.

Dubin JA and McFadden D (1984) An econometric analysis of residential electric appliance holdings and consumption. *Econometrica* **52**, 345–362.

Gebre GG, Isoda H, Rahut DB, Amekawa Y and Nomura H (2019) Gender differences in the adoption of agricultural technology: the case of improved maize varieties in southern Ethiopia. *Women's Studies International Forum* **76**, 102264.

GrainSA (2021) Conservation agriculture. Available at https://www.grainsa.co.za/grain-research/conservation-agriculture (Accessed 2 February 2021).

Greyling JC and Pardey PG (2019) Measuring maize in South Africa: the shifting structure of production during the twentieth century, 1904–2015. *Agrekon* **58**, 1–21.

Johansen C, Haque M, Bell R, Thierfelder C and Esdaile R (2012) Conservation agriculture for small holder rainfed farming: opportunities and constraints of new mechanized seeding systems. *Field Crops Research* **132**, 18–32.

Kassie M, Marenya P, Tessema Y, Jaleta M, Zeng D, Erenstein O and Rahut D (2018) Measuring farm and market-level economic impacts of improved maize production technologies in Ethiopia: evidence from panel data. *Journal of Agricultural Economics* **69**, 76–95.

Kumar A, Mishra A, Saroj S and Joshi PK (2019) Impact of traditional versus modern dairy value chains on food security: evidence from India's dairy sector. *Food Policy* **83**, 260–270.

Kuntashula E, Chabala LM and Mulenga BP (2014) Impact of minimum tillage and crop rotation as climate change adaptation strategies on farmer welfare in smallholder farming systems of Zambia. *Journal of Sustainable Development* **7**, 95–110.

Lehman L (2019) The status of conservation agriculture in rural South Africa. A paper presented at the UNDP SA Agronomist's Association Conference, Durban, South Africa.

Mango N, Siziba S and Makate C (2017) The impact of the adoption of conservation agriculture on smallholder farmers' food security in semi-arid zones of southern Africa. *Agriculture & Food Security* **6**, 32–40.

Mansur ET, Mendelsohn R and Morrison W (2008) Climate change adaptation: a study of fuel choice and consumption in the US energy sector. *Journal of Environmental Economics and Management* **55**, 175–193.

Marie M, Yirga F, Haile M and Tquabo F (2020) Farmers' choices and factors affecting adoption of climate change adaptation strategies: evidence from northwestern Ethiopia. *Heliyon* **6**, e03867.

Masere TP (2015) *An Evaluation of the Role of Extension in the Adoption of New Technology by Small-Scale Resource-Constrained Farmers: A Case of Lower Gweru Communal Area, Zimbabwe.* (Ph.D. dissertation). University of KwaZulu Natal Pietermaritzburg, South Africa.

McFadden D (1973) Conditional logit analysis of qualitative choice be. In Zarembka P (ed.), *Frontiers in Econometrics.* New York: Academic Press, pp. 105–142.

Mngqawa P, Mangena-Netshikweta LM and Katerere DR (2016) Grain production by rural subsistence farmers in selected districts of Limpopo and Mpumalanga Provinces South Africa. *PULA: Botswana Journal of African Studies* **30**, 49–63.

Montt G and Luu T (2018) Does conservation agriculture change labour requirements? Evidence of sustainable intensification in Sub-Saharan Africa. International Labour Organisation (ILO). Research Department Working Paper No. 35.

Oduniyi OS (2018) *Implication of Climate Change on Livelihood and Adaptation of Small and Emerging Maize Farmers in the Northwest Province of South Africa* (A thesis submitted in accordance with the requirements for the degree of Doctor of Philosophy in the subject of agriculture). University of South Africa.

Oduniyi OS (2021) Factors driving the adoption and use extent of sustainable land management practices in South Africa. *Circular Economy and Sustainability* **2**, 1–20.

Osewe M, Mwungu CM and Liu A (2020) Does minimum tillage improve smallholder farmers' welfare? Evidence from southern Tanzania. *Land* **9**, 513.

Prokopy LS, Floress K, Klotthor-Weinkauf D and Baumgart-Getz A (2008) Determinants of agricultural best management practice adoption: evidence from the literature. *Journal of Soil and Water Conservation* **63**, 300–311.

Stats South Africa (2018) *Annual Quarterly and Regional Fourth Quarter 2018.* Stats South Africa. (Accessed 31 May 2022).

Swanepoel CM, Swanepoel LH and Smith HJ (2018) A review of conservation agriculture research in South Africa. *South African Journal of Plant and Soil* **35**, 297–306.

Upadhyay BM, Young DL, Wang HH and Wandschneider P (2003) How do farmers who adopt multiple conservation practices differ from their neighbours? *American Journal of Alternative Agriculture* **18**, 27–36.

Varma P (2019) Adoption and the impact of system of rice intensification on rice yields and household income: an analysis for India. *Applied Economics* **51**, 4956–4972.

von Loeper WJ, Musango J, Brent A and Drimie S (2016) Analysing challenges facing smallholder farmers and conservation agriculture in South Africa: a system dynamics approach. *South Africa Journal of Economic and Management Sciences* **19**, 747–773.

Wekesah FM, Mutua EN and Izugbara CO (2019) Gender and conservation agriculture in sub-Saharan Africa: a systematic review. *International Journal of Agricultural Sustainability* **17**, 78–91.

Wossen T, Abdoulaye T, Alene A, Haile MG, Feleke S, Olanrewaju A and Manyong V (2017) Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies* **54**, 223–233.

Wu JJ and Babcock BA (1998) The choice of tillage, rotation, and soil testing practices: economic and environmental implications. *American Journal of Agricultural Economics* **80**, 494–511.

Yang Z, Mugera AW, Yin N and Wang Y (2018) Soil conservation practices and production efficiency of smallholder farms in Central China. *Environment, Development and Sustainability* **20**, 1517–1533.

Yang Z, Yin N, Mugera AW and Wang Y (2021) Impact of multiple soil conservation practices on rice yields and chemical fertiliser use in China. *China Agricultural Economic Review* **13**, 851–871.

Appendix

Appendix Table A1. Validation of selection instrument

Variable (income)	Coef.	Std. Err.	t	P>|t|
Age	59.168	76.278	0.78	0.440
Gender	954.767	1435.628	0.67	0.507
Access to extension service	−7114.423	3606.173	−1.97**	0.051
Access to agriculture input	722.797	1995.329	0.36	0.718
Years of farming	98.599	128.849	0.77	0.446
Farm size	3.661	3.384	1.08	0.282
Years spent in school	406.097	170.796	2.38**	0.019
Access to credit facilities	5199.557	1932.597	2.69***	0.008
Member of cooperative	−1257.429	1906.339	−0.66	0.511
Number of extension visits	2372.192	1522.621	1.56	0.122
Constant	−137.047	3960.745	−0.03	0.972

Number of obs = 118.
$F_{(10, 107)} = 2.68$.
Prob > F = 0.0058.
$R^2 = 0.2003$.
Adj $R^2 = 0.1256$.
Root MSE = 6879.6.
Source: Author's computation (2021).
Note: *, ** and *** denote statistical significance at 1, 5 and 10% levels, respectively.

Appendix Table A2. Second-stage parameter estimates of income from multinomial endogenous switching regression model (MESR)

	MT_0CD_0		MT_1CD_0		MT_0CD_1		MT_1CD_1	
Variables	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	−81.274	549.861	−696.155	860.766	293.767	1230.175	0.443	2388.031
Gender	−11,871.71	11,735.16	−6353.866	38,889.84	−13,966.15	29,874.4	23,068.15	94,550.52
Access to extension service	−3600.644	22,120.69	26,916.4	18,619.1	12,682.97	46,099.56	8240.851	155,328.2
Access to agriculture input	99.984	1898.887	6416.913	5952.664	7532.357	4611.807	9307.463	13,461.86
Years of farming	120.202	524.506	−962.828	1450.151	−1179.921	1245.675	884.005	4041.06
Farm size	−30.348	21.823	56.628	98.283	−30.088	51.682	−3.612	106.318
Years spent in school	−177.143	1303.94	−214.981	2619.504	51.091	2347.937	950.813	10,995.49
Access to credit facilities	4380.37***	808.400	8947.671***	2656.697	−1782.959	2512.799	−7798.312	11,376.65
Member of cooperative	−627.124	1301.753	4799.72	35,923.56	−12,958.22	8423.739	7262.837	25,796.6
Constant	5562.181	10,943.72	102,728.4	77,404.95	86,978.0	171,676.7	−67,516.79	334,819.1

Source: Author's computation (2021).
Note: *, ** and *** denote statistical significance at 1, 5 and 10% levels, respectively.
Selectivity correction based on multinomial logit.
Second step regression bootstrapped standard errors (500 replications).

Oluwaseun Samuel Odunyi *et al.*