Technology in Society 60 (2020) 101214

Contents lists available at ScienceDirect

Technology in Society

journal homepage: http://www.elsevier.com/locate/techsoc

Technology adoption and household food security among rural households in South Africa: The role of improved maize varieties

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ARTICLE INFO

JEL classification:
I32
Q16

Keywords:
Food security
Improved maize varieties
Technology adoption
Heterogeneous impact
Smallholder farming
South Africa

ABSTRACT

This study aimed to assess the impact of adoption of improved maize varieties on household food security among smallholder farmers in KwaZulu-Natal, South Africa. A sample of 415 maize producers was analysed using the propensity score matching method, the treatment effect model and the Tobit selection model. The results were consistent across the models, indicating that improved maize varieties positively increased household food security, and that the impact of adoption differed according to the adoption level and socio-economic characteristics of the farmers. The results showed that an additional 1 ha of land under improved maize varieties increases annual food expenditure per capita levels by over R4000. Female farmers were more likely to adopt improved maize varieties, and spent more to ensure household food security, and benefitted more from adoption, than their male counterparts. The findings suggest that policies that seek to increase the land under improved maize varieties among smallholder farmers, especially female farmers who are the majority of these farmers, can play a significant and positive role in increasing the levels of household food security in South Africa through technological innovations. The study recommends that policy makers should aim to facilitate the dissemination of less costly improved seed varieties, target female farmers, and improve their access to information to improve the adoption of technological innovations and food security among the poor farming households in South Africa.

1. Introduction

The importance of harnessing innovation to address structural problems of poverty, inequality and unemployment (triple challenges) has been acknowledged in South Africa [1–3]. Accordingly, the South African policy makers have set targets to speed up the country's transformation to a knowledge-based economy [3,4]. Further to exploiting innovation for improved competitiveness and economic growth, the policy documents recognize the importance of including the poor and marginalised rural communities in the national system of innovation to realize inclusive development and reduce inequalities [2,3]. To achieve greater levels of inclusion and poverty reduction, it is imperative that improving productivity in sectors such as farming, which are accessible to the marginalised, is prioritised [5].

A number of studies in Sub-Saharan Africa (SSA) (e.g., Refs. [6–10]) have highlighted the importance of the development and dissemination of productivity-enhancing technological innovations such as improved seed varieties and fertilisers in improving crop productivity among the poor. However, the adoption levels of the innovations by smallholder farmers in SSA remains low [11–17]. The cost of these technological innovations are high, and the liquidity-constrained smallholder farmers cannot afford them [12]. Also, the success of these innovations is not certain, as most succeed under stringent managerial regimes and agro-climatic conditions which are beyond the reach of the smallholder farmers [18].

For example, improved maize varieties produce higher yields under conditions of adequate moisture and good soil and pest management practices, and smallholder farmers generally farm in circumstances where these conditions are rarely met [12,13,19,20]. Additionally, limited market access, inadequate storage and transport infrastructure, as well as increased chances of buying counterfeits, reduce the incentive of smallholder farmers to invest in the modern agricultural technologies [21]. Consequently, these poor farming households generally experience low crop production and/or productivity levels, and oftentimes, total crop failure, leading to poverty and increased vulnerability to food shortages [22].

Against the background of a growing need to adapt to a rapidly changing world (characterised by climate change, urbanisation,

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https://doi.org/10.1016/j.techsoc.2019.101214
Received 19 December 2018; Received in revised form 13 November 2019; Accepted 15 November 2019
Available online 21 November 2019
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globalisation, fourth industrial revolution, and environmental concerns), there is consensus in the literature that smallholders have no alternative but to innovate to sustain their livelihoods [14,18,23]. The South African government, realising the need to intervene as market forces alone have failed to promote transformative innovations for the poor's development [2,5], has been at the forefront of promoting the adoption of improved agricultural technologies among smallholder farmers through several initiatives [12,20,24,25]. For example, since 2001, scientists from the National Department of Agriculture partnered with the Consultative Group on International Agricultural Research (CGIAR) and the International Maize and Wheat Improvement Center (CIMMYT) to develop new maize varieties (named Grace and ZM521) more suitable for smallholder farmers [26].

Also, since 2008, the Agricultural Research Council (ARC) has been participating in two public-private partnerships (the Water Efficient Maize for Africa (WEMA) project and the Improved Maize for African Soils (IMAS) project) aimed at developing drought-tolerant and insect-protected maize varieties for adoption by smallholder farmers royalty-free [27]. The major objective of these initiatives is to develop and disseminate improved maize varieties that can be adopted by the poor resource farmers to improve their yields and food security. Maize is the main crop grown by the smallholder farmers in South Africa, and is the most important grain crop for food security [28,29].

The question is, have these initiatives improved the smallholders' adoption levels of these improved maize varieties? If yes, to what extent has the adoption of the innovations improved the livelihoods of the poor farming households? The need for farmers in South Africa to adopt agricultural technologies such as improved seed varieties can never be over-emphasised. South Africa is generally not suitable for crop production, due to low rainfall and poor soils, with only 13% of the country considered arable [27]. Most of the poor rural households are located in areas that are inherently hot, dry and characterised by infertile soils [20,25]. Access to irrigation is limited in these areas due to inadequate water resources. Where water is available, the smallholder farmers lack the infrastructure to divert water to their plots due to limited financial resources or credit support [30]. About 92% of irrigated land area in South Africa is owned by large-scale commercial producers, with smallholder farmers accounting for just 8% [31].

A growing list of studies on the impact of improved maize varieties in SSA (e.g., Refs. [7,8,19,32–35]) have reported a positive role of improved maize varieties on different household welfare indicators. For example, Kassie, Jaleta [8] evaluated the impact of improved maize varieties in rural Tanzania, and reported that improved maize varieties resulted in improved household food security. In Zambia, Khonje, Manda [32] found that adoption of improved maize varieties led to significant gains in crop incomes, consumption expenditure and food security. Also in Zambia, Smale and Mason [19] found that maize hybrids were associated with higher values of household income, assets and welfare. Bezu, Kassie [7] reported a positive correlation between area under improved maize varieties and own maize consumption, income and asset holdings in Malawi. Mathenge, Smale [33], in Kenya, found that maize hybrid seed use had a positive effect on incomes and assets and resulted in reduced poverty and inequality. Zeng, Alwang [34] reported reduced poverty incidence, depth and severity due to improved maize varieties adoption in Ethiopia.

However, limited research has been done on the potential food security impacts of improved maize varieties in South Africa. The food security studies in South Africa (e.g., Refs. [36–40]) have not investigated the role of technology adoption, in general, or improved seed varieties, in particular, on the food security situation of smallholder farming households. Studies on the adoption of improved maize varieties [20,41–44] have focused on the impact of mainly genetic modified maize varieties on outcomes such as yields, efficiency, profits or risks. The extent to which smallholder farmers have adopted improved maize varieties, and the impact of these varieties on food security is relatively unknown in South Africa.

While the studies from other SSA countries are important, they cannot be generalised to the South African context, due to its unique resource and economic development characteristics. As explained by several authors [45–47], technology adoption is depended on local contextual factors, such that studies conducted in other countries or regions of the country should never be taken to be representative of all. For example, South Africa has most developed, and competitive seed industry in Africa [21,48]. Whereas there is heavy reliance on informal seed markets in other countries in Africa where these studies were conducted, the seed industry is formalised, mature and privatised in South Africa [48]. However, the South African seed industry is biased towards servicing large commercial farmers, and the smallholder farmers face challenges that make it difficult for them to access the improved seed varieties [48,49]. That is, while there is an advanced sectoral innovation system in South Africa, the smallholders remain excluded from participating, and benefitting from it. This study therefore, aims to contribute to the literature by showing the extent to which the South Africa experience is similar or differs from other cases already studied in other countries in the region.

Following other recent studies (e.g., Refs. [8,10]), this study went beyond the simple mean impacts that assume homogenous adoption effects, by investigating heterogeneous adoption effects. First, the adoption of improved maize varieties was not just captured as a binary treatment variable showing whether or not a farmer used improved maize varieties, but also as a continuous variable of the amount of land under improved maize varieties. Use of the continuous treatment variable accounts for the heterogeneous effects of technology adoption, as it captures the impacts of different levels of adoption. Second, the study investigates the differential impact of improved seed varieties on the food security level of farmers with different socio-economic characteristics. These are important issues that can inform policy makers as they seek to improve the use of technological innovations to address developmental challenges facing marginalised rural communities.

The remainder of this paper is organised into three sections. The next section presents the research methodology, in which the data collection approach and the estimation methods are discussed. The study results are interpreted and discussed in the subsequent section, while the main conclusions and policy implications are presented in the final section.

2. Research methodology

2.1. Data

The study relies on survey data involving 513 farmers drawn from the KwaZulu-Natal (KZN) province in South Africa. The KZN province was selected because it is characterised by high levels of poverty, food insecurity and unemployment, especially among the rural dwellers [50]. Also, smallholder farming is very important in the province, as it is the backbone of its rural people's livelihoods [51]. For purposes of this paper, the farmers who had not planted maize the previous season were dropped from the sample. Of the total sample of 513 farmers, 417 had planted maize the previous season, meaning that 96 farmers were dropped during analysis. A further two farmers were dropped because of missing information on important variables. The final sample analysed comprised of 415 maize farmers.

A multistage sampling approach was used to conduct the survey. The first stage involved the purposive selection of three districts out of the 11 districts in KZN. The districts were selected based on the availability of a significant number of households engaged in smallholder farming activities. The districts chosen were Umzinyathi, Uthukela and Harry Gwala. These three districts are among the poorest in the province [51]. The second stage was the random selection of the 513 farmers from the three districts. The lists of farmers were obtained from the respective local offices of KZN Department of Agriculture and Rural Development. In the offices where no ready list was found, a request was made and a list was compiled by the responsible extension officers. It is important to highlight that offices do not keep a comprehensive lists of farmers, and thus the sample should not be used to generalise the results. No stratification was done according to any variable, giving an equal chance for all farmers to be included.

The number of households sampled was not proportional to the population sizes of the respective local municipalities, but proportional to the number of farming households, as received from the local offices of the KZN Department of Agriculture and Rural Development. The sample is thus not representative of the districts, and the results should be interpreted with this in mind. The data were collected during the months of October and November 2014 using a structured questionnaire. The questionnaire was administered by trained enumerators who spoke the local *IsiZulu* language. The enumerators were experienced and had knowledge of the smallholder farming systems. Questionnaire pretesting, involving 15 rural households, was also done to note and remedy ambiguities or difficulties with regards to question wording and flow.

The questionnaire included household demographics and socioeconomic characteristics; income sources and amounts; household expenditure patterns (food and non-food expenditures); agricultural production and marketing activities as well as access to institutional support services and membership in farmer organisations. The questionnaire also captured the use of improved maize varieties, asking the farmers to indicate the types and quantities used in the previous agricultural season as well as the land area under these varieties.

2.2. Theoretical framework and variable selection

The linear model of innovation postulates that innovation begins with basic research, and that researchers develop new technologies which they pass to extension agents for dissemination to the farmers [23,52]. While it remains influential, this pipeline approach to agricultural technology innovations has not led to satisfactory returns, despite the significant investments for SSA, due to the fact that the end-users are considered passive adopters [53,54]. It has thus been abandoned, and the innovation systems approach, which is more participatory, inclusive and holistic, adopted [14,53]. The national system of innovation approach is the preferred model of promoting innovation in South Africa, as entrenched in the recent White Paper on Science, Technology and Innovation [3].

The innovation systems model postulates that innovation is not linear, but occurs within heterogeneous networks, characterised by a diversity of stakeholders, which include government, researchers, farmers, private entrepreneurs and non-governmental organisations (NGOs) [23]. These innovation actors interact in a in a non-linear, iterative and non-predictable pattern to solve a common problem, adapt to a new environment or take advantage of new opportunities [23]. According to Spielman, Ekboir [16], innovation can only have socioeconomic impact only when it is part of sustained processes involving many actors with different capabilities and resources. While the innovation system concepts entrenched in the broader literature, they remain poorly understood in the agriculture content, with little empirical documentation [16,23,53].

This study approaches technology adoption as a choice problem within a random utility framework, following other agricultural technology adoption studies (e.g., Refs. [9,55]). The random utility theory postulates that a farmer who seeks to maximise utility will adopt a technology when the utility from choosing the technology (U_A) is greater than that of not adopting the technology (U_N), whether it is developed with their participation or not. If, for example, the net benefit is denoted as denoted as U_{NB}, then a farmer would adopt improved maize varieties if $U_{NB} = U_A$-$U_N > 0$. The unobservable net utility U^* can be expressed as a function of observable elements in the following latent variable model:

$$U_i^* = \beta x_i + \varepsilon_i, \; U_i = 1 \text{ if } U_i^* > 0 \tag{1}$$

where U_i is a binary indicator variable that equals 1 for farmer *i* in case of adoption and 0 otherwise; β is a vector of parameters to be estimated; x_i is a vector of household and farm characteristics; and ε_i is an error term.

The theory of farm household decision-making under imperfect market conditions was used as the basis of choosing the variables to include in the model [56]. Market failures that are prevalent in rural areas of developing countries imply that it cannot be reasonably assumed that farmers' input use decisions depend only on market prices [7]. Under imperfect market conditions, household technology choices are influenced by a household's economic position and institutional environment. Since farmers are risk averse, and crop production is subject to random shocks, the ability to bear risk, in terms of wealth endowment, social and human capital, may positively influence technology adoption [57]. In this study, wealth endowment was proxied by farm size, livestock size and asset values, whereas human capital was proxied by education. Farmers' membership in farmer groups were used to capture social capital.

Food security was measured in terms of total annual household food expenditures plus the estimated monetary value of the food that was consumed from home production, in Rands per capita. A 30-day recall period was used to capture detailed monthly food expenditure, and the monthly data was converted to one year by multiplying by 12. Consumption expenditure, unlike incomes, is less prone to seasonal fluctuations and measurement errors, hence, more reliable [58,59]. Several other studies (e.g., Refs. [8,10,37,60,61]) have used food expenditure per capita as an objective food security indicator. The food items produced and consumed by the household were converted to their market values using average of local prices and included in the expenditure amount [37,62].

Maize varieties were categorised into two: improved or local varieties. Improved varieties included both hybrids and open pollinated varieties (OPVs). A farmer was assumed to have adopted improved maize varieties if they planted any improved varieties (OPVs and hybrids) in the previous season. Given that the characteristics and productive potential of recycled seed are different from the original generation of improved varieties [34,63], the farmers who planted recycled hybrid seeds were not considered as adopters. However, since OPVs can be recycled for up to three times, those who planted OPVs recycled three times or less were also considered adopters. Adoption of improved maize varieties was captured in two ways: (a) as a binary treatment variable showing whether or not a farmer used improved maize varieties, and (b) a continuous variable showing the amount of land under improved maize varieties. Other variables included personal details of the farmer and their household characteristics (age, gender, education level, employment status, etc.), wealth and asset endowment (land size, livestock size, asset values, etc.), infrastructural and/or institutional support (extension, credit, irrigation, distance to all-weather road, location/district, etc.) and membership in farmer groups.

2.3. Estimation approaches

Three estimation approaches, the propensity score matching (PSM) method, the treatment effect model and the Tobit selection model, were used to evaluate the impact of improved maize varieties on food security. The PSM method and the treatment effect model were used when the treatment variable (improved maize varieties adoption) was captured as a binary dummy variable, while the Tobit selection model was used when the treatment variable was captured in terms of land area under improved maize varieties. These estimation approaches correct for endogeneity problems that arise due to self-selection bias in technology adoption. The adoption of improved maize varieties is not random [8], such that adopters may systematically differ from non-adopters in a number of observable and unobservable characteristics that may have a direct effect on household food security. If selection bias is not accounted for, the estimated impact results will be biased.

2.3.1. Binary treatment impact estimation: propensity score matching (PSM) method and treatment effect model

The PSM approach [64] is a commonly used approach for the estimation of causal effects in a binary treatment framework. PSM corrects for selection bias due to observables by matching a sub-sample of adopters and non-adopters that have similar observable characteristics, and making comparisons in the region of common support [65]. If the unconfoundedness assumption (conditional independence assumption) holds, PSM approaches results in the elimination or reduction of biases in estimated treatment effects [66]. The Stable Unit Treatment Value Assumption (SUTVA) requires that the potential outcomes for any unit do not vary with the treatments assigned to other units, and that for each unit there are no different forms or versions of each treatment level [67]. Compared to estimates based on full samples, the impact estimates based on matched samples are less biased and more reliable [68].

The Average Treatment effect on the Treated (ATT), which is the impact of improved maize varieties adoption on those farmers that are adopters, was estimated as follows:

$$ATT = E[\Delta_i | T_i = 1] = E[Y_{\mathbf{1}\,i} | T_i = 1] - E[Y_{\mathbf{0}\,i} | T_i = 1] \tag{2}$$

where: T_i denotes treatment status of farmer i, and takes two values: $T_i = 1$ if a farmer is an adopter, and $T_i = 0$ if a farmer is a non-adopter. Y_{1i} is the food expenditure per capita if farmer is an adopter, Y_{0i} is the food expenditure per capita if farmer is a non-adopter, E is the expectation operator and Δ_i is the treatment effect. The ATT captures the change in the food expenditure per capita realised by farmers who are adopters subject to their adoption status.

The fundamental problem of causal inference in the context of program evaluation is that of missing data, since the treatment indicator takes either the value of one or zero, but not both [69,70]. This is because the food expenditure per capita of the adopters, had they not been adopters, cannot be observed. Similarly, the food expenditure per capita of non-adopters, had they been adopters, cannot be observed. The PSM method generates the missing data by estimating the propensity score, which is the probability that a household is an adopter [64]. The approach is able to estimate the causal adoption impact as the difference between the food expenditure per capita of the adopters and what would have been the case if they had not adopted improved maize varieties. The logit model was used to estimate the propensity scores. To strengthen the plausibility of PSM's unconfoundedness assumption, which assumes that selection bias is only due to observables, a number of covariates were introduced in the logit model.

The balancing property was selected in estimating the propensity scores so as to ensure that a comparison group is constructed with observable characteristics distributed equivalently across quintiles in both the treatment and comparison groups [71]. Three matching methods, the nearest K-neighbours (K = 5), kernel (bandwidth = 0.06) and radius (caliper = 0.05) matching techniques, were all used to estimate the impact for robustness reasons. In constructing the matching estimates, the common support was imposed. The treatment observations with weak common support were dropped, since inferences can be made about causality only in the area of common support [72]. All the standard errors were bootstrapped with 1000 repetitions, as suggested by Smith and Todd [71].

The PSM technique does not correct for selection bias to unobservable variables. The sensitivity of the estimated effects to hidden bias was tested using the Rosenbaum bounds sensitivity test [73]. This test indicates how strongly an unobservable variable must influence the selection process to undermine or reverse the findings based on matching on observables [73,74]. Even though the Rosenbaum bounds tests indicated that the results were not very sensitive to hidden bias, the treatment effect model, which corrects for the hidden bias that arises from unobservable factors, was estimated for robustness checks. The model first generates the inverse Mills ratio and then adds it to the response equation [75,76], as follows:

$$\mathrm{Y_i} = \beta x_i + \delta \mathrm{A_i} + \beta_\lambda \lambda_i \quad + \varepsilon_i \tag{3}$$

where: $\mathrm{Y_i}$ is food expenditure per capita, x_i is a vector of socio-economic characteristics; $\mathrm{A_i}$ is the adoption status; λ_i is the inverse Mills ratio, ε_i is the error term; while β and δ are parameters that are to be estimated. The impact coefficient δ is unbiased due to the inclusion of the selectivity term (inverse Mills Ratio) [76].

The estimation of the impact as described above assumes a homogenous treatment effect among the adopters. However, the treatment effects are not the same for the adopters with different socio-economic characteristics. To investigate the extent to which the treatment effect on food security varies within adopters, ordinary least squares (OLS) regression of the household-level treatment effect on some background characteristics of the adopters was estimated.

2.3.2. Continuous treatment impact estimation: The Tobit selection model

The Tobit selection model was used to evaluate the impact of the continuous treatment variable, i.e., land area under improved maize varieties. Kassie, Jaleta [8] used the same approach. The model was estimated in two steps: Step 1 involved the estimation of residuals by specifying a selection equation of the censored Tobit form with land area under improved maize varieties as the dependent variable; and Step 2 involved adding the predicted residuals on the outcome equation estimated using ordinary least squares (OLS) with food security as the dependent variable. The addition of the residuals on the outcome equation corrects for the selection bias that arises from unobservable factors [77]. The selection equation in step 1 was specified as follows:

$$\begin{aligned} l_i^* &= w_i^{'}\gamma + u_i \\ l_i = 0 \quad & if\ l_i^* \le 0 \\ l_i = l_i^* \quad & if\ l_i^* > 0 \end{aligned} \tag{4}$$

where: l_i^* is the latent maize varieties adoption variable, which takes the value of 0 if farmer did not adopt the improved maize varieties, or land area under improved maize varieties where adoption took place; w_i is a vector of covariates, γ are parameters to be estimated and u_i are the residuals. The standard Tobit model (Equation (3)) was estimated over all observations to predict residuals as follows:

$$\widehat{u}_i = l_i - w_i\widehat{\gamma} \tag{5}$$

where: $\widehat{u}_i$ and $\widehat{\gamma}$ are estimates of residuals and parameters, respectively. The outcome equation was estimated using OLS including only observations for which $l_i > 0$. The estimated residuals were added to the equation and the equation specified as follows:

$$y_i = x_i\beta + l_i\delta + \widehat{u}_i\alpha + \varepsilon_i \tag{6}$$

where: y_i is food expenditure per capita, x_i is the vector of covariates, $\widehat{u}_i$ are the residuals estimated in Equation (4), β, α and δ are parameters to be estimated and ε_i is the error term. The same covariates were specified in both equations (3) and (5). According to Wooldridge [77], $w_i = x_i$ does not cause estimation problems in this case because u_i always has separate variation from x_i because of variation in l_i. A significant α indicates strong evidence of selection bias problems, while an insignificant value (as was the case in this study), implies little evidence of selection bias problems.

3. Results and discussions

3.1. Descriptive statistics

Maize was grown by about 81% of the sampled 513 farmers, indicating its importance among smallholder farmers. The descriptive statistics presented in Table 1 show that 35% of the maize farmers had planted improved maize varieties the previous agricultural season. This result suggests that a huge proportion of smallholder farmers have not yet adopted improved maize varieties. The low adoption levels of improved maize varieties is in line with literature (e.g., Refs. [12,20]), which have reported that, despite South Africa having the best-developed formal seed system on the African continent, the system was not providing smallholder farmers, and especially resource-poor farmers, with appropriate and affordable seed. Instead, the farmers indicated that they rely on open pollinated varieties or recycled seeds. The adopters indicated that they put an average of 0.70 ha of land under improved varieties, which represents 47% of their total land. However, this represented over 75% of the 0.93 ha land under maize, with most of the adopters planting recycled seed for the remaining 25% of their land under maize. Further discussions with the farmers indicated that they preferred OPVs to hybrids because the former are less costly, can be recycled without losing much productivity and require less inputs to grow.

The results in Table 1 show that both adopters and non-adopters had largely similar socio-economic characteristics. However, the adopters were more likely to be the married, had smaller households and were wealthier (bigger land sizes and higher asset values). Table 1 indicates modest food expenditure levels, as households spent on average over R8000 per capita per year on food. This translates to over R700 per capita per month, and compares favourably with the lower-bound poverty line of R544 per capita per month (R6528 per capita per year). The poverty line was calculated by converting the lower-bound poverty line of R443 per capita per month suggested by NPC [78] to 2014 prices using the consumer prices index (CPI) [79]. The adopters spent almost 60% more on food than the non-adopters, suggesting that improved maize varieties play an important role in improving food security among smallholder farming households. The results further indicate that, unsurprisingly, the farmers who used improved maize varieties were more productive than those who did not. The adopters produced average maize yields of 1.2 tons per hectare, which is about 61% higher than the non-adopters' average yield of 0.78 tons per hectare.

Table 2, which presents the Foster, Greer and Thorbecke (FGT) poverty indices [80], indicates that poverty is more pronounced among non-adopters than among adopters. The pooled sample poverty head count of 51% implies that, in general, a bigger proportion of the farmers experience food poverty in the three study districts. This figure is comparable to other studies in South Africa which reported poverty figures ranging from 30% to 55% in the rural areas of South Africa [28,37,62,81]. The poverty gap index, a measure of depth of poverty, shows that the current food expenditure levels of the poor farmers would have to increase by 22% to lift them out of food poverty. The poverty gap index is slightly higher among non-adopters than adopters.

3.2. Determinants of improved maize varieties adoption, logit and tobit results

Table 3 presents the logit and Tobit models results estimating the determinants of the decision to adopt and the adoption level of improved maize varieties, respectively. The logit model was used to estimate the propensity scores for the PSM method, while the Tobit results presented in Table 3 are from the first step of the Tobit selection model. The results indicate that age was associated with decreasing probability of adoption of improved maize varieties. An additional year was associated with a

Table 2
FGT poverty indices according to improved maize varieties adoption status.

FGT index	Pooled sample (n = 415)	Adopters (n = 144)	Non-adopters (n = 271)
Food poverty headcount index	0.51	0.45	0.57
Food poverty gap index	0.22	0.21	0.24
Food poverty severity index	0.13	0.12	0.13

Table 1
Summary statistics of sample households according to improved maize seed adoption status.

Variables and description	Pooled sample (n = 415)		Adopters (n = 144)		Non-Adopters (n = 271)		*t*-test (χ^2 test)
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	
Treatment variables							
Improved maize seed adoption (1 = Yes, 0 = No)	0.35	–	1		0		
Area under improved maize varieties (ha)	0.25	0.53	0.70	0.69	0		
Outcome variables							
Food expenditure per capita ('000 Rands)	8.42	7.35	11.40	10.30	6.83	4.40	6.30***
Maize yield (tons per hectare)	0.96	1.67	1.28	2.65	0.78	0.68	2.93***
Socio-economic characteristics							
Age (Years)	57.45	12.93	56.75	13.28	57.83	12.73	−0.81
Gender (1 = Male, 0 = Female)	0.45	–	0.47	–	0.45	–	0.14
Education level (Years)	4.54	4.12	4.98	4.26	4.30	4.03	1.61
Household size (Numbers)	6.60	3.02	6.18	2.84	6.83	3.08	−2.13**
Land size (hectares)	1.87	1.85	2.12	1.87	1.73	1.83	2.10**
Livestock size (Tropical livestock units)	2.43	5.96	2.78	5.03	2.25	6.40	0.87
Asset values ('000 Rands)	81.51	43.70	86.93	47.34	78.58	41.41	1.87*
Credit access (1 = Yes, 0 = No)	0.32	–	0.33	–	0.30	–	0.62
Extension (1 = Yes, 0 = No)	0.38	–	0.38	–	0.38	–	0.02
Access to radio (1 = Yes, 0 = No)	0.46	–	0.53	–	0.42	–	4.35**
Group membership (1 = Yes, 0 = No)	0.40	–	0.46	–	0.36	–	4.29**
Fertiliser use (1 = Yes, 0 = No)	0.59	–	0.72	–	0.52	–	15.51***
Soil quality (1 = Good, 0 = Poor)	0.56	–	0.59	–	0.54	–	0.84
Distance to nearest all weather road (km)	2.93	11.11	3.35	16.52	2.70	6.60	0.57
Rainfall (1 = Good, 0 = Poor)	0.57	–	0.58	–	0.56	–	0.58
Irrigation access (1 = Yes, 0 = No)	0.33	–	0.34	–	0.32	–	0.05
Employed non-farm (1 = Yes, 0 = No)	0.18	–	0.23	–	0.16	–	2.55
Non-farm business ownership (1 = Yes, 0 = No)	0.03	–	0.03	–	0.04	–	0.26
Harry Gwala	0.47	–	0.39	–	0.51	–	5.05**
Umzinyathi	0.13	–	0.10	–	0.14	–	1.43
Uthukela	0.41		0.51	–	0.35	–	9.62***

Notes: ***, **, and * means significant at 1%, 5%, and 10% levels, respectively.

Table 3
Determinants of probability and level of improved maize seed adoption.

Variables	Logit model				Tobit selection model (First step)	
	Coef.	Std. Err	Marginal effect	Std. Err	Coef.	Std. Err
Age	−0.030***	0.011	−0.020***	0.002	−0.001	0.005
Gender	−0.632**	0.299	−0.128**	0.060	−0.227*	0.135
Education	0.053**	0.023	0.070**	0.031	0.015*	0.008
Household size	−0.092	0.140	−0.019	0.018	−0.028	0.018
Land size	0.048	0.063	0.010	0.013	−0.051	0.033
Livestock size	0.050***	0.018	0.041***	0.014	0.023**	0.001
Asset values (log)	0.005***	0.012	0.003**	0.001	0.004	0.069
Credit access	0.116	0.256	0.024	0.052	0.098	0.119
Extension	0.388**	0.194	0.079**	0.039	0.194*	0.114
Group membership	0.370*	0.214	0.075*	0.039	0.080	0.158
Access to radio	0.725**	0.289	0.147**	0.057	0.258*	0.132
Fertiliser adoption	0.970***	0.263	0.197***	0.050	0.424***	0.123
Soil quality	0.200*	0.119	0.041*	0.024	−0.004	0.105
Rainfall	−0.016	0.265	−0.003	0.054	0.052	0.123
Irrigation access	0.244*	0.131	−0.067*	0.034	0.240**	0.114
Employed non-farm	0.519*	0.307	0.105*	0.062	0.161	0.141
Non-farm business	−0.051	0.647	−0.010	0.131	−0.072	0.302
Distance to road	−0.040***	0.010	0.031***	0.012	0.001	0.004
Umzinyathi	0.184	0.474	0.037	0.096	0.078	0.216
Uthukela	0.612**	0.291	0.124**	0.058	0.244*	0.136
_constant	−1.378	1.759			−0.353	0.808
N	415				415	
LR χ^2	46.76***				31.77***	
Pseudo R^2	0.19				0.15	
% correctly classified	0.70					

Notes: ***, **, and * means significant at 1%, 5%, and 10% levels, respectively.

2% decrease in the chances of using improved maize varieties. In line with a number of studies (e.g., Refs. [7,35,57,82]), the result indicate that farmers become less receptive to new information or ideas and more risk-averse as they become older, and thus older farmers are less likely to adopt modern technologies compared to younger farmers.

Table 3 also shows that male farmers were less likely to adopt improved maize varieties relative to female farmers. Also, male farmers put less land under improved maize varieties than female farmers. This result is contrary to literature (e.g., Refs. [8,46,55,82]). A possible explanation for this result is that men prioritise cash crops, while women prioritise staples such as maize [83]. As such, men are less likely to invest in improved maize varieties because it is their less preferred crop.

As expected, and in line with the literature (e.g., Refs. [7,32,82,84]), education was positively correlated with both the probability and level of improved maize varieties adoption. An explanation to this result is that the more educated farmers understand and interpret information better, which results in them incurring less transaction costs and benefiting more from technology adoption. The results also indicate that wealthier farmers (in terms of livestock size, asset values and non-farm employment) had higher chances of adopting improved maize varieties. This is because wealthier farmers are in a better position to bear the risks associated with technology adoption, and have financial resources to purchase farm inputs such as improved seeds. Higher livestock numbers may also be indicative of increased manure availability, implying that farmers with access to manure are more likely to meet the soil fertility requirements of improved maize varieties and this adopt them.

The significant and positive estimated coefficients of variables such as extension, radio and group membership highlight the importance of information access in technology adoption among smallholder farmers, as emphasised in the literature (e.g., Refs. [32,57]). Contact with extension officers was associated with about 8% higher likelihood of adopting improved maize seeds. Moreover, farmers with contact with extension officers put 0.194 ha more land under improved maize varieties. Extension officers are an important source of relevant information on modern technologies and their benefits to smallholder farmers. Also, the extension officers have been promoting modern technology adoption among smallholder farmers through giving the farmers free or subsidised improved inputs, say of maize seeds. Membership in farmer groups was associated with increased chances of improved maize seeds adoption because they ease access to and facilitate exchange of important information about modern technologies. Several studies [8,85,86] have made similar findings for different agricultural technologies. The farmer groups in the rural areas of South Africa also facilitate the collective buying of inputs, resulting in sharing of transport and other transaction costs.

Farmers with access to radios had a 15% higher chance of adopting improved maize varieties, and they put 0.258 ha more land under improved maize varieties, when compared to their counterparts. This is because access to a radio enhances a farmer's access to information about expected weather conditions, the advantages of using improved technologies, where to buy the inputs or sell output and at how much. This information is frequently broadcasted on local radio stations in South Africa. On the other hand, difficulties in accessing all-weather roads was negatively impacted the likelihood of adopting improved seed. This could be because farmers located far from accessible roads incur higher information costs, which results in them not accessing sufficient information for them to make decisions to adopt modern technologies.

Table 3 shows that farmers with access to fertile soils, irrigation and those who apply chemical fertilisers were more likely to use improved maize varieties. Farmers with good soils were more likely to adopt improved seeds because they are more likely to expect higher chances of getting better yields, and hence, higher expected returns to their investment on improved seeds. In contrast, farmers with poor soils have less incentives to invest on improved inputs as they may not expect higher returns to their investment. The positive and significant estimates of chemical fertilisers and irrigation suggests that these two technologies have a positive effect on adoption of improved maize varieties. The results also show that farmers from the Uthukela district were more likely to adopt improved maize varieties than those in Harry Gwala district. This implies that there are some unobserved agro-climatic, institutional, market access and socioeconomic heterogeneities peculiar to each of the two districts that impact on technology adoption.

3.3. Impact of improved maize varieties on household food security

The PSM results, showing the impact of the binary adoption treatment variable on food expenditure per capita, are presented in Table 4. The table shows that all the three matching estimators yielded similar results, showing that the adoption of improved maize varieties has a positive and statistically significant effect on food expenditure per capita. The results indicate that food expenditure per capita increased by over R4000 as a result of the adoption of improved maize varieties. The estimates are robust, since the differences among the values estimated using the three matching approaches are very small.

The Rosenbaum bounds sensitivity analysis [73] was done and the bounds tests showed that the conclusion would change at bounds statistic (Γ) = 2.2. This implies that the results are not very sensitive to hidden bias, since it would require a bias of more than 200% to reverse the conclusion. The balancing tests based on the Kernel matching approach were done to evaluate the reliability of the above reported estimates, and the results are presented in Table 5. Table 5 shows that, after matching, the characteristics of adopters and non-adopters are largely similar after matching.

The test for equality of the two group means shows that, with an exception of one variable (chemical fertiliser adoption), there is no statistically significant difference between adopters and non-adopters after matching. This is in contrast to the unmatched sample presented in Table 2 which indicated statistically significant differences in several covariates between the two groups. The standardised differences (% bias) for the mean values of all the covariates, with the exception of fertiliser adoption, between adopters and non-adopters are below 20%, implying that the balancing requirement is largely satisfied [87].

The treatment effect model, which corrects for the hidden bias that arises from unobservable factors, was estimated, and the results of the second step of the model are presented in Table 6 (the first step results are similar to those presented on Table 3).

The estimated coefficient of adoption is positive and statistically significant, supporting the conclusion that technology adoption improves food security levels. Table 6 also shows that increasing age, education level, assets, land and livestock, as well as access to extension and irrigation are associated with increased food security. Also, females have higher incomes than males, while increasing household members are associated with decreasing welfare. Since these results are similar to those Table 7, they will be discussed after the presentation of the Tobit selection model results (second step) to avoid duplications.

Table 7 presents the results of the second step of the Tobit selection model, which involved adding the estimated residuals from the Tobit model estimates presented in Table 3. The insignificant estimated coefficient of the residuals at the 10% significance level indicates little evidence of selection bias. The results indicate that increasing land area under improved maize varieties is likely to lead to increases in food expenditure per capita. An increase of 1 ha of land under improved maize varieties improves food expenditure per capita by over R4500. Table 7 also shows that food expenditure per capita is influenced by a number of other covariates.

The results demonstrate that increasing age of a farmer is positively correlated with increased food expenditure per capita. This is because increasing age results in higher social capital (contacts and networks) as well as more experience, which helps the farmers to be more food secure. Several other studies have reported a similar result in rural South Africa (e.g., Ref. [38]) and in other developing countries [88,89]. Contrary to most studies (e.g., Refs. [38,88–90]), Table 6 indicates that female-headship of households could result in high food expenditure

Table 4
Impact of improved maize varieties on food expenditure per capita ('000 Rands), PSM results.

Matching estimator	ATT	*t*-test
Nearest five neighbours	4.108 (0.922)	4.46***
Kernel matching (bandwidth = 0.06)	4.138 (0.910)	4.55***
Radius matching (Calliper = 0.05)	4.140 (0.910)	4.55***

Notes: *** means significant at 1% level. Figures in parentheses are standard errors.

Table 5
Test of matching quality.

Variables	Mean		%bias	*t*-test	
	Treated	Control		t	p > t
Age	56.97	56.58	3	0.25	0.800
Gender	0.46	0.45	1.5	0.13	0.900
Education level	4.91	4.88	0.7	0.06	0.950
Household size	6.19	6.33	−4.8	−0.43	0.668
Land size	2.04	2.04	0.2	0.02	0.986
Livestock size	2.71	2.44	4.6	0.35	0.724
Asset values (log)	11.16	11.14	2.4	0.21	0.831
Credit access	0.30	0.29	2.4	0.21	0.835
Extension access	0.39	0.39	0.1	0.01	0.991
Group membership	0.46	0.45	0.7	0.06	0.953
Access to radio	0.51	0.51	0.8	0.07	0.948
Fertiliser adoption	0.72	0.57	32	2.70***	0.007
Soil quality	0.60	0.55	8.8	0.74	0.458
Rainfall	0.60	0.59	2.3	0.20	0.845
Irrigation access	0.32	0.30	4.8	0.41	0.680
Employed non-farm	0.23	0.15	18.8	1.61	0.109
Non-farm business ownership	0.03	0.03	0.8	0.07	0.941
Distance to all-weather road	3.38	2.72	5.2	0.44	0.663
Umzinyathi	0.11	0.10	1.4	0.13	0.898
Uthukela	0.50	0.51	−1.2	−0.10	0.919

Summary of the distribution of |bias|.
Min = 0.14, Max = 32.
Mean = 4.65, Std. Dev = 7.52.
Pseudo $R^2 = 0.034$.
LR $\chi^2 = 13.41$, p = 0.894.
Notes: *** means significant at 1% level.

Table 6
Impact of improved maize varieties on food security, treatment effect model results.

Variables	Coef.	Std. Err.
Improved maize seed adoption	3.851***	1.047
Age	0.052**	0.026
Gender	−2.633***	0.751
Education level	0.036	0.082
Household size	−0.776***	0.098
Land size	0.679***	0.162
Livestock size	0.091*	0.048
Asset values (log)	1.371***	0.410
Credit access	1.230**	0.621
Extension access	1.841***	0.605
Group membership	0.043	0.869
Access to radio	0.186	0.748
Fertiliser adoption	−1.124	0.739
Soil quality	0.134	0.563
Rainfall	1.119	0.650
Irrigation access	1.792***	0.600
Employed non-farm	6.270***	0.809
Non-farm business ownership	2.259	1.568
Distance to all-weather road	−0.072	0.025
Umzinyathi	−0.072**	0.025
Uthukela	−2.983***	0.761
_constant	−6.224	4.283
/athrho	−0.001	0.218
/lnsigma	1.695***	0.035
ρ	−0.001	0.218
σ	5.445	0.185
λ	−0.004	1.185
Wald χ^2 [21]	300.73***	
N	415	

Wald test of independent equations. ($\rho = 0$): $\chi2(1) = 0.000$, p = 0.997.
Notes: ***, **, and * means significant at 1%, 5%, and 10% levels, respectively.

Table 7
Impact of area under improved maize varieties on food security, Tobit selection model (second step).

Variables	Coef.	Std. Err.
Area under improved maize varieties	4.453***	0.987
Age	0.055**	0.028
Gender	−2.867***	0.754
Education level	0.043*	0.026
Household size	−0.805***	0.099
Land size	0.904***	0.196
Livestock size	0.127**	0.063
Asset values (log)	1.242***	0.410
Credit access	1.348**	0.671
Extension access	1.826***	0.633
Group membership	0.314	0.904
Access to radio	0.306	0.764
Fertiliser adoption	−0.952	0.692
Soil quality	0.086	0.587
Rainfall	0.901	0.691
Irrigation access	1.758***	0.630
Employed non-farm	6.666***	0.826
Non-farm business ownership	3.192*	1.976
Distance to all-weather road	−0.054	0.036
Umzinyathi	−2.676**	1.204
Uthukela	−2.781***	0.762
Residuals	−7.258	9.358
_constant	−3.228	5.686
N	144	
F	12.52***	
R^2	0.42	

Notes: ***, **, and * means significant at 1%, 5%, and 10% levels, respectively.

Table 8
Heterogeneous food security impact among improved seed adopters, OLS results.

Variables	Coef.	Std. Err.
Age	0.110*	0.058
Gender	−4.352***	1.622
Education level	−0.195	0.175
Household size	−1.024***	0.227
Land size	1.4345***	0.392
Livestock size	−0.024	0.135
Asset values (log)	2.219***	0.840
Credit access	1.398	1.461
Extension access	2.395*	1.382
Group membership	0.802	1.928
Access to radio	−0.260	1.530
Fertiliser adoption	−2.235	1.498
Soil quality	0.080	1.254
Rainfall	2.658*	1.500
Irrigation access	1.982	1.454
Employed non-farm	10.429***	1.638
Non-farm business ownership	6.936*	3.868
Distance to all-weather road	−0.097**	0.038
Umzinyathi	−7.290***	2.589
Uthukela	−5.988***	1.591
_cons	−10.664	9.706
N	144	
R^2	0.59	
F	8.37***	

Notes: ***, **, and * means significant at 1%, 5%, and 10% levels, respectively.

values than male-headed ones. A few studies (e.g., Refs. [37,91,92]) have found a similar result. This suggest that, even though men are have a higher chance to have more incomes due to their better access to capital and resources, women prioritise spending on food compared to men. Bigger households were found to spend less on food per capita, as they require more incomes to do that than smaller households.

As expected, and in line with the literature (e.g., Refs. [8,37]) additional years of education were associated with increased food expenditure per capita. This is because education results in household heads who have improved access to and use of information that can build their capacity to improve their households' food security. Farmers who were employed non-farm have access to more opportunities, hence their increased food expenditure per capita. The results also show that wealthier farmers (in terms of land, livestock and assets) spend more on food per capita than the poorer. The positive and significant estimates of extension and credit demonstrates the importance of support services such as extension and credit in improving the food security status of rural households.

3.4. Food security impact heterogeneity among adopters

To investigate the extent to which the treatment effect on food security differs among improved seed adopters, the OLS regression model was estimated and results are presented in Table 8.

The table shows that the impact of improved seed adoption is not the same among adopters. The results show that technology adoption increases food security more among the younger farmers than among the older farmers. The negative and significant estimated coefficient of gender suggests that female farmers benefit more from adoption than males. Also, the results show that adoption benefits more households that are smaller in size, richer (own bigger farms and assets), and those with access to extension.

4. Conclusions and policy implications

This study has investigated the impact of improved maize varieties on household food security among smallholder farmers in KwaZulu-Natal, South Africa. The study went beyond evaluating causal effects of a binary treatment variable by also capturing improved maize varieties adoption as a continuous treatment variable. A sample of 415 maize producers was analysed using PSM, treatment effect model and the Tobit selection model. The empirical results, which were consistent across the estimation techniques, indicated that improved maize varieties significantly and positively influence household food security. The results showed that an additional 1 ha of land under improved maize varieties increases annual food expenditure per capita level by about R4000. The findings suggest that increasing the adoption of improved maize varieties can result in improved household food security among smallholder farmers. The effect of improved seed adoption was higher among younger and female farmers, as well as richer (own bigger farms and assets) farmers with access to extension.

To increase technology adoption, the study results suggest that policy makers should aim to increase smallholder's asset base, improve their access to information, organise these farmers into groups as well as introduce adult literacy classes to improve education levels. Also, the study recommends disseminating OPVs that are less costly than hybrids, and targeting youths and women as they are more likely to adopt improved technologies for staples such as maize and benefit more these technologies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2019.101214.

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