Accounting for self-selection bias in assessing impacts of agricultural innovations: the case of farmer support programs in the Eastern Cape

By

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DECLARATION OF ORIGINALITY

I, Hlumani Mandla, declare that the thesis/dissertation, which I hereby submit for the degree Master of Science in Agriculture at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

Signature: ________________

Date: **2021/10/06________**

DEDICATIONS

This mini-dissertation is dedicated to my beautiful and loving wife Fhatani Mandla, and my daughter Athandwa Mulandawawe Mandla. Fhatani your patience and belief in me carried me throughout this long journey. To my daughter, I hope this will be motivation to you that anything is possible through hard work.

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ABSTRACT

Dry land rural maize production is often characterized by low yields, which tend to be lower than the land potential. In order to mitigate issues faced by smallholder farmers and improve their sustainability governments across Africa introduced famer support programmes (FSPs). FSPs are intended to support farmers with the required inputs, training and or information required for successful production. Therefore, this study seeks to establish whether the support provided to smallholder farmers through FSPs improves their efficiency.

The study uses cross-sectional data to test whether FSPs improve technical efficiencies (TEs) of smallholder maize farmers. Using plot level data collected from 30 FSP and 66 non-FSP farmers drawn from Mgojweni, Mabetshe, Lujecweni, Bantingville, Canzibe and Dumasi villages of the Eastern Cape, this study estimates a Cobb-Douglas stochastic production frontier and uses it to compare the efficiency scores of the two farmer types. The results show that FSP adopters had relatively higher TE scores, with over 50% having scores of above 70%. However, a t-test for equality of mean TE scores revealed no statistically significant differences between them (t=-1.3969, p=0.1662), suggesting that the FSPs cannot explain the TE variances. Given that participation in FSPs was not random, a propensity score matching techniques was used to account for self-selection bias. After accounting for self-selection bias the results revealed that FSP adopters were on average 205% more efficient relative to non-adopters. These results underscore the importance of accounting for self-selection bias in demonstrating the impact of agricultural innovations.

Keywords: Technical efficiency, stochastic production frontier, farmer support programmes, propensity score matching, self-selection bias

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LIST OF ACRONYMS

ACB	-	The African Centre for Biodiversity
ATT	-	Average treatment effect on the treated
CASP	-	Comprehensive Agricultural Support Programme
CD	-	Cobb-Douglas
COLS	-	Corrected Ordinary Least Squares
DEA	-	Data Envelopment Analysis
DID	-	Difference in difference
DRDLR	-	Department of Rural Development and Land Reform
FSP	-	Farmer Support Programme
IV	-	Instrumental Variable
KM	-	Kernel Matching
KZN	-	Kwa-Zulu Natal
NNM	-	Nearest Neighbour Matching
OLS	-	Ordinary Least Squares
PSM	-	Propensity Score Matching
RM	-	Radius Matching
SM	-	Stratification Matching
SPF	-	Stochastic production frontier
TE	-	Technical Efficiency
UPEB	-	University of Pretoria, Business Enterprises

CHAPTER 1: INTRODUCTION

The need to improve smallholder rain-fed maize production in a sustainable manner is important in South Africa and the rest of Africa as maize is a staple food (Walker and Schulze, 2006). In the region, smallholder maize production is often characterised by low yields, which are often significantly lower than the potential for the land (Walker and Schulze, 2006; Kibirige and Obi, 2015; Chimonyo, Mutengwa and Chiduza, 2014). The key factors in ensuring the sustainability of smallholder farmers include improving the economic viability and efficiency of their activities. In an attempt to improve the sustainability of smallholder maize (and other staple foods) production, Governments across Africa introduced various farmer support programmes (FSPs). FSPs are policies/programmes that are developed to provide smallholder farmers with the support required for successful production. FSPs range from input support, credit provisions, agricultural price support, extension programmes, irrigation schemes and livestock exchange programmes (Gebrehiwot, 2017; Ndoro, Mudhara and Chimonyo, 2014; Elias et al., 2013; Danso-Abbeam, Ehiakpor and Aidoo, 2018; Aboyki et al., 2020).

Since the dawn of democracy, the South African Department of Agriculture through its 9 provincial departments, and the Department of Rural Development and Land Reform (DRDLR), jointly referred to as government, have undertaken various FSPs (the African Centre for Biodiversity (ACB), 2018). The FSPs initiated by the Government include the Comprehensive Agricultural Support Programme (CASP), Ilima/Letsema, Fetsa Tlala Integrated Food Production Initiative (Fetsa Tlala) and the One Household, One Hectare initiative. These FSPs were initiated for the purpose of alleviating the challenges faced by smallholder farmers by facilitating land access as well as providing input supply (e.g. seeds, fertiliser, and pesticides), extension and training, mechanisation, irrigation, infrastructure and market support, and financing. Overtime, investment in FSPs in South Africa increased and began to include programmes and support offered by private companies such as Grain SA. In most instances private companies will offer FSPs in partnership with government. According to ACB (2018), one of the key aims of FSPs was to provide farmers with support and information transfer for a period of five years. During this period, the amount of inputs provided to each farmer would be gradually decreased allowing the farmers to become independent producers by year five, as such ensuring sustainability.

The evidence on whether FSPs have been able to meet their intended purpose is mixed. According to Sikwela and Mushunje (2013) participating in FSPs improved the yield of maize farmers in the Eastern Cape and KwaZulu-Natal (KZN) provinces. This study also found that FSP participants achieve higher profits than non-participants. Kibirige and Obi (2015) also found that irrigation schemes in the Eastern Cape were technically more efficient than their counterparts. Chepape and Maoba (2020) evaluated the effects of FSPs in the Gauteng and found that these programmes improved the standard of living of adopters and their communities at large. However, Ndoro et al. (2014) found that benefits derived from livestock extension programmes were negligible and that these programmes were not demand-driven. Studies by ACB (2018), University of Pretoria, Business Enterprises (UPEB) (2015) and Idsardi et al. (an) show that FSPs have done little in achieving the goals/objectives for which they were initiated (i.e. food security, market access and smallholder commercialisation). ACB (2018), also found that most FSPs have failed to achieve financial independence of smallholder farmers. This study also found that smallholder farmers continue to rely on FSPs and tend to exit the market after support is seized (after five years).

Maize, similar to the rest of the South Africa, is also regarded as a stable food in the Eastern Cape, and is mostly grown by smallholder farmers who have limited resources (Chimonyo et al., 2014). In addition, most smallholder farmers in the province practise dry land (rain-fed) farming. As such, these farmers realise low yields achieved, which in most instances are less than a tonne per hectare. Studies by Tshilambilu (2011), Mokgalabone (2015) and Kibirige and Obi (2015) have also illustrated that smallholder farmers tend to have less yield per hectares due to production inefficiency. As indicated above, the role of FSP is to improve the sustainability and livelihood of smallholder farmers. This is done through the introduction of new adoptable maize varieties, the supply of production inputs such as fertiliser and herbicides, the provision of extension services and training, as well as mechanisation (tractor support) (ACB, 2018). This study will evaluate the effectiveness of farmers in converting inputs provided in FSPs into output. As such, providing much needed knowledge as to whether investment in FSPs that support dry land maize producers improve farmer efficiency, translating into improved productivity. Moreover, the study provides guidance to policy makers regarding rural/smallholder farmer support programmes and their benefits.

Limited studies review the effects of FSPs on farm level TE of dry land maize producers. This study uses Cobb-Douglas (CD) stochastic production frontier to estimate the effects of FSPs on farm level TE of smallholder (dry land) maize farmers.

However, according to the ACB (2018), farmers are required to meet various criteria, such as forming part of a local project, already being involved in farming, and being from a disadvantaged background, prior to participating in FSPs. As such, FSP facilitators (e.g. government) seek for these minimum requirements in order to approve applicants who will benefit from FSPs. In light of this minimum selection criteria, it can be deduced that farmers do not randomly join/adopt FSPs. Adopting FSP is also voluntary, such that certain socio-economic characteristics of farmers also contribute to whether they adopt FSPs (Sikwela and Mushunje, 2013; Udo, 2014). Choice of whether a farmer joins FSP or not, can be referred to as self-selection into these programmes. Self-selection can also arise from unobservable factors (such as willingness to try, innate ability, risk aversion, managerial ability and motivation) and/or observable factors such as farm and farmer characteristics. In most instances self-selection results in biased and misleading impact assessment results by dampening the effects of policy initiatives such as FSPs. Indeed, studies by Ma et al. (2018), Zheng et al. (2021), Danso-Abbeam et al. (2018), have clearly illustrated the negative effects of self-selection bias. As such the main objective of this study is to correct/account for self-selection bias using the propensity score matching model, after which it can be established whether the support provided to farmers through inputs, and information dissemination improves the efficiency of adopters. Given that water is a scarce resource in South Africa (with some arears victim to drought), this study is important in providing evidence to policy makers as to whether investment in FSPs aimed at rain-fed production are worth it. Accounting for self-selection bias will also assist policy makers in identifying the root cause of the limited adoption of these programmes.

In the following section we provide a brief overview of current literature, section 3 outlines the methodology used in this study, section 4 discusses the results and in section 5 we conclude.

CHAPTER 2: LITERATURE RIVIEW

2.1. Impact of FSPs on farm level efficiency and productivity

Extensive research has been carried out on productivity and efficiency in the agricultural sector, as they tend to be a measure of success for various programmes and policies implemented as a means to improve the sector. As a result of the role played by FSPs in improving farmer livelihood, several studies have also been conducted on their effects on productivity and efficiency. The findings on the effects of FSPs on efficiency and productivity show that these programmes grossly have positive outcomes. This section provides an overview of current literature on whether FSPs improve the efficiency and productivity of farmers.

Kibrige and Obi (2015) utilised a CD production function and stochastic frontier analysis to compare the technical and allocative efficiency of smallholder farmers participating in irrigation schemes, with homestead food gardeners in the Eastern Cape (South Africa). Maize yield was used as the output variable in the production function, whereas input variables included land, seed, fertiliser, pesticide, capital (R) and the number of irrigations per ha per season. Even though the study found that both types of farmers were allocative inefficient, the average TE score for irrigation scheme participants was slightly higher at approximately 98.8%. Kibirige and Obi (2015) also conducted a t-test on the average TE scores of the different smallholder farming groups, and found that irrigators were indeed more technically efficient. Ellias, Yasunobu and Ishida (2013) also found that participation in extension programmes increased the productivity of Ethiopian farmers by approximately 6%, prior to accounting for self-selection bias.

A recent study by Chirmo (2017) also found FSPs, in the form of farm input subsidy, to have a positive effect on farm level output. Particularly, the study, found that farmers that had benefited from FSPs realised approximately 9% more output than those that did not benefit from the programme. The study also found that maize yield was inelastic to changes in farm size, seed, labour and fertiliser, with farm size being the most important variable in determining maize yield. Regarding efficiencies, the study found that maize producers in Malawi were technically, allocative and economically inefficient with efficiency scores ranging from, 15.7 to 78.9%, 23.5 to 86.2% and 14.1 to 74.6%, respectively. Even though no thorough comparison of the levels of efficiency of FSP beneficiaries and non-beneficiaries was conducted, the study noted that benefiting from FSPs had little to no effect in improving efficiency.

Gebrehiwot (2017), using a stochastic production frontier technique also found that participation in extension programmes was negatively related to inefficiency amongst farmers in Ethiopia. Moreover, Gebrehiwot (2017) found that participating in extension programmes reduced the level of inefficiency amongst smallholder farmers, which implied that participants in such programmes were more efficient than non-participants. The study also found that plot size, seed and labour had statistically insignificant effects on maize yields realised by smallholder farmers in Ethiopia.

However, while studying the effects of CAP subsidies on the technical efficiency of crop farms in Germany, the Netherlands and Sweden, Zhu and Lansink (2010) found that share crop subsidies had a negative effect on technical efficiency in Germany, a positive effect in Sweden and insignificant effects in the Netherlands. The study also found that the total share in total farm revenues had negative impacts on technical efficiency in all three countries.

2.2. Accounting for self-selection bias

Analysing the impacts of policy and intervention requires random selection of participants and non-participants. However, given voluntary participation in these programmes, various studies have shown that farmers are not randomly selected into FSPs. Moreover, various socio-economic and economic characteristics of farmers determine selection into FSPs. Such pre-existing characteristics amongst farmers (study participants) may result in selection bias into FSPs. This phenomenon is a form of selection bias referred to as self-selection (Heckman, 2010). To this end, self-selection bias in the case of FSPs arises from the farmer's ability to choose whether to participate in such programmes. Below we, review literature on the effects of and accounting for self-selection bias.

Ma et al. (2018) used propensity score matching (PSM) and corrected SPF to correct for self-selection bias stemming from observed and unobserved factors, in evaluating the technical efficiency benefits of joining agricultural cooperatives. The PSM model was used to account for observed factors, such as socio and economic characteristics of the farmer that affect his/her decision to join agricultural cooperatives. Whilst the sample selection correction SPF was used to account for unobservable factors, such as a farmer's innate ability, risk aversion, motivation and managerial ability. The study found that the TE of cooperative members increased after accounting/correcting for self-selection bias. Similar findings were made by Zheng et al. (2021).

In evaluating the effects of agricultural extension programme participation in Ethiopia, using a simple Ordinary Least Squares (OLS), Elias et al. (2013) found that the programme improved farm productivity by approximately 6%. However, the study also found that there were observed and unobserved factors that influenced adoption of the programme. The authors used the Heckman Treatment Effects Model and PSM to account for self-selection bias. The study found that the likelihood of participation in the extension programme increased if the farmer was more educated, owned livestock, had access to more labour, used oxen power, was a member in a farmers' organizations and was involved in administration. Participation was also significantly and negatively affected by the age of the farmer. Upon accounting for self-selection bias, Elias et al. (2013) found that participation in the extension programme increased productivity by up to 20%. Danso-Abbeam et al. (2018), also found that participation in FSPs in the form of agricultural extension programmes was subject to self-selection bias. The study found that the likelihood of adopting or forming part of the extension programme was positively related to age, experience, credit access, membership to an organization, and land cultivated with maize. Using simple OLS, PSM and the Heckman Treatment Effect Model, Danso-Abbeam et al. (2018), also found that the programmes had positive effects on productivity, and income (farm, household and household income per head). The results from the Heckman Treatment Effect Model, revealed that the effects of participation in the extension programmes were higher (more than double) than those of the OLS for all four dependent variables.

In a recent African study, whilst evaluating the effects of adopting improved rice varieties in Ghana, Abdul-Rahaman, Issahaku and Zereyesus (2021) found that adopters were technically more efficient than non-adopters. The study also used PSM and a sample selection correction SPF to account for observed and unobservable (motivation) farmer characteristics/factors. The observed characteristics in the PSM model included age, education, ownership of a mobile phone, credit access, and livestock ownership. The study found that accounting for self-selection does not improve TE within the studied sample. However, using a PSM and a SPF corrected for sample selection bias, Olagunju et al. (2021) found that, after accounting for self-selection bias arising from both observed and unobserved factors, the TE scores of cooperative members and non-members increased.

The studies discussed above suggest that accounting for self-selection bias can improve TE studies. This suggests that indeed the presence of self-selection is likely to result in bias and misleading results.

2.3. Determinants of Technical Efficiency

After evaluating the effects of policy on TE, it is important to look at the determinants of efficiency differences between adopters and non-adopters. Many studies have been carried out in evaluating the determinants of TE. For example, while using a single step approach in evaluating the effects of rural community banks on TE of cocoa and identifying the determinants of such efficiency differences, Attipoe et al. (2020) found that education, membership of FBO, experience, credit access, and participation in government-sponsored mass spraying program had a significant and positive impact on TE scores.

Oyetunde-Usman and Olagunju (2019), found that credit access decreased TE amongst maize farmers in Zambia, whereas these farmers became more TE with increases in household size. Botiabane et al. (2017) found that the determinants of TE amongst sorghum producers in Ga-Masemola village of Limpopo, South Africa included: the measure of land and the quantity of seeds utilized.

More in line with this study Shanmugam and Venkataramani (2006), used a two stage approach in analysing and finding the determinants of TE in agricultural production across various districts in India. The study first measured TE using SPF. In the second stage, TE scores from the SPF were regressed against various socio-economic characteristics. The study found that road infrastructure and literacy rate increased TE scores, whilst electrification, land owned and infant mortality rate reduced the scores. Parikh et al. (1995), using stochastic cost frontiers in a two-stage estimation procedure, found that education, number of working animals, credit per acre and number of extension visits significantly increase cost efficiency, while large land holding size and subsistence significantly decrease cost efficiency amongst Pakistani producers. Guesmi and Serra (2015) found that subsidies and family size had a positive relation to TE scores, whilst non-agricultural income had a negative impact on TE scores.

In a study in the Kogi State of Nigeria, Joseph (2014) found that an increase in the level of education, level of farming experience and farm size led to an increase in TE, whereas an increase in age and family size resulted in a decline in TE. Speelman et al. (2007), found that farm size, landownership, fragmentation, the type of irrigation scheme, crop choice and the irrigation methods applied had a significant impact on the TE of small-scale irrigators in the North West Province of South Africa. Kibirige and Obi (2015) found that household size, farming experience, use of agro-chemicals, gross margins earned from maize sales and off-farm incomes had a positive and significant impact on the farm level TE amongst maize producers in the Eastern Cape. The study also found that the amount of land owned and training on the use of inputs have a negative and significant influence on TE of maize production. While evaluating the determinants of economic farm-size–efficiency relationship in smallholder maize farms in the Eastern Cape Province of South Africa, Obi and Ayodeji (2020), found that gender, marital status, education, credit and experience had a positive relationship to TE, while household size, extension services and main occupation had a negative relation to TE.

The studies discussed above suggest that TE is driven by a combination of demographic characteristics (human capital), and farm characteristics such as land size, chemical use etc.

CHAPTER 3: METHODOLOGY

3.1. Study area

The study was carried out in the Nyandeni Local Municipality (Nyandeni) in the Eastern Cape province of South Africa. Nyandeni forms part of the OR Tambo District Municipality. The municipality is located some 30 km south of Umtata and is largely rural in nature with numerous villages. Nyandeni is characterised with high unemployment levels and the majority of its rural population is dependent on government grants. Crop production opportunities exist in Western parts of the municipality. However, like most of the Eastern Cape province, Nyandeni is characterised by low rainfall. The potential for crop production is further inhibited by institutional issues relating to land (Nyandeni Local Municipality, 2014).

Regardless of being victim to erratic rainfall, agricultural production is regarded as one of the key elements of the Nyandeni local economy. Agriculture is used to combat poverty and increase opportunities for woman, youth and the disabled within the economy of the municipality (Nyandeni Municipality, 2019). Moreover, agriculture is used to improve household income and livelihood, improve food security and nutrition, and increase employment levels. Most farmers in the area are smallholder and/or subsistence farmers that practice farming for purposes of food security. Given low rainfalls, these farmers practise dry crop production.

Figure 1: Nyandeni Local Municipality Map
Source: semanticscholar.org

Maize is amongst the prominent crops in Nyandeni, being grown by almost every farming household within the region. As such, some of the farmers in Nyandeni benefited from various FSPs, by receiving production inputs (seed, fertiliser, mechanisation etc.), cattle exchange and extension services. According to ACB (2018), smallholder farmers are required to formulate local project groups in order to qualify for FSP support. In addition, smallholder farmers should be from a disadvantaged background to qualify. Given the background of Nyandeni's population, most smallholder farmers in the region qualify to receive FSP support.

3.2. Sampling and data collection

Stratified multistage sampling was used to categorise farmers into two types: FSP adopters and non-adopters. Where FSP adopters referred to farmers that received support through FSPs. A database of projects (farmer groups) practising rain-fed maize production that benefited from FSPs obtained from the local agricultural office in Libode, was used to randomly select five projects. FSP adopters were randomly selected from the five projects chosen in the first step.

Extension officers were then used as initial contact persons for FSP adopters that were interviewed.

Non-adopters of FSPs referred to farmers that did not form part of any FSP. To ensure that these farmers represented a good counterfactual, they were selected from villages that were deemed to have the same farm level social and institutional characteristics. The only major difference amongst adopters and non-adopters was participation in FSPs. A database was computed with the assistance local Chiefs and rural representatives (e.g. village chairperson) for non-adopters. Farming households were then randomly selected from the list.

According to statistics provided by the Mthatha Department of Agriculture, as at 2018 there were approximately 50 projects in Nyandeni that benefited from FSPs, with a total of 2 426 beneficiaries amongst them. On the other hand, it is unclear how many non-FSP smallholder maize farmers operate in Nyandeni as no record of these farmers is kept. As such we considered household data reported by Statistics South Africa (Stats SA) on the region. Based on the 2011 census, Stats SA reports that there are approximately 61 647 households in Nyandeni Municipality, with 36 502 of these households being involved in Agriculture in one way or the other (Stats SA, 2011). Of the 36 502 households, 17 361 are involved in Livestock production only. On this basis we assumed that there is likely to be total of approximately 19 141 households that practice crop production (either mixed or not).

Using the formula used by Isreal (1992), Mazvimavi et al. (2012) given by:

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

where n is the sample size needed, N the population and e the level of required precision (e=7%), the sample size was, $\frac{19\,141}{1+19\,141(0.07)^2}$ = 202.

In light of the above, the study had intended to collect data from 200 farmers that would reasonably represent the population of smallholder maize farmers in Nyandeni. However, the data was collected during harvesting period in the study area. As such, even with the help of Extension Officers and local Chiefs, the response was relatively poor. As such, in the end a total of 96 farmers, constituting of 30 FSP adopters and 66 non-adopters, from Mgojweni, Mabetshe, Lujecweni, Bantingville, Canzibe and Dumasi villages participated in the study. The sampled FSP adopters benefited from the Ilima/Letsema, by receiving maize seed, fertiliser, herbicide, top dresser, basic training, tractor support and pesticide. Structured questionnaires were used to collect primary, plot level data from the participants during one on one interviews. The questions used were pre-tested on a sample of farmers in the area of study. The data collected was cross-sectional data for the most recent agricultural season, 2017/18, given the absence of proper record keeping amongst the sample farmers. As a result of the challenges faced in collecting data, it envisaged that the small sample size might introduce bias in the estimated coefficients. As such, it is advised that the results of the study be interpreted with caution.

According to ACB (2018), UPBE (2015), Fanadzo and Ncube (2018), FSPs are developed and introduced to improve farmer livelihoods through reliable food production and improved income. In this regard, the study collected data on the amount of maize, maize yield (Y_i), produced by each farmer in the 2017/18 season. Maize yield is the output variable measured in this study, and was measured in kilogrammes (kg). Prior to being used in the model, maize yield was transformed into logarithmic form, represented as $\ln Y_i$. Maize yield is determined by, inter alia, various inputs used in production. In this regard, data was also collected on inputs used by each maize farmer.

Input variables for which data were collected include land, seed, fertiliser, labour and herbicide and top dresser. The choice of these variables was based on previous studies such as Kibirige and Obi (2015), Ellias et al. (2013), Gebrehiwot (2017), Chirmo (2017).

Table 1: Input variables and their expected relationship to output

Variable	**Description**	**Unit of measure**	**Presentation in model**	**Expected relation to output variable**
Land	Measured the amount of land, in hectares (ha), allocated to producing maize by the sample farmers in the 2017/18 season	Hectares (ha)	lnLand	(+) expected to have a positive relation to maize yield

Seed	Measured the amount of seed used in production in the 2017/18 season by each farmer.	kg	lnSeed	(+)
Fertiliser	Measures access to fertiliser	Dummy	Fertiliser	(+)
Labour	Measured the man hours required from production to packaging. This includes both hired and family labour.	Man hours	lnLabour	(+)
Herbicide	Measures access to herbicide	Dummy	Herbicide	(+)
Top dresser	Measures access to top dresser	Dummy	TopDresser	(+)

It is worth noting that data on top dresser, fertiliser and herbicide were collected and included in the model as dummy variables due to limited adoption by non-FSP adopters. This is in line with suggestions made by Battese (1997), Barret and Hogest (2003). As a result of using dummy variables however, we will only be able to establish the likely effects of using fertiliser, herbicide and top dresser on output, without any ability to quantify such effects. Furthermore, these variables are unlikely to contribute to returns to scale as they are not in percentages. Data was also collected on various demographic characteristics of the sample farmers including household size, income and farming experience.

3.3. Analytical framework and estimation techniques

As illustrated above FSPs are introduced to improve smallholder production sustainability through, amongst others, improving farm level TE. TE can be defined as the effectiveness with which a given set of inputs is converted into outputs. Moreover, technical efficiency measures the ability of an economic entity (the farmer in our case) to produce the highest (maximum) possible output subject to available inputs (Ben-Belhassen and Womack, 2000). Using STATA 15, this study uses a two-stage approach to assess the impacts of FSPs on farm level TE. The two-stage approach has received some criticism from authors such as Wang and Schmidt

(2002), who claimed that the approach may result in biased estimates due to misspecification bias in the first step. However, studies such as Obi and Ayodeji (2020) who used both a single and two-step approach, found that the concern about persistent bias associated with the two-step approach was not obvious. The empirical evidence is inconclusive on which modeling presents the best results. In addition, the two-step approach was adopted for its simplicity and ease with which results can be presented. This approach also continues to be used by other scholars (Shanmugam and Venkataramani (2006); Parikh et al. (1995); Guesmi and Serra (2015); Joseph (2014); Speelman et al. (2007)).

In the first stage, we begin by using a production function to assess the production system used by smallholder maize farmers in the Eastern Cape. A SPF model is then used to assess the efficiency of these farmers as a result of adopting FSPs. In the second stage, the efficiency scores from the SPF model are then regressed on farmer and farm characteristics, using OLS, that are likely to affect TE.

Production functions describe the technical relationship that transforms various input (resources) combinations into output (e.g. commodities) (Debertin, 2012). The general form of a production function can be given as:

$$y = f(x_1, x_2, \ldots . x_n) \tag{1}$$

Where y represents output and $x_1, x_2, \ldots . x_n$ are inputs such as land, seed and fertiliser. There are various types (or functional forms) of production functions, however, the two widely used forms in agriculture are CD and Translog production functions. According to Ben-Belhassen and Womack (2000) the CD production function yields more efficient parameter estimates, and its output elasticities may be equivalent to those of the Translog functional form. In light of the aforementioned, and the ease with which it can be estimated, we adopted a CD production function, as developed by Cobb and Douglas (1928) in estimating the production technology. The generalised form of the CD production function can be given as:

$$Y = A \prod_{i=1}^{n} x_i^{\beta_i} e, \quad x = (x_1, x_2, \ldots \ldots x_n) \tag{2}$$

Where β_i denotes vectors of unknown parameters that will be estimated, $x_1 \ldots \ldots x_n$ are inputs and e represents the error term. Using the variables in our model the generalised form of the CD production function can be given as:

$$Y = X_1^{\beta_1} X_2^{\beta_2} X_3^{\beta_3} X_4^{\beta_4} X_5^{\beta_5} X_6^{\beta_6} X_7^{\beta_7} \quad (3)$$

Where

Y is maize output

$\beta_0, \beta_1, \ldots \beta_7$ represent vectors of unknown parameters to be estimated

X_1 is the area of land allocated to maize

X_2 is the amount of seed used in production

X_3 is the amount of labour used in man-hours

X_4 is a dummy variable for fertiliser use

X_5 is a dummy variable for herbicide use and

X_6 is a dummy variable for top dresser

Conventionally inputs are included as continuous variables in the production function, which allows for the computation of marginal products. However, due to limited use of fertilizer, herbicide and top dresser amongst the sample farmers, these variables were entered into the production function as dummy variables. This is in line with suggestions made by Battese (1997). Attipoe et al. (2020), also used a dummy variable for fertilizer in estimating the production frontier for cocoa production in Ghana. Mazvimavi et al. (2012), have also followed a similar approach.

The generalized functional form of the CD production function, violated the normality assumption and was not linear in parameters. To cater for these issues and allow the model to be estimated using OLS, the CD production function was logged and linearized as presented below:

$$\ln(Y) = \ln(\beta_0) + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + \beta_2 \ln(X_2) + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + e \quad (4)$$

$\beta_0, \beta_1, \ldots \beta_7$ represent vectors of unknown parameters to be estimated and are elasticities. ln(Y), is the natural logarithms of output, whilst $\ln(X_1)$, $\ln(X_2)$ and $\ln(X_3)$ are natural logarithms, for land, seed and labour (man hours), respectively. Whereas, X_4, X_5, and X_6 are dummy variables for fertiliser, herbicide and top dresser, respectively. As indicated above these variables were included as dummies due to limited adoption by non-FSP adopters. Moreover, limited adoption would imply that in the logged model we would only focus on those select few non-FSP members that used these inputs. As such it was better to use dummy variables to focus on all sampled farmers. Battese (1997) illustrated that the use of dummy variables for inputs such as fertilizer and chemicals can be used to solve the problem of limited adoption of such inputs.

To estimate the plot level TE of maize farmers in the Eastern Cape we used a SPF. This model was adopted, over other widely used methods such as Corrected Least Squares (COLS) and Data Envelopment (DEA) methods, as it accounts for deviations from the frontier that are due to factors that are out of the farmer's control, errors in measurement and omitted variables in the functional form (Makombe et al., 2015). Put differently, the DEA and COLS assume that all divergences from the frontier are the result of inefficiencies. SPF models are also suitable in instances where farmers, such as those in the Eastern Cape, have poor record keeping. The general SPF can be specified as follows:

$$Y_i = f(X_i, \beta) + e_i \qquad (5)$$

According to this model the error term e_i is constituted of two components such that: $e_i = v_i - u_i$ (Aigner et al., 1977). Equation 5 can thus be re-written as:

$$Y_i = f(X_i, \beta) + v_i - u_i \qquad (6)$$

The error term v_i is the systematic disturbance/error, representing factors beyond the farmer's control (such as low or late rainfall), measurement errors and omitted variables. We assume that v_i is independently distributed and follows a normal distribution with zero mean and a variance = δ^2_v [$v_i \sim i.i.d.N\ (0, \delta^2_v)$].

The half normal error term (u_i) represents technical inefficiency or deviations from the frontier as a result of farm level factors that are within the farmer's control. The error term is assumed to be non-negative such that $u_i>0$. The error term is also assumed to be independently distributed, following a normal distribution with zero mean and a δ^2_u variance [$u_i \sim i.i.d.N\ (0, \delta^2_u)$]. The negative sign in equation (2), along with positive values of u_i, results in negative deviations from the frontier for each of the farm level observations (Makombe et al., 2015). The magnitude of u_i represents the underperformance/deviance of observed output from maximum possible output given the same technology and combination of inputs available to the farmer, as presented by the frontier output.

The TE of an individual farmer is then calculated as the ratio of observed output to frontier output, given the available technology and input mix.

$$TE_i = \frac{Y_i}{Y_i^*}$$

$$= \frac{f(X_i,\beta)+v_i - u_i}{f(X_i,\beta)+v_i}$$

Where Y_i is observed output and Y_i* is the frontier output (maximum possible output). Given that the model is in logarithmic form TE can be given as:

$$TE_i = \frac{f(X_i,\beta) + \exp(v_i - u_i)}{f(X_i,\beta) + \exp(v_i)}$$

$$= exp\ (-u_i) \qquad (7)$$

In this study, we assume a half normal distribution for u_i [$u_i \sim$ i.i.d.N + (0, $\delta^2 u$)]. TE can take a value between 0 and 1. When a farmer is 100% technically efficient, TE = 1 and u_i = 0 (exp (0) =1).

For purposes of this study we assume that the production function of small scale maize farmers is specified by a CD frontier production function given by:

$$\ln(Y) = \ln(\beta_0) + \beta_1\ln(X_1) + \beta_2\ln(X_2) + \beta_2\ln(X_2) + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + v_i - u_i \qquad (8)$$

Where ln(Y), ln(X_1), ln(X_2) and ln(X_3) are the natural logarithms of output, land, seed and labour (man hours), respectively. Whereas, X_4, X_5, and X_6 are dummy variables for fertiliser, herbicide and top dresser, respectively. βs are coefficients to be estimated, and v_i and u_i are the error terms as described above.

As illustrated above, farmers are required to meet various criteria, such as forming part of a local project, already being involved in farming, and being from a disadvantaged background, prior to participating in FSP. Adopting FSP is also voluntary, such that certain socio-economic characteristics of farmers also contribute to whether they adopt FSPs (Sikwela and Mushunje, 2013; Udo, 2014). Choice of whether a farmer joins FSP or not, can be referred to as self-selection into these programmes. In an attempt to get meaningful and non-bias results, we incorporated a technique to minimise the effects of self-selection bias.

The most commonly used methods in accounting for self-selection bias include, difference-in-difference (DID), instrumental variables (IV) models and PSM (Caliendo and Kopeing, 2008)). We use, the PSM model due to its simplicity (Wang, 2019) and the nature of the study. Moreover, the study uses only cross-sectional data for the 2017/18 maize production season (Wordofa and Sassi, 2017). In our case, the logic behind PSM was to find non-adopters (control) that have initial observable characteristics similar to those of FSP adopters (treatment), with the only difference being participation in FSPs, to be used as representation of the counter-factual (what would happen absent FSPs or farm level TE without FSPs). This allowed us to produce a non-bias estimate of the effects of FSPs on farm level TE, by accounting for self-selection bias arising from differences in farmer characteristics that existed prior to the programmes.

Matching requires two fundamental assumptions to be met, namely the Common Support Assumption and the Conditional Independence Assumption (CIA) (Kirchweger and Kantelhardt, 2012). Under the CIA it is assumed that for a given vector of observable covariates (X), the outcome (Y) of one individual is independent of treatment. Whereas the Common Support Assumption requires some non-adopters to have covariates that are similar to adopters (Harder, Stuart and Anthony, 2010; Kirchweger and Kantelhardt, 2012). When this assumption is met, each treated unit (an FSP adopter) can be matched with at least one corresponding control unit (non-adopter).

PSM is a non-experimental method for estimating the average impact of an intervention (Heckman and Navarro-Lozano, 2004). Where a propensity score is a conditional probability of receiving treatment, given observable characteristics (Bai, 2011; Littnerova et al., 2013), and can be given as.

$$P(X_i) = \Pr(T = 1|X_i)$$

Which represents the probability with which an individual (i) will chose treatment (T) given a set of covariates.

In estimating the PSM model we followed the steps outlined by Bai (2011). First, previous studies (Badal et al., 2006; Sikhwela and Mushunje, 2013; Camar et al., 2019; Udo, 2014; Bahta et al., 2018; Nxumalo and Oladele, 2013; Nhundu et al., 2015) were used to identify age, farming reason/intention, education, income, size of household, and gender as pre-treatment covariates (factors that are likely to determine participation in FSP). Using STATA 15, a probit model with maximum likelihood method was then used to estimate the propensity score of each farmer, where the dependent variable is 1 if a farmer adopts and becomes a member of at least one FSP and 0 otherwise. The probit model used is given as:

$$P(Adopt) = \beta_0 + \beta_1 age + \beta_2 educ + \beta_3 inten + \beta_4 income + \beta_5 hhsize + \beta_6 gender + \beta_8 FarmReason$$

The balancing property of the propensity scores was checked to ensure the treatment and control observations have the same distribution of propensity scores within the region of common support.

Matching was done using 3 matching algorithms to ensure robustness of the results. We first used Nearest Neighbour Matching (NNM), where a non-adopter is identified and paired with the closest eligible adopter (closest propensity score). Secondly, Kernel Matching (KM) was used. In KM, the treated/participants (FSP adopters in our case) are matched with a weighted average of all non-participants. This algorithm achieves lower variance than other forms of matching, as all non-adopters contribute to the weights, (Huber et al. 2017). Lastly, the study used stratification matching, which partitions the region of common support of the propensity score into intervals or strata and calculates each interval's impact by taking the mean difference in outcomes between treated and control observations (Baser, 2006).

The impact of FSPs was then evaluated by estimating the average treatment effect on the treated (ATT). Given that this study seeks to establish the effects of FSPs on farm level TE, ATT can be given as:

$$E(TE_i|\mathrm{I}=1) = E(TE_{i1}|\mathrm{I}=1) - E\,(TE_{i0}|\mathrm{I}=1) \quad (9)$$

Where TE_i is an unbiased estimate of TE effects of FSP, TE_{i1} is the TE of FSP adopters. Since TE of FSP adopters could not be measured pre and post participation in FSPs, TE_{i0} is the TE of non-adopters that represent the non-existent/absent counterfactual.

CHAPTER 4: RESULTS AND DISCUSSION

Table 2 shows *t*-test and chi-square comparisons of means by FSP adopters and non-adopters.

Table 2: Sample characteristics by treatment

Variable	Description	FSP adopters	Non-adopters	Chi^2/t-stat	P>|z|
Sample demographic characteristics					
Age of decision maker	Below 30 years	0	6.67	2.5043	0.114
	31-40 years	5.56	6.67	0.0474	0.828
	41-50 years	11.11	11.67	0.0068	0.934
	51-60 years	11.11	26.67	3.3011	0.069*
	61-65 years	19.44	21.67	0.0674	0.795
	Above 65 years	52.78	26.67	6.6218	0.010**
Household size	Number of people	7.65	6.57	-1.7402	0.0854*
Education	Years in school	9	9.35	0.4593	0.6473
Farming experience	0-5 years	11.43	13.33	0.1016	0.750
	6-10 years	11.43	26.67	3.3011	0.069*
	11-15 years	8.57	6.67	0.0925	0.761
	16-20 years	0	8.33	3.1648	0.075*
	Above 20 years	68.57	45	4.2416	0.039**
Farming characteristics					
Land	Area planted with maize (ha)	1.36	0.54	-5.0595	0.0000***
Seed	Volume (kg)	21.62	8.87	-6.3121	0.0000***
Herbicide	Used herbicide	63.89	10.00	30.9921	0.000***
Top dresser	Used top dresser	100	8.33	77.2683	0.000***
Pesticide	Used pesticide	86.11	76.67	1.2643	0.261
Fertiliser	Used fertiliser	100	51.67	24.9313	0.000***
Improved seed	Used improved seed variety	100	15	65.2800	0.000***
Labour	Man hours	115.86	69.62	-2.5013	0.0144**
Farming Reason	Produced maize for sale	77.78	23.33	27.1012	0.000***
Access to institutional services and social capital					
Access to extension services	Received services	100	0		
Project	Local farming project membership	100	0		

****1% significance level, **5% significance level, *10% significance level*

Table 2 shows that as compared to non-adopters, FSP adopters were, *inter alia*, older, had more farming experience, had larger households, better access to inputs, produced maize for selling, cultivated larger areas of land, had access to extension services, adopted improved seed varieties, and used more seeds. As a result of cultivating larger areas of land, the activities of FSP adopters were also more labour intensive than those of their counterparts. The results also show that FSP adopters are likely to form part of at least one local farming project.

Prior to estimating the SPF, we used three different tests to check the validity of the model specification viz. a skewness test on the residuals of the ordinary least squares (OLS) model, Schmidt and Lin skewness test, and generalised likelihood (LR) ratio test statistic, as suggested by Kumbhakar, Wang and Horncastle (2015). All three test provided results in favour of the SPF model specification.

Following the validation tests, we estimated a SPF using half-normal distribution. Table 3 presents the results.

Table 3: Stochastic Production Frontier estimates

Variables	Coefficient	Standard error	p-value
lnLabour	0.1742669	0.1066744	0.102
lnLand	0.1386481	0.1673883	0.407
Fertiliser (dummy)	0.4268103**	0.1874024	0.023
lnSeed	0.3643704*	0.197108	0.065
Herbicide (dummy)	0.2208715	0.1766938	0.211
TopDresser (dummy)	1.00499***	0.1918351	0.000
Constant	4.759836***	0.6724412	0.000
u-sigmas constant	-0.8943467	0.7459315	0.231
v-sigmas constant	-1.544576***	0.4800818	0.001
Observations			**85**

****1% significance level, **5% significance level, *10% significance level*

Table 3 shows that all the input variables had the correct and expected signs. Moreover, the results show that increases in the amount of seed used, will result in increases in maize output. Whereas the introduction of herbicide, fertiliser and top dresser also result in improvements in maize output.

However, contrary to findings by Kibirige and Obi (2015), Chirmo (2017), Attipoe et al. (2020) the results also show that labour, land area cultivated and herbicide were not statistically significant. However, the results are consistent with Gebrehiwot (2017), who also found land, labour and herbicide to be statistically insignificant in explaining changes in farm level output.

Rural areas, such as the sample area tend to be overpopulated suggesting abundance of labour. As such, the insignificant coefficient of labour is likely to be caused by overpopulation in the sample area, resulting in the marginal product of labour being marginal (near zero) (Gebrehiwot, 2017). On the other hand, some of the limitations faced by smallholder/subsistence farmers in South Africa and as such the sample area include, access to key production inputs such as fertiliser and seed (ACB, 2018). As such increases in land area cultivated are likely to have marginal effects on output, given limited access to other key inputs (fertiliser, seed etc.). This is likely to explain the statistically insignificant, near zero marginal product for land in table 3. However, the focus of this study is to evaluate the effects of FSPs on farm level TE which is discussed below.

TE scores were estimated from the SPF model. The TE scores of the sample farmers ranged from 17.8% to 86.3%. The results suggest that the least efficient farmer, with a TE score of 17.8%, is losing approximately 82.2% yield as a result of technical inefficiency.

On average the sample farmers had a TE score of 64.3%, suggesting that 35.7% potential yield was lost as a result of technical inefficiency. This implies that the sample farmers can significantly improve maize yields by improving production practices, with no new technologies being introduced.

Table 4: Technical efficiency scores

	FSP adopters		**Non-adopters**		**Pooled sample**	
Efficiency	**Frequency**	**Percent (%)**	**Frequency**	**Percent (%)**	**Frequency**	**Percent(%)**
<50	4	13.33	9	16.36	13	15.29
50-59	1	3.33	10	18.18	11	12.94
60-69	9	30.00	18	32.73	27	31.76
70-79	15	50.00	12	21.82	27	31.76

80+	1	3.33	6	10.91	7	8.24
Total	**30**	**100**	**55**	**100**	**85**	**100**
Mean	0.669		0.628		0.643	
Min	0.387		0.178		0.178	
Max	0.836		0.863		0.863	
Std Dev	0.119		0.136		0.131	

As shown in table 4 above more than 80% of the sample farmers were producing at efficiencies levels above 50%. The TE scores of FSP adopters ranged from 38.7% to 83.6%, with an average TE score of 66.9%. This suggests that FSP adopters are only producing approximately 67% of the yield achievable using the current input mix. Put differently, FSP adopters can potentially produce approximately 33% more yield by simply improving production practises. The most inefficient non-adopter had a TE score of 17.8%, whereas the most efficient amongst this type of farmers had a score of 86.3%. The mean TE score of non-adopters was 62.8%, which implies that these farmers can increase maize yields by 37.2% using the same input mix, by simply improving on the level of technical efficiency. There were also higher variations in TE scores amongst non-adopters than adopters of FSPs, depicted by a higher standard deviation. This was expected, as no homogeneous input use occurs amongst non-adopters.

Figure 2 below provides a comparison of the TE score distribution amongst FSP adopters and non-adopters. The skewness of both graphs to the left suggests that FSP adopters and non-adopters alike, were producing towards the frontier. However, there were notable differences between TE levels of FSP adopters and non-adopters. Evidently, more than 50% FSP adopters were producing maize at TE levels greater than 70%, and only 13.33% were producing at levels lower than 50%. Whereas, only a few, approximately 30% of non-adopters were producing maize at TE levels greater than 70%.

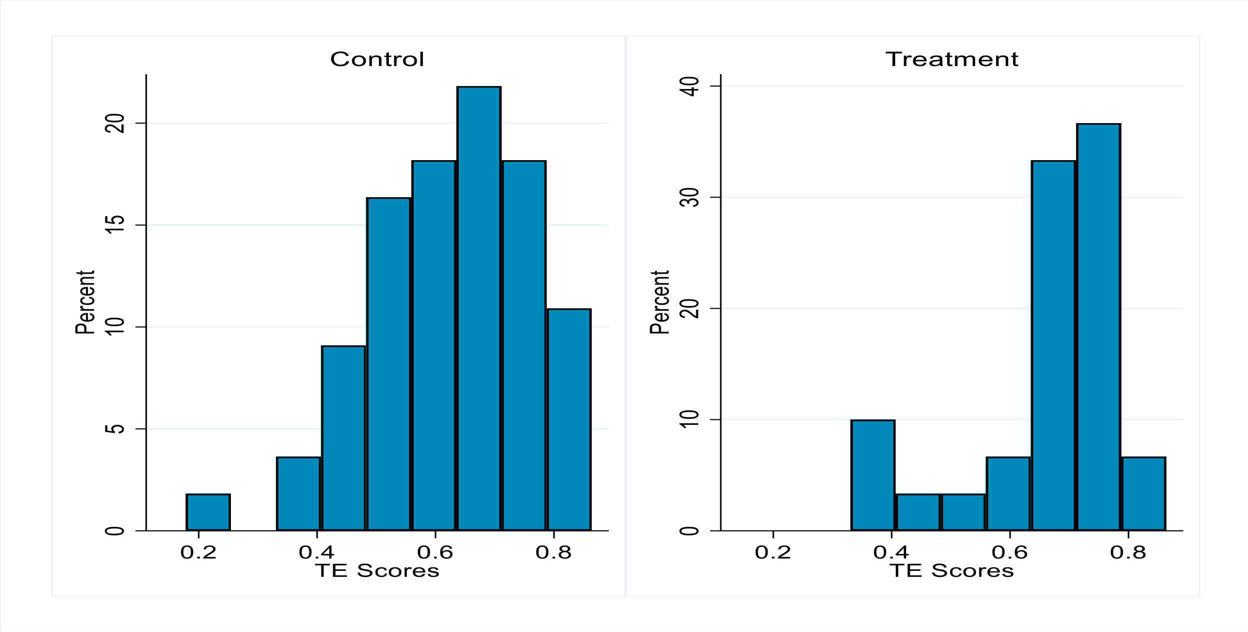

Figure 2: Adopters vs non-adopters TE scores distribution

To further validate the differences in TE levels amongst FSP adopters and non-adopters, shown in table 4 and figure 2, we ran an independent t-test to establish whether there are any statistically significant differences in the average TE scores of the two groups. The results of the t-test show that there was no statistically significant difference between the average TE scores of FSP adopters and non-adopters.

Table 5: Statistical comparison of TE scores

Group	**Observations**	**Mean TE score**	**Std. Error**
Non-adopters	55	0.628	0.018
Adopters	30	0.669	0.021
Diff = mean (Non-adopters) – mean (Adopters)			t = -1.3969
H_0: diff = 0			degrees of freedom = 83
H_a: diff < 0	H_a: diff! =0		H_a: diff > 0
Pr (T < t) = 0.0831	Pr (|T| > |t|) = 0.1662		Pr (T > t) = 0.9169

The t-test results in table 5 suggest that participating in FSPs has no role in explaining the TE variations between non-adopters and adopters of these programmes in the Eastern Cape. Moreover, according to the results investments in FSPs are not yielding the intended results of improving farm level efficiency, amongst others. The results are contrary to *a priori* expectations and previous findings that participation in FSPs results in higher TE (Kibirige and Obi, 2015; Chirmo, 2017).

Contradiction of empirical evidence by the results in table 5 could be the result of errors in data collection, or sample composition of FSP adopters and non-adopters. Thus far we have clearly illustrated that the data is unlikely to be erroneous. Impact evaluation/treatment effect studies require random selection into trial groups (Bai, 2010). However, a closer look at table 2, shows that the characteristics of FSP adopters and non-adopters are not homogeneous, and present various statistically significant differences. These differences coupled with the choice to join FSPs by farmers suggest that participation in FSPs is unlikely to have been random within our sample and that farmers tend to self-select into these programmes (Badal, Kumar, and Bisaria, 2006, Nhundu et al., 2015). As such absent pure randomisation, a simple comparison of the TE scores FSP adopters and non-adopters as conducted thus far, is likely to produce biased results and may be misleading to policy makers. Moreover, the existence of different pre-existing conditions/characteristics do not allow us to use non-FSP adopters as a counterfactual. They do not present a group of similar farmers that did not receive treatment (in our case adoption of FSP).

Various techniques exist for correcting for self-selection bias and as such allowing for the comparison of treatment and non-treatments. The PSM technique was used to account for self-selection bias. A similar approach, was used by Sikwela and Mushunje (2013); Teka and Lee (2019) for reducing bias in estimating the effects of FSPs.

One of the initial steps of PSM, includes the estimation of a probit regression to calculate the probability with which a farmer will participate in FSPs based on a number of pre-treatment independent variables. The predicted probability of participating in a programme produced by the model is referred to as a propensity score. The covariates used in this study where identified on the basis of literature. Moreover, literature shows that farmer participation in various programmes and policies can be affected by observable characteristics such as age, education, farm size, use of chemicals and off-farm income amongst others (Nhundu et al., 2015; and Badal et al., 2006).

Table 6: Maximum likelihood estimation of PSM probit regression

Variables	Coefficient	Standard error	p-value
Age	0.4997329***	0.1642463	0.002
Education	0.0268489	0.059206	0.650
House Hold Size	0.0482283	0.0651688	0.459

Farming Reason	1.976653 ***	0.5606391	0.000
Land Access	0.2441638	0.2763005	0.377
Income	-0.6922254 ***	0.2127493	0.001
Gender	-.6002386	0.4541808	0.186
Constant	-2.991755**	1.509127	0.047
Observations = 82; Pseudo R^2 = 0.4384; P-value = 0.0000			

****1% significance level, **5% significance level, *10% significance level*

Table 6 shows that the covariates that were most likely (statistically significant) to influence a farmer's decision to participate in FSPs were age, farming reason and income. Age was found to have a positive significant relation to the adoption of FSPs, suggesting that as farmers grow old they are more likely to join these programmes. Income was found to have a negative relation to the adoption of FSPs, at 1% significance. The probability of participating in FSPs diminishes as a farmer's overall household income increases.

The variable farming reason is a dummy variable (produce maize for income=1; otherwise=0). Similar to Sikwela and Mushunje (2013) the study found producing maize for the purposes of generating income increases the probability of participating in FSPs. Moreover, producing maize for generating income will increase the probability of participation, with 99% confidence.

Figure 3 below provides a visual/graphical examination of the overlap in the distribution of propensity score of FSP adopters and non-adopters. There was some level of overlap in the propensity score distribution of FSP adopters and non-adopters. The region of overlap was [0.0904134, 0.7607426]. This implies that selection into FSPs was indeed not random within the sample, and is likely to have been affected by the chosen covariates. The desirable outcome, in instances of randomization into FSPs would be a complete overlap (Harder et al., 2010). A complete overlap would imply that the sample farmers are homogeneous with respect to the chosen covariates. The overlap in figure 3, suggests that corrective techniques can be applied to the data to allow for comparison of the two groups of farmers (Harder et al., 2010).

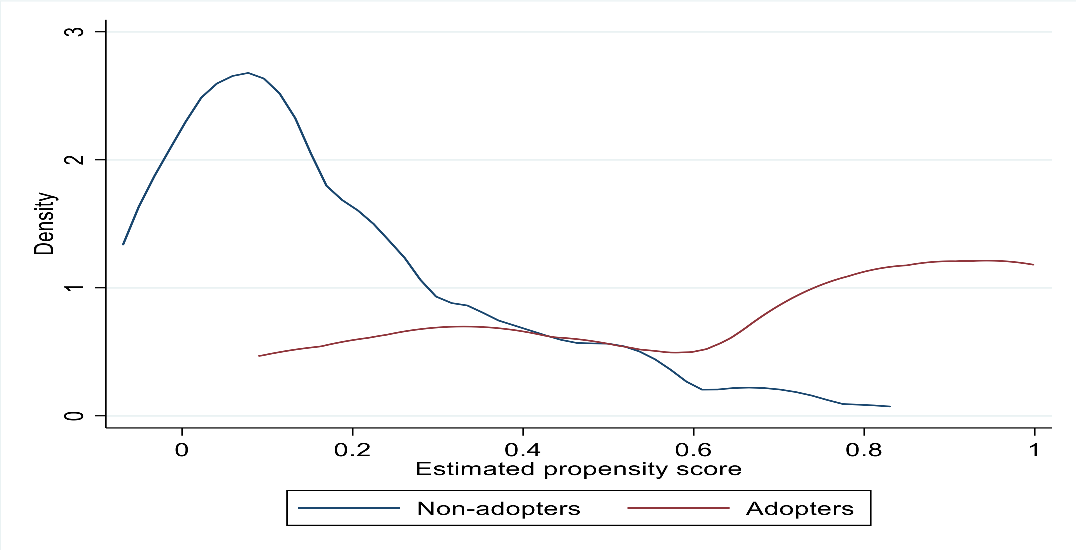

Figure 3: Kernel density of propensity scores

Nearest Neighbour Matching, Stratification and Kernerl Matching algorithms, were used to get the results presented in figure 3 as close as possible to the desired outcome (complete overlap) for randomisation. Moreover, as discussed in section 3.3 under the methodology, matching links adopters to non-adopters with similar characteristics in one way or the other. Table 7 reports the ATT. ATT measures the net effect of FSP on TE, after matching (Ndoro et al., 2014).

Table 7: Treatment effect results

Matching algorithm	**FSP**	**Non-FSP**	**ATT**	**Std Err**	**t**
Stratification	14	42	2.048***	0.279	7.332
Nearest Neighbour Matching (NNM)	28	9	1.787**	0.777	2.301
Kernel Matching (KM)	28	27	1.713***	0.497	3.433

****1% significance level, **5% significance level, *10% significance level*

The results from the matching algorithms were significant at 1% and 5%. This significance in the ATT shows that participation in FSPs can be used to explain variations in TE levels amongst smallholder maize producers in the Eastern Cape. The results also suggest that participating in FSPs will on average improve TE amongst smallholder famers in the Eastern Cape by 171%-205%. For example, the KM method matched 28 FSP adopters to 29 non-adopters and shows that adoption of FSPs can increase TE by up to 171%. Whereas stratification which matched 14 FSP to 42 non-FSP adopters shows that participating in FSPs can increase TE by up to 205%

Given that farmer selection into FSP is not random, the results presented in table 7 highlight the importance of accounting for self-selection in assessing the impact of FSPs on TE of farmers in the Eastern Cape. Moreover, after we used the PSM model to account for self-selection by creating a group of non-FSP adopters that have similar prior characteristics to FSP adopters we were able to make a comparison. The non-FSP adopters with similar characteristics to FSP adopters provided us with a plausible counterfactual. The improved results after correcting for self-selection suggest that a simple impact assessment is likely to have provided us with misleading results, that suggested that FSPs do not improve farm level TE.

Lastly, to establish the determinants of TE amongst smallholder maize farmers in the study area, the TE scores derived from the SPF model were regressed against farmer and farm level characteristics using OLS. The results from the SPF were used because the PSM technique used in accounting for self-selection bias only managed to produce the ATT without necessarily producing any TE scores. The results are presented in table 8 below.

Table 8: Determinants of TE

Variables	**Coefficient**	**Standard error**	**p-value**
Age	0.592096	1.293209	0.648
Education	0.4656991	0.4741678	0.329
House Hold Size	-0.4218904	0.4983988	0.400
Farming Reason	6.592521*	3.801766	0.087
Extension Access	12.21048*	7.304521	0.099
TopDresser	-12.81764 *	6.932882	0.068
Gender	-2.782698	3.048743	0.364
Constant	54.20191***	11.5712	0.000
Observations = 88; R^2 = 0.1101			

****1% significance level, **5% significance level, *10% significance level*

Farming reason, the use of top dresser and access to extension services were found to be significant in explaining the TE amongst small holder maize producers. Moreover, farming reason and extension services were found to have a positive or direct relation to TE. This suggests that farmers that have access to extension services are likely to be more technically efficient than those that do not. In addition, small holder farmers that produce maize for purposes of generating income are also likely to be more technically efficient than those that produce for own consumption. These findings are in line with studies such as Parikh et al. (1995), Guesmi and Serra (2015).

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

This study used a Cobb-Douglas SPF to analyse the TE of smallholder rain-fed maize producers that participate in FSPs in the Eastern Cape. The findings show that FSP adopters only achieve 67% of their potential maize output, losing 33% as a result of technical inefficiency. This suggests that these farmers can increase their maize output by simply improving their production processes. The findings also show that differences in socio-economic characteristics of farmers in the Eastern Cape results in self-selection into FSPs, thus rendering a simple comparison of adopters and non-adopters of these programmes misleading. This can be seen by the t-test on the mean TE scores which suggested that FSPs cannot be used to explain efficiency differences amongst FSP-adopters and non-adopters. Using the PSM approach the study corrected for self-selection bias. The results show that observable characteristics of farmers such as age, farming reason and income determine whether farmers will join FSPs. Matching algorithms, which were used to measure the ATT (net effect of FSPs) after accounting for self-selection bias show that FSP-adopters are 171%-205% more efficient than their counterparts.

The TE scores produced by the SPF were then regressed on a number of farmer and farm characteristics to establish the determinants of TE. The study found that extension services and farming reason improved TE amongst small holder farmers in Nyandeni. Whereas, the use of top dresser was found to reduce TE.

Prior to interpreting the meaning of the results it is important to note that as a result of poor response rate we used a smaller sample size than intended. In this regard, the study is likely to provide bias inferential results. Notwithstanding, the results of this study reveal that accounting for self-selection bias is likely to be of paramount importance in assessing the impacts of FSPs and other policy interventions on smallholder farmers.

The findings made in this study, following the correction for self-selection, suggest that FSPs continue to make a positive contribution towards the sustainability of smallholder rain-fed maize producers in the Eastern Cape. It is thus recommended that policy makers continue to make budgets available for continued investment in FSPs. Since PSM modelling also evaluates the determinants of participation, this study also shows that the intended use of maize produced is important in the decision of whether to join FSPs. Moreover, smallholder farmers who produce maize for selling are more likely to join these programmes. To this end, it is recommended that policy makers and extension officers continue to promote maize production as a form of business and as such a source of income. This can be done by offering farm business management training to potential FSP-adopters, as well as assisting them plan these enterprises. Assistance in finding markets or buyers can also assist in making these programmes more attractive. The study also shows that older farmers are more likely to join FSPs. This is likely to be linked to the attitude towards farming, being viewed as non-income generating by youth. As such, promoting farming as a business and source of income is likely to also draw younger participants.

The determinants of TE suggest that government should continue to invest in the provision of extension services to maize producers in the area. Extension services can also be extended to farmers that are not part of FSPs to improve their TE levels. In addition, as illustrated above investment in promoting farming as a source of income may also be required. Lastly, the negative relation between the use of top dresser and TE suggests that there is a need to invest in training farmers in technical skills relating to the use of inputs and chemicals, which in turn will enhance their production processes. The results also suggest that continuous training of extension officers, who are the primary source of information for farmers, on new products and their use is also important.

As indicated above one of the key limitations of this study was the limited sample size, as such it would be beneficial to policy makers to see what the results would be with a larger sample size. To further address the knowledge gap on the benefits of FSPs, we also suggest conducting TE studies across municipalities in the Eastern Cape or provinces of South Africa to provide a broader picture of how FSPs affect TE of smallholder farmers. This will provide further guidance as to whether investment in these programmes is worth it.

One of the key objectives of FSPs is wean farmers of after 5 years. However, these programmes have failed to meet this objective. In this regard, the use of time series data to analyse the effects of FSPs on farm level TE and farmer welfare would greatly assist policy makers in establishing the weaknesses, strengths and opportunities for these programmes. This is likely to be achievable as government has embarked on a process of collecting plot level data.

Lastly, this study uses a two-stage approach to estimating TE and its determinants. Given the unresolved debate between two-stage and single-stage approaches, the use of a single-stage approach would be beneficial to both literature and policy makers.

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APPENDICES

Appendix A: Multicollinearity test for PSM variables

Variable	**VIF score**
Experience	2.66
Age	2.62
Land Accessed	1.99
Farming Reason	1.73
Income	1.64
Education	1.51
Gender	1.32
Household Size	1.32