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Influence of agricultural extension services on technical efficiency of maize farmers in Malawi

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Abstract

Recognising potential selection bias due to non-randomness of the data, this study used propensity score matching on data from a nationally representative fifth Integrated Household Survey (IHS5) to investigate the effect of agriculture extension services on the technical efficiency of maize farmers in Malawi. Technical efficiency levels were estimated using the stochastic frontier model. The results show that most farmers are technically efficient, with an average technical efficiency of 63%. This indicates that there is still a possibility to increase maize output by 37% using the same level of inputs. The results of the propensity score matching reveal that having access to agricultural extension services significantly increases maize farmers' technical efficiency, by about 4%. This evidence presents an opportunity not only for farmers, but also for the relevant policymakers, to realise the potential of using agricultural extension services to enhance the production capacity of maize farmers.

Key words: agricultural extension services; technical efficiency; maize; propensity score matching; Malawi

1. Introduction

Agricultural transformation has recently been cited as being central to the development of Malawi's agriculture, rural communities, and the national economy. The current key strategic development plan of the Malawi Government – the Malawi 2063 First 10-Year Implementation Plan (MIP-1) – recognises that the transformation of the agriculture sector is central to transforming Malawi into a middle-income economy, the key aspiration the of MW2063 Vision. Increased agricultural production and productivity are crucial catalysts of this transformation process. The transformation process, however, could be hindered by several factors, such as limited access to agricultural extension services, which influence the adoption and use of improved varieties, and poor and limited access to market and inputs. These factors are identified as impediments to improving productivity, which plays a strategic role in transforming the country's agriculture sector. It is recognised in the National Agricultural Policy (NAP) of 2016 that poor agricultural extension services are a major constraint. Consequently, an improvement should present significant potential to increasing productivity and, ultimately, contributing to agricultural transformation in Malawi.

Over the past five years, an estimated average of 1.6 million hectares, 0.4 million hectares and 0.2 million hectares were devoted to the production of maize, groundnut and soybean respectively, with a corresponding estimated yield of 1.9 mt/ha, 0.9 mt/ha, and 1 mt/ha. Despite the government embarking on several initiatives, such as the affordable input programme (AIP), to increase the production of these crops, the yields have been lower than the average estimated potential yields of 7 mt/ha, 2.5 mt/ha and 4 mt/ha for maize, groundnut and soybean respectively. This gap shows that there is room for increased production and productivity.

This yield gap can be attributed to some observable factors that affect farmers' technical efficiency, such as access to agricultural extension services. The efficiency of production as a measure of the ability of a production unit to produce maximum output using available resources in the best possible way given certain technological constraints (Kumbhakar *et al*. 2015) could generally be low for these crops. In this case, there is a need to estimate the level of technical efficiency of the farmers and to analyse the associated determinants. Specifically, this paper focuses on the role that agricultural extension services play in improving technical efficiency in maize production.

The reason for the specific focus on maize farmers in this paper is that maize is a major grain and staple food contributing to food security in Malawi. It is grown by over 90% of farming households in the country. Being a key crop in the nation's food security, the government aims specifically and strategically to increase maize production through input subsidies, promoting household food security and enhancing rural incomes (Ragasa *et al*. 2016). However, input subsidy programmes have received negative reviews in Malawi (Chadza & Duchoslav 2022; De Weerdt & Duchoslav 2022) based on their design,[1] high costs and inconsistent impact.

There have been calls from development partners and research institutions to either graduate from input subsidy programmes, or to redesign the programmes so that they target the relevant productive farmers to achieve both increased production and higher productivity levels. As shown in Table 1, with the subsidy programme accounted for, the national maize yield for the past five years is far below the potential yields. This shows that there is a huge room for increasing maize production and yields.

Table 1: National production and yields of maize in Malawi, the annual average from 2013/2014 to 2019/2020

	Maize	*Local maize*	*Improved maize*
Production, t/maize-farming household	0.97	*0.01*	*0.89*
Yields, t/ha	1.9	*0.7*	*2.2*
Potential yields, t/ha	7.0	*3.0*	*7.0*

Source: Production and actual yields based on analysis of annual data from the Agricultural Production Estimates System, Ministry of Agriculture. Potential yields from the Government of Malawi (2012). 'Improved maize' includes both open-pollinated varieties (OPVs) and hybrids. The number of maize-farming households was estimated from the fifth Integrated Household Survey (IHS5) data.

Input subsidies in Malawi are expected to be in use in the coming years, as the government has indicated resistance to graduating from these programmes. Therefore, to enhance the achievement of the objectives of the input subsidy programme, productivity must be improved by ensuring that farmers produce more without increasing production inputs. That can be achieved if technical efficiency levels are increased. As alluded to, the study therefore focuses on maize, the food security staple crop, in analysing the effect of agricultural extension services on technical efficiency.

[1] Least productive farmers, who cannot make profitable use of subsidised inputs, are eligible for and benefit from the programme, but could instead be assisted by other social safety net programmes such as cash transfers.

Estimated efficiency levels can be used to rank and identify under-performing farmers, as well as those at, or close to, the efficiency frontier (Kumbhakar *et al*. 2015). This information is useful in designing agricultural public policy or subsidy programmes that may aim, for example, at improving the overall efficiency levels of smallholder farmers. One example is establishing what type of farmers are best at producing maize, which would enable government to target funding appropriately. Furthermore, an investigation into the impact of agricultural extension services on technical efficiency should reveal how agricultural extension services can make the farmers attain certain levels of production, and eventually identify processes and extension practices that should be spread or encouraged across less efficient, but otherwise similar, production units.

2. Current literature on agricultural extension services

Agricultural extension services build the capacity of farmers and link them to information, technologies, improved practices, land and finance more effectively. As such, they provide a way of providing relevant management and production skills to farmers engaging in agricultural enterprises. Extension services therefore have become the gold standard for agricultural development programmes to spur farm productivity and enhance farmers' livelihoods (Lampach *et al*. 2018).

However, research on the role of agricultural extension services in farm production presents mixed results. Some research evidence has shown that technical efficiency is significantly positively related to agricultural extension services (Lampach *et al*. 2018; Ngango & Kim 2019). This evidence presents an opportunity not only for farmers, but also for the relevant policymakers, to realise the potential of using agricultural extension services to enhance the production capacity of maize farmers.

Other studies, however, have found that agricultural extension services have no effect on technical efficiency (Kelemu & Negatu 2016; Belete 2020; Olagunju *et al*. 2021). More specifically, while Ragasa *et al*. (2016) found no relationship between agricultural extension services and farm productivity in the Malawian context, a recent study by Cassim and Pemba (2021) found that access to agricultural extension services leads to higher maize output in the country. Ragasa *et al*. (2016) used fixed dummies together with propensity score matching, while Cassim and Pemba (2021) used fixed effects. This slight difference in the estimation techniques to deal with selection bias might explain the difference in their results. Worth noting is that these studies did not focus solely on the effect of agricultural extension services on the technical efficiency of maize farmers in Malawi. For example, Ragasa *et al*. (2016) focused on the interplay between the fertiliser subsidy and access to extension services, and their effect on farm productivity and food security in Malawi, while Cassim and Pemba (2021) examined the interactive effects of access to agricultural extension services and the Farm Input Subsidy Program (FISP) on maize production and its uncertainty and technical efficiency in the country.

This study adds to that literature by focusing on the influence of agricultural extension services on the technical efficiency of maize production using propensity score matching and fixed effects to control for selection bias.

A number of efforts have been made to enhance access to agricultural extension services in Malawi The potential of agricultural extension services in agricultural production, productivity and transformation has been recognised in the country's two agricultural policy and investment guiding documents: The National Agriculture Policy (NAP) and the National Agricultural Investment Plan (NAIP). In the NAP (Government of Malawi 2016), it is stated that "a key constraint for many farmers is access to information to guide their production decision. Improved agricultural extension services from both public and non-state providers that provide farmers with the information that they need to address their challenges and to exploit opportunities with which they are presented are critically important to enable Malawi's farmers to significantly raise their productivity levels".

The National Agricultural Extension Policy ([NAEP] Government of Malawi 2000) was developed in 2000 to promote the provision of decentralised, demand-driven services and encourages the participation of many service providers in agricultural extension to ensure that farmers demand and have access to high-quality extension services. This approach has increased the number of non-state actors involved in the provision of advisory services, resulting in the development of a pluralistic agricultural extension system (Masangano & Mthinda 2012).

However, the government's ability to increase access to agricultural extension services through budgetary allocation has not been promising. The trend in investment in agricultural extension has been low and mixed. For example, the percentage of agriculture sector spending going to extension was 2.0%, 19.0%, 3.1% and 1.6% in the years 1991/1992, 2000/2001, 2010/2011 and 2012/2013 respectively (Ragasa & Niu 2017). This shows that there is a lot more that government and stakeholders can and need to do.

3. Conceptual and analytical framework

Productivity at the individual, firm or industry level, defined as the ratio of output produced by a production unit to the inputs that the production unit uses, thereby yielding a relative measure of performance applied to factors of production (Fried *et al*. 1993), may depend on 1) differences in production technology, 2) differences in the efficiency of the production process, or 3) differences in the environment in which production occurs.

However, even when technology and the production environment are 'essentially the same', individuals may exhibit different productivity levels due to differences in their technical efficiency (Korres 2007). For this reason, it is important to have a way of analysing the extent to which producers fail to optimise the departure from full technical efficiency (Kokkinou 2010). One of the main analytical approaches to efficiency measurement is the analysis of production frontiers, a tool that has expanded greatly in the last decades. Parametric and non-parametric methods have been developed to measure efficiency. The commonly used measures from the theoretical perspective are data envelopment analysis (DEA) and the stochastic frontier analysis (SFA). The stochastic frontier approach uses econometric methods of estimation, and the data envelopment analysis uses mathematical programming methods (Coelli *et al*. 2005).

The stochastic frontier model was suggested independently by Agner *et al*. (1977) and Meeusen and Van den Broeck (1977) and has been used with cross-sectional data to measure efficiency. This study uses the stochastic frontier production model to estimate the efficiency levels of maize farmers in Malawi.

3.1 The stochastic frontier production model (SFM)

Under the stochastic frontier model, technical efficiency can be modelled as:

$$y = f(x;\beta)e^{\varepsilon_i} \quad and \quad \varepsilon = v_i - \mu_i, \tag{1}$$

where y is the maximum potential output on the frontier, x is the vector of the levels of inputs used, β are the unknown parameters and ε_i is the stochastic composed error. The two components of the composed error term are assumed to be independently and identically distributed. Component v is a symmetric normally distributed error term capturing output variation due to factors beyond the control of the farmer, and μ_i is a one-sided error term capturing the inefficiency of the decision-making unit.

Algebraically, technical efficiency is measured as:

$$TE = \frac{\exp(x_i\beta + v_i - \mu_i)}{\exp(x_i\beta + v_i)} = \exp(-\mu_i) \quad (2)$$

If $\mu_i = 0$, the farm is assumed to be efficient, implying that the actual output is equal to the possible output. The farmer will be producing at the level of the production frontier, and hence be technically efficient.

3.2 Methodological and estimation considerations

In general, the empirical literature on agricultural extension services and their effect on technical efficiency distinguishes between two methodological approaches in which agricultural extension services are featured in the analysis of technical efficiency.

In the first approach, agricultural extension services are included as a separate input factor in the production function (Huffman 1977; Jamison & Moock 1984; Owens *et al*. 2003), thereby assuming that producers are producing on the same production frontier. In this approach, the effect of extension services on farm performance is evaluated through its marginal product and, in a sense, its direct effect on output is captured. The second approach relaxes the full efficiency assumption, and agricultural extension services are used as a factor explaining the differences in the technical efficiency levels among groups of farmers, rather than as an input in the production function (Bravo-Ureta & Everson 1994; Seyoum *et al*. 1998; Young & Deng 1999). Thus, agricultural extension services are included along with other socio-economic and demographic variables as a factor influencing technical efficiency in farm production.

The effect of agricultural extension services on technical efficiency should ideally be evaluated using a natural experiment. One way of doing this is to randomly assign a group of farmers to an extension treatment group, and a counterfactual or control group without agricultural extension treatment. However, whenever such an experiment is not possible, for reasons including lack of baseline data for those who have been exposed to the extension treatment, quasi-experimental options are used to estimate the difference in outcomes between those treated and not treated. Some of the available options are propensity score matching (PSM), regression discontinuity design (RDD) and the instrumental variable (IV) approach.

These quasi-experimental options reduce the selection bias that may be present in non-experimental data. Selection bias exists when observations have not been assigned randomly to a particular intervention, and therefore observations that are eligible to participate become systematically different from those that are not eligible. The farmers from the integrated household survey used in this study who had extension contact were not exposed randomly to the extension services. There was no natural experiment or randomisation. Thus, in this study, the closest thing to randomisation has been a mimic of the randomisation itself, using PSM.

Based on the strength that PSM neither requires baseline data nor the existence of an instrumental variable, this study used this method to develop a counterfactual or control group that is as similar to the treatment group (those who had any agricultural extension contact) as possible in terms of observed characteristics. The idea is to find, from a large group of non-participants, households that are observationally similar to participants in terms of characteristics not affected by the intervention

(Shahidur *et al*. 2010). Each participant is matched with an observationally similar non-participant, and then the average difference in outcomes across the two groups is compared to get the programme treatment effect.

3.3 Description of variables

Three categories of variables are used in the analysis of technical efficiency. The first one is the output variable of the production function. In this paper, maize harvest measured in kilograms (kg) per hectare has been used as the output variable in the Cobb-Douglas production function.

Another set of variables contains those that enter as inputs in the production function of maize. Labour (measured in labour hours), land (measured in hectares), capital (proxied by farm implements), maize seed (measured in kg per hectare), and fertiliser applied in kg per hectare were used as inputs in the maize production function in this paper.

The final element is the set of independent variables that are hypothesised to affect technical efficiency in maize production. This study aimed to investigate the effect of agricultural extension services on technical efficiency; hence, the agricultural extension service is the key independent variable of interest in the technical efficiency model. Following arguments by Ragasa *et al*. (2016) concerning measurement challenges of extension services, including attribution, difficulty in determining the incremental contribution of additional advice, and difficulty in measuring the contribution and effect of extension services where services and inputs are usually bundled into a package or programme, this paper constructs the agricultural extension variable as a binary, taking a value of 1 if the farmer had received an agricultural extension visit in the last 12 months and 0 if the farmer did not receive an agricultural extension visit in the last 12 months.

Other independent variables included are location (if a farmer is from a rural or urban area), household size, age of household, which can be taken as a proxy for farming experience, gender of household head, years of schooling of the household head, ownership of livestock, access to credit, access to input subsidy coupons, maize seed planted per hectare, total land owned by the farmer, as well as six agro-ecological zone dummies. These are: lower shire valley development domain; lakeshore with good market access and low population domain; lakeshore with poor market access and low population domain; mid-altitude plateau with poor market access and low population density; mid-altitude plateau with good market access and low population; mid-altitude plateau with good market access; and high population.

3.4 Data

Typical sources of data for this type of study would be farmer surveys. However, integrated household surveys contain rich data on various topics, including agricultural production. For less developed countries, integrated household surveys have become a standardised progress-monitoring instrument. Malawi’s National Statistical Office (NSO) conducts national household surveys every five years, mainly to provide benchmark poverty, vulnerability and socio-economic indicators to foster evidence-based policy formulation and monitor the progress in meeting various development goals. The present study uses data from the Fifth Integrated Household Survey (IHS5), which used a stratified two-stage sample design, in which primary sampling units (PSU) sampled in the first stage were enumeration areas (EAs), and households from each EA were sampled in the second stage. IHS5 covered 779 EAs, each with an average of about 235 households. A total of 11 434 households were sampled. The sample was reduced to maize-farming households and balanced on variables of interest. The final sample on which estimations was carried out comprised 1 781 households.

4. Results

This section provides a description and discussion of the results obtained from the stochastic frontier model and propensity score matching. The analysis was done in Stata and the results are presented using tables, figures and graphs.

4.1 Descriptive statistical analysis

Table 2 presents all the variables that were used in all the analyses in this study. They include those variables that feature as inputs and as outputs in the production function model, and those that were used as independent variables in the efficiency model. Their descriptive statistics, which include mean and standard errors, have been provided in the same table.

Table 2: Descriptive statistics of variables used in the study

Variable	Mean	Standard error
Maize production, t/ha	1.6	0.06
Maize seed per ha	40.4	1.2
Maize fertiliser per ha	436.9	73.3
Land allocated to maize	0.5	0.01
Maize labour hours	252.8	5.3
Capital (value of farm implements, US dollars)	478.0	49.0
Loan value, US dollars	49.9	5.5
Obtained coupon (0/1)	0.13	0.01
Livestock owned (tropical livestock units)	0.6	0.03
Extension contact (0/1)	0.48	0.01
Household size (absolute number of people)	4.7	0.04
Lower shire valley development domain, 0/1	0.03	0.003
Lakeshore, good market access, low population domain, 0/1	0.06	0.005
Lakeshore, poor market access, low population domain, 0/1	0.17	0.009
Mid-altitude plateau with poor market access, low population density, 0/1 [base]	0.28	0.013
Mid-altitude plateau, good market access, low population, 0/1	0.14	0.010
Mid-altitude plateau, good market access, high population, 0/1	0.32	0.012

Source: Analysis of IHS5. Observations: 4 211 maize-farming households.
Note: As of 12 June 2022, 1 US dollar was equivalent to 1 021.59 Malawi kwacha (MWK), the local currency; tropical livestock unit = sum of livestock owned by household, assigning a value of 0.8 for an ox or bull, 0.7 for any other adult head of cattle, 0.3 per calf, 0.6 per donkey, 0.2 per pig, 0.1 per goat or sheep, and 0.01 per bird of any poultry type, rabbit or guinea pig.

Worth mentioning are the maize-related variables. Maize yield per hectare was estimated at around 1 611 kilograms per household, which was cultivated on an average of half a hectare per household in the sample. About 40 kilograms of maize seed were planted per hectare per household. On average, 437 kilograms of fertiliser were applied to maize plots per hectare. The main variable of interest in this study was access to agricultural extension services. It was estimated that 48% of maize farmers had maize production-related agricultural extension service visits. This is somehow worrisome, as fewer than half of maize farmers had access to extension services.

4.2 Results of empirical analysis

In this paper, the stochastic frontier function was estimated using maximum likelihood estimation. However, tests were undertaken to test the validity of the stochastic frontier specification before undertaking the maximum likelihood estimation. These tests included the skewness test on OLS residuals and the likelihood ratio test of inefficiency.

4.2.1 Skewness test on OLS residuals

This test was proposed by Schmidt and Lin (1984) as a pre-test to check the validity of the model's stochastic frontier specification. The test proposes that, for a production-type stochastic frontier model, the residuals from the corresponding OLS estimation should be skewed negatively (Kumbhakar *et al*. 2015). The significant skewness statistic of -1.01 in Table 3 implies negative skewness of the residuals, which is consistent with the stochastic frontier specification. Figure 1 plots a histogram of OLS residuals. Evidence of negative skewness is shown visually. The skewness statistic and its significance were also computed to cement the evidence.

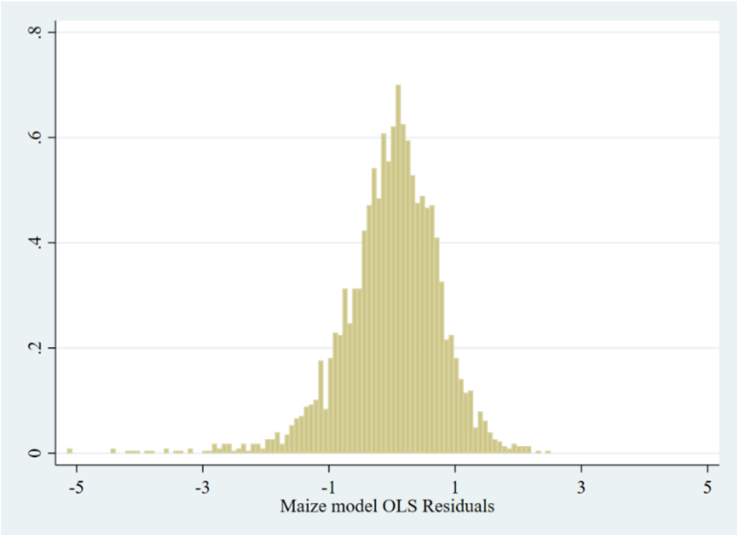

Figure 1: Histogram of OLS residuals

Table 3: Skewness statistic

	Observations	Statistic	P-value
Skewness	2 966	-1.01***	0.000

The asterisks indicate statistical significance: *** = p < 0.01

4.2.2 Likelihood ratio test of inefficiency

Although the skewness test is easy to perform, as it requires only the OLS estimation of the model, it does not use the information from the distribution functions of the random error (Kumbhakar *et al*. 2015). The likelihood ratio test of inefficiency checks the error specification of the stochastic frontier model. The stochastic frontier model with technical inefficiency is supposed to have a one-sided error specification. The absence of a one-sided error specification reduces the stochastic frontier model to the standard OLS model. The model's test statistic was 216.8. With one degree of freedom, this result indicates an outright rejection of no technical inefficiency. Hence, the stochastic frontier model was appropriate.

4.2.3 Estimation results

This section presents the results of the stochastic frontier model and those of the propensity score-matching model. The stochastic frontier model estimates the factors that affect maize yield, expressed as a natural log of maize production in kilograms per hectare. These factors include land, maize seed, fertiliser, labour and capital, expressed in logarithms as well. The propensity score-matching model estimates the effect of agricultural extension services on the technical efficiency of maize production amongst maize farmers.

4.2.3.1 Estimation results of the stochastic frontier model

Table 4 presents the main estimation results from the stochastic frontier model. These results reveal inputs with positive and negative yield effects. In this study, labour, land, maize seed, fertiliser and capital were hypothesised to enhance yield. These inputs are integral to the maize-production process. For example, fertiliser provides nutrients which are essential for maize growth. Its low applicability results in low production and declining soil fertility (Meyo & Egoh 2020).

The results show that, on average, and with all other things being constant, a 1% increase in maize seed planted per hectare increased maize output by 0.1%, while a 1% increase in maize fertiliser applied per hectare increased maize output by 0.4%, and a 1% increase in the capital of a maize farmer increased maize output by 0.1%. These results are significant at the 1% level of significance. This implies that maize seed, maize fertiliser and capita. have positive maize yield effects.

Table 4: Estimation results of the stochastic frontier model

LMPH (Natural logarithm of maize yield per hectare)	**Coefficient**	**Std. error**	**P-value**
Stochastic frontier			
Log of labour hours	0.0446121	0.0294948	0.130
Log of land allocated to maize	-0.294747***	0.034600	0.000
Log of maize seed per ha	0.129201***	0.0242283	0.000
Log of maize fertiliser per ha	0.401739***	0.0228368	0.000
Log of capital	0.062098**	0.01993	0.000
Constant	4.099981***	0.20835	0.000
Mu (technical efficiency)			
Extension contact (0/1)	-2.31533**	1.07255	0.031
Location (1 = rural)	3.161713	2.568557	0.218
Household size	0.094919	0.203778	0.641
Gender of household head (1 = female)	-1.83113	1.210131	0.13
Age of household head	0.011786	0.029187	0.686
Education years of household head	-0.55291**	0.198205	0.005
Livestock owned (tropical livestock units)	-0.01386	0.337626	0.967
Received credit (0/1)	-1.36076	1.00824	0.177
Obtained coupon (0/1)	0.313121	1.011858	0.757
Total cropped area	-0.80226	0.528881	0.129
Maize seed per ha	-0.06851**	0.028416	0.016
Lower shire valley development domain, 0/1	4.128736	4.34727	0.342
Lakeshore, good market access, low population domain, 0/1	4.423809**	2.001375	0.027
Lakeshore, poor market access, low population domain, 0/1	0.841443	1.414579	0.552
Mid-altitude plateau, good market access, low population, 0/1	0.227877	1.524562	0.881
Mid-altitude plateau, good market access, high population, 0/1	4.434482**	1.69609	0.009
Constant	-9.47589**	4.811461	0.049
Sigma_u	2.708776***	0.402665	0.000
Sigma_v	0.521047***	0.01682	0.000
Lambda	5.198718***	0.402713	0.000

Source: Author's weighted analysis of IHS5 (2019/2020). Note: Observations of survey sample households that engage in maize production: 4 211. Asterisks indicate statistical significance: ** = $p < 0.05$, *** = $p < 0.01$; tropical livestock unit = sum of livestock owned by household, assigning a value of 0.8 for an ox or bull, 0.7 for any other adult head of cattle, 0.3 per calf, 0.6 per donkey, 0.2 per pig, 0.1 per goat or sheep, and 0.01 per bird of any poultry type, rabbit or guinea pig.

An unexpected result was found in terms of land allocated to maize. The coefficient of land allocated to maize production was negative and significant (-0.295), indicating an inverse relationship between land size and maize production. This implies that maize yield declined as land allocated to maize production increased. The declining maize yields due to an increase in the amount of land allocated to maize may be due to factors such as households failing to do their weeding in time (Urassa 2015). According to Bisanda *et al*. (1998), late weeding can also lead to seriously low maize yields.

The results further show no evidence for the effect of labour on maize production. The coefficient of labour hours is not significant at all of the levels of significance. Nonetheless, labour cost represents an integral part of production costs and affect production depending on its variability. Meyo and Egoh (2020) argue that, in many instances, a higher increase in labour cost results in the inability of producers to cover the expenses required for functioning. As such, producers opt for alternatives such as diversifying production to divert/spread the risk, replacing several unskilled workers with few skilled ones, and adopting technology.

From the inefficiency model, the result of interest is the coefficient of extension contact. A first step to controlling for possible selection bias, the inefficiency model included fixed dummies for agro-ecological zone. The results show that inefficiency in maize production decreases by 2.3% for maize farmers who had extension contact compared to those who did not have any agricultural extension contact, all things being equal. The result is significant at the 5% level of significance. This implies that contact with agricultural extension services is positively related to technical efficiency in maize production. To fully investigate the effect of agricultural extension services, the study estimated technical efficiency levels and employed propensity score matching to further control for selection bias. The results are discussed below.

4.2.3.2 Propensity score matching (PSM)

The focus of this paper is to evaluate the impact of agricultural extension contact on the technical efficiency of maize production amongst maize farmers. The analysis is done on nationally representative household survey data considering only those maize farming households and those that did not have missing values on the agricultural extension variable. Given that the data is non-experimentally designed, propensity score matching was used to evaluate the impact.

A preliminary result of the effect of agricultural extension service is obtained from the technical inefficiency model in Table 4. It was found that being exposed to any agricultural extension contact in maize farming reduces technical inefficiency by 2.3%. However, a conclusion on the effect of extension contact cannot be drawn from this result without further considering the selection bias arising from the nature of the sample design. PSM reduces such bias, and the results from the PSM estimation would be appropriate to draw the conclusion on the effect.

Matching was done on the following observable characteristic variables: location, household size, gender of household head, age of household head, years of education of household head, livestock owned, receiving credit, obtaining a coupon, total cropped area, and maize seed per hectare. Propensity scores are estimated as the first step in PSM.

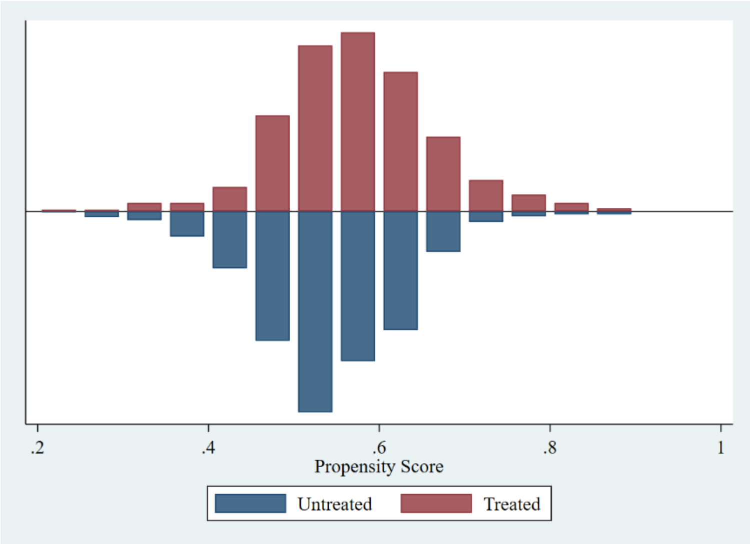

Figure 2: Density of propensity scores and common support

Table 5 shows that there is a high level of common support, with only one observation off support, and its propensity score did not align with the propensity score of corresponding observations in the opposite treatment (untreated) category. However, it is important to evaluate the quality of the match. Figure 2 graphically evaluates the quality of the match. The observations in blue are the untreated (those who were not exposed to any agricultural extension contact) and observations in red are for those maize farmers who were exposed to agricultural extension services. It can be seen from the figure that there are overlaps in the scores between the treated and untreated groups. This indeed provides evidence of common support, just as in Table 5.

Table 5: On and off common support[2]

	Off support	On support	Total
Untreated	0	785	785
Treated	1	996	997
Total	1	1 781	1 782

After evaluating the quality of the match, Table 6 presents the coefficient of the average treatment effect on the treated (ATT).

Table 6: Average treatment effect on maize farmers with any agricultural extension contact

	Coefficient	Bootstrapped standard error	P-value
ATT	0.0397**	0.014	0.004

Source: Author's analysis of IHS5 (2019/2020)

Note: Observations: 1 781; Bootstrapped standard error obtained after 1 000 replications; Asterisks indicate statistical significance: ** = $p < 0.05$

These results indicate that being exposed to agricultural extension services in maize farming increases technical efficiency by 3.97%, holding all other things equal. This implies that this estimate is up by 1.17 percentage points from the 'naïve' estimate of 2.3% in Table 3. The correct standard errors were obtained by bootstrapping with 1 000 replications. This result implies that, if maize farmers have access to agricultural extension services, they will increase their maize output by as much as 4% without increasing input consumption.

[2] Common "support" is the overlap in the range of propensity scores across the treatment group (in this case, those who had extension contact) and the comparison group (those with no extension contact).

4.3 The average technical efficiency

Table 7 presents the estimated mean technical efficiency of maize farmers. It has been found that the mean level of maize technical efficiency is about 63%, implying that maize farmers can increase their maize output by 37% without having to increase inputs allocated to maize production. The minimum and maximum levels of technical efficiency were estimated at 1% and 93% respectively.

Table 7: Technical efficiency levels

	Technical efficiency	Standard error	95% confidence interval
Mean	0.63	0.006	0.6197 to 0.6442
Maximum	0.93	0.174	-
Minimum	0.01	0.174	-

Source: Author's analysis of IHS5 (2019/2020) Note: Observations: 1 782

These estimates are close to those that were estimated for maize farmers in Guji Zone, Ethiopia, at a mean level of 69% (Belete 2020), in Nigeria, at 65% (Olagunju *et al*. 2021), and in Ghana, at 67% (Bempomaa & Acquah 2014).

4.4 Comparability of the results in the Malawian context

A recent study by Cassim and Pemba (2021), which focused on the interactive effects of agricultural extension services on smallholder maize production and technical efficiency in Malawi, estimated the effect of extension services on the technical efficiency of maize farmers. The study found that a household with access to agricultural extension services experiences higher output and lower maize production uncertainty,[3] by about 1.174% and 2.057% respectively, compared to a household with no access to agricultural extension services.

The study further found that most maize farmers were technically inefficient, and that maize yield could be increased by 53%. This study, however, found a mean technical efficiency of about 63%, which implies that maize yield can be increased by about 37% without increasing input usage.

5. Conclusions

This study estimated the effect of agricultural extension services on the technical efficiency of maize farmers in Malawi using propensity score matching. It was found that most farmers are technically efficient, although they still have the possibility of increasing maize output using the same level of inputs. Furthermore, the results of the propensity score matching reveal that having access to agricultural extension services significantly increases maize farmers' technical efficiency. Thus, the role of agricultural extension services in achieving potential maize yields certainly cannot not be understated. These results provide some evidence for the argument of Benson (2021), namely that it should be possible to achieve a doubling or more of maize yield by smallholder farmers with significant investments in both public and private agricultural extension services and strengthened input supply systems.

In addition to the efforts that are already in place to increase maize production and productivity in Malawi, such as the Affordable Input Programme, agricultural extension services therefore are corollary to these efforts. Hence, there is a need to emphasise the provision of accessible agricultural extension services. Increased budgetary allocation to agricultural extension services by government, and private actors including extension services in resource packages for farmers involved in contract

[3] These authors measured production uncertainty by the variance in the inefficiency effects estimates.

farming, for instance, are some of the efforts that are likely to improve farmers' access to agricultural extension services.

The study controlled for selection bias arising from the non-randomness of the data by using propensity score matching and agro-ecological zones fixed effects. However, further research can be done to estimate the incremental contribution of additional advice on maize production efficiency. The present study constructed the agricultural extension variable as a binary. However, data on agricultural extension as a continuous variable (such as the number of extension visits in a specified period) is a viable option to measure incremental contributions.

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