African Journal of
Agricultural and Resource Economics
Volume 20, Number 1 (2025), pp 93–114

Short-term impacts of Zambia's electronic Farmer Input Support Programme (e-FISP) on maize yield

Auckland Namubi Kuteya*
Indaba Agricultural Policy Research Institute, Lusaka, Zambia. E-mail: ankuteya@gmail.com

Thomson H Kalinda
Department of Agricultural Economics and Extension Education, University of Zambia, Lusaka, Zambia. E-mail: thomsonkalinda@gmail.com

Elias Kuntashula
Department of Agricultural Economics and Extension Education, University of Zambia, Lusaka, Zambia. E-mail: ekuntashula@unza.zm

Chewe Nkonde
Department of Agricultural Economics and Extension Education, University of Zambia, Lusaka, Zambia. E-mail: chewe.nkonde@unza.zm

* Corresponding author

Received: January 2025
Published: March 2025

DOI: https://doi.org/10.53936/afjare.2025.20(1).6

Abstract

Zambia has been implementing agricultural input subsidy programmes to stimulate crop production and productivity among smallholder farmers with the goal of increasing national food security. This study assesses the impact of the electronic Farmer Input Support Program (e-FISP) on crop productivity among smallholder farmers. Data analysis was done using propensity score matching and difference-in-difference empirical models. The study findings show that, compared to non-recipients, e-FISP had a 315 kg/ha negative effect on beneficiaries' maize yield over the course of the two years under review. After two years, the beneficiaries' estimated maize yield fell to 1 712 kg/ha from 2 177 kg/ha at the baseline. Given the challenges encountered in implementing e-FISP, this outcome is not surprising. Furthermore, in comparison to non-participants, e-FISP had a negative impact on programme participants' use of fertiliser, at least in the short run. This outcome can be the result of implementation issues during the pilot phase. Given these challenges, it is critical to interpret these findings cautiously.

Key words: crop productivity, impact assessment, input subsidy programme, propensity score matching, Zambia

1. Introduction

Farm input subsidies have become a common policy in sub-Saharan Africa (SSA) over the past two decades, with the primary goals of increasing food security and stimulating smallholder productivity to reduce poverty (Chirwa & Dorward 2013; Jayne & Rashid 2013; Ricker-Gilbert *et al*. 2013; Jayne *et al*. 2018; Holden 2019). These programmes aim to lower the cost of inputs for targeted farmers, thereby boosting crop production.

Although there is mixed evidence on the effectiveness and efficiency of input subsidy programmes across the region, a number of authors have found that the input subsidy programmes are associated with increased maize productivity and household incomes (Chirwa & Dorward 2013; Ricker-Gilbert *et al*. 2013; Sheahan & Barrett 2017; Wossen *et al*. 2017; Jayne *et al*. 2018). Despite these attributed positive successes of the programme, Jayne *et al*. (2018) point out that these effects are small and only attainable in the short term.

On the other hand, Mason *et al*. (2016) found that conventional input subsidies were largely ineffective, inefficient and unsustainable and created dependency, with very little contribution towards poverty reduction, productivity, food security and overall agricultural growth in the SSA region. The authors further argue that these programmes do not actually benefit poor, small-scale farmers, and that the direct beneficiaries are the large input suppliers that do not bear the costs of administration, distribution or marketing.

The Zambian government has been providing fertiliser and mainly maize seed to farmers under the farmer input support programme (FISP). However, the programme has not stimulated overall agricultural growth and poverty reduction (Mason *et al*. 2016). This has been partly due to several challenges associated with the programme.

The major problem has been poor implementation of the programme. Under the traditional FISP, government has been distributing physical inputs (mainly compound D for basal dressing and urea for top dressing) to farmers. This move fails to take into account spatial variability in soil fertility and climatic conditions, and results in a blanket fertiliser recommendation of "one size fits all". As in many other SSA countries, targeting has also been a problem, as part of the subsidised fertiliser has not been reaching the intended beneficiaries (Jayne & Rashid 2013). Consequently, crop productivity among smallholder farmers has remained below the potential of hybrid seeds. Kalinda *et al*. (2014) indicate that low maize productivity among smallholder farming households remains a major challenge facing Zambia.

Owing to the challenges faced under the traditional FISP, the government started piloting an electronic voucher (e-voucher) system or electronic FISP (e-FISP) in 13 districts during the 2015/ 2016 farming season. The e-FISP system was implemented as a delivery system aimed at increasing private sector participation; promoting timely access to inputs; improving beneficiary targeting and reducing costs to the treasury; and promoting agriculture diversification (Ministry of Agriculture and Livestock (MAL) 2015).

However, the effectiveness of the e-voucher in addressing the challenges of the traditional FISP is not known empirically. Therefore, this research sought to assess the impact of e-FISP on agricultural households in terms of crop productivity.

The paper aims to answer the critical question of whether the programme achieved the intended objectives of increasing crop productivity among the smallholder farmers. Based on the intended design of the e-FISP, we hypothesise that participation in the programme led to a statistically significant increase in maize yield among smallholder farmers. We further hypothesise that e-FISP increased fertiliser use among the participating farmers due to improved access and affordability.

The rest of the studies that have been done with regard to e-FISP by a number of authors are basically monitoring and descriptive reports. There is no other rigorous study, to the best of our knowledge, that has been done to assess the impact of the programme in Zambia since its inception, with the exception of the study by Mason *et al*. (2020). The major difference between this study and that of Mason *et al*. (2020) is that, while Mason *et al*. used non-panel-pooled cross-sectional datasets and applied only the difference-in-differences (DiD) approach, our study uses panel data and applied propensity score matching, as well as DiD, to identify the effects of e-FISP on the outcome variables. Using panel data is advantageous in terms of degrees of freedom, variation and identifying individual-level changes. Another advantage over non-panel-pooled cross-section data is the greater ability to address omitted variable bias.

This study is timely for the Ministry of Agriculture, policy makers and other stakeholders in agriculture, as the e-FISP is a new system of delivering the subsidy programme in Zambia. The evidence generated can be used as a guide on how best to make the programme more effective through suggested remedial measures. This study also contributes to the scanty literature on the rigorous assessment of the e-FISP on programme outcomes in Zambia.

2. Methodology

2.1 Study area and data sources

The study covered 10 e-FISP pilot districts and three non-pilot districts of Zambia. The study used data collected by the Indaba Agricultural Policy Research Institute (IAPRI) in 2015. The reference period for the baseline data was the 2014/2015 agricultural season, which was a year before the implementation of the e-voucher pilot scheme. To assess the impact, a follow-up survey was carried out in 2017 on the same 10 e-FISP pilot districts and three non-pilot districts.

The three non e-FISP pilot districts were purposively selected and were under conventional FISP. The selection of these districts was based on their similarities to the pilot districts in terms of agroecological climatic conditions. In addition, these districts were also not selected for inclusion in the expanded phase of the e-voucher implementation programme that was piloted during the 2016/2017 farming season. Figure 1 shows the sampled districts where the household data was collected.

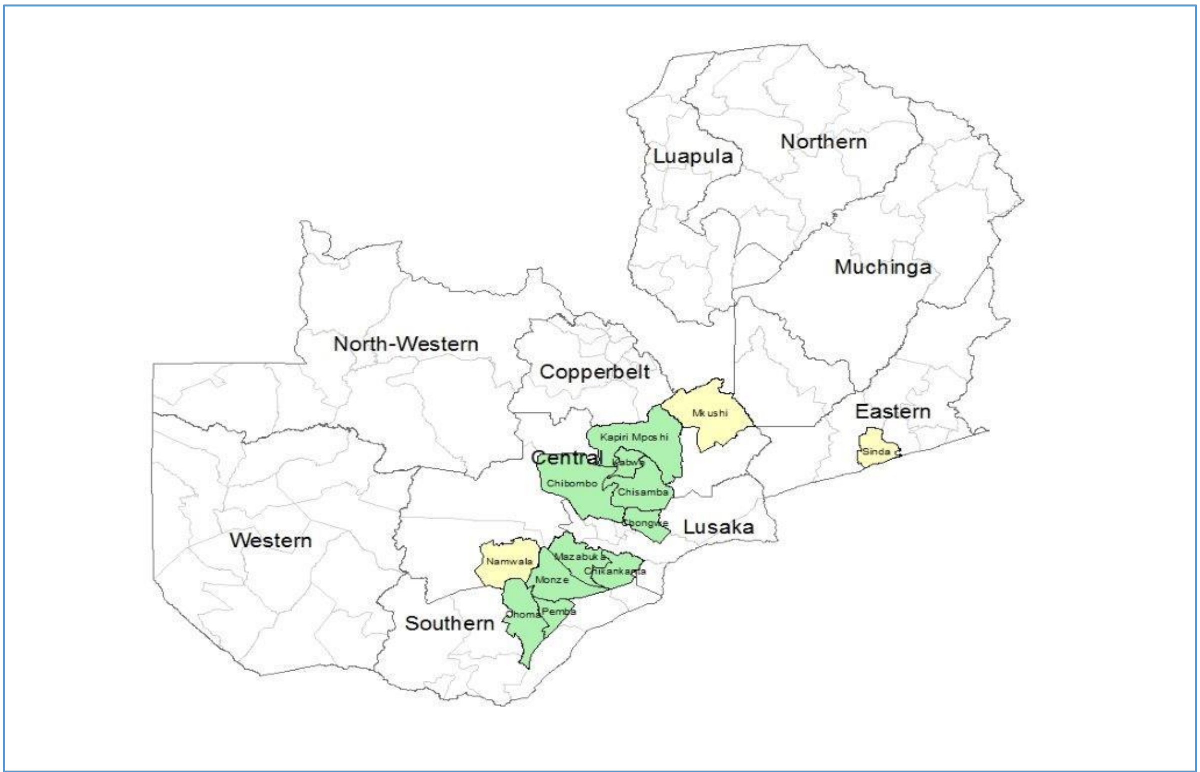

Figure 1: Map of Zambia showing non-FISP and e-FISP pilot districts
Source: Authors' own modelling based on the e-FISP 2015 baseline and 2017 follow-up surveys

Rainfall was one of the variables that were considered in the analysis. This is because rainfall distribution has an effect on both crop yield and production. The annual rainfall data used in this study was collected by the Meteorology Department of Zambia in the respective districts.

2.2 Sampling procedure and sample size

The study employed a multi-stage sampling approach. In each district, two agricultural blocks located on opposite sides of the district were purposively sampled, after which two agricultural camps were sampled. In each sampled camp, two areas (either community or village) were randomly selected. In each community or village, a sample of 15 farm households were randomly selected for household-level interviews. At camp level, a total of 30 households were sampled. The total sample size was 954 (635 from e-FISP pilot districts and 319 from non-pilot districts) at baseline. Due to attrition, the total sample size during the follow-up survey in 2017 dropped to 691 (439 from e-FISP pilot districts and 252 from non-pilot districts). Attrition bias is a cause for concern, and we therefore tested for it. Table A1 (in the Appendix) presents the characteristics of attritted and retained households at baseline (2014/2015 agricultural season). The descriptive statistics presented in Table A1 help to identify any systematic differences between the two groups. We found statistically significant differences in age of household head, household size, adoption of hybrid seed, fertiliser quantity, fertiliser use and rainfall, suggesting that attrition was not completely random. Specifically, attritted households tended to be younger, larger, use fewer inputs, and experience less rainfall.

The sample size of household heads by district and by gender is presented below (Table 1). In addition to the household questionnaires, focus group discussions (FGDs) were conducted with smallholder farmers. Each of the FGDs comprised eight to 10 farmers.

Table 1: Sample size by season, district and gender of household head

Province	District	Number of households by season and sex of head					
		Baseline			2016/2017		
		Male	Female	Total	Male	Female	Total
	e-FISP pilot						
Southern	Chikankata	58	2	60	42	1	43
	Mazabuka	58	2	60	52	1	53
	Monze	116	4	120	69	2	71
	Pemba	59	1	60	36	0	36
	Choma	57	3	60	18	1	19
Central	Chisamba	56	2	58	46	2	48
	Chibombo	55	3	58	49	3	52
	Kabwe	57	3	60	48	0	48
	Kapiri-Mposhi	57	3	60	48	1	49
Lusaka	Chongwe	35	4	39	31	3	34
	Sub-total	**608**	**27**	**635**	**439**	**14**	**453**
	Non-pilot						
Southern	Namwala	117	3	120	82	1	83
Central	Mkushi	116	4	120	99	4	103
Eastern	Sinda	77	2	79	71	1	72
	Sub-total	**310**	**9**	**319**	**252**	**6**	**258**
Grand total of sample size		**918**	**36**	**954**	**691**	**20**	**711**

Source: Authors' computations based on E-FISP 2015 baseline and 2017 follow-up surveys

2.3 Ethical considerations

The data used in this study was obtained from the Indaba Agricultural Policy Research Institute (IAPRI) in Zambia. IAPRI collected the data through household surveys conducted in 2015 and 2017. Prior to data collection, IAPRI obtained the necessary ethical approval and informed consent from all participants. The data was anonymised, and no individual identities are revealed in this publication. The use of the data for this research was approved by IAPRI.

2.4 Non-experimental methods for causal impact assessment

To estimate the influence of the e-FISP on crop productivity, this study employed non-experimental methods. Given the panel nature of our data, propensity score matching (PSM) and difference-in-differences (DiD) were employed. PSM was utilised to establish a control group that was statistically comparable in order to address potential selection bias resulting from the non-random assignment of the e-FISP intervention (Rosenbaum & Rubin 1983; Makate *et al*. 2017; Siziba *et al*. 2019). The DiD technique was employed to evaluate the impact of the intervention by comparing the changes in maize yield over time between the treatment and control groups. One of the main advantages of the DiD model is its ability to mitigate biases arising from permanent differences between the treatment and control groups, as well as differences pre- and post-implementation. The combination of PSM and DiD offers various benefits. While PSM effectively minimises selection bias by ensuring that the treated and control groups are similar based on observed variables, DiD controls for unobserved time-invariant factors that could potentially influence the outcomes.

Other examples of non-experimental designs that can identify causal effects include fixed effects, regression discontinuity and instrumental variables (IV). There are several studies that have employed non-experimental methods to estimate the effect of projects on the variables of interest. For example, a study conducted in Malawi utilised non-experimental methods to show that the subsidy programme gave rise to increased maize production and productivity, both at the national and farm level (Lunduka *et al*. 2013). Chibwana *et al*. (2014) employed the empirical approach of instrumental variable regressions to examine the impacts of the use of subsidised fertiliser and the results showed that the average gain in maize yield attributable to the subsidy programme (seed and fertiliser coupons) was 447 kg/ha.

Mason *et al*. (2016) applied many different econometric methods to estimate the effects of participation in Kenya's targeted input subsidy programme (the National Accelerated Agricultural Input Access Program – NAAIAP) on Kenyan smallholders' cropping patterns, incomes and poverty status. The approaches employed were difference-in-differences (DiD), fixed effects, propensity score matching-DiD and propensity score weighting-DiD with radius matching. All the methods led to similar conclusions, and the results generally suggested that participation in NAAIAP significantly increased maize production by an average of 201 to 471 kilograms, ceteris paribus, mainly by raising maize output/acre.

Wu *et al*. (2010) assessed the impact of improved upland rice technology on farmers' well-being in rural China. Using propensity score matching, the findings of their study indicate that improved agricultural technology has a robust and positive effect on farmers' well-being, as measured by income levels and the incidence of poverty.

2.5 Propensity score-matching procedure

Ever since the propensity score-matching approaches were introduced, they have become among the most popular approaches in estimating causal treatment effects of interest in several non-randomised observational studies in scholarly works (Zagar *et al*. 2017). The PSM model involves predicted probabilities (p-scores) that are matched for the treatment and control groups. In this study, the propensity score was defined as the probability than an individual farming household would participating in e-FISP, conditional on its covariates or observable characteristics, X. The PSM approach matches treated households to non-treated households using propensity scores (Winters *et al*. 2010).

To obtain the impact of the subsidy programme, each beneficiary household was matched with a non-beneficiary household on the basis of a single propensity score. Households for which no match was found were dropped because there was no basis for comparison. To ensure robustness within the PSM model, the nearest neighbour matching (NNM) technique with replacement was used to match the p-scores for the treated and control groups. Matching was performed with replacement to improve the quality of matches, allowing the control units to be used more than once if necessary (Rubin 1973). The NNM method is a commonly employed matching algorithm that links each treated unit with a control unit that has the closest propensity score. The calliper for NNM was set at 0.25 of the standard deviation of the propensity score. This calliper width was chosen to strike a balance between achieving close matches and ensuring an adequate sample size (Smith & Todd 2005). A narrower calliper could lead to more similar matches, but at the cost of discarding too many observations, while a wider calliper could include dissimilar matches, increasing bias.

Other matching algorithms that were employed for robustness checks included the calliper or radius matching (RM), and kernel matching (KM). Each of these matching methods has its advantages and disadvantages (Caliendo & Kopeinig 2008).

Using the "with replacement", the RM Equation (1) is given as:

$$E(\Delta Y) = \frac{1}{N}\sum_{i=1}^{N}([\,Y_{ti} - Y_{c\,j(i)}]), \tag{1}$$

where

$E(\Delta Y)$ indicates the estimator of programme impact;
Y_{ti} denotes the outcome for case i;
$Y_{c\ j(i)}$ symbolises the average outcome for all control households matched with case i; and
N signifies the number of treated cases.

Given the observed characteristics *X*, the propensity score was estimated using Equation (2), as shown below:

$$P(X) = \Pr\,(D_i = 1|X), \tag{2}$$

where

P(X) is – given X – a predicted probability of participating in e-FISP for each household. D_i indicates participation in e-FISP, while X denotes observed characteristics *X*.

To obtain valid outputs under the PSM method, there are basic assumptions that need to be fulfilled. These are the conditional independence assumption (CIA) and the common support condition (CSC) (Becerril & Abdulai 2010; Shahidur *et al*. 2010).

The CIA ensures that the observable covariates X are not affected by the treatment, such that potential outcomes are independent of the treatment status. The CIA, which is also referred to as unconfoundedness, is expressed as in Equation (3):

$$(Y_i^T, Y_i^C) \perp D_i|X_i, \tag{3}$$

where

Y_i^T denotes the outcomes for e-FISP beneficiaries;
Y_i^C represents the outcomes for non-programme beneficiaries;
D_i indicates treatment assignment; and
X_i denotes observable covariates X.

Bearing in mind that the observed characteristics X are not affected by the treatment, this assumption implies that the potential outcomes, *Y*, are independent of the treatment assignment, *D*.

The second assumption is common support. which is the area of overlap area between the propensity scores of the programme beneficiaries and non-beneficiaries. This assumption is expressed as in Equation (4).

$$0 < P(X) < 1 \tag{4}$$

This assumption implies that only those households with propensity scores greater than zero and less than one are included in the estimation. This means that only those households of the comparison group that are similar to the treatment group were considered in the model.

2.6 Difference-in-differences (DiD) model with matching method

The DiD model is another approach that has been widely used in evaluating interventions using either panel or repeated cross-sectional data. The treatment assignment for the exogenous variation is usually not completely random and, as a result, there are normally systematic differences between the treatment and control groups. So the DiD approach tries to correct for those differences (observed and unobserved) between the treatment and control groups that are repeated in a certain period of time. The DiD approach assumes there is unobserved heterogeneity in participation, although such factors are time-invariant. The DiD was applied to the panel data to estimate the impact of e-FISP on crop productivity using Equation (5).

$$Y_{it} = \alpha_0 + \beta EFISP_{it} + \delta YR_t + \gamma(YR_t * EFISP_{it}) + \varepsilon_{it}, \quad i = 1,\ldots n;\ t = 1,2, \tag{5}$$

where Y_{it} represents the outcome variable of interest (i.e. maize yield); $EFISP_{it}$ is a dummy variable that measures participation status in the e-FISP (= 1 if household was a recipient of e-FISP, and 0 otherwise); YR_t denotes agricultural season (= 1 for 2016/2017 season and 0 for the baseline). ε_{it} is the error term; α is the mean for the comparison group on the baseline; β is the effect of any systemic difference between the treatment and comparison groups; δ equals the time-trend effect on the dependent variable, while γ is the treatment effect.

Since maize yield could be susceptible to weather variability and pest outbreaks, which could confound the attribution of impacts to the e-FISP programme, we utilised two strategies to address this potential issue. First, we incorporated district-level rainfall data (total annual rainfall) as a control variable in the DiD regression model (Equation (5)). The rainfall data was obtained from the national meteorological department. Second, as an alternative approach to account for unobserved heterogeneity at the district-year level, we implemented district-year fixed effects in our regression model by including dummy variables for each district-year combination. The model specification is illustrated as Equation (6).

$$Y_{it} = \alpha_0 + \beta EFISP_{it} + \delta YR_t + \gamma(YR_t * EFISP_{it}) + \mu_{it} + \varepsilon_{it}, \quad i = 1,\ldots n;\ t = 1,2, \tag{6}$$

where μ_{it} represents district-year fixed effects.

The inclusion of rainfall did not substantially alter the magnitude or statistical significance of the e-FISP treatment effect. The coefficient of the impact of the e-FISP programme on maize yield (-312.76, $p < 0.05$) remained negative and statistically significant at the 5% level. However, the inclusion of district-year fixed effects reduced the magnitude, and the impact of the e-FISP programme on maize yield (-141.33, $p > 0.05$) became statistically insignificant (see Appendix Table A3). This suggests that our original findings are robust to controlling for weather variability but not robust for unobserved heterogeneity. The district-year fixed effects results imply that some of the initial estimated impact may have been attributable to unobserved factors varying at the district-year level.

While we addressed the potential confounding effects of weather, it is important to acknowledge that the rainfall data is at the district level, which may not capture micro-level variations in rainfall patterns that affect individual farms. Future research could explore the use of more granular weather data to further refine these estimates.

3. Results and discussion

3.1 Descriptive results

The data was first analysed using descriptive statistics techniques that involved means, percentages and standard errors. The comprehensive list of variables that were included under descriptive statistics are shown in Table 2. These results show that the average age of each household head in the non- and e-FISP groups was similar, at 47 years. The marital status was also similar between the non- and e-FISP recipients, with an average of 24%.

In terms of level of education for household heads, there was no difference between the beneficiaries and non-beneficiaries. The average household size was six members, and there was no significant difference between the non- and e-FISP beneficiaries.

In terms of the use of hybrid seed, there was no difference between the two groups. Equally, fertiliser usage was similar between beneficiary and non-beneficiary households, with a mean value of 321 kg/ha in the 2014/2015 agricultural season. With regard to maize production, there was no difference between the two groups. The differences in land cultivated between the beneficiaries and non-beneficiaries were not statistically significant.

The variables presented in Table 2 were used for matching. Using the traditional t-test procedures, the results indicate a few differences between the non- and e-FISP recipients at baseline. In order to adjust for household characteristics, the paper employs the PSM approach to ascertain the impact of e-FISP on outcome variables.

Table 2: Descriptive statistics based on selected baseline characteristics

Variables	Full sample (N = 954)	Beneficiaries (N = 635)	Non-beneficiaries (N = 319)
Explanatory variables			
Age of household head, in years	46.95 (0.45)	47.20 (0.58)	46.48 (0.73)
Number of prime age adults	3.09 (0.55)	3.14 (0.07)	3.00 (0.09)
Female-headed household (= 1 if female) (%)	21.70 (0.01)	23.78 (0.02)	17.55 (0.02)
Marital status (= 1 if married, 0 o/w) (%)	24.11 (0.01)	23.31 (0.02)	25.71 (0.02)
Education of head, years	7.15 (0.10)	7.41 (0.12)	6.64 (0.19)
Household size, number	6.08 (0.08)	6.17 (0.10)	5.89 (0.14)
Land cultivated, ha	1.98 (0.06)	2.07 (0.08)	1.80 (0.09)
Land cultivated for maize, ha	1.54 (0.05)	1.66 (0.07)	1.29 (0.07)
Hybrid seed (= 1 if yes, 0 o/w) (%)	88.28 (0.01)	92.55 (0.01)	79.75 (0.02)
Fertiliser quantity, kg	320.88 (12.19)	349.09 (16.25)	264.72 (16.41)
Fertiliser use (= 1 if yes, 0 o/w) (%)	85.28 (0.01)	87.58 (0.01)	80.70 (0.02)
Commercial fertiliser purchases (= 1 if yes) (%)	44.65 (0.02)	49.61 (0.02)	34.80 (0.03)
Livestock (= 1 if yes, 0 o/w) (%)	88.47 (0.01)	87.72 (0.01)	89.97 (0.02)
Off-farm income, ZMW	4 238.48 (377.93)	4 321.57 (464.44)	4 073.09 (651.09)
Asset value, ZMW	15 216.74 (1 067.11)	16 689.28 (1432.94)	12 285.52 (1419.93)
Maize price, ZMW per kg	1.24 (0.02)	1.23 (0.03)	1.24 (0.02)
Rainfall, mm	761.18 (1.82)	743.86 (1.57)	795.66 (3.77)***
Outcome variables			
Crop production, kg	4 269.79 (196.17)	4 587.98 (266.00)	3 636.39 (249.38)
Maize production, kg	3 768.90 (182.21)	4 139.44 (249.90)	3 031.31 (217.14)
Maize yield, ton/ha	2 564.24 (55.02)	2 499.32 (64.82)	2 692.64 (101.81)**
Inadequate food provisions (yes = 1) (%)	35.85 (0.02)	32.44 (0.02)	42.63 (0.03)***

Notes: o/w = otherwise; ZMW = Zambian kwacha. Figures in parentheses are standard errors of the mean. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Authors' own calculations based on e-FISP 2015 baseline survey data

Before assessing the impact of e-FISP on the outcome variables, we first matched beneficiaries and non-beneficiaries. The basis for estimating the likelihood of being an e-FISP beneficiary was provided by the logit model. Table 3 shows the results of the model. Save for the variables pertaining to the sex of the household head, level of education of household head, area under maize cultivation and use of hybrid maize seed, the majority of the characteristics do not have statistical significance. These results imply that the four above-mentioned factors significantly influence the probability of being a FISP recipient. This simply means households that are female headed, with a higher education level, larger size of land devoted to maize production and using hybrid maize seed, are more likely to be beneficiaries of e-FISP. These results are in line with those of Alavo *et al*. (2019), who found that, among other factors, area cultivated under maize affects the likelihood of being a FISP beneficiary.

Table 3: Logit results for participation in e-FISP (baseline year)

e-FISP benefit	Coefficient	Std error	Z-value
Age of household head (years)	0.0033	0.0056	0.59
Female-headed household (= 1 if female, 0 o/w)	0.9054	0.2043	4.43***
Marital status (= 1 if single, 0 o/w)	0.1548	0.1576	0.98
Education of household head (years)	0.0745	0.0249	3.00***
Household size (number)	0.0458	0.0355	1.29
Farm size (ha)	-0.4166	0.2206	-1.89
Cultivated area under maize (ha)	0.3180	0.1233	2.58**
Fertiliser use (= 1 if used fertiliser, 0 o/w)	0.2056	0.2192	0.94
Total fertiliser acquired (kg)	0.0001	0.0004	0.29
Use of hybrid maize seed (= 1 if used hybrid seed, 0 o/w)	1.1637	0.2331	4.99***
Maize harvested (kg)	-0.00001	0.00003	-0.24
Off-farm income (= 1 if earned off-farm income, 0 o/w)	-0.00001	0.00001	-0.88
Value of assets (ZMW)	0.000001	0.000003	0.33
Cattle ownership (= 1 if household raised cattle, 0 o/w)	0.1392	0.1638	0.85
Constant	-1.7805	0.6116	-2.91***
Logistic regression Log likelihood = -553.37439	Number of observations = 927 χ^2 (14) = 76.10 $p > \chi^2$ = 0.0000 Pseudo R^2 = 0.0643		

Notes: o/w = otherwise; ZMW = Zambian kwacha. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively

Source: Authors' own calculations based on e-FISP 2015 baseline survey data

The multicollinearity diagnostic test revealed that there was no issue with multicollinearity because all pairwise correlation coefficients were less than 0.80 in absolute terms (Greene 2008).

Using the '1-to-1' NNM with the replacement criterion, the propensity score-matching results showed that 310 households from the non-recipients were matched with 597 recipients. A total of 907 households fell within the region of common support (Table 4). All households that were unsupported were dropped so as to have a comparable sample.

Table 4: Matched and unmatched e-FISP beneficiaries and non-beneficiaries

Variable	Off support	On support	Total
Control	0	310	310
Treated	13	597	610
Total	13	907	920

Source: Authors' own calculations based on e-FISP 2015 baseline survey data

A covariate balance test was employed to assess the quality of matching. The common support region with kernel matching is displayed in Figure 2. This figure shows the common support region between the treatment (e-FISP beneficiaries) and control (non-beneficiaries) groups based on the propensity score estimates. The x-axis represents the propensity scores, while the y-axis indicates the density. The overlapping region between the two groups indicates the area of common support, where meaningful comparisons can be made. In order to evaluate the matching visually, probability distribution graphs prior to and following the matching were plotted (see Appendix Figures A1 and A2). There were no significant variations in the matched sample, suggesting that the treatment and control groups were comparable.

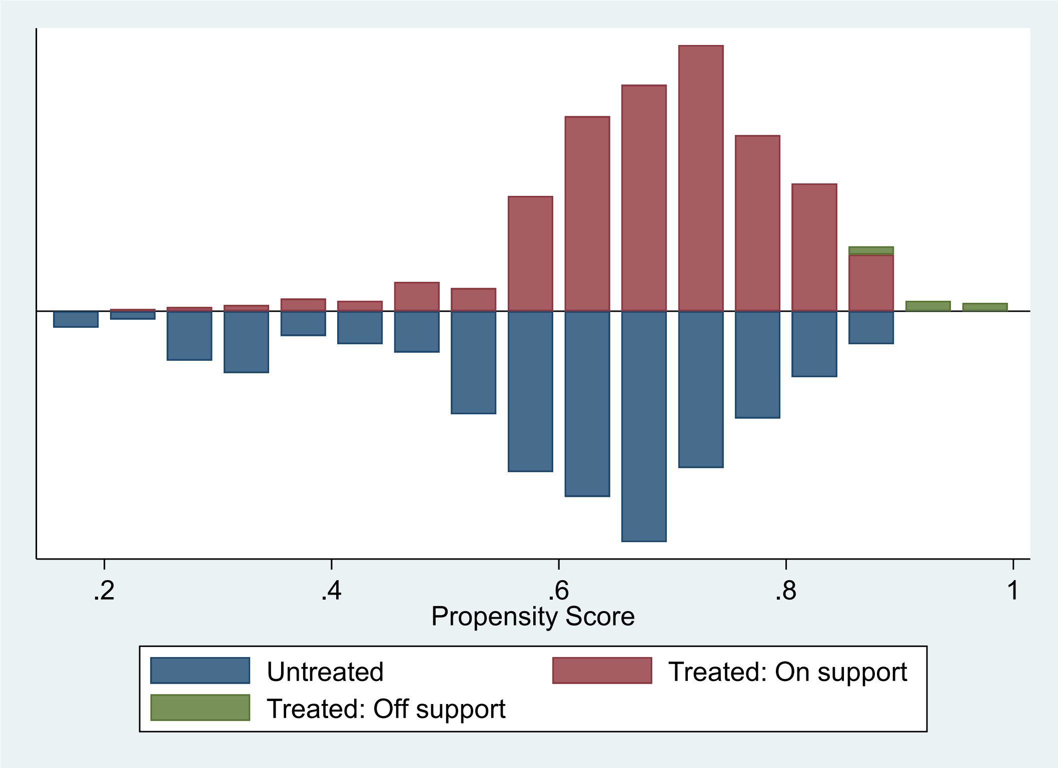

Figure 2: Common support area with kernel matching
Source: Authors' own calculations based on e-FISP 2015 baseline survey data

The t-test results (Table 5) demonstrate that for the matched groups, there are no statistically significant differences for most of the comparable characteristics as revealed by the p-values.

Table 6 provides evidence of bias reduction due to matching. Before matching, the standardised mean difference for the total variables used to calculate the propensity score was 17.0%. After matching, it was about 3.2%. The low pseudo R^2, large bias reduction and insignificant p-values of the likelihood ratio test implies that the baseline observables of the beneficiaries and non-beneficiaries are comparable.

Table 5: Balancing test based on t-tests performed before and after matching

Variable	Sample	Mean		% Bias	% Reduction in bias	*t*-test	
		Treated	Control			*t*	P > *t*
Age of household head	Unmatched	47.18	46.57	4.4		0.62	0.534
	Matched	47.14	46.01	8.2	-86.3	1.45	0.147
Gender of household head	Unmatched	0.24	0.17	17.4		2.45	0.014
	Matched	0.24	0.22	5.0	71.3	0.83	0.407
Marital status	Unmatched	1.29	1.33	-7.0		-1.02	0.309
	Matched	1.30	1.34	-7.9	-12.5	-1.35	0.178
Education of head	Unmatched	7.40	6.64	23.2		3.39	0.001
	Matched	7.35	7.67	-10.0	57.0	-1.78	0.075
Household size	Unmatched	6.21	5.88	13.3		1.90	0.058
	Matched	6.17	6.19	-0.7	95.0	-0.11	0.910
Farm size	Unmatched	1.46	1.38	13.1		1.86	0.063
	Matched	1.43	1.44	-1.1	91.6	-0.18	0.854
Area under maize	Unmatched	1.66	1.32	24.6		3.39	0.001
	Matched	1.53	1.53	0.0	99.9	0.01	0.995
Fertiliser use	Unmatched	0.88	0.81	19.3		2.85	0.004
	Matched	0.88	0.86	4.7	75.7	0.86	0.388
Total fertiliser acquired	Unmatched	351.84	268.21	24.0		3.29	0.001
	Matched	321.38	317.58	1.1	95.5	0.20	0.838
Use of hybrid maize seed	Unmatched	0.94	0.80	41.8		6.50	0.000
	Matched	0.93	0.93	1.0	97.6	0.23	0.817
Maize harvested	Unmatched	4 101.30	3 093.90	21.3		2.90	0.004
	Matched	3 697.20	3 646.10	1.1	94.9	0.20	0.844
Off-farm income	Unmatched	4 075.20	4 042.60	0.3		0.04	0.968
	Matched	4 153.50	3 949.80	1.7	-526.3	0.30	0.765
Value of assets	Unmatched	16 462.00	12 432.00	12.9		1.76	0.079
	Matched	15 522.00	15 427.00	0.3	97.6	0.05	0.960
Cattle ownership	Unmatched	0.51	0.44	14.9		2.14	0.033
	Matched	0.50	0.49	2.0	86.5	0.35	0.729

Source: Authors' own calculations based on e-FISP 2015 baseline survey data

Table 6: Quality test of covariate balance indicators prior to and after matching

Sample	*Ps* R^2	*LR* χ^2	$p > \chi^2$	*Mean bias*	*Median bias*	*B*	*R*	*%Var*
Unmatched	0.071	82.89	0.000	17.0	16.2	62.6*	0.74	60
Matched	0.005	7.69	0.905	3.2	1.4	16.1	1.21	50

Note: * if B > 25%, *R* outside [0.5; 2]

To further assess the quality of our matching procedure, we examined standardised bias before and after matching (see Appendix Figure A3). The results indicate a substantial reduction in bias for most covariates, with the majority falling below the threshold of 0.10 after matching. This suggests that our matching procedure was effective in creating comparable treatment and control groups.

3.2 Empirical results

After matching, the results presented in Table 7 were estimated using the DiD equation. To assess the potential impact of non-random attrition on our results, we conducted a sensitivity analysis. We implemented both optimistic and pessimistic scenarios in which we assumed that the attritted households would have had 10% higher or lower maize yields in 2017 than the retained households. When we re-ran our DiD model using these adjusted maize yield values, the estimated impact of e-FISP was still negative, from -315 to -244 and -210, but remained statistically significant at the $p < 0.05$ and $p < 0.1$ levels, respectively (Appendix Table A2). This suggests that our main findings are relatively robust to the potential bias introduced by attrition, although the magnitude of the effect may be somewhat smaller than our original estimate. Thus, our results may not be fully generalisable to the population of smallholder farmers in the country due to the attrition patterns observed in our sample.

Table 7: Estimated impact of e-FISP on maize yield, production, fertilizer acquisition and use

	Fertiliser acquired		HHs using fertiliser		Maize production		Maize yield	
Before	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**
Control	264.72		0.807		3 031.31		2 151.99	
Treated	349.09		0.876		3 751.68		2 176.60	
Diff (T-C)	84.37***	27.49	0.069***	0.024	720.38**	317.78	24.61	84.15
After								
Control	300.36		0.871		3 202.55		2 002.68	
Treated	429.99		0.879		3 647.29		1 711.98	
Diff (T-C)	129.63***	31.25	0.008	0.027	444.74	361.17	-290.70***	95.84
DiD	**45.26**	**41.62**	**-0.061***	**0.036**	**-275.64**	**481.07**	**-315.32****	**127.53**

Notes: SE = standard error; *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Authors' own calculations based on the e-FISP pilot survey data

During the 2016/2017 period, the estimated coefficient associated with households using fertiliser was negative and statistically significant at the 10% level. The results imply that e-FISP led to a decrease of 6.1% among recipients relative to non-recipients. This is not surprising, because it was revealed during the FGDs that e-FISP implementation during this period was marred by several challenges. These challenges are discussed in detail below. The findings here are similar to those of Mason *et al*. (2020), who found a six to seven percentage point decrease in the likelihood that an e-FISP recipient household used fertiliser.

With regard to maize yield, the results reveal that there was a negative impact of 315 kg/ha among beneficiaries compared to non-beneficiaries during the two-year period under review. These results were statistically significant at the 50% level. The reduction in yield among the subsidy recipients was equivalent to about 21%. The estimated maize yield for non-recipients at the baseline was about 2 152 kg/ha, and 2 177 kg/ha for beneficiaries. After the two-year period, the maize yield for non-beneficiaries and beneficiaries was approximately 2 003 kg/ha and 1 712 kg/ha, respectively.

Other studies, such as the one done by Gine *et al*. (2019), concluded that the National Agricultural Input Voucher Scheme (NAIVS) in Tanzania had no effect on agricultural productivity. However, according to Ray (2019), the NAIVS programme increased yields, which is in contrast to the findings of Gine *et al*. (2019).

To strengthen the quantitative evidence, Table 8 presents the results of the DiD regressions with interaction terms to test for heterogeneous treatment effects. The results indicate that the impact of the e-FISP pilot programme varied significantly with household wealth and education.

Table 8: Results of DiD regression with interaction terms

Variable	Baseline DiD with wealth interaction	Baseline DiD with education interaction
Treatment effect	-278.38*	-557.82**
Treatment*Time*Wealth	0.0004**	
Treatment*Time*Education		37.56*

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively
Source: Authors' own calculations based on e-FISP pilot survey data

The coefficient (-278.38, $p < 0.05$) indicates a statistically significant negative average treatment effect for households with zero wealth. The coefficient (0.0004, $p < 0.01$) suggests that, for every one-unit increase in wealth, the (negative) treatment effect decreases by 0.0004. This implies that, while the average treatment effect is negative, the negative impact is lessened as wealth increases. This could be because wealthier households are better positioned to leverage the benefits of the e-FISP pilot programme due to access to complementary inputs. However, it is important to note that the magnitude of the interaction effect is quite small.

The coefficient (-557.82, $p < 0.01$) indicates a statistically significant negative average treatment effect for households with zero education. The coefficient (37.56, $p < 0.05$) suggests that, for every one-year increase in education, the (negative) treatment effect decreases by 37.56. Thus, the negative impact of the e-FISP pilot on maize yield is less pronounced for households with more educated heads.

3.3 Discussion of results

Our findings indicate a decline in fertiliser use and maize yields among e-FISP beneficiaries relative to non-beneficiaries. This aligns with Mason *et al*. (2020), who reported short-term reductions in fertiliser use among subsidy recipients.

Maize yields furthermore were also negatively affected among beneficiaries compared to non-beneficiaries during the two-year period under review. The results of our analysis reveal a complex picture of the e-FISP pilot programme's impact on maize yield. While we find evidence of heterogeneous treatment effects based on household wealth and education, the average treatment effect is consistently negative. This raises concerns about the overall effectiveness of the e-FISP pilot programme. Similarly, Gine *et al*. (2019) found no positive productivity effects of Tanzania's input voucher scheme. The findings of Kato and Greeley (2016) also indicate that the voucher system had no statistically significant effect on maize yield in Tanzania. The authors attributed these findings to a number of challenges, including farmers' failure to apply the entire input package and delayed voucher delivery.

Furthermore, Aloyce *et al*. (2014), who examined the operational features of the input supply chain under the NAIVS in Tanzania, found that delays in the delivery of subsidised inputs and a lack of regard to the implementation guidelines affected the effectiveness of the programme. The authors attributed the delay in input supply to the long chain involved in voucher distribution and the agro-dealers' lack of sufficient capital. The authors also emphasised the lack of an independent monitoring and evaluation committee in the scheme, and the existence of bureaucracy in the process of choosing agro-dealers as impediments to the implementation of the subsidy programme.

These factors were also brought up in the FGDs, where farmers confessed that one of their challenges was the sharing of redeemed inputs among the cooperative or farmer group members. The FGDs further revealed that e-FISP implementation during this period was marred by several challenges. One example was that there were several people, including some who were not even farmers, who were benefiting under the conventional FISP and therefore could not support the e-FISP. Instead, they made every effort to cause problems for the system.

During the discussions, farmers also cited increases in the prices of inputs stocked by agro-dealers. The rising prices of inputs, especially fertiliser, were attributed to the depreciation of the kwacha against major convertible currencies. In addition, it was revealed during the FGDs that the private sector inflated the prices of inputs under the e-FISP in order to offset the delays in government payments. As a result, the average quantity of inputs that a farmer in the e-FISP districts was able to redeem was less compared to a farmer on the conventional FISP. This made the e-FISP less appealing than the conventional FISP. In response to the outcry of the e-FISP farmers, government raised the value of the e-voucher (e-card) from ZMW 1 400 to ZMW 2 100 (Kuteya *et al*. 2016).

Despite this intervention by the government, farmers and agro-dealers still complained of the protracted delays in e-card activation – the process of loading money onto e-cards. The late release of the funds meant for subsidised inputs by the government also contributed to delays in e-card activations. As a result, farmers were unable to redeem inputs on time. This assertion was also supported by the quantitative data, as 92% of the interviewed farmers stated that the delayed activation of e-cards was one of the challenges in the implementation of the e-FISP system. The lack of digital literacy of some agro-dealers, as well as poor internet connectivity in some rural areas, was also cited as contributing to the delays in redeeming agro-inputs.

Another problem that agro-dealers faced was a lack of input availability in their shops, as most of them lacked the financial capacity to pre-stock inputs. Despite this challenge, agro-dealers had to pre-finance farmers because the government could not release the money on time. This had an even greater detrimental impact on agro-dealers in stocking agricultural inputs. As a way of raising funds to restock their shops, some agro-dealers resorted to redeeming even when they had no stock. But those who were caught in this practice and failed to provide inputs to farmers were arrested by the police.

The challenges discussed above help explain the quantitative results, which show that the e-voucher had a negative impact on the use of fertiliser and on maize yield among the programme beneficiaries relative to non-beneficiaries, at least in the short run.

A key limitation of this study is the use of only two seasons of data - one pre-intervention (2014/2015) and one post-intervention (2016/2017). This relatively short panel may not fully capture the longer term adjustments and effects of the e-FISP, especially given that it represents a structural policy change in the delivery of input subsidies. Farmers and agro-dealers may need more time to fully adapt to the new e-voucher system and overcome the implementation challenges faced during the pilot phase. As such, the estimated impacts presented here may be reflective of the short-run effects of the programme, rather than the longer term outcomes. Future research utilising more recent data with a longer panel would be valuable to validate these findings and provide a more comprehensive assessment of the impacts of the e-FISP programme over time.

4. Conclusions and policy implications

This paper assessed the effectiveness of the e-FISP in improving the crop productivity of farming households in Zambia. Because maize is the nation's staple crop and has been supported by the subsidy programme, the study focussed on the productivity and production of this crop. Maize is the most commonly grown crop among smallholder farmers in Zambia. Both PSM and DiD techniques were used in this investigation. They essentially compared the treatment and comparison groups with regard to outcome variables of interest over the study period. Potential biases resulting from observable and unobservable features between programme beneficiaries and non-beneficiaries were mitigated by applying these two approaches.

The PSM was used to match beneficiaries and non-beneficiaries before evaluating the effect of e-FISP on the outcome variables. The DiD was applied to the panel data to estimate the impact of e-FISP on productivity. Based on the results of the empirical model, it can be inferred that, over the two years under consideration, the e-FISP had a 315 kg/ha negative impact on beneficiaries as opposed to non-beneficiaries. Among the recipients of the subsidy, this yield reduction amounted to roughly 21%. After two years, the estimated maize yield for recipients dropped from 2 177 kg/ha at the baseline to 1 712 kg/ha.

Among the households that used fertiliser, e-FISP resulted in a 6.1% decrease in the yields of the beneficiaries compared to non-recipients. This outcome is not surprising, given the difficulties encountered in implementing e-FISP during the study period. For instance, agro-dealers implemented price hikes for inputs by as a result of the kwacha's decline in value relative to other major convertible currencies. In order to make up for the delays in government payments, agro-dealers also raised the prices of inputs covered under the e-FISP.

Some agro-dealers experienced a shortage of input availability in their shops as a result of not having enough financial capacity to stock up inputs in advance. These challenges help explain the findings, which indicated that, at least in the short run, e-FISP had a negative effect on programme participants' use of fertiliser and their maize yield as compared to non-participants.

During the two years of the e-FISP pilot, the programme's goal of improving small-scale farmers' access to agricultural inputs was not fully achieved because the increase brought about by e-FISP was not substantial enough. As mentioned previously, the difficulties in implementing the programme during the pilot phase may have given rise to these results. Although a well-managed e-FISP is likely to increase access to agricultural inputs for smallholder farmers, these difficulties made it impossible for the programme to be implemented smoothly.

Given the challenges encountered in implementing e-FISP during the pilot phase, these results should be interpreted cautiously. The negative impacts on fertiliser use and maize yields observed in this study may be indicative of the short-term disruptions caused by the transition to the new e-voucher system. However, it is possible that the e-FISP programme could have more favourable impacts on smallholder farmers' access to inputs and productivity in the longer run once the system is fully established and the operational challenges have been resolved. Further research using more recent data with a longer panel would be valuable to reassess the effect of the e-FISP and provide more definitive policy guidance. Nonetheless, the findings of this study suggest the importance of carefully managing the implementation of input subsidy programmes to ensure they achieve their intended objectives of boosting smallholder agricultural productivity and incomes.

Acknowledgements

We are grateful to the Indaba Agricultural Policy Research Institute (IAPRI) for the data used in this study. We also recognise all the enumerators who participated in data collection. We further are thankful to all the farmers who were interviewed, for their support. Finally, our sincere gratitude goes to the agro-dealers and staff in the Ministry of Agriculture for the responses they provided with regard to the e-FISP system.

References

Alavo J-PE, Cogbe E-AS, Xiangmei L, Mwalupaso GE, Abdalgadir EE, Korotoumou M & Mamo A, 2019. Evaluation of the effect of farmer input support program (FISP) on small-scale farmers in the Kara region of Togo. Journal of Agricultural Science 11(4): 35–46. https://doi.org/10.5539/jas.v11n4p35

Aloyce GM, Gabagambi DM & Hella JP, 2014. Assessment of Operational Aspects of the Input Supply Chain Under National Agriculture Input Voucher Scheme (NAIVS) in Tanzania. Journal of Development and Agricultural Economics 6(3): 94–104.

Becerril J & Abdulai A, 2010. The impact of improved maize varieties on poverty in Mexico: The propensity matching approach. World Development 38(7): 1024–35.
Caliendo M & Kopeinig S, 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys 22(1): 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x
Chibwana C, Shively G, Fisher M & Jumbe C, 2014. Measuring the impacts of Malawi's farm input subsidy programme. African Journal of Agriculture and Resource Economics 9(2): 132–47.
Chirwa E & Dorward A, 2013. Agricultural input subsidies: The recent Malawi experience. Oxford: Oxford University Press.
Gine X, Patel S, Ribeiro B & Valley I, 2019. Targeting inputs: Experimental evidence of Tanzania. Policy Research Working Paper 9013, World Bank Group, Washington, DC.
Greene WH, 2008. Econometric analysis. Upper Saddle River, NJ: Pearson Educational International.
Holden ST, 2019. Economics of farm input subsidies in Africa. Annual Review of Resource Economics 11(1): 501–22.
Jayne TS & Rashid S, 2013. Input subsidy programs in Sub-Saharan Africa: A synthesis of recent evidence. Agricultural Economics 44(6): 547–62.
Jayne TS, Mason NM, Burke WJ & Ariga J, 2018. Taking stock of Africa's second-generation agricultural input subsidy programs. Food Policy 75: 1–14.
Kalinda T, Tembo G & Kuntashula E, 2014. Adoption of improved maize seed varieties in southern Zambia. Asian Journal of Agricultural Sciences 6(1): 33–9.
Kato T & Greeley M, 2016. Agricultural input subsidies in sub-Saharan Africa. IDS Bulletin 47(2): 33–48. https://doi.org/10.19088/1968-2016.130
Kuteya AN, Lukama C, Chapoto A & Malata V, 2016. Lessons learnt from the implementation of the e-voucher pilot. Indaba Agricultural Policy Research Institute Policy Brief No. 81, IAPRI, Lusaka, Zambia.
Lunduka R, Ricker-Gilbert J & Fisher M, 2013. What are the farm-level impacts of Malawi's farm input subsidy program? A critical review. Agricultural Economics 44: 563–79.
Makate C, Wang R, Makate M & Mango N, 2017. Impact of drought tolerant maize adoption on maize productivity, sales and consumption in rural Zimbabwe. Agrekon 56(1): 67–81. https://doi.org/10.1080/03031853.2017.1283241
Mason NM, Jayne TS & Van de Walle N, 2016. The political economy of fertilizer subsidy programs in Africa: Evidence from Zambia. American Journal of Agricultural Economics 99(3): 705–31.
Mason NM, Kuteya A, Ngoma H, Tossou DA & Baylis KR, 2020. Does shifting to a flexible e-voucher approach improve input subsidy program outcomes? Quasi-experimental evidence from Zambia's crop forecast surveys. Feed the Future Innovation Lab for Food Security Policy Research Paper No. 165, Department of Agricultural, Food, and Resource Economics, Michigan State University, MI, USA.
Ministry of Agriculture and Livestock (MAL), 2015. Farmer input support programme electronic voucher implementation manual for 2015/16 agricultural season. Lusaka, Zambia: Zambia Ministry of Agriculture and Livestock, Government of the Republic of Zambia (GRZ).
Ray S, 2019. Impact of agricultural input subsidies on food security: The national agricultural input voucher scheme in Tanzania. Selected paper prepared for presentation at the 2019 Agricultural & Applied Economics Association Annual Meeting, 21–23 July, Atlanta, Georgia, USA. https://ideas.repec.org/p/ags/aaea19/290897.html
Ricker-Gilbert J, Jayne TS & Shively G, 2013. Addressing the "wicked problem" of the input subsidy programs in Africa. Applied Agricultural Economic Perspectives and Policy 35(2): 322–40.
Rosenbaum PR & Rubin DB, 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70: 41–55. http://dx.doi.org/10.1093/biomet/70.1.41
Rubin DB, 1973. Matching to remove bias in observational studies. Biometrics 29(1): 159–83.

Shahidur RK, Koolwal GB & Samad HA, 2010. Handbook on impact evaluation: Quantitative methods and practices. Washington, DC: The World Bank.
Sheahan M & Barrett C, 2017. Ten striking facts about agricultural input use in Sub-Saharan Africa. Food Policy 67: 12–25.
Siziba S, Nyikahadzoi K, Makate C & Mango N, 2019. Impact of conservation agriculture on maize yield and food security: Evidence from smallholder farmers in Zimbabwe. African Journal of Agricultural and Resource Economics 14(2): 89–105. https://doi.org/10.22004/ag.econ.292467
Smith JA & Todd PE, 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? Journal of Econometrics 125(1–2): 305–53.
Winters P, Salazar L & Maffioli A, 2010. Designing impact evaluations for agricultural projects impact evaluation guidelines. Inter-American Development Bank.
Wossen T, Abdoulaye T, Alene A, Feleke S, Ricker-Gilbert J, Manyoung V & Awotide BA, 2017. Productivity and welfare effects of Nigeria's e-voucher-based input subsidy program. World Development 97: 251–65.
Wu H, Ding S, Pandey S & Tao D, 2010. Assessing the impact of agricultural technology adoption on farmers' well-being using propensity-score matching analysis in rural China. Asian Economic Journal 24(2): 141–60.
Zagar A, Kadziola Z, Lipkovich I & Faries DE, 2017. Evaluating different strategies for estimating treatment effects in observational studies. Journal of Biopharmaceutical Statistics 27(3): 535–53. https://doi.org/10.1080/10543406.2017.1289953

Appendix

Table A1: Characteristics of attritted vs. retained households

Characteristic	Attritted households	Retained households	*t/χ2*-test
	N = 243	N = 711	
Age of household head (years)	45.39 (14.77)	47.49 (13.69)	-2.01**
Gender of household head (% female)	23.05	21.24	0.35
Marital status (% married)	75.31	76.09	0.06
Education of head (years)	7.41 (2.87)	7.06 (3.32)	1.40
Household size (number)	6.33 (2.82)	5.99 (2.46)	1.81*
Land cultivated (ha)	1.46 (0.65)	1.42 (0.60)	0.97
Land cultivated for maize (ha)	1.57 (1.39)	1.52 (1.66)	0.42
Hybrid seed (% yes)	85.19	89.35	3.02*
Fertiliser quantity (kg)	285.87 (330.95)	332.84 (390.37)	-1.68*
Fertiliser use (% yes)	80.83	86.79	5.06**
Commercial fertiliser purchase (% yes)	41.56	45.71	1.26
Livestock (% yes)	48.15	47.40	0.04
Off-farm income (ZMW)	4 305.16 (11 929.34)	4 215.69 (11 592.72)	0.10
Asset value (ZMW)	14 218.11 (27 107.55)	15 558.05 (34 745.3)	-0.55
Maize price (ZMW per kg)	2.43 (2.44)	4.54 (6.47)	-0.57
Rainfall (mm)	741.97 (48.40)	767.75 (57.11)	-6.30***
Crop production (kg)	3 891.36 (4 181.01)	4 399.12 (6 576.72)	-1.13
Maize production (kg)	3 393.05 (3 754.44)	3 897.35 (6 135.63)	-1.21
Maize yield (ton/ha)	2 422.61 (1 904.71)	2 613.21 (1 600.91)	-1.51

Note: Standard deviation in parentheses; *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Authors' own calculations based on e-FISP pilot survey data

Table A2: Sensitivity analysis on estimated impact of e-FISP on yield of maize

Model	Coefficient	SE	p-value
Original	-315.32**	127.53	0.014
Best case (10% difference)	-243.71**	118.21	0.040
Worst case (10% difference)	-209.52*	119.08	0.079

Notes: SE = standard error; standard errors in parentheses; * and ** denote statistical significance at the 10% and 5% levels, respectively.
Source: Authors' own calculations based on e-FISP pilot survey data

Table A3: DiD regressions results with inclusion of rainfall and district-year fixed effects

Variable	Baseline DiD	Baseline DiD + Rainfall	Baseline DiD + District-Year FE
Treatment Effect	-315.32**	-312.76*	-141.33
District-Year Fixed Effects	No	No	Yes

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' own calculations based on e-FISP pilot survey data

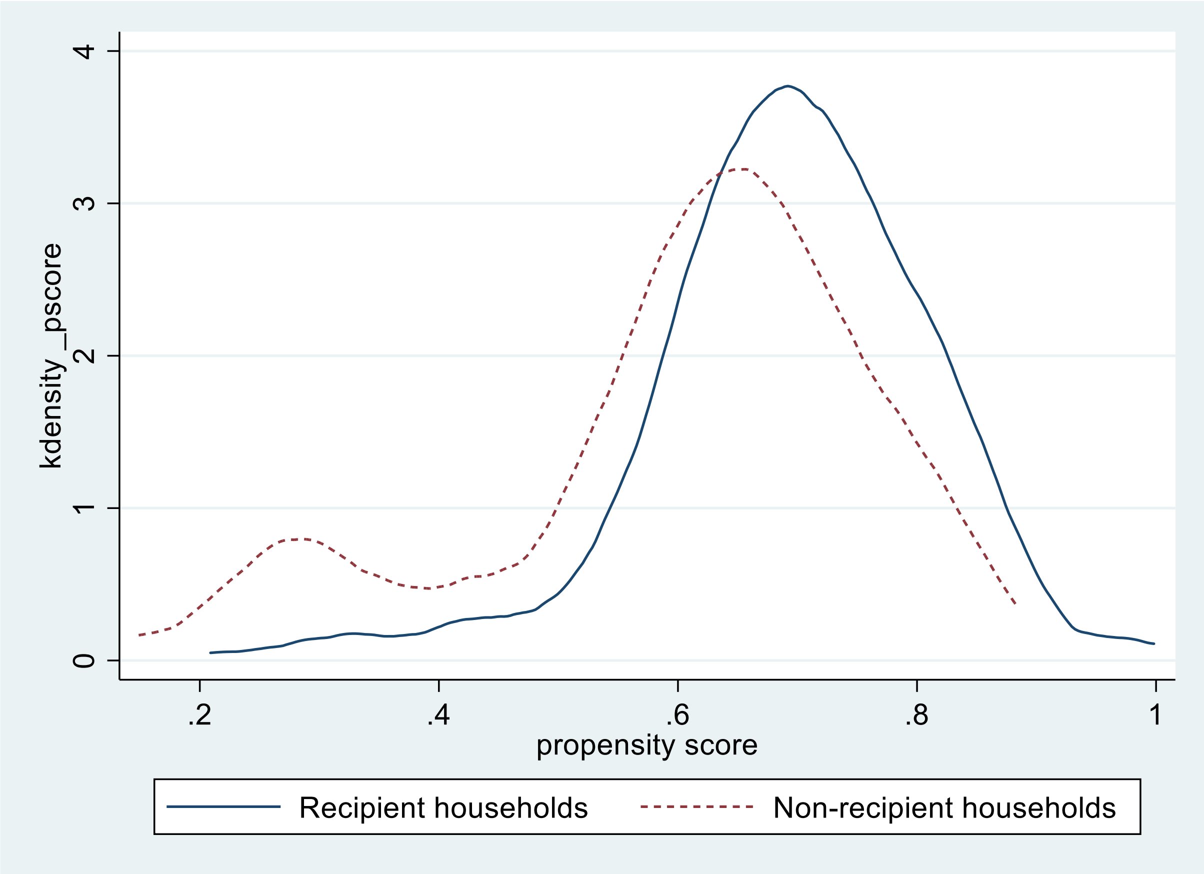

Figure A1: Propensity scores prior to matching
Source: Authors' own calculations based on e-FISP 2015 baseline survey data

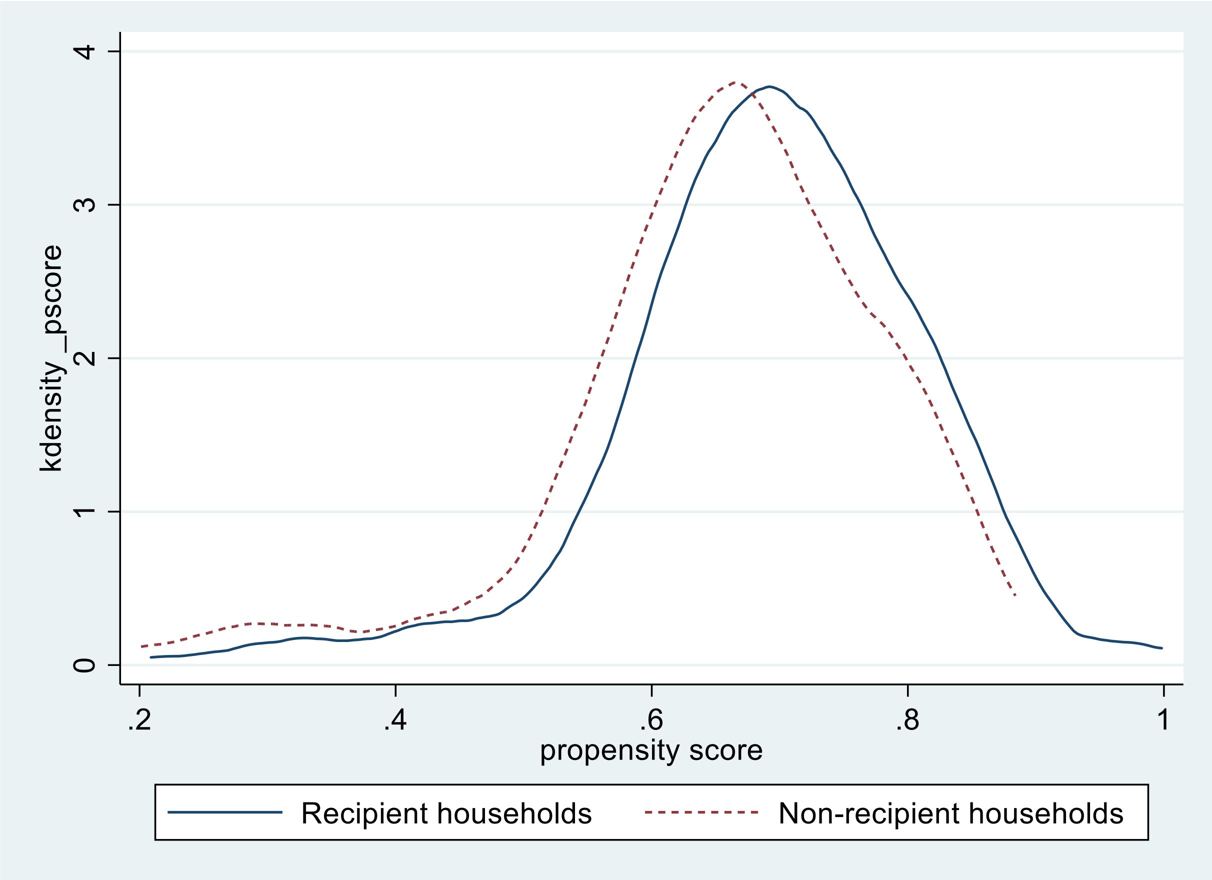

Figure A2: Propensity scores after matching
Source: Authors' own calculations based on e-FISP 2015 baseline survey data

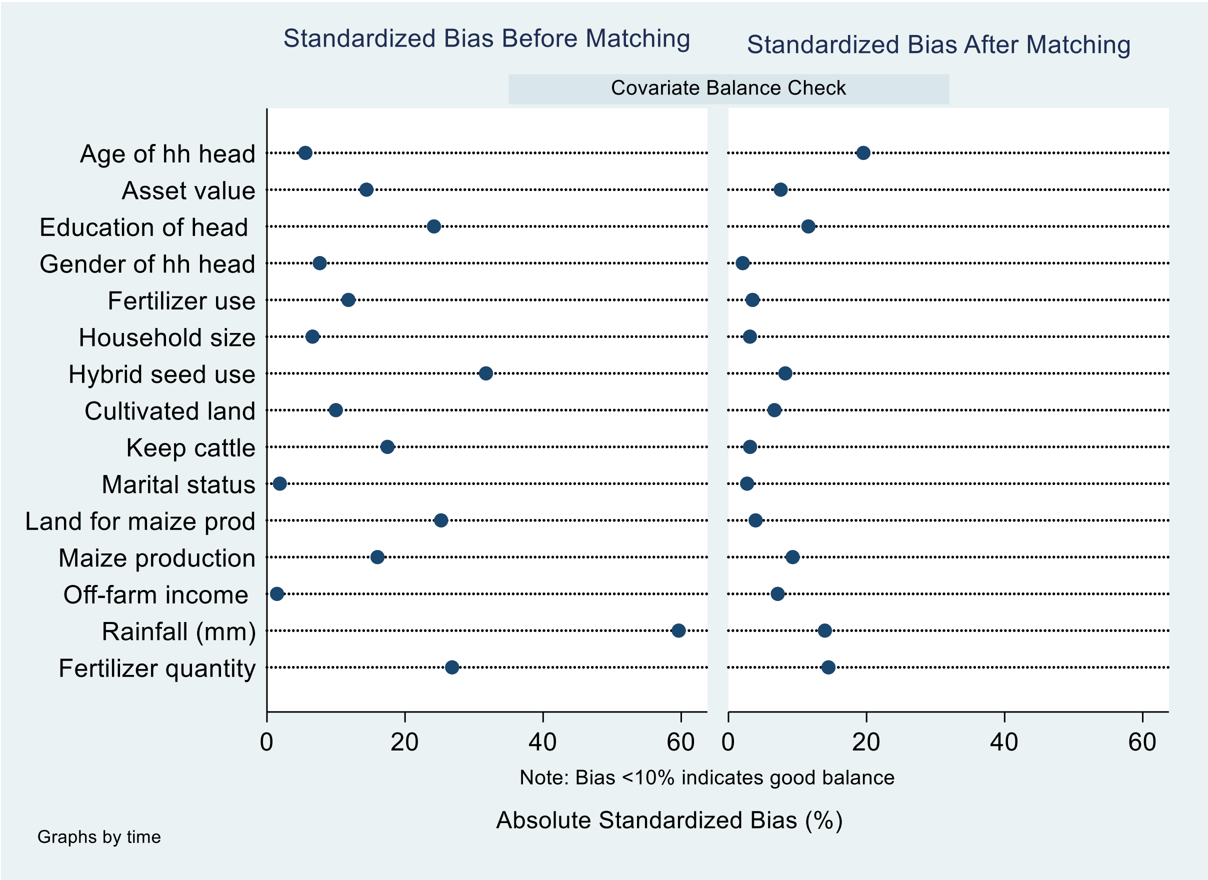

Figure A3: Standardised bias before and after matching

Source: Authors' own calculations based on e-FISP pilot survey data