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Effect of targeted fertiliser subsidy on poverty reduction in Togo

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Abstract

The reintroduction of innovative forms of input subsidies in sub-Saharan Africa (SSA) following the food crisis of 2008 raises concerns about their effectiveness in the fight against poverty. In this context, this paper examines the effect of the targeted fertiliser subsidy implemented in Togo from 2017 to 2019. For this purpose, the propensity score matching and instrumental variables regression approaches were used to control for potential selection and endogeneity bias. Nationwide cross-sectional survey data covering 2 319 smallholder farmers in Togo suggests that participation in the targeted fertiliser subsidy programme significantly improved beneficiaries' poverty status through increased income, leading to a decline in poverty incidence, gap and severity. However, the magnitude of the effect is very small compared to that in some other West African countries. Therefore, to enhance the effect of targeted subsidy policy on income and poverty status, there is a need to improve the rate and composition of the subsidy.

Key words: targeted subsidy, fertiliser, income, poverty, Togo

1. Introduction

It is widely accepted that increased use of productivity-enhancing inputs such as fertilisers is a prerequisite for rural productivity growth and poverty reduction (Wossen *et al*. 2017; Hodjo *et al*. 2021). However, the use of fertilisers and improved seeds in sub-Saharan Africa (SSA) remains among the lowest in the world (Morris *et al*. 2007). Appropriate agricultural investments and the adoption of new agricultural technologies are recommended to maximise the effects of poverty reduction. According to Solaymani (2014), fertiliser subsidy programmes are part of the strategies adopted by countries in sub-Saharan Africa to mitigate the effects of the global food crisis that occurred in 2008. Public investment in input subsidy programmes has increased considerably in the region with the objective of improving the food security of farm households (Wossen *et al*. 2017). According to Hodjo *et al*. (2021), agricultural policies in SSA rely heavily on input subsidy programmes as the primary means of increasing productivity and reducing poverty.

In order to promote the adoption of yield-enhancing technologies such as inorganic fertilisers and improved seeds, many SSA countries implemented large-scale input subsidy programmes throughout the 1970s and 1980s (Jayne & Rashid 2013; Jayne *et al*. 2013). However, with the introduction of the Structural Adjustment Programme (SAP) in the 1980s and 1990s, these universal subsidies were greatly reduced in the region. In particular, under SAP, the World Bank (WB) advised sub-Saharan African countries to phase out input subsidies on the assumption that the private sector could provide them more efficiently through market mechanisms (Ricker-Gilbert *et al*. 2011; Ricker-Gilbert 2014).

However, in the late 1990s and early 2000s, large-scale targeted input subsidies were reintroduced to replace the former universal input subsidy programmes (Jayne & Rashid 2013; Liverpool-Tasie & Takeshima 2013). The Malawi example has been the subject of several works and publications worldwide.

Several empirical studies in SSA have focused on the relationship between subsidies and poverty (Mason & Smale 2013; Wossen *et al*. 2017; Mason *et al*. 2020). However, the results of these studies are often divergent and sometimes ambiguous as to the effects of input subsidies on the well-being of beneficiaries. For example, the study by Wossen *et al*. (2017) in Nigeria found a large improvement in productivity and welfare outcomes. On the other hand, Mason and Smale (2013) found a modest effect on the severity of poverty among agricultural households in Zambia. In general, the contradictory results reported in the literature lie in the different measurement methods used to capture the notion of poverty or well-being. While some authors have evaluated the effect of the subsidy on poverty using the Foster-Greer-Thorbecke (FGT) parameters (Mason *et al*. 2020), others have made use of annual household expenditure or household income instead (Awotide *et al*. 2013; Wossen *et al*. 2017).

Like many SSA countries, Togo implemented a targeted input subsidy project called the 'farmer's electronic wallet' (AgriPME) in 2017. The project was implemented with the objective of promoting agricultural productivity and food security by making fertiliser more affordable for and accessible by smallholders. These increases in productivity and production were expected to subsequently generate higher incomes and give rise to increased food security among smallholder farmers (Zinsou-Klassou *et al*. 2018). The AgriPME fertiliser subsidy targets vulnerable farmers. In addition, the distribution of subsidised fertiliser is handled by state-approved private companies selected on a competitive basis. A subsidy of 22% to 30% on three 50 kg bags of fertiliser (NPK and urea) is provided to beneficiaries through electronic vouchers. There is little empirical evidence of the effect of the targeted subsidy to inform ongoing debates on how effectively the AgriPME project improved the poverty status of smallholders in Togo. Zinsou-Klassou *et al*. (2018) carried out a descriptive analysis of the effect of subsidising fertilisers through mobile money on food security. Yovo (2017) analysed the effect of the removal of subsidies on the profitability and competitiveness of rice production in Togo, and the willingness of farmers to pay for fertiliser at an unsubsidised price. In any case, the analysis of the effect of the fertiliser subsidy on the income and poverty of households in Togo is an area that has not been tackled in the existing literature. This study aims to fill this gap by answering the question of what empirical evidence there is on the effect of Togo's targeted fertiliser subsidy programme on rural poverty. Thus, we empirically test whether a mobile phone-based electronic voucher system for fertiliser subsidies in Togo has improved the poverty status of beneficiaries.

The monetary approach to poverty, based on the Foster-Greer-Thorbecke (FGT) indices, was used to measure the effect on rural poverty. We focused on poverty because it is an important indicator given the objectives of the AgriPME subsidy programme, but also the high incidence of rural poverty in Togo, which is at about 58.8% compared to 26.5% in urban areas (INSEED 2020).

This paper contributes to the literature on input subsidies in several ways: first, by focusing on a new case study or country in the context of the input subsidy debate in sub-Saharan Africa. It explores the persistent question of how and to what extent a smart input subsidy such as AgriPME has an effect on poverty. To date, there is little empirical evidence on the effect of the e-subsidy on poverty status in Togo. This research is therefore one of the first to address this topical issue. Second, in order to examine the robustness of the effects, we employed two alternative approaches – propensity score matching (PSM) and instrumental variables (IV). These methods control for the potential endogeneity of programme participation. For this purpose, the analytical framework of Rosenbaum and Rubin (1983) and Imbens and Wooldridge (2009) was used.

Data from national surveys covering 2 319 agricultural households collected by the Department of Agricultural Statistics (DSID) in 2019 is used. The results indicate modest but statistically significantly effects of the AgriPME subsidy on the income and poverty status of participants. The remainder of the paper is organised as follows: Section 2 provides an overview of the AgriPME project. Materials and methods are presented in Section 3. Section 4 reports the findings and discusses the results, while Section 5 concludes and provides implications for agricultural policy.

2. Overview of the implementation of the targeted subsidy via electronic vouchers in Togo

From 2017 to 2019, Togo implemented a targeted subsidy via mobile money called AgriPME. The mechanism aimed to improve the efficiency of fertiliser distribution to smallholders. It was designed specifically to ensure that subsidies were provided only to vulnerable farmers without intermediaries, and to promote the development of the fertiliser market in Togo through the private sector. The objective of the project was to promote agricultural productivity and food security by making fertilisers more affordable to smallholders. To achieve this objective, the criteria for selecting the beneficiaries of the subsidy were defined. These criteria include: (i) having been resident in the village for the last three (3) years, (ii) being an agricultural worker aged between 18 and 60 years, (iii) having between 0.25 and one hectare of secure cultivable area for targeted food crops (maize, rice, sorghum, millet and vegetables) and being geo-localised, (iv) benefitting from extension services and being receptive to innovations, (v) using improved seeds, (vi) being prepared to reconstitute the subsidised input kit each year, and (vii) having received the guarantee of the village or cantonal project supervision committee. Although the criteria place particular emphasis on vulnerable farmers, difficulties remain in practice in the application of these criteria, as they have remained very vague and fit the profile of a large number of farmers, whereas the number of subsidy vouchers available is often very limited. The supervision of targeting was done on several levels: first, by the cantonal committee, which validates the lists of beneficiaries with the local authorities, and then by the project coordinators, who carry out monitoring and the clearing of the lists. To enable farmers who do not use mobile phones to access the subsidy, mobile sim cards are distributed to them and sponsorship by relatives who are familiar with mobile money has been allowed.

The allocation of targeted subsidies goes through several processes, including awareness raising, identification and registration of vulnerable farmers, creation of mobile money accounts (electronic wallet), sending subsidies to the electronic wallets of eligible farmers via mobile alert, and the purchase of subsidised fertilisers by the beneficiaries. It should be noted that the subsidy covers 22% to 30% of the sale price of a 50 kg bag of fertiliser, and each beneficiary is entitled to a maximum of three bags per year. The total cost of the program is US$ 13.014 million, of which US$ 826.562 thousand is financed by the African Development Bank (AfDB) and US$ 12.188 million by the Togolese government. Table 1 summarises the situation of the number of registrations, the number of beneficiaries, the number of vouchers and the quantity of fertiliser subsidised per crop year.

Table 1: Status of the targeted subsidy via the AgriPME project

Agricultural season	Number of registered farmers	Number of farmers who received the subsidy	Number of farmers who used the subsidy	Quantity of subsidised fertiliser (ton)
2016/2017	79 980	77 536	31 987	4 370.850
2017/2018	75 550	66 186	16 371	2 064.000
2018/2019	198 928	159 832	78 151	11 356.350

Source: CAGIA (2019) activity report

In terms of benefits, the AgriPME programme has made it possible to grant subsidies to more than 150 000 vulnerable farmers and to develop the habit of using ICTs, particularly mobile phones and mobile money, in rural areas. It was also noted that there was better traceability of beneficiaries and increased transparency in the management of the subsidy. Despite these considerable achievements, it should be noted that the programme suffered from some shortcomings and constraints, especially (i) the difficulty of strictly respecting the vulnerability criteria defined in the choice of beneficiaries, (ii) the delay in sending the subsidies on time, (iii) the temporary shortages of fertiliser stocks at supply stores, and (iv) the difficulty of mobilising the supplemented money by some very low-income farmers.

3. Materials and methods

3.1 Model specification

In any evaluation programme, estimating the causal link of a public intervention like input subsidies on various outcomes of interest is in fact a 'wicked problem' (Ricker-Gilbert *et al*. 2013). Because subsidies are rarely distributed randomly across villages and among farmers (Wossen *et al*. 2017), farmers have the choice of participating in the programmes offered to them. As such, identifying the causal effects of an input subsidy programme requires controlling for selection/endogeneity bias from observable and unobservable factors (Wu *et al*. 2010; Wossen *et al*. 2017). Several approaches are found in the literature to identify causal effects in the context of non-experimental data. These approaches include matching techniques, fixed effects, double difference, regression on discontinuity and instrumental variables (IV). The propensity score-matching (PSM) method and IV regression approach are employed in this study, given the cross-sectional nature of our data.

The PSM model is based on the analytical framework of Rosenbaum and Rubin (1983) and Imbens and Wooldridge (2009). The propensity score is defined as the probability of farmer i to be treated, conditional on covariates X.

Two assumptions must be satisfied for the application of the propensity score-matching method. The first is the conditional independence assumption: given a series of observable variables X, participation in the programme intervention does not depend on the potential outcome. The second assumption relates to the condition of the common support. It excludes the perfect predictability of treatment, given observable characteristics X.

In practice, the PSM model estimates the outcome and treatment models as follows: In the first step, we determine the allocation to treatment using a comparison of means, distribution and logistic regression to find the determinants of treatment (subsidy). In order to capture the factors that explain access to the subsidy, we used the following logit model:

$$T_i = \alpha_i + \gamma_i x_i + \varepsilon_i, \tag{1}$$

where T_i is the treatment, x_i is the set of control variables, α_i and γ_i are parameters to be estimated, and ε_i is the error term.

In second step, we estimate the propensity scores and delimit the common support area. The third step is to match the two groups of individuals by indicating the matching method and performing the bias reduction test for the quality of match. Several matching algorithms, such as the nearest neighbour match (NNM), the caliper or radius match, and the kernel match, have been suggested in the literature (Heckman *et al*. 1998; Givord 2014). Each of these methods has its advantages and disadvantages. In practice, it is recommended to test the sensitivity of the results to the method used. This guided the choice of this study to use the three different approaches (nearest neighbour, three nearest neighbours and kernel).

It is important to verify that the distribution of the variables is 'balanced' between the treated and untreated groups. Rosenbaum and Rubin (1983) recommend that standardised bias (SB) and the t-test for differences can be used to check the quality of the match.

The final step is to estimate the effect of the treatment corrected for selection bias. Suppose that the treatment effect is β_i, then Y_i^1 and Y_i^0 are the outcome of farmer i with a subsidy (treatment) and the outcome of a non-participant respectively. Furthermore, suppose that P(X) gives the propensity scores, T is the treatment, which takes a value of one if the farmer participates in the AgriPME programme and zero otherwise, ATT is the average treatment effect on the treated, and X is the set of observable variables. Assuming that conditional independence and the common support condition are met, the propensity score match estimator for ATT is expressed as follows:

$$\beta_{ATT}^{PSM} = E_{P(X)|T=1}\{E[Y^1|T = 1, P(X)] + E[Y^0|T = 0, P(X)]\} \tag{2}$$

Equation (2) reveals that the propensity score match estimator is simply the mean difference of the potential outcomes of the two groups (treated and untreated) over the area of common support.

However, causal identification requires controlling for both observable and unobservable factors that influence participation in the programme and outcomes of interest. Hence, estimates of Equation (2) may yield biased estimates due to biases stemming from unobservable factors (Wossen *et al*. 2017). Therefore, we employed an IV regression approach to control for the potential endogeneity of participation in the AgriPME programme.

However, finding an instrument that satisfies the orthogonality condition is difficult. Instruments traditionally used in the literature include 'number of years the household head has lived in a village' and 'distance to the point of sale of the inputs' (Ricker-Gilbert *et al*. 2011). Following the literature, we used the 'distance to the nearest point of sale of the inputs' as potential instrument for participation in the AgriPME programme. The distance of the household to the point of sale of fertiliser is an indicator of the geographical accessibility of the inputs that could influence a farmer's participation in the programme. We assumed this variable has no direct effect on farm outcome variables, except through its effect on access to subsidy fertilisers. Using this instrument, the two-step least squares (2SLS) to estimate the relationship between programme participation and outcome variables is expressed mathematically below. In the first step, we used the following logit model in order to capture the factors that explain access to the subsidy:

$$SUBV_i = \alpha_0 + \alpha_1 Z_i + \alpha_2 X_i + \varepsilon_i, \tag{3}$$

where $SUBV_i$ represents access to the subsidy, which takes a value of one if the farmer receives and purchases fertilisers using the AgriPME subsidy, and zero otherwise. Z_i is our instrument, which takes a value of one for households that are at a distance of less than 15 km from a point of sale of subsidised fertilisers, and 0 for those that are at a distance of more than 15 km from a subsidised fertiliser outlet. X_i represents the set of socio-economic characteristics of the household and its farm, such as age, gender, level of education, household size, access to extension services, size of the farm and membership of an agricultural cooperative.

In the second step, the outcome equation estimates the effect of participation in the AgriPME programme on income and poverty status. Formally, the empirical specification is presented as follows:

$$\mathrm{Y_i} = \beta_0 + \beta_1 SUBV_{hati} + \beta_2 X_i + \mu_i \tag{4}$$

$SUBV_{hati}$ is the predicted value of accessing the subsidy. μ_i represents the normally distributed error terms for equation (4).

In equation (4) above, the predicted probability of the first-stage treatment is used as an instrument for $SUBV_i$. The instrument should be uncorrelated with the error terms in the estimation equation and correlated with the endogenous variable. A third condition requires the correlation between the endogenous variable and the instrument.

3.2 Outcome indicators

The outcome indicators are related to household income and the Foster-Greer-Thorbecke (1984) poverty metrics. These parameters were chosen for their many advantages. Indeed, they are additively decomposable, which offers the possibility of obtaining them for homogeneous groups of the population (age, sex, etc.). Moreover, the estimates for high degrees of aversion are not influenced by the threshold used, which suggests the robustness of these indices (Foster *et al*. 1984). In addition, these indicators have already been used in several previous studies to measure the impact of subsidies on well-being and poverty (Awotide *et al*. 2013; Mason *et al*. 2016; Wossen *et al*. 2017; Mason *et al*. 2020). These poverty metrics commonly used in the literature include (i) the poverty incidence, (ii) the poverty gap and (iii) the poverty severity (Foster *et al*. 1984). These metrics are calculated from the following formula:

$$P(y_i) = \left(\frac{z - y_i}{z}\right)^{\alpha} \; if \; y_i < z \; and \; 0 \; otherwise, \tag{5}$$

where z is the poverty line, y_i is the income of farmer i and α is a parameter. When α = 0, the index is simply a binary indicator of whether the farmer is below the poverty line or not, and therefore measures the poverty incidence. When α = 1, the index is a measure of the poverty gap. In our situation, it is equal to zero for households whose income is above the poverty line and for the difference in proportion between household income and the poverty line for households below the poverty line. When α = 2, p is equal to the square of the poverty gap, which is used as a measure of the severity of poverty. The poverty severity is the difference of the proportion squared between household income and the poverty line if the household is poor, and zero otherwise. Poverty indicators were calculated based on the poverty line as officially defined in Togo.

3.3 Data source

This study used household survey data collected by the Department of Agricultural Statistics (DSID) in 2019 as part of an effort to evaluate the implementation of the AgriPME project. The sample size was determined by the power test based on standard deviations in relation to field experience. The data contains information from 2 319 farmers obtained after various simulations using the World Bank's optimum design software, made up of 1 350 farmers benefitting from the project and 969 non-beneficiary farmers selected randomly.

3.4 Descriptive statistics

As shown in Table 2, the average household size was about seven members for the whole sample. While comparing household size between AgriPME participants (6.59) and non-participants (6.75), we found no significant difference between the two groups. Moreover, the two groups were similar in term of age and membership of an agricultural cooperative or organisation. On average, there were more women in the group of non-participants. However, we found more literates in the group of participants. We also found a significant difference between the two groups in terms of the number of years the household had resided in the village. We observed that AgriPME participants had better access to credit and improved seeds. Non-participants had more access to extension services than did the participants. Subsidy recipients appeared to be closer to fertiliser selling points than non-recipients, with 48% compared to 33% in the non-participant group.

Table 2: Descriptive statistics

Variables	Full sample (2 319)	AgriPME subsidy beneficiaries (1 350)	AgriPME subsidy non-beneficiaries (969)	Mean difference
Age of head of household	40.44	40.34	40.58	0.24
Gender of household head (1 = female; 0 = male)	0.28	0.27	0.31	0.04**
Education (1 = secondary level, and 0 = otherwise)	0.44	0.49	0.38	-0.10***
Household size	6.66	6.59	6.76	0.16
Number of years of residence in the locality	25.25	23.87	27.17	3.30***
Years of farm experience (number of years)	11.60	10.96	12.50	1.54***
Membership of cooperatives (1 = yes; 0 = no)	0.28	0.29	0.27	-0.02
Distance (≥ 15 km = 1; 0 = otherwise)	0.59	0.52	0.68	0.15***
Use of improved seeds (1 = yes; 0 = no)	0.30	0.33	0.25	-0.08***
Access to credit (1 = yes; 0 = no)	0.166	0.171	0.158	-0.013
Land sown area (ha)	1.930	1.894	1.980	0.085
Access to extension services (1 = yes; 0 = no)	0.294	0.278	0.316	0.038**
Maize production (kg)	1 420.84	1 475.214	1 344.817	130.396**
Agriculture income (FCFA)	240 710.80	243 628.10	236 632.00	- 6 996.11**
Non-agriculture income (FCFA)	116 836.40	117 314.00	116 168.60	- 1 145.34
Total annual income (FCFA)	357 547.20	360 942.10	352 800.60	- 8 141.45**
Poverty incidence (%)	0.56	0.55	0.59	0.05**
Poverty gap (%)	0.31	0.28	0.34	0.06***
Poverty severity (%)	0.21	0.18	0.24	0.05***

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

4. Results and discussion

4.1 Determinants of participation in the AgriPME: Logit model estimates

Table 3 reports the associated logit estimates. The significant of the likelihood ration (LR) chi-square value of 145.98 indicates that the explanatory variables jointly influence access to the AgriPME fertiliser subsidy. These results therefore illustrate socio-economic factors that determine access to the fertiliser subsidy. The age of the head of household has a significant positive effect on access to the targeted subsidy. Women are less likely to benefit from the AgriPME subsidy. This is consistent with the findings of Mustapha *et al*. (2016) in Ghana, namely that access to the subsidy is determined by the gender of the farmer. Farmers with at least a secondary level of education are more likely to benefit from the subsidy. Access to an extension service agent has a negative effect on the probability of purchasing subsidised fertilisers. Similarly, the distance from the producer to the point of sale of the subsidised fertilisers has a significant negative effect on access to the subsidy. On the other hand, farmers with a mobile phone are more likely to benefit from the subsidy. The use of improved seeds and membership of an agricultural cooperative improve the chances of access to the subsidy. However, the number of years of experience and the number of years of residency reduce the chance of accessing the subsidy.

Table 3: Results of logit model estimation of determinants of AgriPME participation

Variables	Coefficients	Z
Age of head of household	0.016	**3.19*** **
Gender of household head	-0.113	-1.09
Educational level	0.238	**2.52** **
Access to extension agent	-0.257	**-2.37** **
Possession of mobile phone	0.957	**5.58*** **
Distance to the fertiliser point of sale	-0.552	**-6.07*** **
Use of improved seeds	0.235	**2.31** **
Access to credit	0.118	0.94
Member of cooperative	0.281	**2.56*** **
Years of farm experience	-0.018	**-2.87*** **
Years of residence	-0.010	**-2.71*** **
Land sown area	0.015	0.60
Household size	0.003	0.28
Constant	-0.629	-2.20**
LR chi^2 (13)	145.98	
Prob > chi^2	0.000	
Pseudo-R^2	0.047	
Number of observations	2 319	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

4.2 Results of propensity score matching (PSM)

Table 4 presents the PSM estimation results for the following outcome indicators: (i) agriculture income, (ii) non-agriculture income, (iii) total annual income, (iv) poverty incidence, (v) poverty gap and (vi) poverty severity. We find a statistically significant effect of participation in the AgriPME programme on smallholder income and poverty status. The results show that participation in the AgriPME programme increased the household agriculture income and total annual income by 9% and 3% respectively. This improvement in income has also translated into a decrease in the probability of falling below the poverty line, as well as a decrease in the gap and severity of poverty. These results corroborate those of Mason *et al*. (2016) and Wossen *et al*. (2017), who found that the subsidy in Kenya and Nigeria respectively contributed to an improvement in the well-being of beneficiary households.

The results also indicate that the different matching methods employed in this study lead to similar conclusions regarding the meaning and statistical significance of the effects of the AgriPME subsidy on all outcome variables. The main difference with these three methods is the magnitude of the estimates. The nearest neighbour matching method provides the highest coefficients and significance rates, while the kernel approach gives the smallest effects and the lowest significance rates in some cases. This may be due to the matching quality, as confirmed by previous research (Wu *et al*. 2010; Mason *et al*. 2016).

Table 4: Effect of AgriPME participation on the outcomes of interest using PSM

Treatment variable = 1 if the household bought the subsidised fertiliser through AgriPME	**Nearest neighbour**			**Three nearest neighbours**			**Kernel**		
	Effects	**Robust std error**	**Z-value**	**Effects**	**Robust std error**	**Z-value**	**Effects**	**Robust std error**	**Z-value**
Agriculture income (FCFA)	1.097	0.16	**6.76*** **	0.096	0.14	**6.67*** **	0.090	0.12	**7.45*** **
Non-agriculture income (FCFA)	0.058	0.26	**2.26** **	0.033	0.23	1.45	0.019	0.23	0.87
Total annual income (FCFA)	0.056	0.11	**4.98*** **	0.040	0.10	**4.22*** **	0.032	0.08	**3.89*** **
Poverty incidence (%)	-0.067	0.03	**-2.55** **	-0.043	0.02	**-1.88* **	-0.036	0.02	**-1.71* **
Poverty gap (%)	-0.064	0.02	**-3.60*** **	-0.047	0.02	**-3.03*** **	-0.044	0.02	**-2.82*** **
Poverty severity (%)	-0.056	0.02	**-3.74*** **	-0.040	0.01	**-3.09*** **	-0.039	0.01	**-3.04*** **

Notes: N = 3 219; *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

The quality of the match is an important factor in the reliability of the results of the PSM approach. We therefore provide some details of the overall covariate balancing and common support. Table 5 presents the overall covariate balancing test before and after matching. Based on the kernel approach, the results reveal that the standardised mean difference for all covariates used in the PSM is reduced from 13.4% pre-matching to 1.3% post-matching. This result implies that matching reduces bias by about 90%. In addition, we rejected the joint significance of covariates post-matching (p-value = 1.00) while the joint significance of covariates was not rejected before matching (p-value = 0.00). Moreover, due to matching, the pseudo-R^2 declined from 0.048 to 0.001.

The above also shows that, for all the different matching methods, the standardised mean bias, pseudo-R^2 and LR chi^2 statistic were reduced after matching. This downward trend indicates that the matching procedures produced a better balance. The kernel matching method shows the best matching quality, while the nearest neighbour method gives the worst. In addition, the joint significance of covariates after matching was rejected for all methods, while it was significant before matching.

The high bias reduction, the insignificant p-values of the likelihood ratio (LR) test after matching, the low pseudo-R^2 and the significant reduction in the mean standardised bias, are indicative of successful balancing of the distribution of covariates between participants and non-participants in the AgriPME. Figure 1 presents the common support region. A visual inspection of the estimated propensity scores indicates that the common support condition is satisfied, as there is overlap in the distribution of the propensity of both participants and non-participants in the AgriPME.

Table 5: Results of matching quality test

Methods	Quality indicators	Before matching	After matching
Nearest neighbour	Pseudo R^2	0.048	0.003
	LR chi^2	150.040	10.940
	Prob	0.000	0.616
	Mean standardised bias	13.400	2.400
Three nearest neighbours	Pseudo R^2	0.048	0.001
	LR chi^2	150.040	3.170
	Prob	0.000	0.997
	Mean standardised bias	13.400	1.400
Kernel	Pseudo R^2	0.048	0.001
	LR chi^2	150.040	1.900
	Probability	0.000	1.000
	Mean standardised bias	13.400	1.300

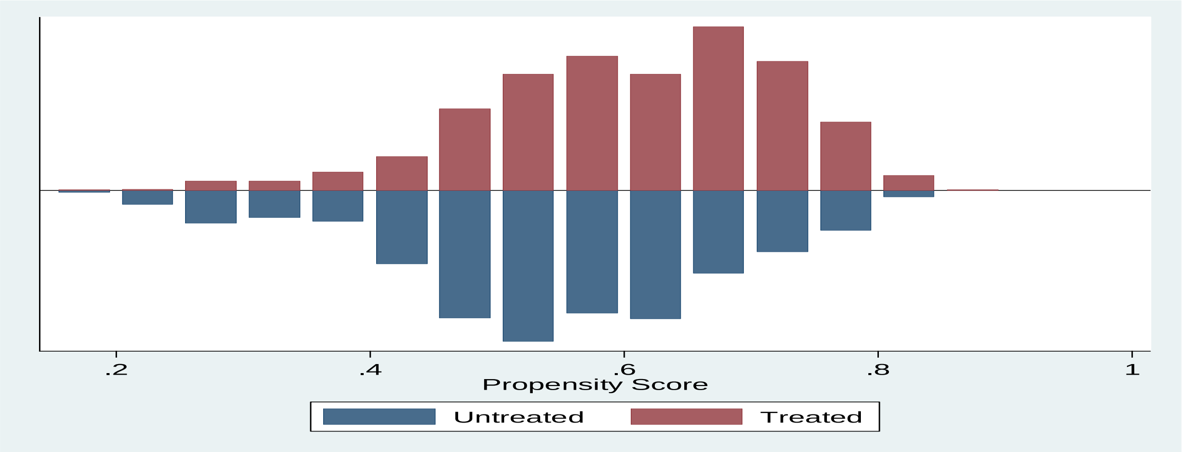

Figure 1: Distribution of propensity scores and area of common support

4.3 Results of instrumental variables (IV) estimation

As mentioned in the methodology section, we used a logit model to examine the determinants of participation in the AgriPME. The results of the logit model presented in Table 3 indicate that the instrument (distance to the nearest point of sale of fertiliser) affects the probability of access to the subsidy. We also found that some characteristics, such as age, education, access to extension service, possession of a mobile phone, use of improved seeds, member of cooperatives, years of farm experience and years of residence in the village, affect access to AgriPME.

Table 6 presents the results of the effects of AgriPME on incomes. These results show that participation in the AgriPME programme has a positive and statistically significant effect on income from agriculture and total annual income. In particular, farmers who participated in the AgriPME increased their total annual income by 8%. This result suggests that the AgriPME programme enables farmers to improve their farm income. It confirms the results reported by Awotide *et al*. (2013), that income inequality declined significantly after the intervention.

Table 6: Effects of AgriPME on smallholder income using IV

Variables	Agriculture income		Non-agriculture income		Total annual income	
	Coef.	P-value	Coef.	P-value	Coef.	P-value
AgriPME	0.056*	0.07	1.165	0.44	0.089**	0.04
Age	-0.001	0.88	-0.029**	0.02	-0.006	0.12
Gender	-0.285**	0.02	0.440*	0.07	-0.203***	0.01
Household size	0.010	0.50	0.045	0.13	0.015	0.13
Education	-0.274**	0.02	0.248	0.28	0.083	0.28
Access to extension services	0.353***	0.00	-0.150	0.56	0.213***	0.01
Use of improved seeds	0.185	0.12	-0.440*	0.07	0.158**	0.05
Access to credit	0.069	0.61	-0.219	0.43	0.052	0.57
Member to cooperatives	0.444***	0.00	0.408	0.11	0.171**	0.04
Years of farm experience	0.019***	0.01	0.015	0.32	-0.004	0.44
Years of residence in the village	-0.003	0.48	-0.023***	0.01	-0.004	0.15
Land sown area	0.326***	0.00	-0.160***	0.01	0.192***	0.00
Constant	10.790	0.00	9.698	0.00	11.930***	0.00
F-test (12, 2 306)	20.76***		5.00***		17.85***	
R^2	0.12		0.05		0.09	
Observations	2 319		2 319		2 319	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

The result showing the effect of the AgriPME subsidy programme on poverty status is presented in Table 7. These results shows that the AgriPME subsidy programme has a negative and statistically significant effect on poverty incidence, poverty gap and poverty severity. On average, these parameters declined by 4%, 7% and 3% respectively. These results are consistent with previous studies. For instance, Wossen *et al*. (2017) found that the Growth Enhancement Support Scheme (GES) programme in Nigeria was effective in improving the productivity and welfare outcomes of beneficiary smallholders. In addition to the direction of the estimated effects, the effect size suggests a modest improvement in poverty status because of participation in the AgriPME programme. This finding, which confirms that of Mason *et al*. (2020) in Zambia, contrasts with that of Wossen *et al*. (2017), whose results indicated a significant improvement in welfare in Nigeria.

Table 7: Effects of AgriPME on poverty status using IV

Variables	Poverty incidence		Poverty gap		Poverty severity	
	Coef.	P-value	Coef.	P-value	Coef.	P-value
AgriPME	-0.041*	0.06	-0.071*	0.08	-0.032**	0.05
Age	0.003***	0.01	0.004***	0.00	0.003***	0.00
Gender	0.108***	0.00	0.060***	0.00	0.041***	0.00
Household size	-0.01***	0.00	-0.010***	0.00	-0.008***	0.00
Education	-0.011	0.64	-0.021	1.85	-0.021	0.11
Access to extension services	-0.080***	0.00	-0.061***	0.00	-0.049***	0.00
Use of improved seeds	-0.061**	0.02	-0.007	0.69	0.002	0.86
Access to credit	-0.031	0.28	-0.019	0.34	-0.011	0.50
Member to cooperative	-0.029	0.26	-039**	0.03	-0.037***	0.01
Years of farm experience	-0.001	0.48	0.001	0.49	0.002	0.09
Years of residence	-0.001	0.71	-0.000	0.60	-0.001	0.88
Land sown area	-0.066***	0.00	-0.048***	0.00	-0.037***	0.00
Constant	0.791***	0.00	0.440***	0.00	0.284	0.00
F-test (12, 2 306)	27.73***		31.79***		27.83***	
R^2	0.11		0.11		0.11	
Observations	2 319		2 319		2 319	

Notes: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

4.4 Discussion

Although the effects are significant in terms of improving the poverty status of beneficiaries, the size of these effects is still quite modest compared to the high poverty rate in Togo. These relatively small effects on poverty indices could be explained by the diversion of fertilisers for other purposes or resale, as mentioned by Ricker-Gilbert *et al*. (2013) in the case of Malawi. This result corroborates those of Mason *et al*. (2020), who also found modest effects in the case of the fertiliser and seed subsidy programme in Zambia. In addition, other reasons, such as the inability of smallholder farmers to convert fertiliser into additional production, late delivery of subsidised inputs, crowding out of commercial demand for fertiliser by the subsidy, diversion of subsidised fertiliser to other uses and lack of improved seed in the subsidy package, could justify these results.

Furthermore, we observed that the magnitude of the effects is relatively smaller in Togo than in other countries, particularly in Nigeria, whose programme greatly inspired the design of that of Togo. In Nigeria, for example, the subsidy reduced the incidence of poverty by 17.7% (Wossen *et al*. 2017). These differences reflect both the design and implementation of the programmes in each country. In Nigeria, the subsidy programme, known as the Growth Enhancement Support Scheme, targeted rural poor farmers who could not afford fertilisers at market prices. It provided a 50% subsidy on two 50 kg bags of fertiliser and a 90% subsidy on a 50 kg bag of improved seeds through electronic vouchers. In Togo, the subsidy targeted vulnerable farmers, but provided a 20% to 30% subsidy on three 50 kg bags of fertiliser and a seed subsidy. Moreover, in the case of Togo, the targeting criteria were not rigorously respected in practice. This latter finding is confirmed by the study conducted by Zinsou-Klassou *et al*. (2018).

5. Conclusion and policy implications

In recent years, many African countries have reinstated fertiliser subsidy programmes in an effort to mitigate food insecurity and poverty. As in other SSA countries, Togo has experimented with the targeted fertiliser subsidy, or so-called ‘smart subsidy’. This article has examined the effect of the targeted fertiliser subsidy on smallholders’ incomes and poverty status in Togo. The propensity score matching and instrumental variable methods were combined to address ‘self-selection’ and potential endogeneity bias. Data from farm households at the national level were used to carry out the analyses on a representative sample of 2 319 farmers. The results indicate that the targeted subsidy has significant effects on beneficiaries’ income and poverty status by raising income, and reducing the incidence of poverty, the poverty gap and poverty severity. However, these effects are modest compared to the results obtained in Nigeria.

In line with the above results, it is important to improve both the design and the implementation of the subsidy programme. Our conjecture, based on our results and speculation from the literature review, is that future subsidy programmes should include improved seeds, define more objective targeting criteria and set a more reasonable subsidy rate according to the socio-economic realities of the beneficiaries.

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