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Does Participation in Ghana's Fertilizer Subsidy Program (GFSP) affect multiple dimensions of food security?

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Abstract

Employing two rounds of pooled data from the Ghana Living Standard Survey (GLSS), a sample of 4,355 maize growing households across the former 10 regions of Ghana, the study evaluates the causal effects of participation in Ghana's Fertilizer Subsidy Program (GFSP) on all the four dimensions of household food security (availability, access, utilization, and stability) for maize growing households. This was done using propensity score matching techniques. The overall average treatment effect of the GFSP is positive and statistically significant for food availability and food access. The GFSP increased maize yield/ Ha between 29 to 34 percent at $p < 0.01$, among program beneficiaries. For food access, the GFSP increased household consumption expenditure by 37 percent at $p < 0.01$. The effect of GFSP on the stability dimension of food security was also positive, though weaker statistically against robustness checks. There was, however, negative effect of GFSP on food utilization. The study points out a not-straight forward relationship between participation in the GFSP and household food security, as food availability may not necessarily leads to better utilization or nutrition. The less impressive performance of GFSP on utilization and stability dimensions imply that maize growing households who benefited from the program are still food insecure.

JEL Codes: Agricultural and Food Policy, Land Economics/Use, Consumer/Household Economics, Environmental Economics and Policy, Farm Management.

1. Introduction

Agricultural input subsidies have once again become central to agricultural development in sub-Sahara Africa (Tsiboe et al., 2021; Ahmad et al., 2022). Recent input subsidies across sub-Sahara Africa have progressed from just improving access to agricultural inputs to being market-smart with emphasis on efficient targeting of beneficiary farmers and the development of private input markets (Jayne et al., 2018; Pauw, 2022). Despite being implemented in various countries, input subsidies remain controversial and debated agricultural policy strategies (Jayne et al., 2018). Input subsidies were common in Africa in the 1960s and 1970s. Their use, however, declined in the 1980s and 90s (Hemming et al., 2018), largely because of inefficiencies, poor targeting and capture by affluent and influential people, stifling the growth of the private input markets (Morris et al., 2007). Unlike in the 70s and 80s, input subsidies seem to have favor with both the multilateral institutions such as the World Bank and the IMF on one hand, and African governments on the other. Input subsidies have also proven to produce visible pay-offs before election cycles. For these reasons, input subsidies will possibly remain in African countries for some time (UNECA, 2018; Walls et al., 2023).

Recent review of empirical studies related to the impact of input subsidies in SSA during periods that they have been argued to be ‘smart’ have revealed that increase in agricultural productivity was only within the short-term. Welfare benefits associated with such programs including reduced food prices, poverty reduction and improved agricultural wages were less than expected (Jayne et al., 2018). For example, Zambia’s subsidy program has not been able to substantially reduce poverty and food insecurity (Zinnbauer et al., 2018; Kaoma and Mpundu, 2023). Poor targeting of beneficiaries, leakages, and diversion of fertilizer have been blamed for the poor performance of Zambia’s fertilizer subsidy program (Zinnbauer et al., 2018). In Nigeria, the program also had minimal effects on the price growth rates for grains between the post planting and post-harvest seasons (Takeshima et al., 2015) though fertilizer use has been found not to be profitable (Liverpool-Tasie et al., 2017). These studies and many others show stronger evidence of associations between input subsidy programs on one side, and poverty reduction and market performance on the other. However, a problem of disconnect emerges which highlights limited evidence on the linkages between agricultural policies (such as fertilizer subsidy programs) and food security and nutrition outcomes. This is despite the important role of agriculture in influencing diets as against the ability of relative food prices to fully explain changes associated with dietary diversity in recent periods (Kadiyala et al., 2014; Singh et al., 2023)

Ghana's FSP introduced in 2008 has the objectives of improving: agricultural productivity, food security, access, affordability and adoption of inputs as well as developing private sector input markets (Houssou et al., 2017; GoG, 2017). In Ghana, fertilizer application significantly explains the differences in yield across maize farms. For example, 22 to 26Kg of additional yield could be achieved from applying one kilogram of additional fertilizer. This explains the importance of making fertilizer affordable through a subsidy program to poor farming households who cannot afford the cost of fertilizer at prevailing market prices. Low adoption rate of fertilizer is still found among farmers in Ghana (Ragasa and Chapoto, 2017). There is also the problem of large scale and well-to-do farmers being the main beneficiaries of Ghana's fertilizer subsidy program. This is contrary to the main goal of the program of supplying subsidized fertilizer to smallholder farmers (Houssou et al., 2017). Few recent studies have, however, highlighted some positive impacts of GFSP (e.g., Iddrisu et al., 2020; Tsiboe et al., 2021; Pauw, 2022).

Iddrisu et al. (2020) found an increase in the subsector productivity of maize, sorghum, and rice by about 8.3%, 5%, and 3.8%, respectively, in 2017. Household consumption expenditure, a proxy for welfare, also increased under the program. Their modeling in calculating household consumption, however, excluded households consuming their own food. This is contrary to what is typical of a smallholder Ghanaian farm household that is largely subsistent. A growth of 42.6 percent in maize output and 43 percent in rice output in 2020 is attributed to GFSP based on the findings of Pauw (2022) who used national output data. However, from a study of 460 rice farmers in the Volta region of Ghana, Vondolia et al. (2021) did not find positive effect of GFSP on productivity among beneficiaries, though farmers who participated in the subsidy program applied fertilizer more by 45 percent. Again, these studies have not linked Ghana's FSP to the multiple dimensions of food security.

Budget allocation to GFSP constituted 20 percent of agriculture's budget in its first year of implementation (2008), 42.36 percent in 2013 and 26.60 percent in 2017 (Tsiboe et al., 2021). Despite this huge financial cost, limited empirical studies exist linking GFSP with food security and nutrition outcomes, especially on the four dimensions of household food security. Where even empirical evidence exists, such evidence is restricted to only one or two dimensions such as output or yield (Iddrisu et al., 2020; Tsiboe et al., 2021; Pauw, 2022) as well total food and non-food consumption expenditures per capita (e.g., Wossen et al., 2017). As input subsidies are on-going programs across SSA, this study may provide lessons for evidence-based decision making by policy makers regarding realigning the objectives of subsidy programs towards achieving food

security and nutrition outcomes, and ultimately the UN sustainable development goals 1 and 2 (no poverty and zero hunger, respectively). Such needed evidence is particularly important at a time when food insecurity persists and is increasing across sub-Saharan Africa (Bjormlund et al., 2021).

1. Conceptual framework and empirical methods

Ghana's fertilizer subsidy program (GFSP) is a nation-wide fertilizer subsidy program targeting smallholder farmers of 2Ha of farmland holding or less (Pauw, 2022). The distribution of the subsidized fertilizer among beneficiaries is, therefore, non-random. To evaluate GFSP's impact on household food security using observational data, propensity scores methods are appropriate when selection bias owing to non-random treatment assignment is a possibility (Rubin, 1974; Rosenbaum and Rubin, 1983; Cameron and Trivedi, 2005) and when estimating average treatment effects of program beneficiaries is the parameter of interest (Cameron and Trivedi, 2005; Caliendo and Kopeinig, 2008). These methods of estimation mostly assume selection on observable variables only (Cameron and Trivedi, 2005). It is, however, required that before estimating treatment effects there is careful testing of the propensity scores (Rubin, 2008; Garrido et al., 2014).

A propensity score is a single score that expresses the probability of a household participating in the GFSP given household's observable socio-economic, institutional and community characteristics such as presence of irrigation schemes and mutual aid schemes in communities (Rosenbaum and Rubin, 1983; Emsley et al., 2008). Selection bias due to confounding from the observed household characteristics which could affect participation in the GFSP is eliminated by adjusting for the scalar propensity score (Rosenbaum and Rubin, 1983). Other methods for removing selection bias due to confounding include stratification, regression methods, or inverse probability weighting (Emsley et al., 2008). The study employs the following propensity score matching techniques: propensity score matching without replacement, nearness neighbor matching, inverse probability weighting, and inverse probability weighted regression adjustment.

Following Hirano et al. (2003) and Kaliba et al. (2021), let T_i represent maize growing households participating in the GFSP and T_i^* is the status of participation that is actually observed. Participation in GFSP (T_i) is binary such that $T_i = t$, and $t \in = \{1,0\}$ represents participation and non-participation of maize growing households, respectively. For each household in the sample $i(i = 1,..., N)$ where N is the sample size, $Y_i,\ T_i,\ and\ X_i$ can be observed, where Y_i is the measure for the dimensions of food security (availability, access, utilization and stability dimensions), T_i is the variable for participation as explained before, and X_i is the matrix of covariates that may explain the food security measures. T_i and X_i are observed for all households in the sample except that Y_i is observed only when $T = 1$. Thus, Y_i is missing at random. We specify the control group (non-participating households) as C_i and the observed outcomes for the control group as Y_j^C and that of the subsidy households as Y_i^T. For each household in the sample, i, only $Y(1)$ or $Y(0)$ is observed but never both. This brings a problem of identification. The unconfoundedness assumption is employed to solve the problem of identification following Rubin (1974), Rosenbaum and Rubin (1983) and Hirano et al. (2003). Thus, conditional on pretreatment covariates, participation in the GFSP is independent of potential food security outcomes. The propensity score matching can be specified as:

$$p(x) = pr[T = 1|X = x]; p(x) = F\{h(X_i)\} \tag{1}$$

where $p(x)$ is the conditional probability measure of treatment participation given household pretreatment covariates, X; $F(.)$ is the normal or logistic distribution and $h(X_i)$ is a function of covariates with linear and higher order terms (Becker and Ichino, 2002). Higher order terms used include age square to obtain an estimate of the propensity score that satisfies the balancing test. Equation 1 was then estimated using maximum likelihood from the logit model following, Cameron and Trivedi (2005). It follows an assumption which requires that conditional on the observed covariates x, impacts of food security outcomes are independent of a household's participation in the GFSP. Thus, there will not be confounding factors as there will not be omitted variable problem once x is included in the regression (Cameron and Trivedi 2005; Abadie et al. 2004). This assumption is often referred to as the Conditional Independence Assumption (CIA) (Rosenbaum and Rubin, 1983; Cameron and Trivedi, 2005), also referred to as selection on observables or unconfoundedness as in Abadie et al. (2004). If this assumption holds, it means that sample selection models or selection on unobservables are not necessary for controlling endogeneity and propensity score and matching estimators can be applied (Cameron and Trivedi, 2005). A second assumption, referred to as the overlap or matching assumption is necessary for identifying some measures of food security impact in the population. The assumption holds that, for each value of the covariate x, there are both participant and control (non-participant) households. There is, therefore, an overlap between the subsidy and non-subsidy households. Thus, for each participating household in the GFSP, there is a matched household who did not participate in the GFSP with similar covariates x (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008). Thus, if all the maize growing households of given covariates decided to participate in the GFSP, there would be no comparison group on similar individuals who decided not to participate in the program against which to compare (Abadie et al., 2004). Matching households on individual covariates of x may be impractical or creates a problem of dimensionality. To address the problem of dimensionality, Rosenbaum and Rubin (1983) proposed that matching is done along the propensity score, $P(X)$, instead of along the individual covariates, x. This restriction ensures that the balancing property test is performed only on observations that overlap, or in other words, found within the common support. This improves the quality of the matches used for estimating the average treatment effect on the treated (ATET) (Becker and Ichino, 2002). The conditional independence and matching or overlap assumptions constitute the strong ignorability assumption (Rosenbaum and Rubin, 1983). The third assumption is the conditional mean independence assumption, which implies the food security outcomes of non-subsidy households does not determine participation (Cameron and Trivedi, 2005). To obtain consistent estimates of treatment effects, the study relied on these three assumptions that permit identification of causal effects between the food security outcomes of subsidy and non-subsidy households (y_{i1}, y_{i0}), respectively.

The sample estimates for the average treatment effect (ATE) and average treatment effect on the treated (ATET), given that probability to participate in GFSP is random and given the pre-treatment covariates and $p(X)$ is also random (Rosenbaum and Rubin, 1983), can be defined, respectively, as follows:

$$\widehat{ATE} = \frac{1}{N_T} \sum_{i=1}^{N_T} [\delta_i, p(X_i)] \tag{2}$$

$$\widehat{ATET} = \frac{1}{N_T}\sum_{i=1}^{N_T}[\delta_i|I_i = 1, (p(X_i)] \quad (3)$$

where $N_T = \sum_{i=1}^{N} I_I$, thus, the number of participating farmers in the sample, δ is the difference between the outcomes of participating and non-participating farmers, y_1 and $y_{0,}$ respectively. According to Cameron and Trivedi (2005), obtaining δ_i is not straight-forward due to an unobserved component in the formulae that requires estimation. However, as noted earlier adjusting for the scaler propensity score is able to remove selection bias due to confounding factors.

The $\widehat{ATET}$ is appropriate when we are considering the average gain for participating among the participants in the context where programs are narrowly targeting beneficiaries (Heckman and Robb, 1985; Heckman et al., 1997). The $\widehat{ATE}$ is most appropriate when participation in a program is universal. It is, therefore, possible to estimate the average gain or impact of participation from a randomly selected sample from the population (Cameron and Trivedi, 2005). The study reports on both the ATE and ATET. This is because though GFSP is universal across the country, specific farmers of 2Ha of land or less under cultivation are targeted, in principle. Though $p(X)$ solves the problem of dimensionality, it is not enough to estimate the ATE of interest since it is a continuous variable. For example, y_i can not be observed for two households that have the same value of $p(X)$. Nearest-Neighbor Matching (NNM) can overcome this problem where treated and control units are matched by taking each treated unit and searching for the control unit with the closest $p(X)$ (Becker and Ichino, 2002). The NNM provides that the non-subsidy household units (y_{i0}) and the subsidy household units (y_{i1}) are matched together with an estimated value of the propensity score, p_i. NNM in a single closet match by a distance between any two households (i and j) can be specified as:

$$y_{i0,} = \min_j ||p_i - p_j|| \quad (4)$$

The NN represents the number of controls matched with the treated observation $i \in T$ by N_i^C and the weights defined as $w_{ij} = \frac{1}{N_i^C}$ if $j \in C(i)$ and $w_{ij} = 0$ otherwise. The matching estimator then becomes:

$$T^Z = \frac{1}{N^T}\sum_{i=T} Y_i^T - \frac{1}{N^T}\sum_{j\in C} w_j Y_j^C, \quad (5)$$

where Z stands for the nearest matching and the number of units in the treated group is represented by N^T; the weights w_j are defined by $w_j \sum_i w_{ij}$. In deriving the variance for the NN estimator, Becker and Ichino (2002) showed that the weights are assumed to be fixed and the outcomes are assumed to be independent across units. The NN match method allows individual observations to be used as a match more than once. It reduces the bias as compared to matching without replacement, but not the variance. Substantial bias could arise due to matching on multidimensional covariates. Subsequently, the study employed the bias adjustment approach. The bias adjustment approach incorporated into the NN match is able to produce estimators with no or limited remaining bias (Abadie et al., 2004). Bias from the estimates of average treatment effects also disappears with increasing sample size. However, the variance is nonzero since the matches remain fixed (Imbens, 2004). Specifying more multiple covariates in the NN method ensures that the matching uses the weighting matrix to define a vector norm. Two choices of the weighting matrices were used in this study; the inverse variance-weighting matrix (IVWM) and the mahalonobis. The IVWM accounts for the differences in the scale of the covariates (Abadie et al., 2004) whereas the mahalonobis accounts for the inverse sample covariate covariance. Following Austin (2009), the standardized differences method was used for testing if the propensity score model has been correctly specified. It does this by comparing the means and prevalence of pretreatment covariates (Rosenbaum and Rubin, 1985; Austin, 2009).

However, Austin (2009) also showed that observing balance in the measured covariates does not mean that the model is correctly specified. He recommends the use of variance ratios to complement the comparison of means between treated and control groups. Variance ratios compare the similarity of the distribution of pretreatment covariates between the treatment and control units in the matched sample. Imai et al. (2008) also recommend the use of higher order moments such as variance to compare pretreatment covariates between treated and untreated units. Consequently, interaction terms of household farm equipment and adult equivalent scale, level of education of household head and membership to a mutual aid scheme, as well as access to agricultural extension services in the year 2017 were employed, in addition to the age squared of a household head as mentioned earlier. A perfectly balanced covariate has a standardized difference closer to zero and variance ratio close to unity (Austin, 2009). It can be observed from

Table 1 that the variance ratio of all the interaction terms is either one or very close to one, implying that the model was correctly specified. The description of the covariates is, however, explained in Table 2.

Table 1: Balancing diagnostics of covariates for propensity score matching

	Standardized	Differences	Variance	Ratio
	Raw	Weighted	Raw	Weighted
Agric_equipment	0.265	0.080	0.746	1.062
Adult_ES	-0.112	-0.090	0.527	1.054
Agri_equip_Adult_ES	0.106	0.070	0.792	0.873
Non_farm enterprise	0.164	0.053	0.088	1.031
Sex	0.082	0.043	0.825	0.906
Farm_size	0.097	0.023	0.097	0.934
TLUs	0.068	0.033	1.380	1.071
Age	-0.037	-0.056	0.439	0.958
Extension	0.361	0.015	0.567	1.017
Mech_use	0.135	-0.051	0.042	0.977
Irrigation	0.137	-0.003	0.372	1.991
Insecticide_use	0.043	0.036	0.014	1.021
Weedicide_use	-0.228	0.061	0.130	0.914
Age_sq	-0.043	-0.058	0.497	0.879
Farm-size__sq	0.007	-0.022	0.116	0.929
Year_2017	-0.546	0.014	0.117	0.991
Educ_Years*Aid_scheme	0.252	-0.017	0.739	1.057
Extension*2017	-0.167	0.000	0.818	1.000

Source: Authors' estimations using GLSS 6 & 7 data

Besides controlling for bias and model misspecification, the study also used two "doubly robust" estimators (IPW and IPWA) to obtain consistent estimators even under circumstances where only one of the models is specified correctly (Robins and Ritov, 1997; Imbens, 2004). Refer to Imbens (2004) and Kaliba et al. (2021) for the model approach of the IPW and IPWA.

2. Data source and description

This study uses the GLSS data for rounds six (data collected in 2013) and seven (data collected in 2017). The Ghana Statistical Service collects the GLSS data with technical assistance from the World Bank. The information covers demographic characteristics, household agricultural production, asset ownership, access to financial services, education, and housing conditions, among others. The GLSS data are not a panel. They are a set of repeated cross-section surveys. Households are the unit of analysis of GLSS data (GSS, 2019). For this study, the pooled sample size for only maize-growing households and who reported expenditure on mineral fertilizer for GLSS6 and GLSS7 is 4,365. The GLSS7 consists of 1,977 and GLSS6 consists of 2,388 maize growing households. Out of the pool, only 481 farm households participated in the GFSP (11%). Thus, 357 maize growing farm households in 2013 as against 124 maize farm households in 2017. The reasons for using pooled data were to increase the sample size and to achieve statistical reliability of the results. Accuracy of the estimated parameters is also achieved with pooled data compared to a single cross-sectional data (Gerdtham et al., 1998; Zieman et al., 2002). Data on the source of fertilizer purchased determined if households participated in the GFSP, following Tsiboe et al. (2021). The source of obtaining subsidized fertilizer was from the government through the Ministry of Food and Agriculture (MoFA). Such fertilizers were always labeled, making it easy for farmers to link subsidized fertilizer to MoFA. Farmers who indicated the private sector (i.e., buying from the open market retail input shops) were considered to have not participated in the GFSP. Households who stated that they got their fertilizer from cooperatives, NGOs, or others were removed from the sample to make the data easier to understand and interpret.

To estimate the dimensions of food security, the study employs food consumption and dietary diversity measures using recall data on foods eaten and their frequency, following Upton et al. (2016) and Sahu et al. (2017). As observed by Upton et al. (2016), food security measurements at the household level from survey data give adequate information regarding individual food consumption. They also have the advantage of accounting for household demographic and socio-economic characteristics as a function of food calorie intake (Pérez-Escamilla and Segall-Corrêa, 2008). Following the definition of food security by FAO (1996, 2008) and the empirical work of Magrini and Vigani (2016), a household's food availability is proxied by the supply of food per unit of farm land under cultivation using maize yield per hectare. Food access is measured using a household's food consumption expenditure per adult equivalent. It has the advantage of taking into account a household's intake of calories and micronutrients. Food utilization is measured using Household Food Consumption Score (HFCS). HFCS is a composite score and has the advantage of incorporating dietary diversity, food frequency, and relative nutritional importance of different food groups consumed by a household (Magrini and Vigani, 2016). Thus, the HFCS is an indicator of both quantity and quality of food consumed by the household (Leroy et al., 2015). Following WFP (2008) and Tiwari et al. (2013), HFCS is calculated as the number of different food groups consumed by the household in the last seven days before the interview, with each group given a weight representing the nutrient density of that food group. The seven food groups used in the study were: "cereals", "roots and tubers", "pulses and legumes", "dairy products, oils and fats", "meat, fish, and eggs", "fruits", and "vegetables". The stability dimension was measured as an additional indicator of household resilience, following Magrini and Vigani (2016), using the availability of food stock at the time of the interview from the previous harvest. Keeping food in stock for household consumption explains coping against food shortages in the future (Magrini and Vigani, 2016). Value of physical assets per adult equivalent was used as an additional measure of household food stability and resilience. This is because households may deplete assets to survive during shocks. Total household expenditure per adult equivalent was used as a proxy for household income only for the purpose of comparison with previous literature (Magrini and Vigani, 2016). It is also considered as a better measurement of well-being compared to household income since household income is more susceptible to seasonal fluctuations and measurement error (Tambo and Wunscher, 2015).

4. Results and discussions

4.1 Descriptive statistics

Descriptive statistics for the surveyed households are presented in Table 2. The level of participation in the subsidy program in 2013 was 14% among maize growing households. This declined to 6% in 2017, following the restructuring of the program. The restructuring ensured that only farmers of land size of 2Ha or less under cultivation, in principle, benefitted from the GFSP.

This was unlike in the past when the program was universally targeted (Pauw, 2022). The level of participation in the overall sample was 11%, indicating that nationwide there was low coverage of the program. The food availability dimension in terms of average yield of maize was 1.5 ton/Ha, still lower than the potential yield of 5.5 tons/Ha (MoFA, 2019). It implies that complementary adoption of technologies such as weedicides and insecticides, for example, is key for bridging this productivity gap. From Table 2, there was about 33% use of insecticides as against 61% use of weedicides. Food access and stability dimensions also increased in 2017 compared to 2013, as shown in Table 2. However, the utilization dimension of food security declined, implying that the diversity of food intake may not necessarily be explained by increases in the access dimension of food security in terms of food and total household expenditures. However, the increase in food access and stability as well as the decrease in food utilization as contained in Table 2 does not take into account both observed and unobserved factors.

Table 2: Definition of variables and descriptive statistics

Variable	**Description**	**2013**		**2017**		**Pooled sample**	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Outcome variables							
Availability dimension	Yield, measured as maize output in Kg per hectare	1932.3	101.63	1000.8	173.74	1530.2	775.96
Food access dimension	Consumption expenditure on food and beverages per adult equivalent in Ghana Cedis (GHS) over a 12-month period	1205.7	121.16	1331.7	125.93	1260.0	123.4
Food access and household welfare/ income	Total expenditure (per adult equivalent) on food and non-food items in GHS	2000.4	190.86	2347	227.6	2150	2082
Food utilization	Composite household food consumption score (HFCS) from specific food groups and their weights	56.6	19.01	46.2	16.6	52.1	18.8
Stability dimension	Food stored from the last harvest (in Kg) at the time of interview	318	1424.5	363	1235	377	1346

Stability dimension	The total value of household assets per adult equivalent in Ghana Cedis)	15	66.6	35	197.1	23.5	139
Socio-economic variables							
Subsidy	1 if the household was part of the fertilizer subsidy from government; 0 otherwise	0.149	0.356	0.063	0.243	0.11	0.313
Sex	1 if head is a male; 0 otherwise	0.824	0.381	0.813	0.39	0.819	0.385
Farm_Size	Size of land allocated to maize (in hectares)	1.096	1.432	1.04	1.948	1.072	1.675
Agri_Equipment	Value of agricultural equipment in working condition (GHS)	178.522	2150.282	290.279	3952.149	226.766	3061.443
Adult_ES	Adult Equivalent Scale	3.987	2.279	4.21	2.453	4.083	2.358
Agri_equip*Adult_ES	Interaction between value of agric. equipment and Adult Equivalent Scale	2.115	2.726	3.234	2.836	2.598	2.829
TLUs	Tropical Livestock Units	1.838	4.789	1.287	4.881	1.6	4.837
Age	Age in years of household head	47.50	15.32	47.62	15.30	48.00	15.32
Non-farm_Enterprise	1 if head of household engages in non-farm enterprise; 0 otherwise	0.335	0.472	0.32	0.466	0.328	0.47
Mech_use	Farm household used farm machinery			0.335	0.472	0.356	0.479
Insecticide_use	Farm households applied insecticide	0.328	0.469	0.32	0.467	0.325	0.468
Weedicide_use	Farm households applied weedicides	0.617	0.486	0.612	0.487	0.615	0.486
Irrigation	1 if the household belongs to a community which has irrigation fields; 0 otherwise	0.094	0.291	0.133	0.34	0.111	0.314
Age_sq	The square of the age of head of household	2572.41	1682.808	2587.72	1605.43	2579.02	1649.79

Extension	1 if agricultural extension officers visit farm households; 0 otherwise	0.977	0.151	0.588	0.492	0.809	0.393
Year_2017	Year of data collection, 1 if 2017; 0 if 2013	-	-	-	-	0.432	0.495
Educ_Years*Aid_scheme	Interaction between years of education and if community had mutual aid scheme	3.904	4.684	2.144	4.075	2.854	4.416
Farm_size_sq	Square of land size allocated to maize cultivation	3.25	20.923	4.877	40.78	3.953	93.83
Extension*2017	A household's access to agricultural extension in 2017	-	-	0.588	0.492	0.254	0.435

Source: Authors' calculations using GLSS 6 & 7 data

The inclusion of variables in Table 1 as noted before, into the propensity score matching techniques are those that influenced both assignment into the GFSP and food security outcomes but not influenced by participation in the GFSP (Caliendo and Kopeinig, 2008). This allows the food security outcomes to be attributed to the effect of participation in the GFSP (Faltermeier and Abdulai, 2009). The covariates employed in the PSM satisfied the balancing property. A visual comparison is contained in Figure 1, indicating the before and after matching. It confirms that the propensity score matching was able to produce very similar subsidy and non-subsidy households. From Figure 1, the differences in distribution before matching (column 1) disappear upon executing the matching procedure (column 2).

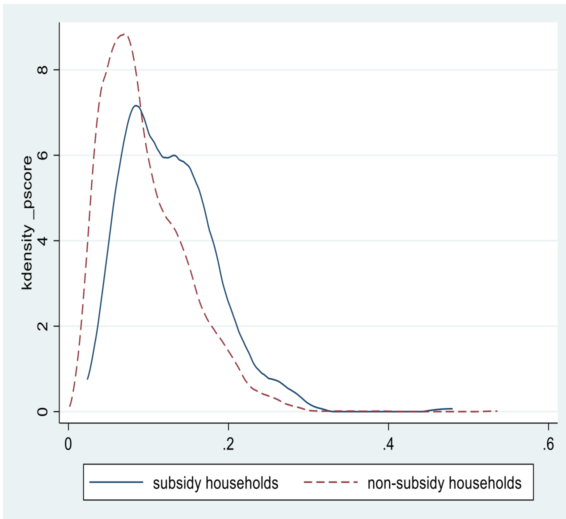
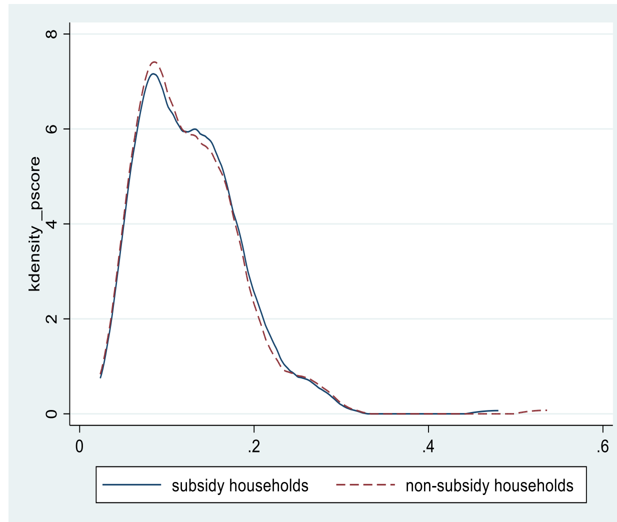
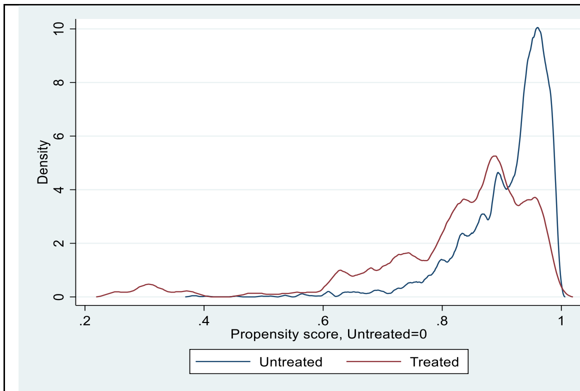
Column 1: Propensity score before matching	Column 2: Propensity score after matching
	

Figure 1: Density of the propensity scores before and after matching

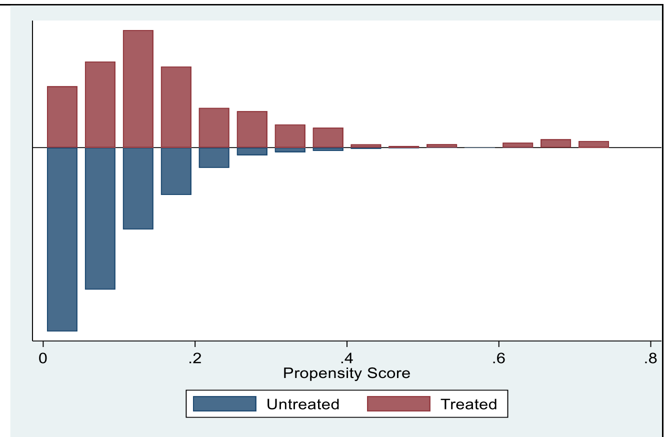
Source: Authors’ calculations using GLSS 6 & 7 data

4.2 Empirical results and discussion

It is recommended to present results on average treatment effects from matching estimators using different approaches (Busso et al., 2014) as it is the case in this study. This requires rigorous testing of the overlap assumption using different techniques that validate one another in obtaining quality matches. After the balancing property test (Figure 1), propensity scores were estimated from the logit model by matching subsidy and non-subsidy households. Figure 2, panel A, shows the estimated density distribution of the predicted probabilities of subsidy and non-subsidy households, indicating the absence of probability mass near zero or one (using the Stata command “teffects overlap”). The respective masses of estimated densities for the two groups mostly occur in regions where they overlap with each other. This implies that the overlap assumption was not violated, and sufficient common support exists between the two different groups of farm households. The overlap assumption is tested further to ensure the quality matches (using the Stata command “psgraph”), as contained in panel B of Figure 2. It also indicates good quality matches between subsidy and non-subsidy households.



Panel A: Common support density distribution for the propensity score, using "teffects overlap".



Panel B: Propensity score distribution and region of common support, using "psgraph".

Figure 2: Propensity score common support distributions

Source: Authors' calculations using GLSS 6 & 7 data

There is also a balance in the covariates employed in the estimated model from the *tebalance overid command* (a chi-squared test of the balance) at $p = 0.5651$, following Austin (2009) and Imai and Ratkovic (2014). It implies that the null hypothesis that the specified treatment model balances the covariates is accepted. Following Lee (2008) and Faltermeier and Abdulai (2009), increased number of covariates including interaction terms as can be observed in Table 2 was used to reduce any likelihood of bias due to unobservable factors remaining after the matching procedure. The maximum likelihood estimates of a household's participation in GFSP from the logit model are contained in Table 3.

Table 3: Logit estimates of participation of Ghana's Fertilizer Subsidy Program

Variable	Coefficient	Standard Error	Marginal effect
Sex	0.210	0.216	0.014
Farm_size	0.162^{***}	0.046	0.011^{***}
Agri_Equipment	0.709^{**}	0.326	0.0477^{**}
Adult ES	-0.118	0.072	-0.01^{*}
Agri_equip*Adult_ES	0.075	0.077	0.01

Non-farm_Enterprise	0.371***	0.132	0.025***
tlu	0.004	0.011	0.000
Age	0.013	0.028	0.001
Mech_Use	0.361***	0.13	0.024***
Insecticide_use	0.356**	0.169	0.024**
Weedicides_Use	0.223	0.227	0.015
Irrigation	0.176	0.188	0.012
Age_sg	0.000	0.000	0.000
Extension	1.904***	0.459	0.128***
Year_2017	-3.683***	0.499	-0.248***
Educ_Years*Aid_scheme	0.011	0.014	0.001
Farm_size_sq	-0.002**	0.001	-0.001*
Extension*2017	2.772***	0.516	0.186***
Constant	-0.49	0.813	-

Source: Authors' calculations using GLSS 6 & 7 data

The results showed that value of agricultural equipment owned by a household, engaging in non-farm income, access to extension in 2017, farm size, use of mechanization and insecticides as well as year of implementation of the subsidy program tended to predict the probability of household participation in the GFSP. However, for sake of brevity, the discussion is focused on whether participation in the GFSP influenced the four dimensions of food security based on the average treatment effects, other than the factors that influenced participation in the GFSP.

The results from Table 4 show the estimates of the average treatment effects using the different matching methods. The nearness neighbour inverse variance-weighting matrix (IVWM) is used as the benchmark estimation. The study reports on IPW and IPWRA as robustness checks. The logarithm of the outcome variables is used in the estimation so the results are interpreted in terms of percentage difference. The results show that the overall average treatment effect of the GFSP is statistically significant across the food security outcomes from the various matching methods.

Results from the IVWM implies that participation in the GFSP in the sample increases household food availability by 18% at 1% level of significance. The ATET result shows 32 percent increase in food availability among beneficiaries of the program. The IVWM uses four (4) matches since it offers the benefit of relying on sufficient information by including observations that are very similar, following Abadie et al. (2004). Matching on two or more continuous covariates may render NN matching estimators inconsistent. A bias-corrected estimator that is consistent was, therefore, employed (Abadie et al., 2004; Abadie and Imbens, 2011). It adjusts the difference within the matches for the differences in their covariate values (Abadie et al., 2004). The results indicate that employing the bias adjustment decreases the coefficient of the estimated ATET to 29%, though still at 1% level of statistical significance. It is not surprising that the ATET coefficient is still higher than that of the ATE since it focuses narrowly on GFSP beneficiaries.

There is stability in the findings of positive impact of GFSP on food availability when consideration is given to the other matching algorithms. For example, the ATE coefficients from the NN Mahalonobis and propensity score matching estimators are almost the same as that of the benchmark estimator. However, the ATET coefficients from the NN Mahalonobis and propensity score matching estimators are slightly higher than the ATE and ATET coefficients from the benchmark estimators. The same can be said about the IPW and IPWRA estimators. Whereas the increase in food availability due to participation in GFSP on both the sample and beneficiaries from the doubly robust estimators (IPW and IPWRA) was positive, 21% and 30% increase at 1% statistical significance for ATE and ATET, respectively, compared to about 19% at 1% level of statistical significance. The consistent finding of positive increase in the availability dimension due to GFSP participation across all the matching algorithms supports the findings of existing literature on the positive impact of GFSP on crop yield in Ghana (Iddrisu et al., 2020; Tsiboe et al., 2021; Pauw, 2022) and fertilizer subsidy programs in sub-Sahara Africa (Ricker-Gilbert and Jayne, 2016).

For the access dimension of food security, participation in the program benefited participants more compared to non-participants in the sample. The estimated IVWM indicates an increase of 58% in household access to food among GFSP participants compared to non-participants in the sample. The estimated IVWM-ATET suggests 37% increase at 1% significance level, on average, in household food access among beneficiaries of GFSP. The bias-adjustment ATET gave a similar value of 37% increase in food access at 1% level of significance. Also estimates from propensity score matching, IPW and IPWRA suggest positive impact of GFSP on food access though with relatively slightly higher coefficients compared to that of the benchmark estimator. For example, the propensity score matching estimator suggests an increase in household access to food by 45% at 1% level of statistical significance. Similarly, both the IPW and IPWRA estimators found 47% increase in household access to food at 1% level of statistical significance. The NN Mahalonobis also showed similar consistent and relatively slightly higher impact of GFSP on subsidy beneficiaries.

Regarding the impact of GFSP on the additional measure of household food access and general household welfare (total household expenditure per adult equivalent), the study finds positive and consistent results across all the matching estimators. The bias-adjustment ATET suggests that participation in the GFSP increased household's food access and welfare by 56% higher than households that did not benefit from the program. The positive impacts of GFSP on both food access and household welfare confirm the income effect of input subsidies. Savings made by farm households due to reduced input costs could be spent not only on purchasing more farm inputs (Ricker-Gilbert and Jayne, 2016) but also on food and total household expenses for improved food security and overall household welfare. This finding is consistent with some other studies that have found positive impact of input subsidies on household food expenditure (Iddrisu et al., 2020) and total household expenditure (Wossen et al., 2017). This finding, however, does not indicate the level and diversity of nutrition and food intake, unlike food consumption score.

Participation in the GFSP has negative and significant effect on household food utilization (measured by food consumption score). This is confirmed by the benchmark estimator which is equal to about 6% at 5% significance level, as contained in Table 4. Thus, participation in the GFSP lowers the probability of a household having to consume foodstuffs from diversified sources by almost 6%. This finding confirms the growing concern that input subsidies in sub-Saharan Africa are concentrating more on mono-cropping systems to the detriment of mixed and intercropping systems (Mason et al., 2013; Levine and Mason, 2014; Ahmad et al., 2023). Smallholder farmers are, therefore, unable to access diversified diet sources since they mostly consume what they grow. The finding of negative impact of GFSP on food utilization is contrary to that of Novignon et al. (2020) who found Malawi's FSP to have increased participating households' dietary diversity, food diversity and micronutrients dietary scores. However, participation in the GFSP positively and significantly increased stability dimension of household food security. The benchmark estimator and the mahalonobis are the only estimators that indicate statistical level of significance. The direction of the coefficients of the other estimators are, however, consistent with that of the benchmark and mahalonabis estimators. The stability dimension of food security is investigated further to see if household food security needs are stable over the long-term, using total household asset value as a proxy. From Table 4, the benchmark estimate suggests an increase by 33% at 1% level of significance among beneficiaries of GFSP compared to those households that did not benefit from the program. When adjusted for bias, the estimated impact reduced to 29%, though still at the 1% level of significance slightly lower compared to the 30% estimates (both ATET and ATET-adjusted) from the mahalonabis estimator. This, to some extent, explains the positive effect of GFSP on improving farm household resilience to vulnerability to food insecurity i.e. during shocks households usually deplete household assets to survive. This finding was, however, weaker in terms of the robustness checks.

Table 4: Treatment effects of participation in the Ghana Fertilizer Subsidy Program (GFSP) on multiple dimensions of food security

Matching algorithm	Food availability dimension	Food access dimension	Food access & household welfare	Food utilization dimension	Stability dimension	Stability dimension
NN IVW						
ATE	0.187*** (0.056)	0.584*** (0.138)	1.666*** (0.128)	-0.0127 (0.03)	0.175 (0.198)	0.05 (0.127)
ATET	0.321***(.0583)	0.379*** (0.131)	1.626*** (0.116)	-0.055** (0.029)	0.483*** (0.18)	0.33*** (0.115)
ATET_adjust.	0.291*** (0.079)	0.373*** (0.131)	1.569*** (0.137)	-0.057** (0.029)	0.342** (0.181)	0.293*** (0.113)
Mahalanobis: Matches (4)						
ATE	0.165*** (0.396)	0.594*** (0.125)	1.648*** (0.064)	0.002 (0.024)	0.217 (0.189)	0.148 (0.112)
ATET	0.319*** (0.056)	0.542*** (0.127)	1.683*** (0.103)	-0.03 (0.03)	0.598*** (0.181)	0.30*** (0.115)
ATET_adjusted	0.319*** (0.056)	0.542*** (0.127)	1.683*** (0.103)	-0.03 (0.03)	0.598*** (0.181)	0.30*** (0.115)
Propensity score matching:						
ATE	0.181*** (0.045)	0.759*** (0.142)	1.756*** (0.077)	0.01 (0.027)	0.093 (0.25)	0.095 (0.128)
ATET	0.343*** (0.087)	0.45*** (0.204)	1.428*** (0.227)	-0.01 (0.041)	0.209 (0.226)	0.060 (0.158)
Inverse probability weighting (IPW):						
ATE	0.217*** (0.042)	0.713*** (0.11)	1.749*** (0.066)	-0.019* (0.033)	0.167 (0.241)	0.161*** (0.28)
ATET	0.309*** (0.052)	0.47*** (0.12)	1.494*** (0.084)	-0.04* (0.04)	0.218 (0.174)	0.149 (0.109)
IPWRA:						
ATE	0.218*** (0.218)	0.713*** (0.11)	1.749*** (0.066)	-0.019* (0.033)	0.167 (0.241)	0.161 (0.128)
ATET	0.309*** (0.052)	0.47*** (0.12)	1.494*** (0.084)	-0.04* (0.03)	0.218 (0.174)	0.149 (0.109)

Note: ***, ** and * denote statistical significance at levels of 1%, 5% and 10%, respectively. Standard errors are in brackets.

Source: Authors' estimation using GLSS 6 & 7 data

5. Conclusion

The study assessed the effect of maize growing household participation in GFSP on the four dimensions of food security (availability, access, utilization, and stability). The study employed pooled cross-sectional data of the GLSS for rounds six and seven. The data is a typical non-experimental one, hence the problem of self-selection bias was addressed using the PSM techniques.

The empirical results indicate the value of households' agricultural equipment, engaging in non-farm income by head of a household, access to extension in 2017, farm size, farm size square, use of mechanization and insecticides as well as year of implementation of the subsidy program influenced the probability of a household's participation in the GFSP. The significant and negative correlation between increasing farm size (farm size square) and participation in the subsidy program indicates a better targeting approach of potential project beneficiaries. It means that farmers with farm sizes greater than 2Ha have not benefitted from the program. However, the positive and significant relationship of the value of agricultural equipment owned by the household and engaging in off-farm enterprise with participation in GFSP, may imply that smallholder farmers who may have 2Ha or less of farmland under cultivation but can afford the full cost of fertilizer are benefitting from the subsidy program. It is therefore important that the subsidy targeting approach is looked at again to consider the value of agricultural equipment owned by households as part of the criteria for selecting GFSP beneficiaries. This will help target most vulnerable farming households and with lesser value of agricultural equipment. Afterall, households with agricultural equipment with higher value such as power tillers and oxen normally rent them out to other farmers to earn extra income which could pay for the full cost of mineral fertilizers.

In addition, the empirical results showed a positive effect of GFSP on the availability dimension of food security in terms of yield. Thus, increased output from maize production is attributable to the GFSP among beneficiaries. Increased maize yield increases the probability of higher food consumption at the household as well as the higher income from the sale of surplus maize. Income from the sale of surplus maize can be used to buy what the household does not produce. Consequently, participation in the GFSP has positive effects on household food access and welfare. This positive effect of GFSP on food availability notwithstanding, the finding from the descriptive results indicating maize yield achieved/ Kg is far below the potential yield calls for vigorous promotion of productivity-enhancing technologies by research and policy makers.

In terms of the stability dimension of food security, GFSP increased both maize stock and household total assets value, with higher effect size (intensity) for food stock. Both maize stock and household total assets value were, however, weaker when the robustness checks were done. Maize growing households may have short-term resilience to food security, resulting from food price hikes and weather shocks since the study finds a mean of about 265Kg of maize in stock. However, prolonged weather shocks or other risky events may deplete this limited stock, reducing the stability effect of the GFSP. It is recommended that government put in place policies that promote non-farm income for smallholder farmers which serve as shock absorbers during crop failure at the same time provide extra income for the purchase of farm inputs.

Finally, the negative effect of the GFSP on the utilization dimension of food security, suggests that increased yield and possibly increased income did not translate into households consuming diversified foods. Households depend more on the staples such as maize and other cereals with less calorie intake from diversified food sources, including vegetables and fruits. This could be as a result of the concentration of subsidy programs on sole cropping systems, instead of promoting crop diversification and mixed farming. The study, therefore, recommends agricultural policies that target improving household food nutrition through crop diversification and mixed farming.

The findings of the study indicate a positive pay-off on government's investment in improving agricultural productivity through the GFSP. The GFSP could move away from the over concentration of mineral fertilizers to include organic fertilizers. As it is common to find mineral fertilizers in all agro-input shops across the country, it should be same for organic fertilizers. This requires that forms of organic fertilizers should be well packaged. Such an approach will sustainably improve soil fertility as crop yields eventually decline with sole application of mineral fertilizers in the long term. There is currently no exit strategy for GFSP despite its financial cost. Government together with NGOs and farmer institutions should encourage adoption of climate-smart Integrated Soil Fertility Management (ISFM) technologies as an alternative to GFSP. Considering the fact that adoption of such technologies is still low among farmers despite positive evidence from experimental fields, effective communication is required by all stakeholders based on empirical evidence of the impacts of adoption of ISFM on food security and other welfare indices from household surveys. Future studies should therefore research into the impacts of the complementarity of ISFM technologies on food security since food security still persists in Ghana and other SSA countries and eliminating food insecurity is key to achieving SDGs 1 and 2 by the 2030 deadline. Such studies should also explore the socio-economic and demographic characteristics of farm households, institutional and community factors that influence the adoption of these technologies. Other requirements for improving food security include environmental awareness and consciousness, adoption of climate smart technologies, SIPs, as well as building the technical know-how of farmers on how to use fertilizers and other inputs. Consequently, beneficiaries of GFSP could also in turn undertake soil and water conservation practices.

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