Journal of Energy and Natural Resource Management (JENRM), Vol. 8, No. 1, 9-16, 2022
10.26796/jenrm.v8i1.189 (Research Article)

Effects of Fertilizer Adoption on Household Welfare: The case of Cereal Farmers in Ghana

Enmanuel Adu Boahen[1*]

Abstract
This paper provides evidence on the causal effect of fertilizer adoption on the welfare of households that cultivate cereals. The data comes from a 2012 survey by the International Food Policy Institute (IFPRI) on farmers in 8 districts of Ghana. A total of 4,521 cereal farmers were retrieved from the dataset. The study adopts a propensity score matching (PSM) technique to compare the welfare of farmers that use fertilizer on their farms to those that do not use fertilizer. Results indicate that fertilizer adoption by cereal farmers leads to significant gains in total expenditure, annual expenditure on food and non-alcoholic products, and value of non-farm assets. The study finds more welfare gains in fertilizer adoption for cereal farmers that cultivate rice, millet, and sorghum but finds inconclusive evidence for farmers that cultivate maize. The study concludes by recommending policymakers to design an effective strategy that will increase fertilizer application on millet, rice, and sorghum.

Keywords
Fertilizer adoption; household welfare; cereal farming; non-farm assets; non-alcoholic products

[1] Department of Entrepreneurship and Business Sciences, University of Energy and Natural Resources, Sunyani, Ghana
***Corresponding author**: emmanuel.boahen@uenr.edu.gh
DOI: 10.26796/jenrm.v8i1.189
Received: 12th June 2021; **Received in revised form:** 18th October 2022; **Accepted:** 05 March 2022; **Published:** 30th April 2022

Contents

1 Introduction **9**
2 Literature Review **11**
3 Materials and Method **11**
3.1 Data and descriptive statistics 12
4 Results and Discussion **13**
4.1 Probability of fertilizer adoption 14
4.2 Identification and validity of the matching 14
4.3 Propensity Score Matching Results 15
5 Discussion and conclusion **21**
References **23**

1. Introduction

The majority of the people in Sub-Saharan Africa's (SSA) livelihood depends on agriculture and most of these individuals are smallholder farmers who produce crop . In West Africa, the crop sector accounts for more than 90 per cent of the total value in agriculture (FAO, 2016). Irrespective of the importance of agriculture to countries in SSA, the sector is dominated by smallholder farmers with little or no knowledge about soil productivity and the wider environmental implications of conventional agricultural practices (Asfaw & Neka, 2017). Proper modern farming techniques such as the use of improved seeds, irrigation, and application of pesticides and fertilizers by these smallholder farmers will increase productivity in the agricultural sector which will improve the welfare of farmers (Kassie et al., 2018; Manda et al., 2016; Abebe and Sewnet, 2014; Kassie et al., 2011; Becerril & Abdulai, 2010). More than half of the active labour force in Ghana is employed in agriculture and the sector also contributes not less than 15% of the country's gross domestic product (FAO, 2016).

Maize, rice, sorghum, and millet are the main cereal crops grown in Ghana and they remain the primary source of energy for many Ghanaians. Although Ghanaians heavily depend on wheat flour for the preparation of bread, cakes, and other pastries, the country does not cultivate wheat as a result of the hot climatic condition which does not favour wheat cultivation (Effraim, 2013). The study, therefore, focuses on the fertilizer adoption of farmers that grow any of the four main cereal crops in the country. Maize accounts for over 50 per cent of the total grains that are cultivated in the country, and it is mostly grown in the middle to the southern part of the country (Darfour & Rosentrater, 2016). Sorghum is the third-highest cultivated cereal after maize and rice in the country. Sorghum and millet are principally cultivated in the northern part of the country. Like many African countries, fertilizer application by cereal growers is very low. A study by FAO (2016) indicates that SSA applies less than 20 per cent of the fertilizer usage per hectare than what farmers in the United States or India apply.

The rapid population growth and urbanisation in Ghana is causing scarcity of farmlands. This has resulted in the transition from fallow-based cultivation to a permanent system of tilling the land. More intensive cultivation of farmland and the rampant deforestation of vegetation for mining activities and settlements with little concern for conservation and poor soil management practices may significantly affect soil fertility (Demeke, 1998) which may lead to low productivity of farmlands and negatively affect the welfare of households that depend on farming. To restore the loss of soil fertility caused by deforestation and intensive utilisation of farmlands, farmers must increase the use of organic and inorganic fertilizers (Demeke, 1998). An application of mineral fertilizers on farmlands will likely reduce food insecurity and improve the welfare of households either directly by raising income from farming or indirectly by reducing prices of foodstuff (Kassie, Shiferaw & Muricho, 2011; Becerril & Abdulai, 2010; Duflo, Kremer & Robinson, 2008; Minten & Barret, 2008).

Several studies show a significant positive impact of fertilizer subsidy programmes or fertilizer adoption on the welfare of smallholder farmers in SSA (Iddrisu et al.,2020; Martey et al., 2019; Kassie et al. 2018; Nyangena and Ogada, 2014; Nata et al., 2014; Matsumoto and Yamano, 2010). Legesse et al. (2019) found that intensive fertilizer application leads to welfare improvement for all household types. They argued that despite that intensive fertilizer application reduces market prices through increase in supply, farmers still gain through increase in yield and consumers also benefits through price reduction . Using Kenya as a country case study, Duflo et al. (2008) experimentally demonstrated that when mineral fertilizer is appropriately utilized, it is highly profitable with mean annual returns of 36 percent over a season.

In the Ghanaian context, Martey (2018) evaluated the impact of organic fertilizer use on welfare using propensity score matching. He found that organic fertilizer adoption significantly increased the log of productivity by 1.43 and crop income by US $132, and reduced food expenditure by US $174. Compared to non-adopters of organic fertilizer, Martey (2018) found that the poverty of organic fertilizer adopters reduced by 8%. In a similar study that evaluated effects of fertilizer use on welfare of Ghanaian farmers, the paper found the fertilizer subsidy programme implemented in 2017 improved productivity of maize, rice and sorghum subsectors of the economy. The paper revealed further that the fertilizer subsidy programme increased household consumption and improved welfare in general (Iddrisu et al., 2020). Employing endogenous switching regression and propensity score matching methods and using farm household survey data from northern Ghana, Martey et al. (2019) found that the adoption of fertilizer by rice growers in northern Ghana significantly improved land productivity by 55% and agricultural income by 30

The emphasis on previous studies in the country that use countrywide data to assess the effect of fertilizer adoption on welfare evaluates the effectiveness of a fertilizer-subsidy programme in the country. On the other hand, studies that are closer to this study either concentrate on a specific locality, district or region or analyse the effect of fertilizer adoption of only one crop. Literature suggests that there is no study that evaluates fertilizer adoption of all cereal growers using nationwide data. It is against this consideration that the present study seeks to investigate whether the welfare of fertilizer adopters of cereal growers is higher than that of non-adopters. Specifically, the general objective would be achieved by first examining whether per capita expenditure on food and non-alcoholic by fertilizer adopters is higher than non-adopters Second, whether per capita expenditure of fertilizer adopters is higher than that of non-adopters. Third, to examine whether the value of non-farm assets of fertilizer adopters is higher than those of non-adopters, and to finally examine the cereal crop that fertilizer adopters benefit from most as regards welfare gains.

Several studies that use non-experimental data to study the effect of fertilizer adoption on household welfare often adopt the quasi-experimental empirical design. This is because farmers with low soil quality or high knowledge in fertilizer application are more likely to adopt fertilizer than those with better soil quality or those who lack knowledge in fertilizer application. This, therefore, suggests that comparing welfare outcomes between fertilizer adopters and non-adopters may yield a biased estimate since there may be other unobserved factors that could affect both fertilizer adoption and the welfare of farmers. To address the endogeneity problem, I used the propensity score matching (PSM) technique because a simple OLS may be biased upwards due to the unobserved factors that affect both fertilizer adoption and the welfare of farmers. PSM technique requires a two-stage regression procedure. In the first stage, the selection into fertilizer adoption is modelled as a choice dependent variable using the probit model, after which the propensity score for each observation is calculated. The same set of covariates are used for both the first and second stage equation. The main variables used to calculate the propensity score for each observation are years of education, age of household head, gender, the value of farm assets, farm size, marital status, if farmer cultivates only cereals, if farmer cultivates cassava, if farmer cultivated groundnut, a dummy indicating. If the farmer has borrowed or wish to borrow, if the farmer operates susu/saving account, the ethnicity of the farmer, if the farmer has non-farm enterprise and the location of the farmer.

The paper is organized as follows: Section 3 provides an empirical framework for the regression analysis. Section 4 discusses the sources of data, definition of key variables, and relevant descriptive statistics. Findings are discussed in sections 5 and 6.

2. Literature Review

In recent years, there has been conscious efforts by successive governments in SSA to promote the use of modern inputs, agrochemicals, and irrigation by farmers to address food insecurity in the sub-region (Sheahan and Barrett, 2017). However, fertilizer adoption in the sub-region is still very low due to lack of agronomic knowledge, high prices of the input, and weak distributional networks (Druilhe and Barreiro-Hurle, 2012). Fertilizer adoption by farmers improve crop yield and household welfare. The benefits are even stronger when there are complementarities in the adoption of fertilizer, improved seeds, mechanization, and natural resource management technologies (see, inter alia, Liverpool-Tasie et al., 2017; Wainaina et al., 2016; Sommer et al., 2013; Kassie et al., 2013; Teklewold et al., 2013; Place et al., 2003)

Fertilizer adoption is low in Africa compared to other developing countries because of higher prices of fertilizers in Africa (Rashid et al. 2013; Zerfu & Larson, 2013). Liquidity constraints and high illiteracy levels that lead to wrong application of fertilizers have also been cited as some of the causes of low fertilizer application in SSA (see, inter alia, Diiro, & Sam, 2015; Yu & Nin-Pratt, 2014; Minten and Barret, 2008). Inefficient application of fertilizer reduces crop responses to fertilizer application and thereby affects profitability as this may lead to low adoption of fertilizers (Legesse et al., 2019). A study in Ethiopia by Yu et al. (2011) finds that the application of fertilizers does not provide a significant gain in crop yield resulting in a lower response to fertilizer adoption by farmers. Other studies have attributed the low adoption of fertilizers by farmers in SSA to the supply of inferior chemical fertilizers in Sub-Saharan African markets. A study in Uganda finds that many of the chemical fertilizers in the Ugandan market have 30 percent of their nutrient missing (Bold et al., 2015). It has been found that age does not have any relationship with fertilizer adoption (Danso-Abbeam & Baiyeguhi, 2019; Tesfay, 2020). Years of education has also been found to be negatively correlated to fertilizer adoption (Tesfay, 2020). Value of farm asset, household size and access to credit has also been found to have a positive correlation with fertilizer adoption (see, inter alia Danso-Abbeam & Baiyeguhi, 2019; Tesfay, 2020; Martey, 2018)

Several studies show a significant positive impact of fertilizer subsidy programmes or fertilizer adoption on the welfare of smallholder farmers in SSA (Iddrisu et al., 2020; Martey et al., 2019; Kassie et al. 2018; Nyangena and Ogada, 2014; Nata et al., 2014; Matsumoto and Yamano, 2010). Legesse et al. (2019) discover that intensive fertilizer application leads to welfare improvement for all household types. They argued that despite the fact that intensive fertilizer application reduces market prices through increase in supply, farmers still gain through increase in yield and consumers also benefits through a reduction in price. Using Kenya as a country case-study, Duflo et al. (2008) experimentally demonstrated that when mineral fertilizer is appropriately utilized, it is highly profitable with mean annual returns of 36 percent over a season.

Danso-Abbeam & Baiyeghuni (2019) studied the effect of fertilizer adoption on the welfare of cocoa growers in Ghana. They employed the propensity score matching (PSM) technique for their study and they found that fertilizer adopters achieved significant gains in farm yields, farm income, consumption expenditure, and value of productive farm assets. A similar methodology is employed by Martey (2018) to study the welfare effect of using organic fertilizers in Ghana. The study finds that the application of organic fertilizer causes an increase in productivity and crop income by 1.43 and \$132 respectively. Disaggregating the results into landholdings and household size, Martey (2018) finds the strongest impact of using organic fertilizer on families with large households. Employing endogenous switching regression and propensity score matching methods and using farm household survey data from northern Ghana, Martey et al. (2019) discover that the adoption of fertilizer by rice growers in northern Ghana significantly improved land productivity by 55% and agricultural income by 30%. Another study that evaluated effects of fertilizer use on welfare of Ghanaian farmers found that, the fertilizer subsidy programme implemented in 2017 by the Government of Ghana increased the cultivation of maize, rice and Sorghum and demonstrated that the fertilizer subsidy programme increased household consumption and overall welfare of farmers (Iddrisu et al., 2020).

3. Materials and Method

Farmers that apply fertilizers in their farms are most likely to be different from those that do not in both observable and unobservable characteristics. The bias that may result from directly estimating the effect of fertilizer adoption on the welfare of farmers by the use of the ordinary least square (OLS) regression technique can be mitigated or address by using PSM. PSM regression technique requires a two-stage estimation procedure. In the first stage, the selection into fertilizer adoption is modelled as a choice dependent variable using the probit/logit model. Suppose Ai is a dummy for fertilizer adoption by a farmer that cultivate cereals and Xi is a vector of the observed independent variables of the farmer, then the PSM model can be specified as:

$$P(A_i) = Pr[A_i = \frac{1}{X_i}] = E[\frac{A_i}{X_i}]; p(X_i) = F\{h(X_i)\} \quad (1)$$

$$P(A_i) = \frac{P - r(p = 1)}{X_i} \quad (2)$$

where F{ · } can be a probit/logit cumulative distribution function. Equation (2) is the probability of fertilizer adoption or the propensity score as defined by Rosenbaum and Rubin (1983). Once the propensity score has been computed, the average treatment effect on the treated (ATT) can be estimated by matching each fertilizer adopter to non-adopter conditioned on similar characteristics, which is the second stage. The matching can be 1 to 1 or 1 to many. The ATT would be the difference in the outcome of the treatment group (fertilizer adoption) with treatment ($Y_i(1)$) and control group(non-adopters) with non-treatment ($Y_i(0)$). Thus, the average treatment effects on the treated can be specified as:

$$ATT = E[Y_i(1) - \frac{Y_i(0)}{A_i} = 1] \tag{3}$$

$$= E[\frac{Y_i(1)}{A_i} = 1] - E[\frac{Y_i(0)}{A_i} = 1] \tag{4}$$

However, equation (3) is only true under the assumption that the conditional independence assumption (CIA) is satisfied. This is achieved under equation (1) where the probability of selecting into fertilizer adoption is conditioned on a given set of observable Characteristics to estimate the propensity scores of adopters and non-adopters. The richer the set of observable characteristics use as independent variables for the model, the more reliable to interpret results from PSM as a causal effect.

In the dataset, the value of household farm assets and non-farm assets is determined by the respondents' valuation of how much they would sell those household items. Though the value of assets is provided by respondents, it can be assumed that the errors in reporting it by respondents are more likely to be random across fertilizer adoption and non-adoption subgroups. Thus, the ATT estimate from PSM for these two variables is unlikely to be biased. In the regression equation, I also controlled for two major crops that most of these cereal farmers cultivate in addition to their cereal crops. In the dataset, Cassava and groundnuts were identified as the two major what?. The dataset shows that 20 percent of the cereal farmers also cultivate cassava and 14 percent of the cereal farmers also cultivate groundnut. It is also important to control for non-farm enterprise in the regression equation since households with non-farm enterprise may earn additional income that may increase household expenditure and at the same time affect fertilizer adoption. The rest of the dummies serve as characteristics of the farmer and household head that may affect the dependent variables.

So far, the matching estimators are based on the conditional independence assumption (CIA), that is selection into fertilizer adoption is based on observable characteristics. However, there is the possibility that an unobserved variable may simultaneously affect selection into fertilizer adoption and farmers' welfare. If that happens a hidden bias may occur and this would cause the ATT from the PSM to be upward bias. The effect of the selection bias that may occur due to unobservable characteristics may be detected by using bounding approach proposed by Rosenbaum (2002) The test statistics determine how strongly an unobserved variable is likely to influence the selection process so that the matching analysis may be undermined (Becker & Caliendo, 2007). The study, therefore, checks the robustness of the estimates obtained from the matching analysis to some possible unobserved confounders that may simultaneously affect both assignments into treatment and outcome variables by using Rosenbaum bound (rbounds) test statics.

3.1 Data and descriptive statistics

The main source of data for this study is taken from a 2013 survey in Ghana by the International Food Policy Research Institute (IFPRI). The survey purposively sampled 8 districts out of the 173 districts that existed in 2013. Those districts were purposively sampled because they were identified through fieldwork as having relatively large numbers of large-scale and medium-scale farmers and also scattered in both the savannah and transitional agro-ecological zones of Ghana. The survey captures the heterogeneity of non-cocoa farming in the country even though it is not a nationally representative sample. Hence, one should be cautious in the generalization of the findings in this paper to all cereal farmers in the country. The survey adopted a two-stage stratified cluster sampling technique. In the first step, the target population was stratified by districts and farm size. After stratification, a simple random sampling technique was used to sample villages within each stratum (i.e. district and farm size category), thus designating the village as the Primary Sampling Unit (PSU). Twenty (20) villages were sampled from each district but some villages were replaced because some selected farmers could not be located during the fieldwork. Farmers were then randomly selected from the PSUs.

Given the interest of this study, only cereal farmers are taken from the IFPRI (2013) dataset. A total of 4,521 cereal farmers who were into cultivation of maize, rice, sorghum, and millet were identified. Out of this total, 1,988 of them adopt fertilizer. Table 1 provides the distribution of cereal farmers categorized into fertilizer adoption. Column (1) of Table 1 provides total cereal farmers categorized into the specific cereal crop they cultivate and their associated percentages. Columns (2) and (3) provide the total sample of farmers that adopt the use of fertilizers and those that do not use fertilizer for each cereal crop. The percentages in the curly brackets in column (2) are for the proportion of fertilizer users of a particular crop to the total fertilizer users. The percentages in the curly brackets of column (3) are similarly explained. From the table, out of a total of 4,521 farmers who are into cultivation of cereals, 3,991 cultivate maize, constituting 88.3% of the total cereal farmers. Similarly, 1,368, 1,355, and 1,368 grow millet, sorghum, and rice respectively. It can be inferred from the table that some of these farmers cultivate more than 1 cereal crop, and this is why the sum of the percentages in column (1) exceeded 100.

Table 1. Distribution of cereal growers into the adoption of fertilizers

	(1)	(2)	(3)
Variable description	**Full Sample** (N=4,521)	**Adopters** (N=1,988)	**Non-adopters** (N=2,533)
Maize growers	3,991	1,870	2,122
	-88.30%	-94.10%	-83.80%
Millet growers	1,368	738	630
	-30.30%	-37.10%	-24.90%
Sorghum growers	1,355	668	687
	-30.00%	-33.60%	-27.10%
Rice growers	1,368	800	568
	-30.30%	-40.20%	-22.40%

Source: Author's calculations from IFPRI (2013) dataset

Table 2 provides descriptive statistics on the choice variables used as dependent and independent variables for the regression estimation. Columns (1), (2), and (3) present mean values for the whole sample, adopters, and non-adopters respectively. It can be observed from the table that fertilizer adopters show favourable outcomes in terms of per capita expenditure than non-adopters. The table shows that the average per capita food expenditure by the farmers in the dataset is 1052.11 Ghana Cedis which is equivalent to ($465.54) in 2013 cedi to the dollar exchange rate.

Table 2. Descriptive statistics

	(1)	(2)	(3)
Variables description	Full Sample (N=4,521)	Adopters (N=1,988)	Non-adopters (N=2,533)
Outcome Variables			
Per capita annual expenditure on food & non-alcoholic	1052.11	982.34	1,106.87
Per capita annual expenditure	1865.75	1,804.01	1,914.13
Value of annual household non-farm asset	8,196.98	8,925.97	7,626.18
Independent Variables			
Years of education of household head	4.25	3.96	4.48
Age of household head	48.65	47.58	49.5
1 if male	0.78	0.83	0.73
Value of farm asset	362.03	522.57	236.04
Size of farm in acres	6.94	7.91	6.17
1 if married	0.73	0.79	0.69
1 if cultivate only cereals	0.32	0.32	0.32
1 if cassava	0.2	0.13	0.27
1 if groundnut	0.15	0.16	0.13
1 if borrowed or wish to borrow	0.48	0.51	0.46
1 if have Susu/Saving account	0.37	0.4	0.34
1 if urban	0.13	0.12	0.13
Ethnicity 1 if Akan)	0.39	0.44	0.35
1 if have non-farm enterprise	0.32	0.35	0.29

Note: Mean of outcome variables are in Ghana cedis. The dollar-Cedi exchange rate in 2013 is $1=GH¢2.26. Source: Author's own calculation based on IFPRI (2013) dataset

The table reveals that per capita expenditures for fertilizer adopters are lower than non-adopters. Similarly, it can be seen from the table that per capital expenditure is higher for non-adopters than adopters. A formal statistical estimation and disaggregation of the sample may provide an understanding of why per capita expenditures

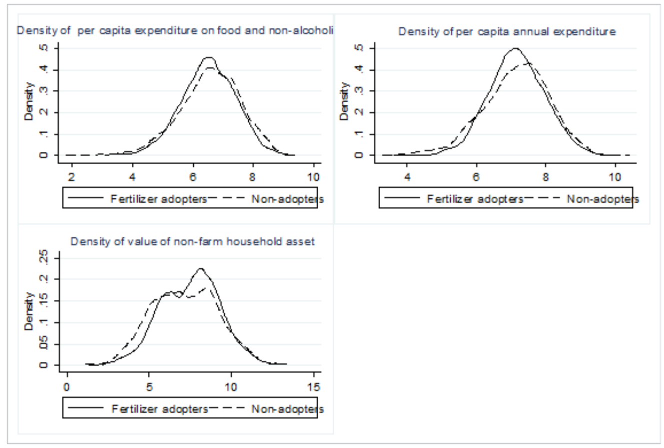

Figure 1. Kernel densities of the five outcome variables in Table 2. Source: Authors estimation based on IFPRI (2013)

of adopters are lower than non-adopters. Figure 1 is a kernel density that shows the distribution of the three outcome variables between adopters and non-adopters. The figure corroborates evidence in part A of Table 2 that fertilizer adopters have lower per capita expenditure on food and non-alcoholic and per capita annual expenditure. More so, the figure affirms that value of household non-farm asset is higher for fertilizer adopters than non-adopters. A regression model would be used to test all these observations from the graphs and Table1.

The result from the second part of Table 2 reveals that fertilizer adopters are averagely younger and have fewer years of schooling than non-adopters. Understandably, young people are more likely to embrace new forms of doing things than the aged. Thus, one should expect younger people to adopt fertilizer in their farming activities than older people. Surprisingly, people with shorter years of education adopted fertilizer usage than those with long years of education. From the table, 83% of fertilizer adopters are males and 73% of the non-adopters are males indicating that men who are into cultivation of cereals are more likely to apply fertilizer than their female counterparts. Compared to non-adopters, fertilizer adopters are more likely to have quality farm assets, bigger farmlands, have borrowed or wish to borrow, have a susu/savings account, and have a non-farm enterprise but they are less likely to live in an urban area or have cultivated cassava. From the table, the percentage of adopters that grows only cereals is the same as non-adopters. The table shows 32% for both adopters and non-adopters that cultivate cereals only.

4. Results and Discussion

4.1 Probability of fertilizer adoption

As explained earlier, farmers who use fertilizer are most likely to be different from farmers who do not use fertilizer, in both observable and unobservable characteristics. Following the examples of Danso-Abbeam and Baiyeghuni (2019) and Martey (2018), the conditional probability of fertilizer adoption can be estimated using probit or logit. The estimated results from the logit or probit regression predict the propensity score of fertilizer adoption. Table 3 reports a probit regression for the determinants of fertilizer adoption. Column (1) reports the coefficient of the probit estimate and column (2) of the table presents marginal effects. Results from the table indicate a negative relationship between age and fertilizer adoption. The results show that one additional year in the age of household head causes a reduction in fertilizer adoption by 0.1 percentage points. The implication from this result is that farmers who are old tend to apply less fertilizer on their farms. This does not mean that as one is aging, one tends to reduce fertilizer adoption but the realistic explanation from the regression result is that fertilizer adoption varies along age-cohorts and younger age-cohorts prefer to use fertilizer than older age-cohort probably because the older cohorts prefer to continue on their old ways of farming. The finding in this paper contradicts earlier studies that found no relationship between age and fertilizer adoption (Danso-Abbeam & Baiyeguhi, 2019; Tesfay, 2020). The sign of the coefficient on years of education is also negative and the marginal effect shows that an increase in education by one year will reduced fertilizer adoption by one percentage points. The results from this study support the findings from Danso-Abbeam and Baiyeguhi (2019) and Tesfay (2020) but contradict the findings from Martey (2018).

The regression results show a positive relationship between fertilizer adoption and non-farm business, borrowed or wish to borrow, and susu/saving account. Danso-Abbeam and Baiyeguhi (2019) found similar results in their study concerning fertilizer adoption and welfare of cocoa farmers. There is no evidence that growing groundnut affects fertilizer adoption or living in an urban area affects fertilizer adoption. Results in the table further reveal that an increase in the value of farm assets increases the probability of fertilizer adoption and the size of farm land also has a positive relationship with fertilizer adoption. A similar finding was realized by Danso-Abbeam and Baiyeguhi (2019) that there is a negative relationship between fertilizer adoption and growing cereals only. Similarly, there is a negative relationship between fertilizer adoption and cereal growers that also cultivate cassava. Since the majority of farmers in the transitional ecological zones that cultivate maize and cassava (mixed cropping) together hardly apply fertilizer, it is therefore not surprising that the regression results from the probit estimate show negative relationship between fertilizer adoption and adding cassava cultivation to cereal production. This result show that the greater the cassava the lesser the adoption

Table 3. Determinants of fertilizer adoption by cereal growers

	(1)	(2)
Variables	*Coefficient*	*Marginal effect*
Years of education of household head	-0.02***	-0.01***
	0	0
Age of household head	-0.001***	-0.001***
	0	0
1 if male	0.26***	0.10***
	-0.06	-0.02
Value of farm asset	0.001**	0.00**
	0	0
Size of farm	0.001***	0.001***
	0	0
1 if married	0.12**	0.05**
	-0.05	-0.02
1 if cultivate only cereals	-0.11**	-0.04**
	-0.04	-0.02
1 if cassava	-0.51***	-0.19***
	-0.06	-0.02
1 if groundnut	0	-0.002
	-0.06	-0.02
1 if borrowed or wish to borrow	0.09**	0.03**
	-0.04	-0.01
1 if have susu/saving account	0.20***	0.07***
	-0.04	-0.02
1 if urban	-0.05	-0.02
	-0.06	-0.02
Ethnicity (1 if Akan)	0.08**	0.03**
	-0.04	-0.02
1 if have non-farm enterprise	0.14***	0.05***
	-0.04	-0.02
Observations	4,521	4,521

Notes: Standard errors are in parentheses below. p-values: *<0.05; **<0.01; ***<0.001. Source: Author's own calculations from IFPRI (2013) dataset

4.2 Identification and validity of the matching

The study performs some checks to evaluate the quality of the matching after predicting the propensity score for fertilizer adoption. The first diagnostic check is a figure to illustrate observations that are on-support and the variables that are off-support. Figure 2 illustrates the density of propensity scores of fertilizer adopters and non-adopters. There is a significant overlap of the propensity scores for both adopters and non-adopters. It can be seen from the figure that only a few observations are off the common support.

As a further diagnostic check on the quality of matching within the support, a test of covariates before and after matching was conducted. Table 4 reports the balancing test of equality of means for all the explanatory variables. Clearly, the test of equality of means for

The unmatched sample shows significance at the 0.01 confidence level for all the variables apart from the urban dummy and the dummy for cultivating only cereals which are not significant. However, the significance in the mean difference between adopters and non-adopters of several of the covariates disappears after matching. Apart from

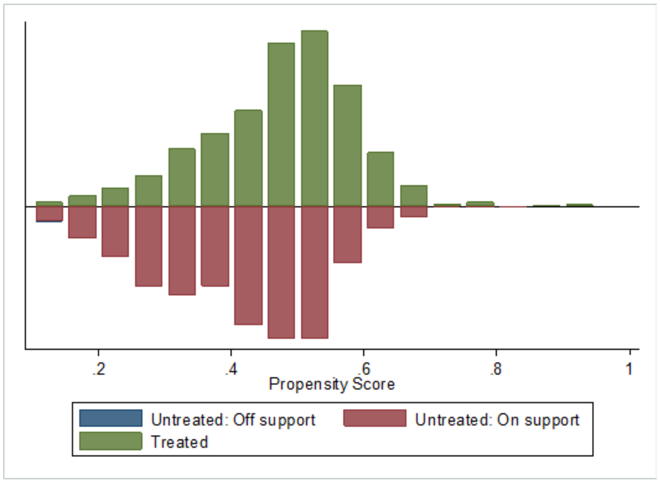

Figure 2. Common support for the density of propensity scores of fertilizer adoption. Notes: Treated on-support indicates that fertilizer adopters have a suitable comparison group (non-adopters). Treated off-support indicates that fertilizer adopters do not have a suitable comparison group. Estimation is done using psmatch2, a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. Source: Author's own calculations from IFPRI (2013) dataset

the value of farm asset, farm size, and non-farm enterprise that are still significant under 5 percent confidence level, the rest of the covariates are all insignificant indicating that conditional on the covariates in the regression equation, fertilizer adopters are comparable to non-adopters after matching. This is so because the balancing test suggests that the two groups are similar in education, age, gender, marital status, growing of only cereals, growing of cassava or groundnuts in addition to cereals, borrowed or wish to borrow, having susu/savings account, urban dummy and ethnicity.

The unmatched sample shows significance at the 0.01 confidence level for all the variables apart from the urban dummy and the dummy for cultivating only cereals which are not significant. However, the significance in the mean difference between adopters and non-adopters of several of the covariates disappears after matching. Apart from the value of farm asset, farm size, and non-farm enterprise that are still significant under 5 percent confidence level, the rest of the covariates are all insignificant indicating that conditional on the covariates in the regression equation, fertilizer adopters are comparable to non-adopters after matching. This is so because the balancing test suggests that the two groups are similar in education, age, gender, marital status, growing of only cereals, growing of cassava or groundnuts in addition to cereals, borrowed or wish to borrow, having susu/savings account, urban dummy and ethnicity.

Table 4. Test for equality of means before and after matching

		Balancing test of the full sample		
Variables	*Sample*	*Treated*	*Control*	*P-value*
Years of education of household head	Unmatched	3.96	4.47	0.001
	Matched	3.96	4.09	0.425
Age of household head	Unmatched	57.6	49.5	<0.001
	Matched	47.6	48.29	0.16
1 if male	Unmatched	0.83	0.73	<0.001
	Matched	0.83	0.81	0.074
Value of farm asset	Unmatched	523.01	234.41	0.001
	Matched	523.01	271.45	0.01
Size of farm	Unmatched	7.92	6.17	<0.001
	Matched	7.92	6.89	0.006
1 if married	Unmatched	0.79	0.69	<0.001
	Matched	0.79	0.76	0.082
1 if cultivate only cereals	Unmatched	0.32	0.32	0.84
	Matched	0.32	0.35	0.07
1 if cassava	Unmatched	0.13	0.27	<0.001
	Matched	0.13	0.14	0.23
1 if groundnut	Unmatched	0.16	0.13	0.005
	Matched	0.16	0.16	0.6
1 if borrowed or wish to borrow	Unmatched	0.51	0.46	0.001
	Matched	0.51	0.49	0.13
1 if have susu/saving account	Unmatched	0.4	0.34	<0.001
	Matched	0.4	0.36	0.01
1 if urban	Unmatched	0.12	0.13	0.17
	Matched	0.12	0.12	0.85
Ethnicity (1 if Akan)	Unmatched	0.44	0.35	<0.001
	Matched	0.44	0.41	0.12
1 if have non-farm enterprise	Unmatched	0.34	0.29	<0.001
	Matched	0.34	0.31	0.03

Notes: Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. Source: Author's own calculations from IFPRI (2013) dataset

dummy and ethnicity.

4.3 Propensity Score Matching Results

4.3.1 Difference in welfare between fertilizer adopters and non-adopters

This section now examines the effect of fertilizer adoption on several outcomes that are used as proxies for welfare. The estimation is done using four different matching methods— nearest-neighbor, kernel, radius, and Mahalanobis-metric matching. Table 5 present the results of the four matching techniques on three different proxies used as a measure of welfare— (1) annual per capita expenditure on food and non-alcoholic, (2) annual per capita expenditure, and (3) value of a household non-farm asset. As standard practice, all the three variables are converted to logarithms before using it in the estimation. The logarithm transformation helps to reduce the noise in the dataset that may affect the size of the standard errors. Standard errors reported in Table 5 are bootstrapped standard errors with 100 replications.

The results in Table 5 indicate that the log of per capita expenditure on food and non-alcoholic for fertilizer adopters is 0.059 lower than non-adopters. The results reported in the table is significant at 5 percent confidence level for nearest neighbour and kernel matching but 10 percent significant for radius and Malanobis metric matching. The magnitude is however the same for all the different matching estimation technique. This suggests that the proportion of per capita expenditure on food and non-alcoholic for fertilizer adopters to non-adopters is 0.94 ((exp (-0.059)) per cent. Thus, on average, per capita annual expenditure on food and non-alcoholic by fertilizer adopters is 6%((exp(-0.059)-1)*100) lower than non-adopters. Similarly, Value of household non-farm asset for fertilizer adopters is 41.2% ((exp(0.3448)-1)*100) higher than non-adopters. However, evidence from the table suggests that annual per capita expenditure of fertilizer adopters is not different from non-adopters. The results are robust for all the different matching estimation techniques. To understand the effect of fertilizer adoption on welfare for each cereal crop, I estimate the ATT for each crop, and these are represented in Table 6-9.

Surprisingly, the ATT for annual per capita expenditure on food and non-alcoholic and annual per capita expenditure is negative. The result from the table therefore suggests that annual per capita expenditure on food and non-alcoholic for fertilizer adopters of maize farmers is 15.8%((exp(-0.1720)-1)*100)lower than non-adopters. Similarly, the per capita expenditure of adopters is 8.9% lower than non-adopters. On the contrary, we can see from the table that value of household non-farm asset for fertilizer adopters is 30.4% higher than non-adopter. Based on the result of the proxies used as welfare indicators, the results from Table 6 suggests inconclusive evidence on fertilizer adoption by maize growers.

The results from Table 7-9 reveal that fertilizer adoption has a positive impact on the welfare of farmers that

Table 5. Impact of fertilizer adoption on the welfare of cereal farmers

	Matching on propensity score			
	(1) Nearest Neighbour	(2) Kernel Matching (Bandwidth=0. 05)	(3) Radius Matching (caliper=0.01)	(4) Mahalanobis-Metric Matching
	ATT	**ATT**	**ATT**	**ATT**
Per capita expenditure on food & non-alcoholic	-0.0590**	-0.0590**	-0.0590*	-0.0590**
	(0.0283)	(0.0281)	(0.0305)	(0.0295)
Per capita expenditure	0.0158	0.0159	0.0159	0.0159
	(0.0246)	(0.0285)	(0.0258)	(0.0237)
Value of household non-farm asset	0.3448***	0.3448***	0.3448***	0.3448***
	(0.057)	(0.058)	(0.059)	(0.0583)

Notes: Bootstrapped standard errors in parentheses below. p-values: *<0.1; **<0.05; ***<0.01. Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. The estimated difference in the proxies for welfare can be converted to a percentage as (exp(ATT)-1)*100 Source: Author's calculations from IFPRI (2013) dataset

Table 6. Impact of fertilizer adoption on the welfare of maize growers

	Matching on propensity score			
	(1) Nearest Neighbour	**(2)** Kernel Matching (Bandwidth=0. 05)	**(3)** Radius Matching (caliper=0.01)	**(4)** Mahalanobis-Metric Matching
	ATT	**ATT**	**ATT**	**ATT**
Per capita expenditure on food & non-alcoholic	-0.1720***	-0.1720***	-0.1720***	-0.1720***
	(0.0292)	(0.0296)	(0.0313)	(0.0292)
Per capita expenditure	-0.0933***	-0.0933***	-0.0933***	-0.0933***
	(0.0297)	(0.0271)	(0.0316)	(0.0266)
Value of household non-farm asset	0.2654***	0.2654***	0.2654***	0.2655***
	(0.0566)	(0.0670)	(0.0611)	(0.0616)

Notes: Bootstrapped standard errors in parentheses below. p-values: *<0.1; **<0.05; ***<0.01. Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. The estimated difference in the proxies for welfare can be converted to a percentage as (exp(ATT)-1)*100 Source: Author's calculations from IFPRI (2013) dataset

Table 7. Impact of fertilizer adoption on the welfare of Millet growers

	Matching on propensity score			
	(1) Nearest Neighbour	**(2)** Kernel Matching (Bandwidth=0. 05)	**(3)** Radius Matching (caliper=0.01)	**(4)** Mahalanobis-Metric Matching
	ATT	**ATT**	**ATT**	**ATT**
Per capita expenditure on food & non-alcoholic	0.3088***	0.3088***	0.3088***	0.3088***
	(0.0502)	(0.0517)	(0.0528)	(0.0465)
Per capita expenditure	0.3997***	0.3997***	0.3997***	0.3997***
	(0.0404)	(0.0499)	(0.0446)	(0.0408)
Value of household non-farm asset	0.4849***	0.4849***	0.4849***	0.4849***
	(0.1099)	(0.0857)	(0.1047)	(0.0858)

Notes: Bootstrapped standard errors in parentheses below. p-values: *<0.1; **<0.05; ***<0.01. Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. The estimated difference in the proxies for welfare can be converted to a percentage as (exp(ATT)-1)*100 Source: Author's calculations from IFPRI (2013) dataset

cultivate sorghum, millet, and rice. The impact is seen to be the largest for farmers that cultivate millet. Taking all the variables that are used as proxies for welfare measurements, the difference in log points of fertilizer adoption and non-adoption on welfare ranges from 0.3088-0.4849, 0.1438-0.3276, and, 0.2394-0.6115 for millet, rice, and sorghum respectively. On the whole, fertilizer adoption has a stronger positive impact on the welfare of farmers cultivating millet, rice, and sorghum but the impact on maize growers is inconclusive. Given that millet, sorghum and rice are mostly cultivated within the northern savannah belt of Ghana and people within this agro-ecological belt are poorer compared to people in the other ecological zone, then fertilizer subsidies and training should be intensified in the northern savannah agro-ecological zone, especially among rice, maize, and sorghum farmers. This may help in improving the welfare of people living in this agro-ecological zone.

Table 8. Impact of fertilizer adoption on the welfare of rice growers

	Matching on propensity score			
	(1) Nearest Neighbour **ATT**	**(2)** Kernel Matching (Bandwidth=0. 05) **ATT**	**(3)** Radius Matching (caliper=0.01) **ATT**	**(4)** Mahalanobis-Metric Matching **ATT**
Per capita expenditure on food & non-alcoholic	0.1438*** (0.0494)	0.1438*** (0.0466)	0.1438*** (0.0479)	0.1438*** (0.0467)
Per capita expenditure	0.2082*** (0.0412)	0.2082*** (0.0427)	0.2082*** (0.0457)	0.2082*** (0.0402)
Value of household non-farm asset	0.3276*** (0.0981)	0.3276*** (0.1035)	0.3276*** (0.1008)	0.3276*** (0.1028)

Notes: Bootstrapped standard errors in parentheses below. p-values: *<0.1; **<0.05; ***<0.01. Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. The estimated difference in the proxies for welfare can be converted to a percentage as (exp(ATT)-1)*100 Source: Author's calculations from IFPRI (2013) dataset

Table 9. Impact of fertilizer adoption on the welfare of Sorghum growers

	Matching on propensity score			
	(1) Nearest Neighbour	**(2)** Kernel Matching (Bandwidth=0. 05)	**(3)** Radius Matching (caliper=0.01)	**(4)** Mahalanobis-Metric Matching
	ATT	**ATT**	**ATT**	**ATT**
Per capita expenditure on food & non-alcoholic	0.2394***	0.2394***	0.2394***	0.2394***
	(0.0474)	(0.0429)	(0.0438)	(0.0495)
Per capita expenditure	0.2848***	0.2848***	0.2848***	0.2848***
	(0.0432)	(0.0482)	(0.0415)	(0.0394)
Value of household non-farm asset	0.6115***	0.6115***	0.6115***	0.6115***
	(0.0966)	(0.1008)	(0.0916)	(0.1140)

Notes: Bootstrapped standard errors in parentheses below. p-values: *<0.1; **<0.05; ***<0.01. Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. The estimated difference in the proxies for welfare can be converted to a percentage as (exp(ATT)-1)*100 Source: Author's calculations from IFPRI (2013) dataset

4.3.2 Sensitivity analysis to unobserved heterogeneity

So far, the matching estimators in PSM are based on the conditional independence assumption, that is selection into fertilizer adoption is based on observable characteristics. However, a hidden bias may occur if there exist unobserved variables that simultaneously affect fertilizer adoption and welfare. Rosenbaum (2002) proposes an estimator to check the sensitivity of the ATT to a hidden bias. The present study, therefore, checks the robustness of the estimates obtained from the matching analysis to some possible unobserved confounders that may simultaneously affect both assignments into fertilizer adoption and the outcome variables by using the Rosenbaum bound (rbounds) test statics. Table 10 reports the test statistics of the rbounds. Although rbounds report both negative significance and positive significance, theory may help to explain which of them is appropriate. Given the assignment variable used in this study, it is more likely that people who are motivated to improve their welfare or have lower soil fertility are more likely to use fertilizers in their farms. This means that the unobserved effect that is likely to threaten the robustness of the ATT is likely to be a result of positive selection and therefore the emphasis of my explanation will be on column (1) of Table 10 where rbounds present the odds of positive selection into an assignment. Clearly, the results of the ATT for the per capita expenditure on food and non-alcoholic are the least robust to any hidden bias. This is because results from the rbounds show that the ATT estimate for per capita expenditure on food and non-alcoholic is questionable. Per-capita annual expenditure and value of non-farm assets are less sensitive to unobserved covariates. The critical level of gamma at which we would have to question our conclusion of a positive effect is between 1 and 1.1 for these two variables—i.e., interpretation of the ATT should be treated with caution if an unobserved covariate caused the odds ratio of treatment assignment to differ between treatment and control cases by a factor of about 1.1.

Table 10. Robustness of the ATT to unobserved heterogeneity using rbounds test

Rosenbaum Bounds for per capita expenditure on food and non-alcoholic						
Gamma	sign+	sign-	t-hat+	t-hat-	CI+	CI-
1	0.1339	0.1339	0.033	0.33	-0.0248	0.0913
1.1	0.7675	0.0016	-0.0213	0.0877	-0.0787	0.1458
1.2	0.992	<0.001	-0.0703	0.1373	-0.1273	0.1949
1.3	1	<0.001	-0.1149	0.1822	-0.1722	0.2407
1.4	1	<0.001	-0.156	0.2243	-0.2141	0.283
Rosenbaum Bounds for per capita annual expenditure						
Gamma	sign+	sign-	t-hat+	t-hat-	CI+	CI-
1	0.0036	0.0036	0.07682	0.0768	0.021	0.132
1.1	0.1986	<0.001	0.0246	0.1287	-0.0317	0.1847
1.2	0.7963	<0.001	-0.0236	0.1764	-0.0794	0.2327
1.3	0.9911	<0.001	-0.0668	0.2204	-0.123	0.2771
1.4	1	0	-0.1074	0.2614	-0.1635	0.3188
Rosenbaum Bounds for value of non-farm assets						
Gamma	sign+	sign-	t-hat+	t-hat-	CI+	CI-
1	0.0594	0.0594	0.0966	0.0966	0.026	0.2186
1.1	0.60005	<0.001	-0.0167	0.2098	-0.1394	0.3319
1.2	0.972	<0.001	-0.1193	0.3126	-0.2457	0.4342
1.3	1	<0.001	-0.2169	0.4064	-0.343	0.5289
1.4	1	<0.001	-0.3062	0.4929	-0.4325	0.6173

Notes: gamma = log odds of differential assignment due to unobserved factors. sig+ = upper bound significance level sig- = lower bound significance level. t-hat+ = upper bound Hodges-Lehmann point estimate t-hat- = lower bound Hodges-Lehmann point estimate. CI+ = upper bound 95% confidence interval, CI- = lower bound 95% confidence interval. Estimation is done using rbounds a user-written command by Markus Gangl of Social Science Center-Berlin. Source: Author's calculations from IFPRI (2013) dataset

4.3.3 Robustness checks

This section discusses the robustness of the results with respect to two considerations. First, I present the results of farmers who cultivate only cereals on their farm(s). This exercise is useful because if farmers that cultivate cereals and other crops are not distributed evenly between adoption and non-adoption, our estimate will be biased since household expenditures can also be done with incomes generated from the sale of other crops. Second, I present results on farmers who cultivate only cereals on their farm(s) and also do not operate non-farm enterprise. This way, we can argue that the only source of income for these farmers is income from the sales of cereal production, and hence, their expenditures will necessarily depend on income from cereals only.

4.3.3.1 Difference in welfare between fertilizer adopters and non-adopters for farmers who cultivate only cereals

Out of the total cereal growers of 4,521, only 1,446 cultivate cereals only. Table 11 presents the results of the effect of fertilizer adoption on the welfare of these 1,446 farmers who cultivate cereals only. From the table, the estimated results presented are slightly different in magnitude from the baseline results reported in Table 5. For example, the ATT in Table 11 shows that the effect of fertilizer adoption of value of household non-farm asset is 0.2237 log points. This result is slightly different from the results obtained in the baseline estimate. While the baseline estimate suggests that fertilizer adopters' expenditure is 41.2% higher than non-adopters, the estimate in Table 11 suggests 25.1%. Similarly, the difference in per capita expenditure between adopters and non-adopters is 0.0519 log points for the baseline estimate and 0.1185 for that of Table 11. The results on per capita expenditure on food and non-alcoholic differ from the baseline estimate significantly.

4.3.3.2 Difference in welfare between fertilizer adopters and non-adopters for farmers who cultivate only cereals and also do not have non-farm enterprise

As a further check on the robustness of the ATT estimate, I used farmers whose only occupation is growing cereal crops only and do not have non-farm enterprise. In this way, the only source of income from the farmer is likely to be the income that he/she generate from the cultivation of cereals. Out of the total of 1,446 farmers who cultivate only cereals, 963 of them do not have non-farm enterprise. The ATT results presented in Table12 is based on these 963 farmers that do not have non-farm enterprise and also cultivate only cereals. The magnitude of the results in

Table 12 is closer to the baseline estimate. For example, while the difference in value of household non-farm asset for adopters and non-adopters is 42.2% for the baseline estimate, it is 31% in table 12. Like Table 11, a similar pattern is observed in Table 12. By comparing Table 11 and Table 12 to the baseline estimate in Table 5, one can conclude that the ATT results are robust, especially the results for per capita expenditure and value of non-farm household asset.

Table 11. Impact of fertilizer adoption on the welfare of farmers that cultivate only cereals

	Matching on propensity score			
	(1) Nearest Neighbour	**(2)** Kernel Matching (Bandwidth=0. 05)	**(3)** Radius Matching (caliper=0.01)	**(4)** Mahalanobis-Metric Matching
	ATT	**ATT**	**ATT**	**ATT**
Per capita expenditure on food & non-alcoholic	0.0076	0.0076	0.0075	0.0075
	(0.0527)	(0.0472)	(0.0527)	(0.0515)
Per capita expenditure	0.1185***	0.1185**	0.1185***	0.1185***
	(0.0432)	(0.0529)	(0.0432)	(0.0475)
Value of household non-farm asset	0.2237**	0.2237**	0.2237**	0.2237*
	(0.1016)	(0.1111)	(0.1034)	(0.1166)

Notes: Bootstrapped standard errors in parentheses below. p-values: *<0.1; **<0.05; ***<0.01. Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. The estimated difference in the proxies for welfare can be converted to a percentage as (exp(ATT)-1)*100 Source: Author's calculations from IFPRI (2013) dataset

Table 12. Impact of fertilizer adoption on the welfare of farmers that cultivate only cereals and do not have farm enterprise

	Matching on propensity score			
	(1) Nearest Neighbour	(2) Kernel Matching (Bandwidth=0. 05)	(3) Radius Matching (caliper=0.01)	(4) Mahalanobis-Metric Matching
	ATT	**ATT**	**ATT**	**ATT**
Per capita expenditure on food & non-alcoholic	0.0728	0.0728	0.0728	0.0728
	(0.0658)	(0.0656)	(0.0672)	(0.0634)
Per capita expenditure	0.1829***	0.1829***	0.1829***	0.1829***
	(0.0654)	(0.0553)	(0.0571)	(0.0658)
Value of household non-farm asset	0.2676**	0.2676**	0.2676**	0.2676**
	(0.0935)	(0.1361)	(0.1226)	(0.1188)

Notes: Bootstrapped standard errors in parentheses below. p-values: *<0.1; **<0.05; ***<0.01. Estimation is done using psmatch2 a user-written command by Edwin Leuven of the University of Oslo and Barbara Sianesi of Institute for Fiscal Studies, U.K. The estimated difference in the proxies for welfare can be converted to a percentage as (exp(ATT)-1)*100 Source: Author's calculations from IFPRI (2013) dataset

5. Discussion and conclusion

The analysis in this paper compares the welfare of fertilizer adopters to non-adopters who share similar observable characteristics such as age, education, ethnicity, gender, having a non-farm enterprise, size of farm, the value of farm asset, having cultivated cassava and groundnut. The study adopts per capita expenditure on food and non-alcoholic, per capita expenditure and value of household non-farm asset as proxy variables to represent welfare. The welfare literature that has focused on the impact of fertilizer adoption on welfare has consistently reported a positive relationship between fertilizer adoption and welfare (see, inter alia, Iddrisu et al.,2020; Martey et al., 2019; Kassie et al., 2018; Manda et al., 2016; Abebe and Sewnet, 2014; Kassie et al., 2011). Some studies have found the importance of fertilizer adoption on welfare for tree crop growers (Danso-Abbeam & Baiyeghuni, 2019). Specific to cereal crops, several studies have found fertilizer adoption to improve welfare (see, inter alia, Iddrisu et al., 2020; Martey et al., 2019; Martey, 2018). Although, Iddrisu et al. (2020) have conducted a study in Ghana that evaluates the impact of fertilizer-subsidy on welfare of cereal growers, the emphasis of their study is slightly different from this study as the focus of their study is on the policy but not on adoption. A closer study to this paper is Mantey et al. (2019) which studied fertilizer adoption on welfare of maize growers in Ghana. Results from this investigation add to literature by providing the benefits of fertilizer adoption on welfare of farmers of four different cereal crops and also evaluates the welfare benefit of adopters of each cereal crop. The results and implications of the study is discussed in more detail below.

The study shows that fertilizer adoption has a significant effect on welfare of farmers growing cereals. For example, the average effect of adoption of fertilizer on value of household non-farm asset for cereal growers is 41.2 percent higher than those who do not apply fertilizer and this is similar to the findings by Martey et al. (2019) who find that fertilizer adoption increases household farm income by 44%. In the case of maize growers, adoption of fertilizer increases the value of household asset by 30.4% and this result is similar to the findings of Danso-Abbeam & Baiyeghunhi (2019) who find that fertilizer adoption increases value of household non-farm asset by 24.1%. Since the non-farm assets include but not limited to the value of television sets, radio, chairs, bed etc., it can be deduced that fertilizer adoption improve the welfare of cereal farmers.

Regression results from the study show that per-capita expenditure on food and non-alcoholic by cereal farmers who apply fertilizer to their farms is lower than those who do not apply fertilizer. Further analysis by dividing the sample into the four specific cereal crops reveals that fertilizer adoption has a negative effect on per capita expenditure and per capita expenditure on food and non-alcoholic for maize growers and this finding is similar to a similar study by Martey (2018) who also found a lower total expenditure on food and non-alcoholic for fertilizer adopters of maize farmers. On the contrary, the results suggest that fertilizer adoption has positive impact on per capita expenditure and per capita expenditure on food and non-alcoholic of farmers that cultivate sorghum, millet and rice. The impact is seen to be strongest for farmers that cultivate millet. Per capita expenditure may include but not limited to expenditure on food, education and transportation. However, per capita expenditure of fertilizer adopters may also include expenditure on fertilizers and this may affect this variable as a proxy for welfare since non-adopters will not spend on fertilizer. In fact, expenditure on fertilizers cannot be use as a proxy for welfare. Although, expenditure on food and non-alcoholic may not capture important welfare variables such as tourism, education etc., it also excludes expenditure on fertilizers which only affect expenditure made by fertilizer adopters. Thus, both per capita expenditure and per capita expenditure on food and non-alcoholic provides a unique contribution on how fertilizer adoption influence welfare.

Combining the results from Table 5-9, it can be deduced that fertilizer adoption improves the welfare of farmers that cultivate sorghum, rice and millet. Thus, this finding corroborates the study by Iddrisu et al. (2020) who found that the 2017 fertilizer subsidy programme in Ghana improves the welfare of farmers that cultivate maize, sorghum and millet and that of Martey et al. (2019) who found fertilizer adoption to improve the welfare of rice farmers. On the other hand, the evidence from Table 5-9 suggests that the impact of fertilizer adoption on the welfare of maize farmers is inconclusive. This finding contradicts the evidence by Legesse et al. (2019) who adopted a micro simulation to study the effect of fertilizer use on welfare of Ethiopian maize farmers and found a positive welfare impact of fertilizer adoption on welfare of both Ethiopian maize farmers and consumers.

There are few limitations to this study. First, the identification of the empirical model strongly relies on the selection on observables and therefore any unobserved uncounfounding effect may cause our estimate to be bias. For example, an important variable like the motivation of an individual to improve his/her welfare is unobserved. However, a variable like this can affect both welfare and fertilizer adoption and this positive selection can affect the magnitude of ATT results. Nevertheless, the rbounds sensitivity test suggests that per capita expenditure and value of household non-farm asset that were used as proxies for welfare are less sensitive to unobserved confounders. Second, the use of cross-sectional data for causal inferences may be problematic as relevant time-variant variables cannot be captured with cross-sectional data. Thus, the study is limited in terms of its inability to test the dynamics of fertilizer adoption. Third, using the quantity of fertilizer per acre of land would have been more appropriate than the use of the adoption variable which is a dummy. In view of these weaknesses identified in this study, a careful interpretation of the findings from this study still provides an important contribution to literature.

The majority of farmers in Ghana are below the poverty line. This study provides evidence that fertilizer adoption by cereal growers is likely to improve their welfare. Given a very strong impact of fertilizer adoption on the welfare of farmers that cultivate millet, rice, and sorghum. The government and other development partners should therefore design policies that would increase fertilizer application of farmers that cultivate these three crops. Such a policy is likely to improve the welfare of people within the savannah belt of the country since these three crops are mostly cultivated within this agro-ecological zone. Given that people within this agro-ecological zone are poorer when they are compared to those in the other ecological zones, any policy that seeks to increase fertilizer adoption in these three crops is likely to reduce the welfare gap between people within the savannah agro-ecological zone and those in the other ecological zones.

For the country to realize the potential benefits listed above, there should be a deliberate policy to reduce transaction costs of fertilizer acquisition and this could be achieved in several ways. First, feeder roads linking farming communities to major roads should be constructed to reduce the cost markup of fertilizer from harbor to farm. This will eventually increase market participation and increase household income. Second, bureaucratic obstacles in fertilizer acquisition should be reduced, especially on the acquisition of fertilizers that falls under government subsidized programs. This may likely reduce the delayed in fertilizer application on farmlands to ensure that the maximum benefits in fertilizer application is obtained. Finally, there should be policies to increase agriculture extension officers to enable farmers to get easy access to them. This will reduce the knowledge gap in efficient application of fertilizers and this would possibly increase the yield of fertilizer adopters.

Since fertilizers are not produced in the country, increased in fertilizer adoption may increase the importation of fertilizers into the Ghanaian economy and this has the tendency to further worsen the country's balance of payment (BoP). However, the four crops studied in this paper are non-tradable, this means, an increase in adoption which will result in an increase in yield may end up in a decrease in domestic price of the product which may likely have a negative effect on income of farmers. Hence, policies to ensure that the cereals grown in the country can be exported to other countries would increase the net benefits of fertilizer adoption when fertilizer adoption is scaled-up. First, the increase in foreign exchange as a result of income received from exportation of cereals may offset the BOP deficit that comes from increase in fertilizer importation. Second, exportation of the crops would serve farmers to get better price for their produce.

In conclusion, policies that seek to strengthen the agriculture – industry linkages should be adopted. This would make any growth experienced in the agriculture sector spread to the non-agriculture sectors of the economy. This can be achieved through (1) the establishment of domestic fertilizer production industry which may help in timely supply of fertilizers and reduce the BoP deficit that may occur as a result of fertilizer imports. (2) expanding the food processing industry in the country. As this may help in stabilizing prices of farm produce by farmers, it will also ensure food security in the country. Policy focus on these kinds of industries could benefit the economy with strong linkage between the agriculture and non-agriculture sectors of the economy. Future studies should investigate how the quantity of mineral fertilizer per acre of land cultivated affects the welfare of farmers. Second, future studies should adopt panel data so as to be able to analyze the time dynamics in fertilizer adoption and welfare. Finally, future studies should evaluate the effect of complementing fertilizer adoption with other agricultural technologies on the welfare of farmers and also access the spillovers of these benefits to other non-farm households.

References

[1] Abebe, Z. D., Sewnet, M. A. (2014). Adoption of soil conservation practices in North Achefer District, Northwest Ethiopia. Chinese Journal of Population Resources and Environment, 12(3), 261–268.

[2] Asfaw, D., & Neka, M. (2017). Factors affecting adoption of soil and water conservation practices: The case of Wereillu Woreda (District), South Wollo Zone, Amhara Region, Ethiopia. International Soil and Water Conservation Research, 5(4), 273–279.

[3] Becerril, J., Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: A propensity score matching approach. World Development. 38(7);1024–1035. doi: 10.1016/j.worlddev.2009.11.017.

[4] Becker, S.O. and Caliendo, M., 2007. Sensitivity analysis for the average treatment effects. The Stata Journal, 7, 71–83.

[5] Bold, T., Kaizzi, K., Svensson, J., Yanagizawa-Drott, D. (2015). Low Quality, Low Returns, Low Adoption: Evidence from the Market for Fertilizer and Hybrid Seed in Uganda; Working Paper Series rwp15-033; Harvard University, John

[6] F. Kennedy School of Government: Cambridge, MA, USA. Daffour, B. & Rosentrater, A.K. (2016) Grain Cultivation and Its Association Problems: Overview of Ghana. Available at: https://lib.dr.iastate.edu/cgi/viewcontent.cgi ?article=1481&context=abe_eng_conf. (Accessed May 2020)

[7] Danso-Abbeam, G., Baiyegunhi, J. S. L. (2019). Does fertiliser use improve household welfare? Evidence from Ghana's cocoa industry. Development in Practice. 29(2);170-182, doi: 10.1080/09614524.2018.1526887

[8] Demeke, M., Kelly, V., Jayne, T. S., Said, A., Le Vallee, J.C., Chen, H. (1998). Agricultural Market Performance and Determinants of Fertilizer Use in Ethiopia. Grain Market Research Project; Working Paper No.10; Ministry of Economic Development and Cooperation: Addis Ababa, Ethiopia, 1998.

[9] Diiro, G. M., & Sam, A. G. (2015). Agricultural technology adoption and nonfarm earnings in Uganda: A semiparametric analysis. Journal of Developing Areas. 49(2), 145–162. doi:10.1353/jda.2015.0013

[10] Druilhe, Z., Barreiro-Hurle´, J. (2012). Fertilizer Subsidies in Sub-Saharan Africa. ESA Working paper No.12-04. FAO, Rome. Available at: www.fao.org/economic/esa. (Accessed July 2020)

[11] Duflo, E. Kremer, M. Robinson, J. (2008) How High are Rates of Return to Fertilizer?Experimental Evidence from Kenya. American Economic Review. 98(2008); 482–488.

[12] Effraim, K. P. (2013). Help Tools and Investment Potentials of a wheat business in Ghana: A Case Study of Olam-Ghana. Available at: theseus.fi/handle/10024/70276. (Accessed November 2020)

[13] FAO (Food and Agricultural Organisation). (2016). Agriculture in Sub-Saharan Africa: Prospects and challenges for the next decade. Available at: http://www.fao.org/3/a-bo092e.pdf. (Accessed October 2020).

[14] Iddrisu, M. A., Gafa, W. D., Abubakari, M., Emini, A. C. & Beaumais, O. (2020). Implications of the Fertilizer-Subsidy Programme on Income Growth, Productivity, and Employment in Ghana. Partnership for Economic Policy Working Paper No. 2020-05

[15] International Food Policy Research Institute (IFPRI). (2013). Food Policy Research Capacity Indicators. doi.org/10.7910/DVN/LS09OT. Havard Dataverse, V5.

[16] Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., et al. (2018).

Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data. Journal of Agricultural Economics, 69(1), 76–95.

[17] Kassie, M., Shiferaw, B., Muricho, G. (2011). Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda. World Development. 39(10);1784–1795. doi.org/10.1016/j.worlddev.2011.04.023.

[18] Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., Mekuria, M., (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: evidence from rural Tanzania. Technol. Forecast. Soc. Change. 80 (3); 525-540.

[19] Legesse, E. E., Srivastava, K. A. Kuhn, A., Gaiser, T. (2019). Household Welfare Implications of Better Fertilizer Access and Lower Use Inefficiency: Long-Term Scenarios for Ethiopia. Sustainability. 11(14), 39-52.doi: 10.3390/su11143952

[20] Liverpool-Tasie, L.S.O., Omonona, B.T., Sanou, A., Ogunleye, W.O. (2017). Is increasing inorganic fertilizer use for maize production in SSA a profitable proposition? Evidence from Nigeria. Food Policy. 67(2017); 41-51.

[21] Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. Journal of Agricultural Economics, 67(1), 130–153.

[22] Martey, E.(2018). Welfare effect of organic fertilizer use in Ghana. Heliyon. 4 (2018) doi: 10.1016/j.heliyon.2018.e00844.

[23] Martey, E., Kuwornu, K. M. J. & Adjebeng-Danquah, J.(2019). Estimating the effect of mineral fertilizer use on Land productivity and income: Evidence from Ghana. Land Use Policy. 85 (2019), 463–475. doi.org/10.1016/j.landusepol.2019.04.027

[24] Matsumoto, T., Yamano, T. (2010). The impacts of fertilizer credit on crop production and income in Ethiopia. GRIPS Discussion Paper 10–23.

[25] Minten, B., Barrett, C. B. (2008). Agricultural Technology, Productivity, and Poverty in Madagascar. World Development. 36(5); 797-822.

[26] Nata, J.T., Mjelde, J.W., Boadu, F.O. (2014). Household adoption of soil-improving practices and food insecurity in Ghana. Agric. Food Secur. 3 (17), 1–12.

[27] Nyangena, W. & Ogada, O. M. (2014). Impact of improved farm technologies on yields: the case of improved maize varieties and inorganic fertilizer in Kenya. Environment for Development Discussion Paper Series (EfD DP) 14-02.

[28] Place, F., Barrett, C.B., Freeman, H.A., Ramisch, J.J., Vanlauwe, B. (2003). Prospects for integrated soil fertility management using organic and inorganic inputs: evidence from smallholder African agricultural systems. Food Policy. 28 (4);365-378

[29] Rashid, S., Tefera, N., Minot, N., Ayele, G.(2013). Fertilizer in Ethiopia: An Assessment of Policies, Value Chain, and Profitability; Discussion Paper 1304; International Food Policy Research Institute: Washington, DC, USA

[30] Rosenbaum, P. R., and D. B. Rubin. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” Biometrika 70: 41–55.

[31] Rosenbaum, P. R. (2002). Observational Studies. 2nd ed. New York: Springer.

[32] Sheahan, M., Barrett, C.B. (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. Food Policy. 67(2017); 12-25.

[33] Sommer, R., Bossio, D., Desta, L., Dimes, J., Kihara, J., Koala, S., Mango, N., Rodriguez, D., Thierfelder, C., Winowiecki, L. (2013). Profitable and Sustainable Nutrient Management Systems for East and Southern African Smallholder Farming Systems, Challenges and Opportunities. Available at: https://repository.cimmyt.org/handle/10883/4035. (Accessed August 2020).

[34] Teklewold, H., Kassie, M., Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. Journal of Agricultural Economics. 64 (3);597-623.

[35] Tesfay, G. M. (2020). Does fertilizer adoption enhance smallholders' commercialization? An endogenous switching regression model from northern Ethiopia. Agriculture & Food Security, 9(3);1-18.doi.org/10.1186/s40066-020-0256-y.

[36] Wainaina, P., Tongruksawattana, S., Qaim, M. (2016). Tradeoffs and complementarities in the adoption of improved seeds, fertilizer, and natural resource management technologies in Kenya. Agric. Econ. 47 (3); 351-362.

[37] Yu, B., Nin-Pratt, A., Funes, J., Gemessa, S. A. (2011). Cereal production and technology adoption in Ethiopia. ESSP working papers 31. International Food Policy Research Institute (IFPRI).

[38] Zerfu, D., Larson, D.(2010). Incomplete Market and Fertilizer Use: Evidence from Ethiopia; Policy Research Working Paper, WPS5235; World Bank: Washington, DC, USA.