Abstract

Most soils in Sub-Saharan Africa (SSA) are substantially degraded and are in need of restoration to enhance sustainable food production. This is a harder problem given that population is projected to increase with a corresponding increase in demand for food. Organic fertilizer can improve soil health by reducing the rate of nutrient leaching. However, there are limited studies on the economic effect of organic fertilizer use in SSA. Lack of in-depth understanding of the economics of organic fertilizer use and the welfare effect has the tendency to mislead policy. This paper employs the double selection and propensity score matching techniques to analyze the welfare impacts of organic fertilizer use. The results show that organic fertilizer use significantly increases the log of productivity and crop income by 1.43 and US$132 respectively and reduce total household expenditure, food expenditure and poverty by US$174, US$58, and 8% respectively. Disaggregation of the results based on landholdings and household size suggest that adopters of organic fertilizer with large farm size and household members recorded the lowest probability of being poor. Findings of this study demonstrate that the gains in the use of organic fertilizer can be consolidated with complementary input support and increased market participation.

Keywords: Agriculture, Economics
1. Introduction

Soil infertility is a major challenge among smallholder farmers in Sub-Saharan Africa (SSA) due to rapid population growth and food demand. The increasing demand for food leads to continuous and intensive cropping and depletion of the forest cover and subsequently creating adverse environmental problems. Improved fallow is almost impossible for most resource-poor farmers given the limited land available for crop production (Tittonell and Giller, 2013). Research have shown that more than half of the world’s 1.5 billion hectares of arable land is severely depleted resulting in low crop yield (FAO, 2015) and leaving about 220 million people in SSA undernourished (FAO, IFAD, WFP, 2015) and over 50 million African children experiencing stunted growth (UNICEF, 2016). This is a major developmental challenge given that population will continue to grow with a corresponding increase in food demand.

In SSA, conscious efforts have been made by successive governments and development practitioners to promote the use of modern inputs such as improved seed, fertilizers, and other agrochemicals, machinery, and irrigation (Sheahan and Barrett, 2017) to address food insecurity and poverty challenges. Recently, the notion of low fertilizer use in SSA (Sheahan and Barrett, 2014; Sommer et al., 2013) among smallholder farmers despite its economic benefit on crop yield have been challenged (Sheahan and Barrett, 2017; Liverpool-Tasie et al., 2017). However, poor infrastructure and storage, weak distribution networks, local blending facilities, and lack of agronomic knowledge (Druilhe and Barreiro-Hurlé, 2012) are among the constraints limiting the number of fertilizer users. Lack of site-specific fertilizer recommendations also constrain optimal fertilizer use, therefore, resulting in varying yield effects. The input subsidy programs in most SSA failed to achieve the intended objectives though considerable positive gains have been realized (Mason and Ricker-Gilbert, 2013). The focus is now on “smart” subsidies designed to enhance effective input delivery systems (Morris et al., 2007). However, the challenge is how to complement the use of mineral fertilizer with organic fertilizer due to the high labor requirements.

Organic fertilizers are carbon-based compounds that increase the productivity and growth quality of plants (Organic Facts, 2017). Nutrients from organic sources are released slowly and consistently which prevent the possibility of a boom-and-bust pattern. It also increases the organic matter of the soil, improves the structure, and prevents topsoil erosion and is relatively less costly (Bationo et al., 2012).

Several studies (Wainaina et al., 2016; Kassie et al., 2013; Teklewold et al., 2013; Marenya and Barrett, 2007; Place et al., 2003) have investigated the joint effect of organic and inorganic fertilizer on crop production and welfare outcomes. Similarly, impact and profitability of inorganic fertilizer use have also been explored in SSA since it is more widespread in terms of coverage and use intensity (Liverpool-
Tasie et al., 2017; Sommer et al., 2013). On the contrary, studies on the economic effect of organic fertilizer use have received little attention, especially within a national context (Valbuena et al., 2015; Chukwuka, 2009; Ayuk, 2001). Meanwhile, Sheahan and Barrett (2017) have shown that farmers are failing to combine inputs appropriately at the plot level due to their perceived functions and interrelationships among the inputs, therefore, leading to lower crop yields.

The few studies that analyzed the impact of organic fertilizer focused on yield and profitability with evidence from on-farm and on-station agronomic research (Masarirambi et al., 2010; Zhang et al., 2009; Tejada et al., 2008; Dawe et al., 2003). A more robust evidence is required to be able to support arguments regarding the promotion and use of organic fertilizers considering the climatic and soil variabilities in SSA. This study makes three primary contributions to the agricultural innovation systems research. First, exploring the welfare effect of organic fertilizer use requires adequate agronomic information, input, and transportation cost, food expenditure, crop income, and poverty data. The sixth wave of the Ghana Living Standard Survey (GLSS 6) provides a unique opportunity to explore the potential impact of organic fertilizer use in Ghana. Second, the study highlights the profitability of using green and animal manure which is less explored. Finally, I employed the double selection method in the estimation of the welfare effect. This method ensures that variables that are highly predictive of productivity, crop income, total, and food expenditures, and poverty are included in the estimation thus avoiding p hacking. The findings of this study will guide development practitioners in designing appropriate training manuals for effective soil fertility campaigns to improve income and food security.

The paper is organized as follows: the next section discussed the material and methods used to achieve the objectives of the study. Section 3 highlights the results of the study and the discussion of the results are presented in section 4. Section 5 summarizes and concludes the paper.

2. Material and methods

2.1. Study site and data collection

Fig. 1 shows the study regions in Ghana differentiated by poverty. Ghana is made up of 10 administrative regions and five main agro-ecological zones (Rain Forest,
Deciduous Forest, Transitional Zone, Coastal Savannah and Northern Savannah) defined on the basis of climate. The population currently stands at 28 million and spanning a land mass of 238,535 km² with a tropical climate. Agriculture is mainly on smallholder basis with less than 2 hectares despite existence of large plantations for rubber, oil palm, and coconut (MoFA, 2016). Agricultural production is predominantly rain-fed. The three northern regions in Ghana (Upper West, Northern, and Upper East regions) recorded the highest poverty rate while the transition regions followed with the highest recorded by Volta, Brong-Ahafo and Eastern regions in that order. Greater Accra region had the lowest poverty rate in Ghana (Fig. 1).

The data for this study is based on the GLSS 6, a nationally representative household survey conducted over a period of 12 months (October 18, 2012 to October 17, 2013). A two-stage stratified sampling design was employed to sample 18,000 households across the ten administrative regions of Ghana. In the first stage,
1,200 census enumeration areas (EAs) were sampled. The EAs are the primary sampling units stratified into the ten administrative regions of Ghana based on the population in each of the regions. In the second stage, 15 households per EA were randomly sampled. Trained enumerators employed by the Ghana Statistical Service (GSS) successfully interviewed 16,772 households out of the 18,000 sampled households. A subsample of 2,188 agricultural households (consists of 201 adopters and 1987 non-adopters) were used for this study. A large sample was drawn from the regions noted for agricultural production. The survey data includes information on household demographics, migration, remittances, income and expenditures (food, health, education, housing, consumer goods and durables), technology choices and preferences, agricultural production, market participation, and household investment decisions.

2.2. Empirical approach

2.2.1. Adoption decision and household welfare

Adoption of organic fertilizer is likely to influence crop income, total expenditure, food expenditure, and poverty status. Considering that the outcome variables of interest are a linear function of an observed vector of explanatory ($X$) variables along with a dummy variable for organic fertilizer use, the linear regression can be expressed as:

$$Y_i = \delta X_i + \alpha T_i + \mu_i$$

where $Y_i$ represents the outcome variables, $T_i$ is an indicator variable for adoption, $\delta$ and $\alpha$ are vector of parameters to be estimated, and $\mu_i$ is an error term. The impact of adoption on the outcome variables are measured by the estimate of the parameter $\alpha$ if farmers are randomly assigned to adoption or non-adoption groups (Faltermeyer and Abdulai, 2009). However, this method will generate biased estimate since the adoption decision is not random. Second, farmers’ decision to adopt is based on individual self-selection and anticipated benefits such that adopters of organic fertilizer may be systematically different from non-adopters (Amare et al., 2012). Third, unobservable characteristics of farmers and their farms may be correlated with the adoption decision and the welfare outcomes, which may also lead to an inconsistent estimate of technology adoption on welfare outcomes. Given that the use of organic fertilizer is non-random, any causal inference made will be erroneous. This study employs both the double selection and propensity score matching estimation methods to address these challenges.

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4 Adopters in this study refer to farmers who use any of the organic fertilizers such as green or animal manure. Farmers who use both organic and inorganic fertilizers were dropped from the sample.
2.2.2. Double selection

This method addresses the selection problem and omitted variables which are likely to bias the estimate of organic fertilizer adoption on the outcome variables. According to Tibshirani (1996), LASSO\(^5\) regression is a regularization method that helps researchers to select variables by shrinking some model coefficients to zero. This method reduces the variance of predictions and simplifies model interpretation by eliminating less influential variables from the model. Whereas \(\hat{\beta}\) in OLS minimizes the residual sum of squares, a penalty term is added to the residual sum of squares when LASSO is used.

\[
\hat{\beta}_{\text{LASSO}} = \arg \min_{\beta \in \mathbb{R}^n} \frac{1}{n} E \left[ (y_i - X_i' \beta)^2 + \lambda \| \beta \|_1 \right]
\]  

(2)

where \(\| \beta \|_1\) and the threshold \(\lambda\) is the tuning parameter which govern how strictly additional regressors are penalized and usually chosen based on theoretical properties or cross-validations. The penalty term shrinks the estimated regression coefficient towards zero and potentially sets coefficients on some variables to exactly zero. Due to the shrinkage property, LASSO regression is able to recover the true data-generating process when the number of covariates is larger than the number of observations (Bajari et al., 2015; James et al., 2013). Nevertheless, LASSO may mistakenly exclude variables with non-zero coefficients especially those with a moderate but non-zero coefficient. This may lead to significant regularization bias that affects the inference about the treatment effect (\(\alpha\)).

The double selection method proposed by Belloni et al. (2014) is used to address the selection problem in quasi-experimental studies, which rely on a conditional-on-observables identification strategy for estimating a structural effect. In such circumstances, lack of clear guidance about variable selection will lead to ad hoc sensitivity analysis, which shows how the estimated results change by using a different set of controls. Based on this challenge, Belloni et al. (2014) propose the double selection as follows:

\[
Y_i = \delta' X_i + \alpha' T_i + \mu_i, \quad E[\mu_i | X_i, T_i] = 0
\]

(3)

\[
T_i = \vartheta' H_i + \epsilon_i, \quad E[\epsilon_i | H_i] = 0
\]

(4)

where \(E[\mu_i, \epsilon_i] \neq 0\) leading to endogeneity; \(H_i\) represents a p-dimensional vector of instruments (access to extension services interacted with each of the explanatory variables) where the number of observations may be smaller than the number of instruments \(p\) and \(\mu_i\) and \(\epsilon_i\) are disturbances. Some studies (Khonje et al., 2015; Sanglestsawai et al., 2015; Asfaw et al., 2012a,b; Di Falco et al., 2011) have also explored access to information as an instrument for agricultural technology adoption.

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\(^5\) LASSO stands for Least Absolute Shrinkage and Selection Operator.
Estimating Eq. (3) using a standard LASSO regression could lead to omitted variable bias when omitted variables in the outcome equation are important determinant of the treatment variable $T$. Following Belloni et al. (2014), “double selection” objectively select variables in such a way to avoid inflated type I errors. This approach is carried out in three steps as follows:

**Step 1**: Run a LASSO regression on Eq. (4) by predicting adoption of organic fertilizer and keeping the variables $H_r$ with non-zero estimated coefficients.

**Step 2**: Run a LASSO regression by predicting the dependent (outcome) variable $Y_i$ and keeping the variable $X_y$ with non-zero estimated coefficients.

**Step 3**: Run a linear regression of the dependent (outcome) variable on the selected variables from steps 1 and 2 as:

$$Y_i = \alpha T_i + \delta^X Y_i + \delta^H H_r + \varepsilon_i$$  \hspace{1cm} (5)

where $m$ and $g$ are the set of variables estimated to have non-zero coefficients in steps 1 and 2 respectively. However, additional variables are also included in the model especially where their effect is known *a priori* to be important.

### 2.2.3. Propensity score matching

The PSM is employed to complement the double selection. This method controls for selection bias and provides unbiased estimates through controlling for observable confounding factors and reducing the dimensionality of the matching problem (Francesconi and Heerink, 2010; Becker and Ichino, 2002). Nevertheless, PSM may also produce a biased estimate in the presence of “selection on unobservables” or “hidden bias”. According to Keele (2010), Rosenbaum (2002), Rosenbaum and Rubin (1983), unobserved heterogeneity (hidden bias) occurs when unobserved variables influence both the treated variable and outcome variable simultaneously. The Rosenbaum bounds sensitivity analysis is used to evaluate the presence of unobserved heterogeneity. Detailed description about the PSM and the estimation of the unobserved heterogeneity can be found in Sanglestswai et al. (2015).

### 2.3. Measurement of outcome variables

Adoption of organic fertilizer is expected to impact on crop income, food expenditure, total expenditure, and poverty status. Crop income consists of all income generated from household crop production expressed in annual per adult equivalent unit (AEU$^6$) basis. Despite using income as a measurement of household welfare, total

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$^6$ I use the OECD adult equivalent scale which is given by $1 + 0.7(A - 1) + 0.5C$, where $A$ and $C$ represent the number of adults and children in a household, respectively.
expenditure is mostly preferred because it is more reliable welfare indicator and less prone to measurement error and seasonal fluctuations (Deaton, 1997). However, this study uses total household expenditure to capture all the sources of expenditure within a year. Total household expenditure consists of food, consumer goods (clothing, shoes, and clothes), household durables (refrigerator, furniture, television, and car), health, education, housing and other expenditures (utilities, communication, and transportation). Food expenditure per AEU is used as a proxy measurement of household food security. It consists of purchased food grains, livestock, vegetables, beverages and other food items such as sugar, salt and pepper. The final outcome is poverty status. Poverty is measured as a binary indicator based on the poverty-line (US$1.25/capita/day\textsuperscript{7}) adjusted for purchasing power parity and the total expenditure per capita. A poor household is defined as a household with total expenditure per capita at or below the poverty-line.

3. Results

3.1. Descriptive statistics

The distribution of the sampled households by region and gender is shown in Table 1. The proportions of male-headed and female-headed farm households vary across the regions. Adopters are largely drawn from the Savannah Accelerated Development Authority (SADA) zones of Ghana, consisting of Volta, Brong-Ahafo, Northern, Upper East and Upper West Regions. These regions are relatively poor therefore attracting myriad of agricultural development projects with the intention of bridging the poverty gap.

Table 2 shows the summary statistics and statistical significance tests on equality of means for both adopters and non-adopters. Adopters are significantly different from non-adopters in terms of productivity, crop income, total expenditure per AEU, and food expenditure per AEU. Nevertheless, adopters are not statistically significantly different from non-adopters in terms of poverty measurement. With the exception of crop income, non-adopters recorded higher outcome than adopters. A significant difference is observed in all the socio-economic and demographic variables of the adopting categories with the exception of age and remittances. Adopters have significantly higher males and females engaged in agriculture and farm size than non-adopters. Total asset holdings including livestock are higher among adopters. Distance travelled by adopters to the nearest extension office is relatively shorter compared to the non-adopters. The proportion of educated farmers among non-adopters (34%) is higher than adopters (21%).

\textsuperscript{7}The value is based on the 2012/2013 definition of poverty line when the data was captured.
In order to ascertain the economic benefit of using organic fertilizer, analysis of farm-level economic benefits and variable costs incurred in household agricultural production is discussed in Table 3. Adopters of organic fertilizer realized gross value production of 1,988 GHS/ha representing a gross production gain of 105%. The results further show that adopters of organic fertilizer incur a relatively higher variable cost than non-adopters. Variable cost was higher by 193% for organic fertilizer adoption. Despite higher variable cost for adopters, the net returns per hectare were comparatively high by 90% for organic fertilizer adoption. The results indicate that organic fertilizer adoption is profitable. However, no conclusive statement can be made regarding the causal inference of organic fertilizer use. Three different poverty measures (headcount index, poverty gap index and severity index) are reported in Table 3. Headcount index and poverty severity index is almost the same for adopters and non-adopters with a difference of 3% and 0.5% respectively. However, there is relatively wide variation (23%) in the poverty gap index among adopters and non-adopters. The preceding empirical analysis provides evidence on the impact of organic fertilizer adoption taking into account the fact that those who adopt might have achieved higher welfare outcomes even had they not adopted.

Table 1. Distribution of the sample households by region, adoption and gender.

| Region          | Number of districts | Organic fertilizer | Number of households | Total |
|-----------------|---------------------|--------------------|----------------------|-------|
|                 |                     | Non-adopters       | Adopters             |       |
| Western         | 189                 | 165                | 24                   | 56    | 133   | 189   |
| Central         | 212                 | 209                | 3                    | 77    | 135   | 212   |
| Greater Accra   | 53                  | 51                 | 2                    | 14    | 39    | 53    |
| Volta           | 226                 | 210                | 16                   | 58    | 168   | 226   |
| Eastern         | 361                 | 353                | 8                    | 112   | 249   | 361   |
| Ashanti         | 232                 | 214                | 18                   | 78    | 154   | 232   |
| Brong Ahafo     | 373                 | 345                | 28                   | 130   | 243   | 373   |
| Northern        | 275                 | 221                | 54                   | 19    | 256   | 275   |
| Upper East      | 188                 | 151                | 37                   | 43    | 145   | 188   |
| Upper West      | 79                  | 68                 | 11                   | 14    | 65    | 79    |
| Total           | 2,188               | 1,987              | 201                  | 601   | 1,587 | 2,188 |

Source: Author’s calculations using the GLSS 6 data.

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$R_{a}$ reduces to the headcount index or proportion of people who are poor when $\alpha = 0$; $R_{a}$ reduces to the poverty gap index when $\alpha = 1$. The poverty gap index measures the depth of poverty, which is defined as the mean distance to the poverty line where the mean is formed over the entire population with the non-poor, counted as having a zero poverty gap. $R_{a}$ reduces to the severity of poverty when $\alpha = 2$. The severity of poverty reflects the degree of inequality among the poor.
3.2. Welfare effect of technology adoption: PSM results

The maximum likelihood estimates of the probit model of organic fertilizer adoption in Ghana is presented in Table 4. Farm size, access to market, access to nearest motorable road, public transport, distance to extension services and tropical livestock unit significantly determine the probability of organic fertilizer adoption. Market, transport, and extension access variables decrease the probability of organic fertilizer adoption in Ghana.
adoption while farm size and TLU increase the probability of organic fertilizer adoption. Table 5 indicates that the explanatory variables used in the PSM satisfy the balancing property.

Following from the balancing property test\(^8\) (Table 4), a matching of adopters and non-adopters is carried out using the propensity scores estimated from the probit model. Fig. 2 shows the distribution of the propensity scores for adopters and non-adopters. Sufficient common support exists among the different group of farmers. However, treated (1) and untreated (258) farmers who are outside the common support were dropped, therefore, restricting the matching algorithm to the common support region (consisting of 200 treated and 1729 untreated). Fig. 3 shows the density distribution of the two groups indicating substantial overlap in the distribution of the propensity scores for adopters and non-adopters.

This study employs two different matching methods (inverse probability weighing (IPW)) and nearest neighbor matching (NNM) based on the “t effects” commands

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\(^8\)This shows the test of significance before and after the matching. Almost all the explanatory variables were significant before the matching. However, after the matching, none of the variables significant. Therefore the balancing test is satisfied.

### Table 3. Comparative farm-level economic benefits from organic fertilizer adoption.

| Variable                  | Organic fertilizer (Green and animal manure) | Gain (%) |
|---------------------------|---------------------------------------------|----------|
|                           | Adopters (N = 201)                          | Non-adopters (N = 1987) |
|                           | Gain (%)                                    | Gain (%) |
|---------------------------|---------------------------------------------|----------|
| Gross value of production (GHS/ha) | 1988.49                                    | 967.77   | 105  |
| Variable cost (GHS/ha)    | 418.57                                      | 142.91   | 193  |
| Net income (GHS/ha)       | 1569.92                                     | 824.86   | 90   |

**Poverty measures**

|                           | Adopters (N = 201)                          | Non-adopters (N = 1987) |
|---------------------------|---------------------------------------------|-------------------------|
| Head count index          | 0.134                                       | 0.162                   | 0.028 |
| Poverty gap index         | 0.272                                       | 0.039                   | 0.233 |
| Poverty severity index    | 0.009                                       | 0.014                   | 0.005 |

**Note:** Variable cost captures seed, fertilizer, pesticide, weedicide, land rental and labor cost. Gain (%) is computed as the ratio of the difference between adopters and non-adopters to non-adopters and expressed as percentage. Difference is calculated as adopters minus non-adopters. Poverty measurement is based on the Foster et al. (1984) indices. The index measure of poverty is defined as: 

\[
R_a = \frac{1}{N} \sum_{i=1}^{H} \left[ \frac{l - e_i}{l} \right]^a,
\]

where \( l \) is the poverty-line (US$1.25/capita/day) adjusted for purchasing power parity, \( N \) is the number of people in the sample population, \( H \) is the number of poor (those with total expenditure per capita at or below \( l \)), \( e \) is the total expenditure per capita for the \( i \)th person, and \( a \) is a poverty aversion parameter. Exchange rate at the time of survey (2012) is GHS = US$0.25 (Source: Bank of Ghana, 2017). Source: Author’s calculations using the GLSS 6 data.
### Table 4. Probit estimates of organic fertilizer adoption.

| Variable                              | Coefficient | Robust Std. error | Marginal effect |
|---------------------------------------|-------------|-------------------|-----------------|
| Age                                   | 0.000       | 0.003             | 0.000           |
| Gender                                | 0.121       | 0.101             | 0.017           |
| Number of males (6–18)                | 0.166       | 0.149             | 0.024           |
| Number of females (6–18)              | −0.161      | 0.154             | −0.024          |
| Farm size                             | 0.026       | 0.009             | 0.004***        |
| Access to market                      | 0.485       | 0.197             | 0.095**         |
| Access to road                        | −0.686      | 0.347             | −0.143**        |
| Access to public transport            | −0.533      | 0.143             | −0.089***       |
| Distance to motorable road            | 0.000       | 0.003             | 0.000           |
| Distance to extension services        | −0.026      | 0.008             | −0.004***       |
| Remittance                            | −0.050      | 0.089             | −0.007          |
| Tropical livestock unit (log)         | 0.020       | 0.009             | 0.003**         |
| Constant                              | −0.385      | 0.408             |                 |

|                                | Number of observations | Log likelihood | Wald Chi² (12) | Prob. > Chi² | Pseudo R² |
|--------------------------------|------------------------|----------------|---------------|-------------|-----------|
|                                | 2,188                  | −623.782       | 94.730        | 0.000       | 0.071     |

***Significant at 1%, **Significant at 5%.

Source: Author’s calculations using the GLSS 6 data.

### Table 5. Balancing test of the explanatory variables.

| Variable                              | Before matching |          | After matching |          |
|---------------------------------------|-----------------|----------|----------------|----------|
|                                      | Treated         | Control  | Treated        | Control  |
| Age                                   | 48.468          | 48.900   | 48.525         | 48.412   | 0.938     |
| Gender                                | 0.821           | 0.716    | 0.820          | 0.805    | 0.702     |
| Number of males (6–18)                | 1.463           | 1.284    | 1.550          | 1.613    | 0.694     |
| Number of females (6–18)              | 1.408           | 1.284    | 1.470          | 1.529    | 0.703     |
| Farm size                             | 4.469           | 2.888    | 4.371          | 3.563    | 0.104     |
| Access to market                      | 0.050           | 0.038    | 0.050          | 0.055    | 0.823     |
| Access to road                        | 0.920           | 0.894    | 0.920          | 0.905    | 0.604     |
| Access to public transport            | 0.460           | 0.680    | 0.460          | 0.446    | 0.779     |
| Distance to motorable road            | 20.280          | 12.660   | 20.125         | 20.665   | 0.817     |
| Distance to extension services        | 0.602           | 0.471    | 4.683          | 4.760    | 0.951     |
| Remittance                            | 0.284           | 0.370    | 0.285          | 0.273    | 0.790     |
| TLU (log)                             | −3.426          | −4.975   | −3.449         | −3.273   | 0.687     |

Notes: The matched sample are based on one to five (5) nearest neighbor matching.

Source: Author’s calculations using the GLSS 6 data.
in STATA. All the matching methods show significant impact of organic fertilizer on all the outcome variables. Table 6 shows the PSM results of the impact of organic fertilizer on productivity, crop income per AEU, total expenditure per AEU, food expenditure per AEU and poverty. The magnitude of the ATT effect is consistently higher for the NNM compared to the IPW. The results of the IPW showed that after
controlling for socioeconomic, farm and institutional characteristics, organic fertilizer use significantly increased log of productivity and crop income by 2.89 and GHS549 (US$137.25) respectively, but decreases total expenditure per AEU (US$122), food expenditure per AEU (US$41) and poverty (7%) when compared to non-adopters. Similarly, the NNM results shows an increase of 2.27 in log productivity, US$168 in crop income and a decrease in total expenditure and food expenditure per AEU and poverty by US$174, US$58 and 8% respectively.

The “Rosenbaum bounds” analysis assessed the sensitivity of the PSM results to unobservable variables. The analysis is based only on the NNM and results are reported in Table 7. The sensitivity analysis results suggest that in order to eliminate the estimated decrease in total expenditure per AEA and poverty, the unobservable variables would have to increase the ratio of the odds by more than 1% (Gamma, $e^\gamma = 1.00$). Similarly, the negative impact of organic fertilizer adoption on food expenditure per AEU could be eliminated if unobservables can increase the ratio of the odds only by 45% ($e^\gamma = 1.45$). The results show no unobservable variables that could eliminate the positive impact of organic fertilizer adoption on crop income.

### 3.3. Welfare effect of technology adoption: double selection results

Results of the double selection are reported in Table 8. The determinants of productivity are participation in a market, the number of males and females engaged in

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**Table 6.** PSM estimates of the impact of organic fertilizer adoption on selected variables.

| Matching algorithm                | Outcome variables          | ATE         | ATT          |
|-----------------------------------|----------------------------|-------------|-------------|
| Inverse-probability weighting (IPW) | Productivity (log)          | 4.22*** (0.48) | 2.89*** (0.45) |
|                                   | Crop income (GHS/ha)        | 796.77** (370.10) | 549.47* (317.40) |
|                                   | Total expenditure per AEU   | −293.17 (191.07) | −485.75*** (178.56) |
|                                   | Food expenditure per AEU    | −69.65 (106.73) | −164.29* (93.89) |
|                                   | Poverty (headcount ratio)   | −0.06** (0.02)  | −0.07** (0.03)  |
| Nearest-neighbour matching (NNM)  | Productivity (log)          | 4.32*** (0.63)  | 2.27*** (0.56)  |
|                                   | Crop income (GHS/ha)        | 655.63* (336.70) | 672.07* (342.21) |
|                                   | Total expenditure per AEU   | −224.05 (266.56) | −695.56** (325.10) |
|                                   | Food expenditure per AEU    | −30.02 (114.41) | −229.64* (122.52) |
|                                   | Poverty (headcount ratio)   | −0.08*** (0.03) | −0.08** (0.04)  |

**Notes:** The inverse probability weighting and nearest-neighbour matching are based on the “teffects” command in stata. Abadie-Imbens robust standard errors for NNM and robust standard errors for IPW are in parentheses. ***Significant at 1%, **Significant at 5% and *Significant at 10%. Exchange rate at the time of survey (2012) is 1GHS = US$0.25 (Source: Bank of Ghana, 2017).

Source: Author’s calculations using the GLSS 6 data.

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9 I used the command “rbounds” in STATA to conduct the “Rosenbaum bounds” analysis.
farming, access to public transport, education of household head, and use of improved seed. Crop income is significantly influenced by the adoption of organic fertilizer, gender, number of male household members who participate in farming, participation in a market, and access to public transport. Education of male-headed household, education of spouse of household head, household size and use of improved seed and the interaction between distance to public transport and extension access significantly influence total expenditure. Food expenditure is significantly determined by access to public transport and household size. Factors such as access to public transport, education of male-headed household, household size, and use of improved seed significantly influence poverty. Among the set of co-variates, participation in a market, education of spouse, household size, and access to public transport had the highest magnitude of effect on crop income, total, food expenditure and poverty respectively. In all the models, organic fertilizer

Table 7. Rosenbaum bounds sensitivity analysis for hidden bias.

| Gamma | Crop income (GHS/ha) | Total expenditure (GHS/ha) | Food expenditure (GHS/ha) | Poverty (headcount) |
|-------|---------------------|---------------------------|--------------------------|--------------------|
|       | sig +   | sig - | sig +   | sig - | sig +   | sig - | sig +   | sig - |
| 1     | 0.00    | 0.00  | 1.00    | 1.00  | 0.00    | 0.00  | 1.00    | 1.00  |
| 1.05  | 0.00    | 0.00  | 1.00    | 1.00  | 0.00    | 0.00  | 1.00    | 1.00  |
| 1.1   | 0.00    | 0.00  | 1.00    | 1.00  | 0.00    | 0.00  | 1.00    | 1.00  |
| 1.15  | 0.00    | 0.00  | 1.00    | 1.00  | 0.00    | 0.00  | 1.00    | 1.00  |
| 1.2   | 0.00    | 0.00  | 1.00    | 1.00  | 0.00    | 0.00  | 1.00    | 1.00  |
| 1.25  | 0.00    | 0.00  | 1.00    | 1.00  | 0.00    | 0.00  | 1.00    | 0.98  |
| 1.3   | 0.00    | 0.00  | 1.00    | 0.98  | 0.00    | 0.00  | 1.00    | 0.94  |
| 1.35  | 0.00    | 0.00  | 1.00    | 0.90  | 0.00    | 0.02  | 1.00    | 0.84  |
| 1.4   | 0.00    | 0.00  | 1.00    | 0.73  | 0.00    | 0.08  | 1.00    | 0.68  |
| 1.45  | 0.00    | 0.00  | 1.00    | 0.48  | 0.00    | 0.23  | 1.00    | 0.48  |
| 1.5   | 0.00    | 0.00  | 1.00    | 0.25  | 0.00    | 0.46  | 1.00    | 0.29  |
| 1.55  | 0.00    | 0.00  | 1.00    | 0.10  | 0.00    | 0.70  | 1.00    | 0.15  |
| 1.6   | 0.00    | 0.00  | 1.00    | 0.03  | 0.00    | 0.87  | 1.00    | 0.06  |
| 1.65  | 0.00    | 0.00  | 1.00    | 0.01  | 0.00    | 0.95  | 1.00    | 0.02  |
| 1.7   | 0.00    | 0.00  | 1.00    | 0.00  | 0.00    | 0.99  | 1.00    | 0.01  |
| 1.75  | 0.00    | 0.00  | 1.00    | 0.00  | 0.00    | 1.00  | 1.00    | 0.00  |
| 1.8   | 0.00    | 0.00  | 1.00    | 0.00  | 0.00    | 1.00  | 1.00    | 0.00  |
| 1.85  | 0.00    | 0.00  | 1.00    | 0.00  | 0.00    | 1.00  | 1.00    | 0.00  |
| 1.9   | 0.00    | 0.00  | 1.00    | 0.00  | 0.00    | 1.00  | 1.00    | 0.00  |
| 1.95  | 0.00    | 0.00  | 1.00    | 0.00  | 0.00    | 1.00  | 1.00    | 0.00  |
| 2     | 0.00    | 0.00  | 1.00    | 0.00  | 0.00    | 1.00  | 1.00    | 0.00  |

Note: Gamma refers to the critical value of hidden bias (Γ).
Source: Author’s calculations using the GLSS 6 data.
Table 8. Double selection estimate of organic fertilizer adoption on selected outcome variables.

| Variables                          | Productivity (log) | Crop income (GHS/ha) | Total expenditure per AEU | Food expenditure per AEU | Poverty (headcount ratio) |
|------------------------------------|--------------------|----------------------|---------------------------|--------------------------|---------------------------|
| Organic fertilizer adoption (1 = adopt) | 1.433*** (0.397)  | 527.713* (318.777)  | −128.977 (138.758)       | −61.337 (73.508)         | −0.082*** (0.026)         |
| Gender of head (1 = male)          | 319.720*** (91.842) |                     |                           |                          |                           |
| Number of female farmers in household | 0.775*** (0.161)  | 128.707*** (40.635) |                           |                          |                           |
| Number of male farmers in household  | 0.971*** (0.107)   |                     |                           |                          |                           |
| Participate in market (1 = yes)     | 7.089*** (0.223)   | 1,344.077*** (123.383) | −159.694 (113.202)       | 58.653 (55.809)          | 0.023 (0.016)             |
| Access to road (1 = yes)            | −336.694 (388.948) |                     |                           |                          |                           |
| Distance to extension services      | −8.579 (8.648)     |                     |                           |                          |                           |
| Access to public transport (1 = yes)| −0.464* (0.255)   | 461.822*** (109.817) | 44.121 (176.478)         | 94.706* (56.280)         | −0.073*** (0.017)         |
| Education of male head (1 = educated) | −1.295*** (0.247) |                     | 310.576** (138.385)      |                          | −0.094*** (0.014)         |
| Education of spouse (1 = educated)  |                     | 873.708*** (192.898) |                           |                          |                           |
| Household size                      | −376.193*** (26.076) | −212.799*** (12.477) |                           |                          | 0.039*** (0.003)          |
| Distance to public transport × extension access | −9.540** (3.984) |                     |                           |                          |                           |
| Purchase improved seed (1 = yes)    | 1.465*** (0.331)   | 234.474 (176.147)   | 477.776*** (180.731)     | 106.463 (80.576)         | −0.044** (0.022)          |
| Constant                            | −3.587*** (0.277)  | −203.343 (381.860)  | 4,816.343*** (244.572)   | 2,463.928*** (84.327)    | 0.066*** (0.020)          |
| Observations                        | 2,188              | 2,188               | 2,188                     | 2,188                    | 2,188                     |

Note: Robust standard errors are reported in parentheses. ***Significant at 1%, **Significant at 5% and *Significant at 10%.

Source: Author’s calculations using the GLSS 6 data.
significantly increased log productivity and crop income by 1.43 and GHS528 (US$132) respectively. Poverty reduces by 8% among adopters of organic fertilizer.

The double selection and PSM results have shown that farmers who use organic fertilizer have higher welfare outcomes in terms of higher crop income and lower poverty relative to non-users of organic fertilizer. The magnitude of the welfare effect is almost the same for the IPW and double selection results. However, the magnitude of crop income is relatively higher in the NNM results (US$168) when compared to the double selection (US$132). Total and food expenditure per AEU significantly decrease with organic fertilizer adoption by US$174 and US$58 respectively as reported per the NNM results. However, the result is not significant per the double selection result. The differences in the results may largely be attributed to unobserved heterogeneity, which is a weakness of the PSM.

4. Discussion

Discussion of the results is based on the double selection model. Adopters of organic fertilizer have higher productivity and crop income than non-adopters. The crop income effect is realized through an increase in productivity. The use of organic fertilizers such as green and animal manure increase the organic matter of the soil with subsequent long-term effect on crop yield. The biological, chemical and physical properties of the soils are enhanced with increasing organic fertilizer use, which subsequently leads to lower evapotranspiration and soil erosion. Lal (2006) showed that increase in soil organic carbon pool in root zone significantly increases crop (wheat, maize, and rice) yield. Most of the organic sources of fertilizer are relatively cheaper when compared to the inorganic fertilizers. However, the productivity is augmented through market participation and use of improved seed. The implication of the result is that productivity can be enhanced by linking farmers to market through improvement in road infrastructure and creating an enabling environment for private input dealers to locate closely to farming communities. Ghana has witnessed infrastructural development over the last decade and it is projected that development will continue in order to enhance the agricultural sector by reducing postharvest losses, transaction cost, and food insecurity.

An increase in productivity may translate to higher crop income assuming market conditions are favorable. Farmer’s income can be improved by increasing access to organic fertilizer and ensuring that the site-specific recommended application rates are strictly adhered to with technical support from agricultural extension agents and lead farmers. Male-headed households are more likely to increase their crop income from the adoption of organic fertilizer relative to the female-headed households. This confirms the wide gender inequality in Ghana. Tambo (2016) found that men are more likely to adopt climate adaptation measures than female-heads in north-east
Ghana. Agricultural development programs must support female-headed households in order to reduce the gender productivity and income gaps. Crop income is augmented by market participation and access to public transport. There is the need to improve feeder roads that links the communities to the main roads to enable public transport operators access the communities to facilitate transportation of humans, farm inputs, and food to other parts of the country. A study by Bezu et al. (2014) revealed a positive effect of improved maize varieties on maize total income and asset holdings per AEU. Similarly, Mazvimavi and Twomlow (2009) established that profitability associated with the use of conservation farming practices further increase adoption of these practices.

Total and food expenditures per AEU is lower among adopters of organic fertilizer relative to non-adopters although not significant. Disaggregation of total household expenditure reveals that adoption of organic fertilizer decreases expenditures on health, housing, consumption and other expenditures (electricity, water, gas, communication, transport, and remittances expenses) while increases expenditure on education. The findings are however not significant with the exception of housing which reduced significantly by GH₵50 (US$12.5) among adopters of organic fertilizer (Table 9). The possible explanation for the lower expenditure on food is that farm households are more likely to invest in capital goods as income increases. Farm households’ dependency on own farm output increases as crop productivity increases with less expenditure on purchased food. The results suggest that when farmers use organic fertilizer, there is a higher possibility of increasing productivity and consumption from own production. Use of improved seed significantly increase total household expenditure per AEU. This finding is consistent with the results of Asfaw et al. (2012a) who reported a positive impact of improved chickpea and pigeonpea on total expenditure per AEU in rural Ethiopia and Tanzania.

The result shows evidence of lower poverty among adopters of organic fertilizer relative to non-adopters. The possible mechanism is through productivity and crop income. Increase in crop income due to increase in productivity reduces the potential of farm households being trapped in poverty. As crop income increases, farm households have the flexibility in making choices and given that the household is rational; decisions that will inure to the benefit of the household members will be pursued. This result implies that encouraging farmers to use organic fertilizer will lead to a reduction in poverty ceteris paribus. However, the use of organic fertilizer alone is not enough to generate a relatively higher magnitude of poverty reduction. Education of male-headed households, access to public transport, and use of improved seed reduce the probability of being poor by 7%, 9%, and 4% respectively. There is the need to intensify the promotion and use of complementary agricultural inputs among farmers. The present result is consistent with the findings of Khonje et al. (2015) who established that adoption of improved maize seed reduces the probability of being poor by 11%. The findings suggest that Ghana’s economic transformation in terms of
Table 9. Double selection estimates of organic fertilizer adoption on total household expenditure.

| Variables                        | Total household expenditure categories |
|----------------------------------|----------------------------------------|
|                                  | Health per AEU | Education per AEU | Housing per AEU | Consumption per AEU | Other per AUE |
|----------------------------------|----------------|------------------|-----------------|---------------------|--------------|
| Organic fertilizer adoption (1 = adopt) | -5.695 (4.021) | 22.339 (31.603) | -49.971* (28.631) | -5.042 (19.337) | -75.607 (54.909) |
| Purchase improved seed (1 = yes)  | 15.514** (6.635) | 35.178 (27.039) | 47.823 (37.071) | 60.103** (23.494) | 241.847*** (87.052) |
| Household size                    | -4.195*** (0.721) | -40.140*** (4.899) | -41.629*** (3.545) | -105.093*** (11.288) |
| Market access × extension access  | -21.674*** (4.176) |                  |                  |                     |              |
| Sale of crop (1 = yes)            | 3.833 (4.094) | -70.563*** (19.112) | -69.798*** (23.995) | -26.701* (16.060) | -108.664** (50.150) |
| Access to public transport (1 = yes) | 7.489** (3.242) | 32.043 (32.404) | 25.541 (25.966) | -12.170 (23.272) | -24.765 (95.793) |
| Education of male head (1 = educated) | 99.305*** (24.049) |                  |                  |                     |              |
| Distance to public transport × extension access | -1.666** (0.652) |                  |                  |                     |              |
| Education of spouse (1 = educated) |                   |                  |                  |                     |              |
| Gender of head (1 = male)         |                   |                  |                  |                     |              |
| Constant                          | 43.862*** (4.267) | 229.135*** (33.741) | 505.784*** (34.449) | 528.011*** (31.332) | 879.936*** (110.949) |
| Observations                      | 2,188           | 2,188            | 2,188           | 2,188               | 2,188        |

Notes: Robust standard errors are reported in parentheses. ***Significant at 1%, **Significant at 5% and *Significant at 10%.

Source: Author’s calculations using the GLSS 6 data.
poverty reduction can be achieved through the agricultural sector and augmented by human capital formation and infrastructural development.

Finally, the result is disaggregated based on landholdings and household size to ascertain whether the impact of organic fertilizer use have heterogeneous effects on poverty. Farm households were categorized into quintiles based on farm size and household size. Results reported in Tables 10 and 11 show that the impact of adoption of organic fertilizer on poverty decreases with farm size and household size. Reduction in poverty is highest in the second (0.19 ha) and fourth (3.38 ha) quintiles of farm size. The results also show evidence of high poverty reduction in the fifth (9 members) quintile of household size. Similarly, farm households within the fifth quintile of farm size (9 ha) have no significant effect on poverty reduction. In addition, first, third and fourth quintiles of household size do not significantly reduce poverty. These results suggest that farm households with large farm size (below 9 ha) and household members (above 6) might benefit more from using organic fertilizer. The use of organic fertilizer is labor-intensive, therefore, farm households with large farm size and more household members may supply labor for increase farm output which might translate to higher farm incomes and reduction in poverty ceteris paribus.

Table 10. Differential impact of organic fertilizer adoption on poverty (stratification by farm size).

| Quintiles | Number of observations | Farm size (ha) | Poverty (headcount ratio) |
|-----------|------------------------|----------------|--------------------------|
|           |                        |                | Coefficient | Robust Std. Error |
| First     | 566                    | 0.00           | −0.092*      | 0.052            |
| Second    | 322                    | 0.19           | −0.153**     | 0.067            |
| Third     | 522                    | 1.53           | −0.114**     | 0.048            |
| Fourth    | 369                    | 3.38           | −0.144***    | 0.047            |
| Fifth     | 409                    | 9.13           | −0.037       | 0.051            |

Source: Author’s calculations using the GLSS 6 data.

Table 11. Differential impact of organic fertilizer adoption (stratification by household size).

| Quintiles | Number of observations | Household size (number) | Poverty (headcount ratio) |
|-----------|------------------------|-------------------------|--------------------------|
|           |                        |                         | Coefficient | Robust Std. Error |
| First     | 498                    | 1.44                    | −0.029     | 0.043            |
| Second    | 659                    | 3.53                    | −0.090***  | 0.030            |
| Third     | 347                    | 5.00                    | 0.003      | 0.075            |
| Fourth    | 250                    | 6.00                    | −0.117     | 0.079            |
| Fifth     | 434                    | 8.54                    | −0.146**   | 0.067            |

Source: Author’s calculations using the GLSS 6 data.
5. Conclusion

Improving the welfare of farm households has been a major policy concern in SSA. Several investments and interventions have been put in place to stimulate agricultural productivity with a long-term impact of improving welfare outcomes. Despite these efforts, adoption of soil fertility management practices remains low with wide disparities across geographical areas. This study evaluates the effect of organic fertilizer adoption on profitability, productivity, crop income, total household, food expenditures per AEU and poverty using the GLSS 6 data.

Profitability analysis indicates that organic fertilizer use increase average annual net returns whiles adoption of organic fertilizer has considerable effect on productivity and crop income. Organic fertilizer improves soil fertility by increasing organic matter, microbial activity and chemical properties of the soil with a subsequent increase in yield. Secondly, organic fertilizer enables farmers to save and invest in other complementary technologies that increase yield and crop income given that market conditions such as market price are relatively favorable. Total household and food expenditure also decreased among adopters of organic fertilizer. Finally, adopters experienced a lower probability of becoming poor. While these welfare estimates are informative, the study may suffer from external validity due to the small sample size of the adopters, therefore, the results should be interpreted cautiously. Second, the use of cross-sectional data in impact evaluation may be problematic due to endogeneity problem and inability to examine dynamic adoption on welfare. Nevertheless, the method employed in this study controls for omitted variable bias but unable to control for time-variant characteristics that are likely to influence the results.

From policy perspective, these gains can be consolidated and sustained via linking farmers to markets and improving road infrastructure. Feeder roads linking farming communities to major roads must be constructed to reduce the cost of transportation. This will eventually increase market participation and increase household income. Disaggregation of the results based on landholdings and household size suggest that farm households with large farm size and household members benefit more from using organic fertilizer. This indicates that agricultural development interventions that seek to reduce poverty must also target farm households with large landholdings and members. There is the need for development practitioners to raise awareness and support farmers to use green and animal manure to enhance soil fertility and ensure long-term impact on food security and poverty reduction. Future studies must analyze the welfare impact of the combinations of organic and inorganic fertilizer use on the investment behavior of farm households in Ghana using a panel data.
Declarations

Author contribution statement

Edward Martey: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Competing interest statement

The author declares no conflict of interest.

Additional information

No additional information is available for this paper.

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