Journal of Agricultural and Applied Economics (2021), **53**, 435–458
doi:10.1017/aae.2021.8

CAMBRIDGE
UNIVERSITY PRESS

RESEARCH ARTICLE

Organic Fertilizer Adoption, Household Food Access, and Gender-Based Farm Labor Use: Empirical Insights from Northern Ghana

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Abstract
This paper examined organic fertilizer adoption and its effects on two household food security indicators and gender-based farm labor use among smallholder farmers in Northern Ghana. An endogenous switching regression analysis shows that observed and unobserved farmer background factors determine farmers' decision to adopt organic fertilizer as well as the outcomes from adoption. On average, adoption is associated with an 11% increase in per capita food consumption and a 55% reduction in household food gap duration. Adoption is also related to an increased labor use by 5.9 (90%) of female worker days and 1.3 (9%) of male worker days per acre, placing nearly all (82%) of the increased labor burden on female farmhands. We recommend mitigation of factors that hinder farmers from adopting the input and provision of female-user-friendly labor-saving devices for organic fertilizer use tasks.

Keywords: endogenous switching regression; food access; labor use; Northern Ghana; organic fertilizer; smallholder farmers

JEL Classifications: O33; Q12; Q16

1. Introduction

Food insecurity will persist in sub-Saharan Africa (SSA) unless the decline in agricultural productivity, caused mainly by soil degradation, is halted and the trend reversed (AfDB, 2006; Nkonya et al., 2015). Soil erosion and related factors, including nutrient mining, loss of organic matter, and declining biodiversity, are responsible for increasing crop productivity gaps in the region (FAO, 2015; Kassie et al., 2013; Martey, 2018). Erosion has affected more than 22% of the arable lands of many countries, particularly in West Africa, jeopardizing the livelihoods of over 65% of national populations depending on agriculture (FAO, 2015; Nkonya et al., 2015). Meanwhile, the farm household population in the region is rapidly growing, thus exerting more pressure on the lands (FAO, 2015). This limits access to arable land and renders traditional soil maintenance practices, like fallowing land to restore nutrients, impracticable (Pandey et al., 2002). Yet, the resource-poor farmers in the region apply mineral fertilizer at a rate far below world standard (AfDB, 2006; Ayalew et al., 2020; Sheahan and Barrett, 2017), though there is quite recent evidence of increased fertilizer use, particularly for cereal production in some countries (Liverpool-Tasie et al., 2017). This implies that majority of the farmers intensify cropping under negative nutrient balances (Martey, 2018).

In Ghana, farmers in the northeastern part are the most affected by soil degradation nationwise. Semi-desert conditions in the area combine with intense farming activities to accelerate degradation of the arable lands (Atakora et al., 2014; Danquah et al., 2019; Owusu et al., 2020). The area lies within the Sudan Savannah zone, where a larger proportion of the landmass is hilly and rocky, having very thin vegetation cover (Government of Ghana, 2015). Continual removal of the scanty vegetation through cultivation and annual bush fires accelerates the loss of soil organic matter and useful biodiversity (Tittonell and Giller, 2013). The area also experiences the least and most erratic rainfall country-wide (Amikuzuno and Donkor, 2012; Issahaku et al., 2016; Wiredu, 2015).

Cereals (maize, millet, and sorghum) are the main staple crops, the production of which constitutes the primary livelihood of the subsistence rural households (Government of Ghana, 2015). The farmer-population of the area is dense; hence, the limited land has been put under traditional exploitative cultivation practices without sufficient nutrient replacement (Atakora et al., 2014; Danquah et al., 2019; Owusu et al., 2020). Consequently, yield of the main crops continues to decline; thus, trapping many of the farm households in poverty (Atakoral et al., 2014) and food insecurity cycle (Government of Ghana, 2015).

As the farmers try to cope with poor soil conditions, the apply nearly all their mineral fertilizer purchases on cereal crops. Thus, rate of fertilizer application for the area is usually higher than the national average (FAO, 2005) and has been increasing since the introduction of a national fertilizer subsidy program in 2008 (Wiredu, 2015). However, experts have begun warning about negative effects of inappropriate modes of fertilizer application. They fear that the repetitive use of existing formulations of mineral fertilizer in the area without site-specific soil test-based recommendations further deteriorates soil health (Atakora et al., 2014; Ayalew et al., 2020). Already, soils have become increasingly non-responsive to the fertilizers (Atakora et al., 2014). A condition under which the farmers do not fully benefit from their investment in any high-value external input without rehabilitating the soils (Tittonell and Giller, 2013).

Meanwhile, ecological intensification (EI)[1] is a win-win approach to addressing soil degradation, cutting down mineral fertilizer cost, and simultaneously improving food security through reduction in yield variability (Abagale and Ayuegabe, 2015; Kassie et al., 2013, 2015; Teklewold et al., 2013; Zeweld et al., 2017). EI relies on locally available organic options for maintaining ecological competitiveness and economic viability of agriculture. Thus, it allows reduced use of inputs that are potentially harmful to the environment (Zeweld et al., 2017). EI practices help improve soil health and thus enhance the return on investments in mineral fertilizer and other external inputs (Kousar and Abdulai, 2015; Zeweld et al., 2017).

Therefore, farmers within the affected area are being encouraged to adopt EI practices, particularly the use of organic fertilizer to resuscitate degraded soils for sustainable[2] crop production (Government of Ghana, 2015; Zeweld et al., 2017). Organic fertilizer[3] plays a crucial role in sustaining soil ecology. It maintains organic matter content at levels necessary for conserving soil moisture, plant nutrients, and other properties required for healthy plant growth (Abebe and Debebe, 2019; Kassam et al., 2017; Zeweld et al., 2017).

In economic terms, the literature (e.g., Abebe and Debebe, 2019; Kassie et al., 2009; Usman et al., 2015; Zerihun and Haile, 2017) provides ample evidence regarding the positive effects of organic fertilizer on crop productivity; hence farmer welfare. For instance, Gelgo et al. (2016) reported increased incomes of farmers who adopted the input in the Shashemene District of Ethiopia. In

[1]Cropping practices that help to improve environmental services and increase crop yields while reducing the need for external inputs like agrochemicals and fuel (Tittonell and Giller 2013).

[2]Crop production is environmentally non-degrading, resource conserving, socially acceptable, technically appropriate, and economically viable (FAO, 1995 as quoted in Nadia et al., 2017). This means that organic fertilizer maintains good yields and farm profits without undermining the soil resources on which crops depend.

[3]Organic fertilizers are carbon-based compounds that increase the productivity and growth quality of plants. These include crop residue, green manure and agroforestry, compost, animal manure, agro-processing by-products and excreta/sewage sludges and organic waste from urban centers.

Ghana, Martey (2018) found that adoption of the input improves crop productivity, incomes, and poverty status, while reducing the total and per capita food expenditure of farm households.

Though findings of the previous studies relating organic fertilizer to the welfare indicators mentioned above are useful in assessing overall farm household food access, they do not capture the stability dimension of food access, especially through self-provisioning capacity. Self-provisioning is a critical element of farm households' food access because farmers primarily consume their own produce, either directly from the farm or from storage. Furthermore, Martey's (2018) study, for instance, involved a sample with observations from heterogeneous populations across different ecological zones having divergent organic fertilizer types and related practices. Findings of such a study would not reflect agroecology-specific situations, wherein practices are homogenous, and Meso-level agricultural policies are often designed to suit.

Besides, we expect organic fertilizer adoption to occur at a cost for other input, especially labor, adjustments (Fuglie and Bosch, 1995; Teklewold et al., 2013). The potential increased labor requirements could hinder organic fertilizer adoption and application rate, and thus diminish the associated benefits to farmers (Teklewold et al., 2013). However, to the best of our knowledge, the extent to which organic fertilizer adoption affects farm-labor use in the entire SSA has not been empirically examined. These are shortcomings in the literature, underscoring the need to further analyze the impacts of organic fertilizer on farm-household welfare, especially within agro-ecologies, to adequately inform micro-/meso-level organic fertilizer use policies.

The main objective of this study is to evaluate the effects of organic fertilizer adoption on farm household food access and labor use among rural farmers. Using a set of observational data obtained from farmers in the northeastern part of Ghana, we adopted the potential outcome framework (see Imbens and Wooldridge, 2009) and applied the endogenous the switching regression (ESR) to model organic fertilizer adoption process, simultaneously with 1) per capita food expenditure, 2) household food gap (FG), and 3) gender-segregated farm labor used, as outcome variables. Subsequently, we estimated the effects of organic fertilizer on the outcomes. The study analyzes for the first time the effect of organic fertilizer on FG and farm labor use. It thus contributes to organic fertilizer literature, particularly in Ghana, by providing firsthand empirical links between farm labor use and household FG, on the one hand, and organic fertilizer adoption on the other.

The rest of the paper is structured as follows: the next section (section 2) describes the background to organic fertilizer practices in the study area. Section 3 outlines the study methodology, including sampling and the data used, the theoretical model and empirical specification applied. Section 4 provides data summary, presents econometric results for the ESR model, and discusses the effects of organic fertilizer adoption on food expenditure, FG, and labor use. Finally, section 5 summarizes the study's findings and concludes with key policy suggestions.

2. Organic Fertilizer use in Northeastern Ghana

Local organic fertilizer practices and their potentials to improve soil condition; hence farm productivity depend, to a large extent, on the agroecology, the farming system and population dynamics of an area (Tittonell and Giller, 2013; Adnana et al., 2017). Organic practices such as agroforestry and green manuring are almost impracticable in northeastern Ghana because arable land is increasingly scarce, and agriculture depends entirely on a unimodal rain season which is too short to grow green manure before the main crops. Thus, the common organic fertilizer practices among farmers in the area include crop residue restitution, composting, and the use of livestock manures (Martey, 2018). Yet, competing uses for crop residues in particular (e.g., for feeding livestock, as fuel, or for house construction) limit its availability for use as the primary biomass for maintaining the required level of organic matter (Wekesah et al., 2019). Crop-livestock integration is a traditional component of farming systems in the area, and farmers thus have some path dependencies in using manures for soil maintenance. However, livestock densities and the carrying capacity of local grasslands in the region cannot support the rate of manure turnover needed to supply more than one-third of household crop fields (Bationo and Buerkert, 2001; Tittonell and Giller, 2013).

Nonetheless, farmers are aware of the conservational values and the good returns on investment in organic fertilizers, and as a result many are motivated to increase its use (Nkonya et al., 2015; Powell and Williams, 1995). As soil and weather conditions change, the farmers must continue to adapt their traditional practices to prevailing agroecological conditions in order to sustain the quantities of organic matter they require for use (Fairhurst, 2012; Tittonell and Giller, 2013).

In support of farmers' adaptation, the Ministry of Food and Agriculture (MoFA) and other agencies (e.g., PAS [Presbyterian Agriculture Station], AGRA [Alliance for Green Revolution in Africa], NRGP [Northern Rural Growth Project], ACDI/VOCA [Agricultural Cooperative Development International/Volunteers in Overseas Cooperative Assistance], and GIZ [Gesellschaft für Internationale Zusammenarbeit])[4] have been sensitizing smallholder farmers and building their capacity to source and use organic fertilizers. Capacity-building efforts have focused mainly on developing skills for enhanced collection of agro-processing and domestic waste, harnessing animal manure and crop residues, and preparing compost using these materials (Bellwood-Howard, 2013). Dynamic kraaling[5] of cattle for in-situ accumulation of manure on cereal plots has become a popular organic fertilizer practice among the rural farmers. In communities where human excreta/sewage is accessible, farmers have also been educated on its safe use, and some combine it with other organic amendments to fertilizer their fields (Cofie et al., 2005, 2010). PAS and Opportunity for Industrialization Center (OIC), in particular, have trained farmers on the pit and heap methods of preparing, and supported some farmer groups to acquire equipment such as donkey carts for gathering compost materials (Bellwood-Howard, 2013). ACDI/VOCA, NRGP, and AGRA Ghana primed farmers on efficient and effective ways, including the *zai-pit*[6] method of applying the input for moisture conservation and the micro-dosing with mineral fertilizers for initial crop growth before organic fertilizer nutrients become available to the crop. They have also adopted intercropping and rotation of the grains with legumes and learned to augment organic fertilizers with significant quantities of mineral, especially Nitrogen-phosphrus-Potassium (NPK) fertilizers (Chapoto et al., 2015; Martey et al., 2014). Through such capacity-building programs, farmers now prioritize using their scarce organic amendments for the production of staple cereals as the most important food security crops (Martey, 2018). This study drew farmers from PAS and MoFA project areas to examine the effects of organic fertilizer adoption on food security and farm labor use.

3. Methodology

3.1. Sampling, Data, and Measurements

The data for this study was obtained through a recent farm household survey we conducted, in partnership with PAS in the North East and Upper East Regions of Ghana. As stated earlier, PAS, AGRA, and NRGP have under different projects at various locations within the study area, primed farmers to use organic fertilizer to sustain soil health. Except for the Bunkpurugu area where there is no PAS extension agent, we followed the operational areas of PAS to sample the study

[4]The full names of the organizations are PAS-Presbyterian Agriculture Station; AGRA-Alliance for Green Revolution in Africa; NRGP-Northern Rural Growth Project; ACDI/VOCA-Agricultural Cooperative Development International/ Volunteers in Overseas Cooperative Assistance; and GIZ-Gesellschaft für Internationale Zusammenarbeit.

[5]Abagale and Ayuegabe 2015 defined dynamic kraaling as a system of keeping cattle in temporary ranches usually farmlands, and rotating them with the main aim of accumulating the droppings and urine of the animals for fertilizer value to improve soil fertility for annual crop production.

[6]Zai is a term that refers to small planting pits that typically measure 20–30cm wide, 10–20cm deep and spaced 60–80cm apart. It is a technique used to rehabilitate degraded drylands with hard pans and to restore soil health. The pits break through soil pan and collects and conserves water and organic matter which supports crop growth and in the long run, help soften and gradually break the entire soil (Danquah et al., 2019).

participants. Prior to sampling, a discussion was held with MoFA (Bunkpurugu area) and the PAS extension agents to identify the types of organic fertilizer and related practices the farmers currently use.

We selected 504 households across 52 communities clustered around 3 PAS and 1 MoFA extension zones through a multistage cross-sectional sampling approach. At the first stage, we purposively selected the PAS and MoFA extension zones to ensure equal chances of including farmers the various organic fertilizer types in the sample. PAS and MoFA extension agents in the selected zones provided lists of farming communities from which we randomly drew 30% of the communities to represent each zone. At the community level, farmer-group and opinion leaders helped enumerators to identify and compile lists of organic fertilizer adopter and non-adopter households. Households were then randomly selected from the lists to represent each subsample group. Farmers who applied, at least, one ton per acre of any biomass (e.g., crop residue, animal manure, compost, domestic/urban waste, agro by-products, excreta slurry, or a combination of these) constituted the organic fertilizer user group (adopters)[7].

The data was collected through a face-to-face personal interview (PI) with sample participant farmers. Appendix 4A shows the number of communities and sampled households across the study locations. Since the main objective is to evaluate the effects of organic fertilizer on food access and labor use, the questionnaire elicited data on these as the outcome variables of organic fertilizer adoption. For food access, we considered two indicator variables critical in farm household settings: per capita food expenditure and food stability through self-provision (indicated by FG)[8]. Per capita food expenditure was measured in Ghana Cedis based on market value of adult equivalent units (AEU)[9] of food consumed, while household FG was captured as the duration of the period (in months) a household had difficulties securing sufficient foodstuff (Tambo and Wünscher, 2017). We used the AEU for per capita food expenditure because it is more directly linked to food access status of subsistent farm households and is less prone to measurement errors than the income-based indicators (Tambo and Wünscher, 2017). Following Tambo and Wünscher (2017) and Martey (2018), our questionnaire used a 7-day recall period to identify food items consumed by a household and thus captured the corresponding expenditure. Non-purchased food items were valued at current market prices. Regarding labor use, farmers reported the number of worker-days used per acre during the most recent crop season. This was subdivided into male and female worker-days[10] used in order to examine gender-based effects of organic fertilizer adoption on labor.

Following the strands of literature on farm technology in general (e.g., Di Falco et al., 2011; Fuglei and Bosch, 1995; Manthenge et al., 2014; Sheferaw et al., 2014; Tambo and Wünscher, 2017; Teklewold et al., 2013) and specifically, organic fertilizer adoption (e.g., Chen et al., 2018a, 2018b; Martey, 2018; Ullah et al., 2015; Waithaka et al., 2007), the survey also captured data on six categories of farmer background factors (explanatory variables). These moderator variables are farmer/household characteristics, resource constraints, and plot-specific factors. Other groups of explanatory variables include social capital, governance and institutional variables, information access factors, and environmental shocks. Empirically, the literature has proven that these variables significantly influence farmers' decision to adopt farm technology (Ayalew et al., 2020; Shiferaw et al., 2009; Teklewold et al., 2013). Table 1 shows the description and summary

[7]Adopters in this study are farm households who applied at least one ton of organic fertilizer (e.g., crop residue, animal manure, compost, domestic/urban waste, agro by-products, excreta slurry, or a combination of these) per acre.

[8]Food access is the ability to acquire sufficient quality and quantities of food, while food stability refers to the continuous availability of food under all conditions (FAO, 2008).

[9]We used a 1-week recall period to capture household food consumption expenditure by all components and then the OECD's [Organization for Economic Co-operation and Development] adult equivalent scale given as; $1+0.7(A-1) + 0.5C$, where A is the number of adults while C represents the number of children in a household, to arrive at adult equivalence units (AEU) of per capita food expenditure.

[10]A worker day is equivalent to 8 hours of farm work time of a man or woman.

Table 1. Summary statistics of variables

Variable	Description and measurement of variable	Sample mean	Adopters	Non-adopter	Mean diff.
Explanatory variables					
Dist. to exten.	Distance (minutes' walk) to agric. ext. office	80.3	59.3	100.9	−41.60
Gender	Gender of the family head (1 = male, 0 = female)	0.8	0.8	0.7	0.1***
Age	Number of years	42.3	43.0	41.5	1.45
Education	Number of years of formal schooling	5.2	6.6	3.9	2.74***
Household size	Number of people in the household	9.4	9.9	8.9	0.94***
Female2male	Ratio of female to male adults in a household	3.1	3.2	3.1	0.05
Off-farm work	Off-farm work participation (dummy)	0.4	0.4	0.4	0.01
Means_Trans	0 = no means, 1 = bicycle, 2 = motorbike/truck	1.2	1.2	1.2	0.04
FAssets	Value of farm assets (thousands of GHS)	5.6	6.2	5.0	1.16
TLUs	Livestock size (tropical livestock units)	3.6	5.0	2.2	2.82***
Farmland	Number of acres of farmland.	10.0	10.0	9.9	0.16
Plotsize	Number of acres of maize plot	3.7	3.9	3.6	0.29
Walkdist~T	Distance (walking minutes) to plot	31.1	26.8	35.3	−8.48
Extension	Frequency of visit during the cropping season	0.4	0.7	0.0	0.70***
Inputmktdis	Walking distance (minutes) to inputs market	45.8	50.7	40.9	9.80***
Groupmember	Household head is member of a Farmer Based Organization (FBO) (1 = yes, 0 = no)	0.4	0.7	0.1	0.63***
Mrktrelations	Number of grain traders a farmer knows	1.4	1.5	1.2	0.22
LandTenure	Farmland tenure dummy (1 = own, 0 = rented)	0.9	0.9	0.8	0.04
Peststress	Whether pests ever affected crops (dummy)	0.8	0.7	0.8	−0.12
Disease	Whether disease ever affected crops(yes = 1, no = 0)	0.2	0.2	0.3	−0.14
Droughts	Whether drought ever affected crops (yes = 1, no = 0)	0.4	0.6	0.2	0.40***
Watrlogg	Water-logging experience (yes = 1, no = 0)	0.1	0.2	0.0	0.13***
Soil status	Average of soil quality scores (1 to 3)	2.1	2.2	2.1	0.06*
Capital exp.	Capital expenditure on the plot (in GHS)	78.4	77.2	79.6	−2.39
Herbicides	Herbicides cost (in GHS) per acre.	21.0	22.7	19.3	3.48
Tillage mode	Minimum tillage dummy (1 = minimum, 0 = conventional)	0.1	0.2	0.0	0.22***
Mineral fert.	Kilograms of mineral fertilizer used per acre	99.3	89.1	109.2	−20.10
Seedgrade	Seed quality- (1 = improved seed, 0 = land-race)	0.5	0.5	0.5	−0.05
Bunpk. _Zone 0	Bunkpurugu extension cluster dummy	0.33	0.26	0.41	−0.15
Langb. _Zone 1	Langbinsi extension cluster dummy	0.21	0.27	0.15	0.12***
Garuwest _Zone 2	Manga-Bazua extension cluster dummy	0.13	0.21	0.04	0.17***
GaruEast _Zone 3	Garu-Tempane extension cluster dummy	0.33	0.26	0.41	−0.15

(*Continued*)

Table 1. (*Continued*)

Variable	Description and measurement of variable	Sample mean	Adopters	Non-adopter	Mean diff.
Outcome variables					
Food cons. Exp (FCE)	Adult equivalence of food expenditure (in GHS)	597.91	605.51	590.43	15.07
Food gap	Number of months of inadequate food supply	1.16	0.74	1.56	−0.82
Female labor	Number of female worker days used/acre	11.60	15.37	9.48	5.89***
Male labor	Number of male worker days used/acre	14.14	16.93	11.39	5.55***
Observations		504	250	254	

statistics, including mean differences between adopters and non-adopters regarding for all explanatory variables used in the study.

3.2. Theoretical Model and Estimation Strategy

Assuming farm households aim at maximizing access to food through organic fertilizer farm enterprise under optimal input use. We assume further that they are risk-neutral, and consider only the net benefits to be derived between organic fertilizer use and otherwise when deciding to adopt it. The decision task then is to choose the option that maximizes their welfare, subject to household resource endowment or constraints. Subsequently, the observed inputs used and resultant welfare indicators (food expenditure and FG) are outcomes of the binary adoption decision a household made (Sanglestsawai et al., 2015; Teklewold et al., 2013).

To specify the adoption model, let Q_{ja} and Q_{jn} represent the net outcome farmer j derives from organic fertilizer adoption and non-adoption, respectively. The farmer adopts organic fertilizer if $Q_{ja} > Q_{jn}$ (i.e., the benefit from adoption exceeds that from non-adoption). Also, let U_j^* (the difference between Q_{ja} and Q_{jn}) be a latent criterion variable on which farmer j bases his/her decision. Further, let D_j indicates the observed binary decision such that $U_j^* = Q_{ja} - Q_{jn} > 0$ when $D_j = 1$ (i.e., if farmer j adopts organic fertilizer) and $Q_{ja} - Q_{jn} \leq 0$ when $D_j = 0$ (i.e., when farmer j does not adopt organic fertilizer). By expressing U_j^* as a function of observed farmer characteristics denoted Z, we obtain a latent variable (adoption or selection) model that sorts farmers into adopters and non-adopter as (Di Falco et al., 2011):

$$U_j^* = \gamma' Z_j + \varepsilon_j \text{ with } D_j = \begin{Bmatrix} 1 & if\ U_j^* > 0 \\ 0 & otherwise \end{Bmatrix} \tag{1}$$

where Z_j is a vector of household and farm characteristics; γ is a vector of parameters to be estimated, while ϵ_j is a random term with zero mean and variance σ_ε^2, capturing measurement errors and effects of unobserved factors (Abdulai, 2016). Even though we cannot observe U_j^*, it can be indexed by the observed adoption decision D_j of farmer j, such that the probability of adoption is specified as:

$$\begin{aligned} \Pr(D_j = 1) = \Pr(U_j^* > 0) = \Pr(\varepsilon_j > -\gamma' Z_j) \\ = 1 - F(-\gamma' Z_j) \end{aligned} \tag{2}$$

where F is the cumulative distribution function of ϵ. Since D_j is the binary decision with value 1 or 0, equation (2) is an adoption model and can be estimated consistently by a standard probit estimator if ε_j is assumed normal. We can assess the effect of adoption on any of the outcomes (Q_j) by regressing Q_j on the binary adoption decision, D_j, and other explanatory variables as below (Tambo and Wünscher, 2017);

$$Q_j = \boldsymbol{X}_j'\beta + \omega D_j + \mu_j, \tag{3}$$

where $\boldsymbol{X}_j$ is a vector of household/farm characteristics such as age, gender, educational attainment of the household head, household size, resource endowment, social network, geographical location, and inputs/production characteristics; ω measures the effect of organic fertilizer adoption on outcome Q_j; μ captures measurement errors as well as the effects of unobserved factors, with j indexing individual farmers (Abdulai and Huffman, 2014; Tambo and Wünscher, 2017).

Equation (3) could be estimated by standard regression (ordinary least squares) if adoption were randomly assigned. In this observational case, however, adopters selected themselves into adoption probably because their personal characteristics like innate managerial and technical abilities support both the decision to adopt and the outcomes, such that they are also the ones who obtain higher outcomes even if they do not adopt (Fuglie and Bosch 1995). It means adopters systematically differ from non-adopters in terms of their background characteristics. Such a systematic difference obscures the true effect of adoption if ω is estimated by through equation (3) (Tambo and Wünscher, 2017). For this cross-sectional evaluation, where we have no counterfactual information for observed outcomes, using either a propensity score-matched (PSM) sample or adopting the ESR approach allows us to control for biases arising from systematic difference (Abdulai and Huffman, 2014). However, the PSM-based model assumes conditional unconfoundedness and thus becomes an invalid approach, where there is insufficient overlap in characteristics of adopters and non-adopters. Even in cases where it is applicable, the probit model coefficients usually, obtained after the PSM are not true coefficients of determination of adoption and cannot be interpreted as such. Since we wished to identify factors determining organic fertilizer adoption among the farmers in this case, we had to apply the ESR (Abdulai, 2016; Abdulai and Huffman, 2014).

3.3. Empirical Specification of ESR Model

In the ESR framework, equation (2) sorts farmers into adopters and non-adopters, having different outcome regimes. Because we observed either Q_{ja} or Q_{jn} for every farmer, there is no counterfactual information on the outcome. Thus, the ESR approach specified potential outcome equations conditional on adoption decision D_j as:

$$Q_{ja} = \boldsymbol{X}_{ja}'\beta_a + u_{ja} \quad \text{if } D_j = 1 \tag{4a}$$

$$Q_{jn} = \boldsymbol{X}_{jn}'\beta_n + u_{jn} \quad \text{if } D_j = 0 \tag{4b}$$

With a continuous outcome variable Q, linear regressions could be applied to estimate β_a and β_n. However, OLS estimator will give biased βs if the error term ϵ_j of equation (2) correlates with those (u_{ja} and u_{jn}) of the outcome equations (4a) and (4b). In other words, OLS cannot be applied when there is selection bias to be addressed. Bias is addressed by including selectivity correction terms in the outcome equations to capture the effect of selection (Abdulai and Huffman, 2014; Khonje et al., 2015; Lokshin and Sajaia 2004; Shiferaw et al., 2014; Tambo and Wünscher, 2017).

Error terms u_{ja} and u_{jn} correlating with ϵ_j implies that the expected values of u_{ja} and u_{jn}, conditional on the sample selection (adoption decision) are not zeros. But we can assume that ϵ_j has a variance $\sigma^2_{\varepsilon_j} = 1$, and the correlation coefficients between u_js and ϵ_j sum up to zero, meaning that they have a trivariate normal distribution with a zero-mean vector and a variance–covariance matrix (Σ) as defined below (Manthenge et al., 2014):

$$\Sigma = \begin{bmatrix} \sigma^2_{\varepsilon_j} & \sigma_{u_{ja}\varepsilon_j} & \sigma_{u_{jn}\varepsilon_j} \\ \sigma_{\varepsilon_j u_{ja}} & \sigma^2_{\mu_{ja}} & . \\ \sigma_{\varepsilon_j u_{jn}} & . & \sigma^2_{u_{jn}} \end{bmatrix},$$

where $\sigma^2_{u_{ja}} = \text{var}\ (u_{ja})$, $\sigma^2_{u_{jn}} = \text{var}(u_{jn})$, $\sigma_{u_{ja}\varepsilon_j} = \text{cov}(u_{ja}, \epsilon_j)$ and $\sigma_{u_{jn}\varepsilon_j} = \text{cov}(u_{jn}, \epsilon_j)$. The $\text{cov}(u_{ja,}\ u_{jn})$ is undefined since we cannot observe Q_{ja} and Q_{jn} simultaneously from any farmer (Maddalla, 1983). The expected values of u_{ja} ($\text{E}(u_{ja}\ |\text{D}_j = 1)$) and u_{jn} ($\text{E}(u_{jn}\ |D_j = 0)$) contain the selection bias and are statistically equivalent to the product of the error covariances ($\sigma_{u_{ja}\varepsilon_j}$ and $\sigma_{u_{jn}\varepsilon_j}$) and inverse Mills ratios (IMRs) for study participants computed from probabilities obtained by (2) at $\gamma' Z_j$. Thus, we calculate the IMRs (λ_{ja} and λ_{jn}) as:

$$\lambda_{ja} = \frac{\phi(\gamma' Z_j)}{\Phi(\gamma' Z_j)} \text{ if } \text{D}_j = 1 \tag{5a}$$

$$\lambda_{jn} = \frac{\phi(\gamma' Z_j)}{1 - \Phi(\gamma' Z_j)} \text{ if } \text{D}_j = 0 \tag{5b}$$

where φ is the standard normal probability density function and Φ represents cumulative density function of equation (2).

Including λ_{ja} and λ_{jn} in equations (4a) and (4b), respectively, gives the switching outcome equations that correct for selection bias as follows:

$$Q_{ja} = \boldsymbol{X}_{ja}\beta_a + \sigma_{\mu_{ja}\varepsilon_j}\lambda_{ja} + \ \xi_{ja} \quad \textit{if } D_j = 1 \tag{6a}$$

$$Q_{jn} = \boldsymbol{X}_{jn}\beta_n + \sigma_{\mu_{jn}\varepsilon_j}\lambda_{jn} + \ \xi_{jn} \quad \textit{if } D_j = 0, \tag{6b}$$

where $\sigma_{\mu_{ja}\varepsilon_j}$ and $\sigma_{\mu_{jn}\varepsilon_j}$ become coefficients of the selection control terms λ_{ja} and λ_{jn}, capturing effects of all unobserved selection variables on outcomes. ξ_{ja} and ξ_{jn} become the standard error terms with zero expectations. Equation (6) gives more consistent and efficient estimates if estimated simultaneously with the adoption equation (2), using the full information maximum likelihood (FIML)[11] estimator rather than Maddala's (1983) two-step approach (Lokshin and Sajaia, 2004; Tambo and Wünscher, 2017).

The FIML ESR model is identified through non-linearity of λ_{ja} and λ_{jn} (Lokshin and Sajaia, 2004), but identification is better when, at least, one variable (exclusion variable) affecting the adoption decision D_j but not the outcomes is included in equation (2) (Tambo and Wünscher, 2017). Following Di Falco et al. (2011) and Tambo and Wünscher (2017), we conducted falsification tests (see Appendix 4C)[12] for several potential instrumental variables to identify relevant exclusion variables. The tests revealed that the distance between household's location and the nearest agricultural extension office is the only valid instrument for use in our case. After estimating equations (2) and (6) simultaneously, we derived conditional expectations of the outcomes as follows:

Adopters with adoption (actual/observed outcome for adopters):

$$E(Q_{ja}|D_j = 1; \boldsymbol{X}) = \boldsymbol{X}_{\text{ja}}\boldsymbol{\beta}_{\text{a}} + \sigma_{\mu_{ja}\varepsilon_j}\lambda_{ja}, \tag{7a}$$

[11]The FIML estimation is implemented in STATA using the **movestay** command by Lokshin and Sajaia (2004), which implements the simultaneous estimation of the first- and second-stage equations.

[12]According to Di Falco et al. (2011), Khonje et al. (2015) and Tambo and Wünscher (2017) variables to be added in the selection model as instruments to improve ESR model identification are those that affect farmers' decision to adopt organic fertilizer do not directly affect any of the outcome variables, at least among non-adopter.

Non-adopters without adoption (actual/observed outcome for non-adopters):

$$E(Q_{jn}|D_j = 0; \boldsymbol{X}) = \boldsymbol{X}_{jn}\boldsymbol{\beta}_n + \sigma_{\mu_{jn}\varepsilon_j}\lambda_{jn}, \tag{7b}$$

Adopters had they not adopted (counterfactual outcome for adopters):

$$E(Q_{jn}|D_j = 1; \boldsymbol{X}) = \boldsymbol{X}_{ja}\boldsymbol{\beta}_n + \sigma_{\mu_{jn}\varepsilon_j}\lambda_{ja}, \tag{7c}$$

Non-adopters had they adopted (counterfactual outcome for non-adopters):

$$E(Q_{ja}|D_j = 0; \boldsymbol{X}) = \boldsymbol{X}_{jn}\boldsymbol{\beta}_a + \sigma_{\mu_{ja}\varepsilon_j}\lambda_{jn}, \tag{7d}$$

From these expectations, we calculate the average effect of adoption on adopters (AEAA) as:

$$\begin{aligned} \text{AEAA} = (7\text{a}) - (7\text{c}) = E(Q_{ja}|D_j = 1; \boldsymbol{X}) - E(Q_{jn}|D_j = 1; \boldsymbol{X}) \\ = \boldsymbol{X}_{ja}(\beta_a - \beta_n) + \lambda_{ja}(\sigma_{u_{ja}\varepsilon_j} - \sigma_{u_{jn}\varepsilon_j}), \end{aligned} \tag{8}$$

where $X_{ja}(\beta_a - \beta_n)$ captures the expected change in adopters' mean outcome if they have the characteristics similar to non-adopters.

AEAA estimates obtained from FIML are consistent but not efficient if there is effect heterogeneity (Wooldridge, 2015). Therefore, we checked the robustness of the AEAA estimates by comparing them with their precise but inconsistent counterparts obtained from endogenous adoption effect (**eteffect)** model, using the control function approach. Detail econometric results of the **eteffect** model are not presented in this paper but are available upon request. Further, we also analyzed farmer-level pre-adoption and transitional adoption effect heterogeneity, following the procedure outlined by Di Falco et al. (2011). However, for policy purposes, it is essential to examine heterogeneity across relevant farmer groups. This could be done by estimating and comparing the local average effects of adoption (LAEA) within different quantiles of the outcomes (Issahaku and Abdulai, 2019). This implies discrete measures of heterogeneity for groups. Yet, effect heterogeneity could be continuous; meaning that discrete measures would not reflect its true nature (Xie et al. 2012). Thus, following Xie et al.'s (2012) approach, we expressed farmer-specific effect of adoption (effect of adoption on adopters (EAA) and effect of adoption on non-adopters (EAN)) as a function of the probability to adopt organic fertilizer. We then visualized the trends of EAA and EAN by two-way scatter plots fitted with local polynomials of degree 1. (Xie et al., 2012). That allows us to observe how effect heterogeneity (the gap between polynomials lines) differs across levels of probability to adopt.

4. Empirical Results and Discussion

In this section, we show descriptive statistics of the sample data, and present and discuss the econometric results of organic fertilizer adoption probability model, followed by the results of the ESR outcome models. Next, we present and discuss estimated effects of organic fertilizer adoption on food access and labor outcomes variables. We then conclude the section with a discussion on adoption effect's heterogeneity.

4.1. Data Summary Statistics

Table 1 presents the summary statistics of the data we used in the study. Column three shows the pooled sample means, while columns four to six display subsample means for adopters and non-adopters and their differences, respectively. Mean-difference tests showed significant difference between adopter and non-adopter households regarding key socioeconomic variables, including gender, education, household size, and livestock size. Adopters also differ from non-adopters in terms of information access and social leverage profiles, such as extension visits, distance to the nearest input market, and membership of a farmer-based organization. Other characteristics

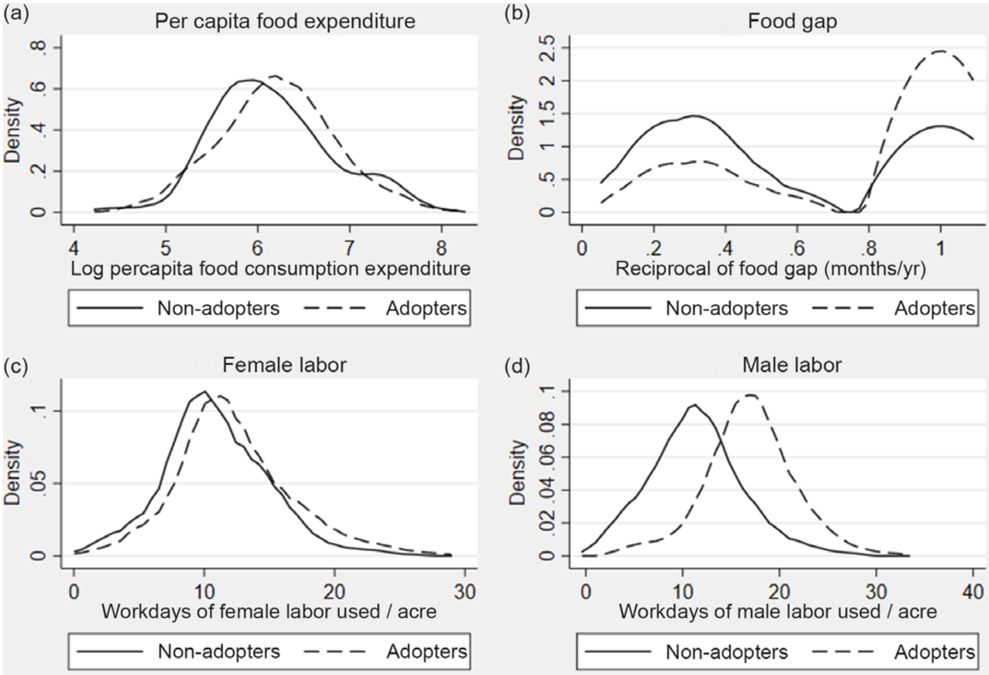

Figure 1. Kernel density distribution of outcome variables by adoption status.

distinguishing adopters from non-adopters are soil quality status, type of soil tillage practiced, and experience regarding production shocks such as drought and waterlogging. These differences mean that the randomized selection of communities during sampling did not yield a sample with participants of similar characteristics across the adoption regimes. This indicates that the observed characteristics and, probably, other unobserved factors determine self-selection of farmers into adoption as well as the outcomes.

The summary statistics of the outcome variables reported at the bottom of Table 1 show that the average per capita (adult equivalence) food expenditure is about 598GHS (Ghana Cedis) per annum. An average sample household experiences about 1 month of foodstuff shortages, usually from late April to late May. This period seems shorter (0.74 months) for adopters than for non-adopters (1.5 months), although the difference is not statistically significant. Regarding labor use, an average sample farmer deploys 11.6 worker days of female labor and 14.14 worker days of male labor, totaling 25.74 worker days per acre of maize. Organic fertilizer adopters, however, use significantly (at 1%) more labor than non-adopters.

Figure 1 shows kernel density distributions of the four outcome variables. These distributions highlight the systematic differences between adopters and non-adopters, affirming the validity of ESR model. Since the ESR command we used relies on a linear function of outcome variable, we carried out Box–Cox's functional form tests to identify and appropriately specify each outcome equation. The test reveals (see appendix 4B) that food consumption expenditure follows a log-linear function, while FG follows a multiplicative inverse (**reciprocal**) function. Female labor and male labor each support a linear identity process.

4.2. Determinants of Organic Fertilizer Adoption

An initial probit model for organic fertilizer adoption showed that the explanatory variables in our empirical model jointly determine adoption (LR $\chi^2(34) = 545.02$ [0.000], Pseudo $R^2 = 0.78$) and

Table 2. First-stage FIML estimates of organic fertilizer adoption probit model

	Adoption probit model, jointly estimated with:			
Explanatory variable	LogFood consump. expenditure	Recip. food gap	Female labor	Male labor
EXTFdistance	−0.019***	−0.020***	−0.021***	−0.020***
	(0.003)	(0.002)	(0.002)	(0.001)
Gender	−0.302	−0.426*	−0.487**	−0.476
	(0.279)	(0.239)	(0.228)	(0.296)
Age	0.098***	0.087*	0.085	0.073
	(0.029)	(0.053)	(0.053)	(0.047)
Age^2	−0.001***	−0.001	−0.001	−0.001
	(0.000)	(0.001)	(0.001)	(0.000)
Edu	0.036***	0.054***	0.042***	0.033**
	(0.012)	(0.007)	(0.014)	(0.014)
Household size	0.090***	0.088***	0.084***	0.102***
	(0.026)	(0.028)	(0.022)	(0.017)
F2M_Ratio	−0.018***	−0.017***	−0.020***	−0.018***
	(0.003)	(0.003)	(0.002)	(0.002)
Input market distance	0.224	0.012***	0.011***	0.010***
	(0.142)	(0.002)	(0.003)	(0.001)
Farm assets	−0.075	−0.013	−0.013	−0.015
	(0.115)	(0.008)	(0.014)	(0.010)
Lifestocksize (TLUs)	0.053***	0.055***	0.057***	0.055***
	(0.016)	(0.014)	(0.021)	(0.021)
Farmland	−0.426***	−0.039*	−0.028	−0.039
	(0.101)	(0.021)	(0.039)	(0.029)
Extension	2.012***	1.800***	2.093***	1.943***
	(0.084)	(0.201)	(0.041)	(0.076)
LandTenure	0.422***	0.370**	0.425	0.470**
	(0.164)	(0.156)	(0.341)	(0.190)
Groupmember	2.223***	2.094***	2.229***	2.183***
	(0.470)	(0.251)	(0.379)	(0.383)
Market relations	−0.167***	−0.122**	−0.201***	−0.183***
	(0.037)	(0.047)	(0.043)	(0.055)
Tillage mode	1.548***	2.031***	1.961***	1.967***
	(0.516)	(0.372)	(0.507)	(0.529)
Mineral fertilizer	−0.236***	−0.006	−0.005	−0.004
	(0.040)	(0.004)	(0.005)	(0.005)

(*Continued*)

Table 2. (*Continued*)

Explanatory variable	Adoption probit model, jointly estimated with: LogFood consump. expenditure	Recip. food gap	Female labor	Male labor
Peststress	0.36***	0.63***	0.57**	0.55**
	(0.12)	(0.22)	(0.28)	(0.25)
Diseases	−1.00	−1.15*	−1.01*	−1.06
	(0.63)	(0.69)	(0.60)	(0.72)
Drought	1.09***	0.94***	0.86**	0.93***
	(0.39)	(0.26)	(0.44)	(0.20)
Langb. _Zone 1	2.399***	2.447***	2.695***	2.598***
	(0.331)	(0.445)	(0.300)	(0.277)
Garuwest _Zone 2	4.682***	4.503***	5.024***	4.922***
	(0.514)	(0.303)	(0.399)	(0.364)
Garueast _Zone 3	3.588***	3.933***	4.042***	3.959***
	(0.745)	(0.504)	(0.575)	(0.600)
Joint sig. of plot-specific	9.120*	177.76***	2.340*	23.71***
Variables. $\chi^2(3)$	[0.028]	[0.000]	[0.505]	[0.000]
Constant	−2.879	−4.806**	−4.420**	−4.408**
	(1.897)	(2.052)	(1.960)	(2.170)
Log pseudo LR	−384.292	−173.837	−1470.334	−1502.731
Observations	504	504	504	504

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ and [ ] $= p>\chi^2$. Robust standard errors in parentheses. Other variables controlled for are meanstrans, plot-size, walkdisttoplot,watrlog, SoilStat, capitalexp herbvaluacre, seedgrade, off-farmincom, and OffFarmRes.

correctly predict about 94% of observed organic fertilizer adoption. The results for this first-stage adoption (selection) model are presented in Table 2. The excluded variable (i.e., distance to extension office) is statistically significant, proofing its validity as an instrument for identifying the empirical model. The coefficients of the other variables remained almost the same when the model is estimated simultaneously with any of the outcome's model. The error term of the adoption model correlates with that of FG and female labor use equations.

Organic fertilizer adoption is significantly explained by: (a) household characteristics (gender, age, and educational attainment of household head, household size, and female-to-male adults ratio); (b) resource endowment (tropical livestock units [TLUs], arable farmland available, and land tenure); (c) market, information, and social leverage constraints (extension visit, distance to input market, farmer group membership, and market relationships), and (d) husbandry practices and plot-specific production shocks (tillage type, mineral fertilizer use, pest stress, disease occurrence, drought, and waterlogged conditions). Finally, the probability of adoption also correlates positively with PAS extension clusters (zone) location relative to the Bunkpurugu zone.

Female-headed households are more likely to adopt organic fertilizer than male-headed ones. Age of the household head shows a quadratic relationship with the likelihood of organic fertilizer adoption. From youth, it increases with the likelihood of adoption, but the relationship tends to decrease for farmers beyond prime age, as indicated by the quadratic age term (age^2). Unlike the mixed findings by Martey (2018), this study finds that education is associated with an increased likelihood of adoption. This supports previous findings (e.g., Kassie et al. (2015) that better-educated farmers are able to access information required to understand farm technology; in this case, the complex relationship between soil health and organic practices and, therefore, are more likely to adopt than less the educated ones. Household size is significant and positively related to adoption, meaning that large households are more likely to adopt than their small counterparts with few members. This is in line with the assertion that organic fertilizer use is labor-demanding, and therefore, households who are capable of meeting the requirement will, more likely, adopt the technology (Chikowo et al., 2014). However, households with more female farmworkers are less likely to adopt the input's use than those having more male farmworkers.

Among the resource endowment factors, the number of TLUs a farmer owns has a significant positive relationship with organic fertilizer adoption. Since organic fertilizers are not commercially available, farmers who have substantial livestock herds may have better access to it in the form of animal manure than those without livestock. Hence, they are more likely to use organic fertilizer than those without livestock. The number of acres of arable land (farmland) a household has seems to reduce the probability of using organic fertilizer. On the contrary, ownership (tenure) of the organic fertilizer plot on which organic fertilizer is applied is associated with increased tendency to use organic fertilizer. Organic fertilizers release nutrients and build organic matter content of soil slowly, with the yield benefits accruing in the medium to long-run time span (Waithaka et al., 2007). Thus only the farmers who own plots on which organic fertilizer is applied are sure to derive the benefits themselves. Hence they are more motivated and likely to invest in organic fertilizer than those farming on rented plots (Abdulai, Owusu and Goetz, 2011; Chen et al., 2018a; Jacoby et al., 2002; Jacoby et al., 2008; Kousar and Abdulai, 2015).

Of the information and social leverage factors, the distance between a farm household and local input market, the number of extension visits, and membership of farmer-based organization(s) significantly increase the probability of organic fertilizer adoption. This is in line with previous studies that extension services, through information and skill enhancement, enable farmers to adopt new technologies (Abdulai, 2016; Abdulai and Huffman, 2014; Issahaku and Abdulai, 2019). Improved access to information through interaction with extension agents and fellow farmers increases awareness about the need to use organic soil amendments, hence, the probability of adoption. Distance to the nearest input market has a similar relationship with organic fertilizer use, probably by limiting access to the commercial alternative (i.e., mineral fertilizer), and thus, inducing the farmers to adopt organic fertilizers, which they can produce locally by themselves. On the contrary, the number of trusted marketing relations (traders) negatively correlates with adoption. Access to traders seems to enhance farmers' capacity to access and use mineral fertilizers (Teklewold et al., 2013). In summing up the results of the social leverage factors, it is reasonable to assert that organic fertilizer is a traditional resource-poor soil management technique rather than a modern technology to the sample farmers.

Regarding husbandry practices, minimum tillage is related to an increased probability of using organic fertilizer. That is because farmers in the area generally do not practice minimum tillage, except when they have to apply organic fertilizer by the *Zai pit* method. On the contrary, the quantity of mineral fertilizer a farmer applies tends to relate with reduced likelihood of organic fertilizer adoption, indicating farmers might have perceived the inputs as substitutes (Bellwood-Howard and Al-hassan, 2016). Experience in production shocks such as droughts and pest stress encourage adoption, while previous crop disease incidence seems to discourage adoption, even though statistically not very significant. This result is consistent with Teklewold et al.'s (2013) findings about factors affecting adoption of sustainable agricultural practices in Ethiopia.

Lastly, the location of a farm household, relative to extension zone 0 (Bunkp., reference zone), significantly determines organic fertilizer adoption. Households in zone 1 (Langbinsi area), zone 3 (Garu-Tempane area), and zone 2 (Manga-Basua area) are more likely to use organic fertilizer than their counterparts in zone 0. This could be attributed to better access to extension through organic fertilizer interventions by PAS and its affiliates.

Table 3. ESR estimates for determinants of household food access and labor use

Variable	Log FCE		(Food Gap)^-1		Female labor		Male labor	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Gender	−0.010	0.050	0.016	0.038	−0.071	−1.338*	−1.532***	−0.256**
	(0.125)	(0.041)	(0.033)	(0.076)	(0.473)	(0.800)	(0.484)	(0.111)
Age	0.001	0.014	−0.001	−0.001	0.235***	0.177**	−0.217	0.088
	(0.004)	(0.012)	(0.009)	(0.003)	(0.047)	(0.078)	(0.135)	(0.096)
Age^2	0.000	−0.000	0.000	0.000	−0.002***	−0.002**	0.002*	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Edu	0.009*	0.006	0.001	0.002	0.105*	−0.031	0.073	0.172**
	(0.005)	(0.004)	(0.003)	(0.008)	(0.063)	(0.046)	(0.074)	(0.079)
Household size	−0.039***	−0.090***	0.007	−0.004***	0.033***	−0.036	0.108	0.079
	(0.006)	(0.014)	(0.010)	(0.000)	(0.013)	(0.091)	(0.115)	(0.160)
F2M_ratio	0.001	0.000	−0.002***	−0.001	−0.009***	−0.001	0.007	−0.007
	(0.001)	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)	(0.006)	(0.006)
Input market dist.	0.012	−0.041***	−0.001	−0.001	0.018***	−0.014	0.016	−0.002
	(0.032)	(0.014)	(0.000)	(0.001)	(0.005)	(0.013)	(0.015)	(0.011)
FAssets	0.039	0.055***	0.000	0.004***	−0.037*	0.078***	−0.013	0.006
	(0.029)	(0.010)	(0.002)	(0.001)	(0.021)	(0.022)	(0.026)	(0.030)
Livestock (TLUs)	0.004	−0.001	−0.000	−0.006	0.053***	−0.068**	−0.034***	0.200***
	(0.002)	(0.004)	(0.001)	(0.007)	(0.005)	(0.029)	(0.011)	(0.059)
Farmland	−0.014	0.074*	−0.005**	0.001	0.121***	−0.075*	0.072	−0.034
	(0.095)	(0.045)	(0.002)	(0.008)	(0.031)	(0.041)	(0.050)	(0.068)
Extension	−0.032	−0.548***	0.029	0.330***	0.082	−0.927***	−1.017**	2.684***
	(0.030)	(0.057)	(0.023)	(0.023)	(0.466)	(0.180)	(0.434)	(0.821)
LandTenure	0.071	−0.123***	0.022	0.093	−1.210*	−0.622	−0.727	0.223
	(0.123)	(0.033)	(0.044)	(0.061)	(0.652)	(0.696)	(0.461)	(0.826)
Tillage mode	0.240**	−0.026	−0.020	0.999***	−1.139	−2.218	0.724	3.444**
	(0.097)	(0.053)	(0.048)	(0.115)	(0.898)	(1.679)	(0.635)	(1.681)
Mineral fert	−0.007	0.016	−0.000	0.000	0.006	0.019***	0.002	0.001
	(0.013)	(0.012)	(0.001)	(0.000)	(0.009)	(0.005)	(0.009)	(0.006)
Groupmember	0.081**	−0.006	0.162	0.207*	0.101	−1.760***	−1.142	−0.722
	(0.035)	(0.157)	(0.103)	(0.107)	(1.944)	(0.682)	(1.076)	(0.982)
Mrktrelations	0.041	−0.069***	−0.028	−0.017**	−0.014	0.389***	0.393***	0.550
	(0.025)	(0.025)	(0.029)	(0.008)	(0.205)	(0.081)	(0.094)	(0.343)
Langb. Zone 1	0.117***	−0.344***	−0.153*	0.020	1.455*	0.230	0.647	2.365***
	(0.030)	(0.112)	(0.088)	(0.086)	(0.783)	(0.391)	(0.813)	(0.762)

(*Continued*)

Table 3. (*Continued*)

Variable	Log FCE Adopters	Log FCE Non-adopters	(Food Gap)^-1 Adopters	(Food Gap)^-1 Non-adopters	Female labor Adopters	Female labor Non-adopters	Male labor Adopters	Male labor Non-adopters
Garuwest Zone 2	0.267*	−0.683***	−0.124	−0.371***	1.296**	−1.636*	0.016	4.669***
	(0.138)	(0.117)	(0.082)	(0.143)	(0.551)	(0.892)	(1.963)	(0.955)
Garueast Zone 3	0.050	−0.218	−0.249***	0.177**	2.535***	−2.502***	1.370	2.708***
	(0.118)	(0.142)	(0.085)	(0.073)	(0.485)	(0.333)	(1.551)	(0.738)
Joint sig.(plot vars) $\chi^2(37)$	69.24***	72.40***	71.12***	72.81***	65.17***	66.96 ***	64.20***	63.17**
	[0.001]	[0.000]	[0.000]	[0.000]	[0.003]	[0.002]	[0.004]	[0.005]
$ln\sigma_{ja\varepsilon}/ln\sigma_{jn\varepsilon}$	*−0.737****	*−0.863****	*−1.266****	*−1.151****	*1.408****	*1.302****	*1.404****	*1.424****
	(0.133)	*(0.123)*	*(0.295)*	*(0.089)*	*(0.015)*	*(0.021)*	*(0.006)*	*(0.022)*
$\rho_{ja\varepsilon}/\rho_{jn\varepsilon}$	***0.139***	***0.128***	***0.545***	***0.511****	***0.013***	***−0.485****	***−0.176***	***0.280***
	(0.127)	*(0.378)*	*(0.577)*	*(0.294)*	*(0.723)*	*(0.278)*	*(0.415)*	*(0.470)*
Wald test of indep. ($\rho = 0$)	0.61		6.90***		3.72*		1.32	
	[0.4363]		[0.008]		[0.053]		[0.250]	
Constant	6.023***	6.090***	0.731***	0.392	6.909	9.700***	20.347***	0.830
	(0.263)	(0.216)	(0.151)	(0.241)	(4.424)	(1.411)	(1.461)	(2.065)
Observations	250	254	250	254	250	254	250	254

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Other variables included are meanstrans, plot size, walkdisttoplot, disease, Drought, watrlogg, SoilStat, capitalexp herbvaluacre, seedgrade, peststress, OffFarmRes, and offfarmincom. For their coefficients and sig. level, the unedited Stata model outputs are available upon request.

4.3. Factors Explaining Household Food Expenditure, Food Gap, and Gender-Based Labor Use

Table 3 presents the results of second-stage ESR outcome model for adopters and non-adopters, respectively. At the bottom of the table are correlation coefficients ($\rho_{ja\epsilon}$ and $\rho_{jn\epsilon}$) between error the terms of the adoption equation and that of the outcome regime equations. Statistically significant values for these coefficients indicate a considerable self-selection of farmers into the outcome regimes based on some unobserved factors that influence both the adoption and the outcomes. Self-selection could lead to biased estimates for organic fertilizer effects, had it not been accounted for (Tambo and Wünscher, 2017). The $\rho_{jn\epsilon}$ between adoption model and non-adopter regimes and the Wald test of independence of the equations are also statistically significant, meaning that outcomes are not independent of adoption decision. Thus, we had to apply the ESR to control for selection bias in order to obtain accurate estimates of adoption effects on FG and female labor. A positive $\rho_{jn\epsilon}$ (in the non-adopter regime) between the reciprocal of FG and the adoption model suggests that non-adopters' decision not to adopt leads them to reduced FG. Similarly, the negative correlation ($\rho_{jn\epsilon}$) with the female labor equation indicates a reduction in female labor use under non-adoption.

Such kind of biases could exist in the other outcome (logFCE and male labor) equations without being detected, probably due to low statistical power. Thus, empirically we needed to employ the ESR approach in this study (Issahaku and Abdulai, 2019), even though the insignificant $\rho_{ja\epsilon}$s between adoption and adopter outcome equations suggest that adopters do not do better than a farmer selected at random. The transformed error covariances, $ln\sigma_{ja\epsilon,}$ and $ln\sigma_{jn\epsilon}$, also reported at the bottom, are highly significant, implying endogenous switching of outcomes between adoption and non-adoption (Tambo and Wünscher, 2017). These coefficients having the same sign, in this case, imply that farmers' decision to adopt organic fertilizer is not based on any comparative advantage of organic fertilizer. Rather farmers choose fertilizer regime that makes them better off in terms of the outcomes.

The estimates in Table 3 show that gender, age, and education of household heads do not affect food consumption expenditure (logFCE) and FG but they negatively influence labor, especially female labor use. Household size is negatively related to logFCE of both regimes and the FG of non-adopters, but positively associated with female labor use of adopters. This means that large households generally have low FCE, while only non-adopter large households experience higher FG compared with their small counterparts. Large adopter-households use female labor more than small households, probably because they (large adopter-households) have more household labor. Similarly, female-to-male ratio in a household is associated with extended periods of FG and more female labor use. Farm asset value is also significant and positively affects FCE, FG, and female labor of non-adopters, but negatively relates to adopters' female labor use. TLU statistically relates to only labor use, with opposing signs on adopters and non-adopters. The size of total arable land a household possesses has a similar alternate relationship with outcomes of adopters and non-adopters, even though it is not statistically significant in the case of FCE of adopters, FG of non-adopters, and male labor use of both regimes.

Besides the household characteristics presented above, market and information access variables, including extension visits, membership of farmer-group(s), and relationship with traders also significantly influence outcomes of the regimes differently. The same holds for geographical location (cluster) of households relative to Bunkpurugu area (reference zone). Lastly, we refer the reader to Table 3 for the joint effects of plot-specific variables. Even though some of them have insignificant coefficients, their joint-significance test result (see χ^2 (37)) is highly significant (at 1%). Based on equations 7a to 7d, we obtained both conditional and unconditional expected outcomes for each adoption regime. We then computed different measures of organic fertilizer effect from the expectations, as presented below.

4.4. Effects of Organic Fertilizer Adoption on Food Security and Labor Use[13]

Table 4 shows the expected outcomes, average effect of adoption on adopters (AEAA)[14], average effect of adoption on non-adopters (AEAN), as well as adoption effect heterogeneity indexes (BH1, BH2, and AH) for each outcome variable (i.e., under the first column). BH1 and BH2 are the transitional and base heterogeneity, respectively, while AH indicates average effect heterogeneity, showing whether the effect of organic fertilizer is more or less on adopters than non-adopters, in a counterfactual situation that non-adopters did adopt (Di Falco et al., 2011). In other words, it represents the effect of selection on adoption (Wooldridge, 2015).

We obtained alternative estimates for the adoption effects (see appendix 4D) using the endogenous adoption effect (eteffects) model to check the robustness of ESR estimates. The **eteffects**-based AEAA estimates have the same signs and are close to those from the ESR model even though, except for female labor use, they are not statistically significant. The **eteffect**s model employs the control function estimator, which gives precise but inconsistent estimates because it is sensitive to self-selection and influential observations (Wooldridge, 2015). Thus, its estimates are subject to larger standard errors than those of ESR in cases where there is self-selectivity ($ln\sigma_{ja\varepsilon}/ln\sigma_{jn\varepsilon}$) and effect heterogeneities (BH and AH). On the other hand, the ESR model if

[13]We defined the average effect of adoption on adopters as the average effect treatment on the treated (AEAA), and the average potential effect of adoption on non-adopters as the average effect of treatment on untreated (AEAN), so that we continue to use the latter set of terms, because they are well established in the literature

[14]AEAA is the average difference between the actual expected outcome of adopters (^{a}) and its counterfactual expected outcome (^{c}) had they not adopted. Similarly, AEAN is the difference between (^{d}) the counterfactual expected outcome of non-adopters had they adopted and the actual expected outcome (^{b}). BH1, BH2, and AH are (a)–(d), (c)–(b), and AEAA–AEAN, respectively.

Table 4. ESR-based expected outcomes; adoption effects and heterogeneity

Outcome variable	Subsample	Expected outcomes: With adoption	Expected outcomes: Without adoption	Adoption (adoption) effects	Difference	% change
Log FCE per AE	**Adopters**	6.212[a]	5.620[c]	AEAA	0.595***	11
		(0.025)	(0.050)		(0.040)	
	Non-adopters	6.033[d]	6.159[b]	AEAN	−0.126***	
		(0.027)	(0.031)		(0.021)	
	Heterogeneity effects	BH1 = 0.179***	BH2 = −0.539***	AH	0.721***	
		(0.014)	(0.018)		(0.016)	
Food Gap	Adopters	1.231	0.793	AEAA	0.438***	55
		(0.047)	(0.010)		(0.044)	
	Non-adopters	0.591	0.623	AEAN	−0.032**	
		(0.010)	(0.008)		(0.0126)	
	Heterogeneity effects	BH1 = 0.640***	BH2 = 0.170***	AH	0.470***	
		(0.015)	(0.001)		(0.015)	
Female labor days/acre	Adopters	12.316	6.466	AEAA	5.850***	90
		(0.108)	(0.159)		(0.198)	
	Non-adopters	11.455	10.893	AEAN	0.562***	
		(0.100)	(0.104)		(0.152)	
	Heterogeneity effects	BH1 = 0.861***	BH2 = −4.427***	AH	5.288***	
		(0.029)	(0.032)		(0.037)	
Male labor days/acre	Adopters	16.932	15.605	AEAA	1.327***	9
		(0.127)	(0.263)		(0.320)	
	Non-adopters	18.618	11.387	AEAN	7.230***	
		(0.117)	(0.143)		(0.189)	
	Heterogeneity effects	BH1 = −1.686***	BH2 = 4.218***	AH	−5.903***	
		(0.031)	(0.040)		(0.037)	

Standard error in parenthesis. **, *** significant at 5% and 1%, respectively. [a] and [b] are actual expected outcomes for adopters and non-adopter, respectively, while [c] and [d] are their counterfactual outcomes. For food gap, +AEAA means decrease, while the reverse is true for AEAN, since the estimates are in reciprocals.

estimated by the FIML, exploits all available information in the data to fit the model. Hence, the estimates are more consistent than those of the control function estimator (Issahaku and Abdulai, 2019).

The estimated average effects of adoption show that food consumption expenditure for adopter households increased by about 0.6 log units (AEAA = 0.595) over what it would be, had they not adopted. This represents about 11% (GHS 30.35) increased consumption under organic fertilizer adoption in adopter households. However, food consumption would have been 2% lower in non-adopter households (GHS 9.46) had they adopted organic fertilizer (AEAN = −0.126 log units). These results, as indicated earlier, imply that while adopters are better off adopting organic fertilizer, non-adopters are also better off not adopting. Yet, adopters are far better off under their decision to adopt than non-adopters are under non-adoption. The base and transitional effect heterogeneity estimates (BH1, BH2, and AH) indicate that adopters systematically differ from non-adopters are regarding their background characteristics. And adoption makes adopters a higher per capita food consumers than non-adopters. This meso-level finding is at variance with Martey (2018) macro-level conclusion that organic fertilizer adoption insignificantly lowers food consumption expenditure. The difference could be due to the fact that the present study consisted more subsistent farm households whose additional farm proceeds from adoption reflect in higher food consumption rather than in other expenditures such as report in Martey (2018). It could also be that the previous study's estimates were biased through averaging over different agroecological zones.

The FG estimate gives an AEAA of 0.438 reciprocal months of FG, representing 0.69 months (55%) decrease from the mean FG that adopter households would have experienced, had they not adopted. Non-adopter households, on the other hand, have a reciprocal of 0.623 FG months but would have had 0.591 with an AEAN (−0.032) representing a 5% increase in the duration of the FG, had non-adopters adopted organic fertilizer. These results show that organic fertilizer adoption decreases food deficits in adopter households, though they still would have experienced fewer months of food inadequacy than non-adopters, had they not adopted.

Regarding labor use, the AEAA shows that organic fertilizer adoption results in a vast increase (5.9) in female worker days from 6.5/acre to 12.3/acre, representing 90%. For non-adopters, the difference (i.e., AEAN) between expected labor use, if they had adopted, and the actual labor use under non-adoption is 0.56 worker days, representing a 5% increase. Hence the transitional heterogeneity (AH = 5.3 worker days) indicates that the effect is more on adopters than non-adopters. However, the pattern is reversed in the case of male labor use. The AEAA on male labor used by adopters is about 9% (1.3 worker days) more than they would have used if they had not adopted organic fertilizer. In the counterfactual case that non-adopters would have adopted, the AEAN indicates they would have used 7.2 worker days (63%) more male labor. This means that the effect of organic fertilizer adoption on male labor use (as indicated by the negative AH) is less for adopter households than for non-adopters. In general, the results regarding labor use are consistent with Teklewold et al.'s (2013) findings that sustainable intensification practices increase farm labor use, with female workers supplying the extra labor needed. For organic fertilizer in particular, much human effort is required in place of carting equipments to collect, transport, and apply the high tonnage (Xu et al., 2014). Farmers in the study area generally lack such equipments. Thus, traditionally they employ young women to carry out such operations.

4.5 Organic Fertilizer Effect Heterogeneity

The indexes (BH1, BH2, and AH) in Table 4 are average difference adoption effects on adopters and non-adopters. They indicate the presence and general direction of pre-adoption and adoption effects heterogeneity between adopters and non-adopters. We can observe the heterogeneity trend by analyzing and comparing farmer-specific deviations from their sub-sample means (AEAA and AEAN).

Figure 2 shows scatter plots of EAA, EAN, with fitted polynomial lines representing AEAA (pink) and AEAN (green) for each outcome against the probability of adopting organic fertilizer. The gap between the fitted lines indicates the transitional heterogeneity between adopters and non-adopters of equal probability at every point along the probability continuum. For per capita food consumption expenditure, adoption effect heterogeneity is high between farmers with probability ranging from 0.3 to 0.6, where the majority of non-adopters have a negative AEAN. The heterogeneity between farmers with probabilities beyond 0.6 is low, but positive and appears increasing with the probabilities approaching 0.9. The intuition behind this is that non-adopters with an adoption probability above 0.6 will improve their per capita food consumption if they are facilitated to adopt, whereas the same cannot be said about those with low adoption probabilities.

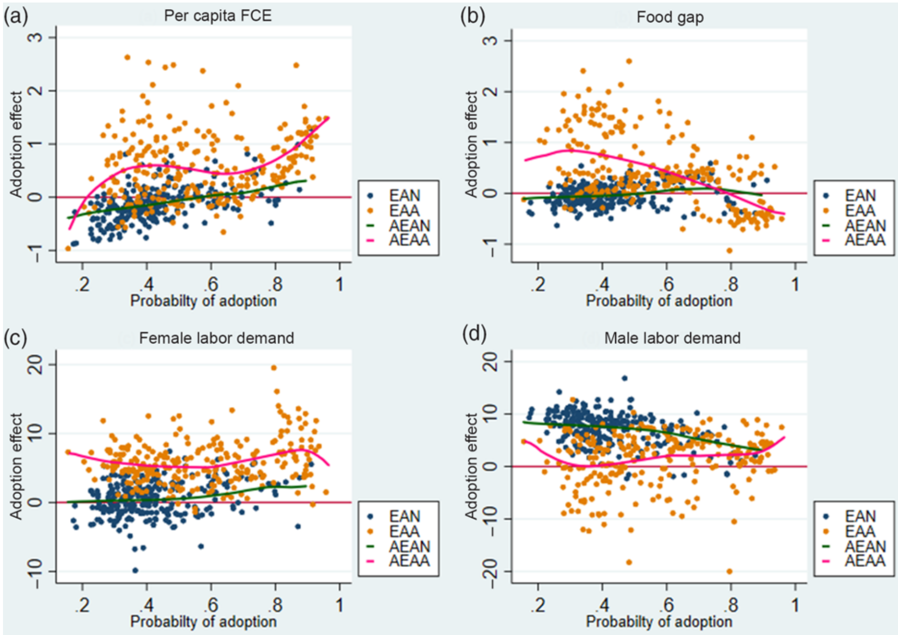

Figure 2. Adoption effects on food access (a and b) and labor demand (c and d) by adoption regime.

The adoption effect on the FG among adopters decreases from positive to negative as the probability of adoption increases, while that of non-adopters remains negative except for those with probabilities between 0.6 and 0.8. Thus, AH becomes negative at probabilities beyond, where non-adopters have almost zero but higher adoption effects than adopters. In that case, encouraging non-adopters to adopt without first changing ground conditions that select them on non-adoption will yield no benefit. Similar to the trend observed in AH of the FG is that of male labor use but the AH effect in that case is negative at all probabilities of adoption, meaning that non-adopters, if adopt, will use more male labor than adopters. Finally, for female labor use, the effect of adoption is positive for both adopters and non-adopters but higher on the adopters than the non-adopters. However, the difference (AH) between the two remains relatively unchanged at all probabilities of adoption.

5. Summary and Conclusions

This paper used a set of observational data obtained from 504 smallholder maize farmers in Northeastern Ghana to examine organic fertilizer adoption and its effects on farm household food access on the one hand and farm labor use on the other. Given that adopters, through their characteristics, self-selected to adopt, we employed the ESR approach to account for self-selectivity bias while modeling adoption and expected outcome for each regime.

The adoption model estimates show that household characteristics, such as the age, gender, education of household head, household size, and location of household within PAS extension zone significantly correlate with the probability of adopting organic fertilizer. Resource-based, plot-specific, and environmental factors like households' livestock size, farmland ownership, minimum tillage practice, and previous drought experience also tend motivate farmers to adopt organic fertilizer. Social capital, governance, and institutional factors supporting organic fertilizer adoption include household distance to input market, membership to farmer group, and access to extension services. On the other hand, factors like farm size (acres of arable land), farm capital expenses, mineral fertilizer use, the number of grain buyers a household has contact with, and the distance to agricultural extension office negatively correlate with the probability of organic fertilizer adoption.

These characteristics have mixed effects across adopters and non-adopters outcome equations, except education, which positively affects all the outcomes of both regimes. Generally, the ESR results show that adoption is not based on any comparative advantage organic fertilizer has. Instead, farmers choose to adopt or otherwise based on the regime that gives the farm household the best outcome.

The ESR model results also reveal that observed and some unobserved factors influence farmers' outcomes, not only through adoption but also directly. This means that our estimates for organic fertilizer effects would have been biased, had we not applied the ESR model. Adoption effect heterogeneity trends indicate that we would have underestimated the effects on food consumption expenditure, FG and female labor use and yet overestimate that of male labor use. The effect estimates show that organic fertilizer adoption improves household food access by increasing per capita food consumption expenditure significantly, while reducing FG period. Unfortunately, adoption increases labor requirement by about one-third, placing nearly all the increased labor burden on female farmhands. This means that though organic fertilizer adoption can improve food security among farm households, it could be severely hindered, especially by female labor constraints.

From a policy perspective, findings of this study have implications for current and future interventions seeking increased organic fertilizer use in the country. Investment in rural education and improved access to organic fertilizer use information through farmer-based organizations and extension services are strategic measures to promote adoption. For short-term measures to draw in non-adopters, unobserved factors opposing farmers' motivations to use organic fertilizer, including misconceptions about the input, need to be identified and mitigated. The negative effect of mineral fertilizer in the adoption process suggests that farmers have wrongly perceived mineral and organic fertilizers to be substitutes (Bellwood-Howard and Al-hassan, 2016). Hence, the need to sensitize farmers further on the complementary roles the inputs play in sustainable crop production. Interventions should consider providing female-user-friendly and labor-saving equipments for collection, transportation, and application of organic fertilizer to facilitate uptake and intensification of the inputs' use in the area.

Finally, we note that, though this paper contributes significant empirical evidence to the literature on organic fertilizer use and farm household welfare, the analysis used a cross-sectional dataset. Thus, it does not account for time adjustments in organic fertilizer use and associated long-term beneficial effects on the welfare outcomes (Chen et al., 2018b; Martey, 2018). Hence, the results should be interpreted and appropriated with caution.

Funding. Funding for this publication was provided by the Deutsche Forschungsgemeinschaft (DFG)-OA Fund of the Christian-Albrechts University of Kiel (CAU).

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Cite this article: Daadi BE and Latacz-Lohmann U (2021). Organic Fertilizer Adoption, Household Food Access, and Gender-Based Farm Labor Use: Empirical Insights from Northern Ghana. *Journal of Agricultural and Applied Economics* **53**, 435–458. https://doi.org/10.1017/aae.2021.8