The Impact of Sludge Manure Adoption on Household Welfare in Rural Uganda

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Abstract

Soil deterioration and infertility are major concerns for smallholder farmers in developing countries, Sub-Saharan Africa (SSA) included. In addition, loss in size and quality of arable land in SSA has resulted into reduced productivity, making the region vulnerable to food insecurity. Therefore, the study aimed at quantifying the effect of sludge manure adoption on rural farm household welfare in Uganda. The study uses data from the 2023 cross-sectional survey of 522 farming households from six districts of central Uganda. The study used an endogenous switching regression (ESR) model and Propensity Score Matching (PSM) to analyse the impact of sludge manure on household welfare. The findings show that a household's decision to use sludge manure is primarily influenced by socio-economic and institutional factors, plot characteristics, and location. Specifically, adoption decisions are influenced positively by use of hired labour and distance to input suppliers but negatively by credit access, distance from the water supply, time spent on farming, and pesticide use. Furthermore, results from the ESR show that, on average, sludge manure adopters have higher per capita household food expenditure and per capita total household expenditure. These results are robustly similar to the PSM results. As a way of conclusion, sludge manure adoption increases both per capita food and per capita total household expenditure. In terms of recommendation, government should promote the use of sludge manure by farming households in Uganda, to improve agricultural productivity and general welfare.

Keywords: Sludge manure, household welfare, adoption, endogenous switching.

Introduction

Globally, the quality of soils has continuously degraded due to continuous utilization for economic gains or increased population densities (Bouma & Batjes, 2000). This concern of soil deterioration and infertility is a major concern especially among for smallholder farmers in developing countries (Chianu *et al.*, 2012; Chikowo *et al.,* 2014; Zingore *et al.*, 2015) and it is expected to rise due to the rising trend in the world's population. For example, it is projected that by the end of the century, the population in Sub-Saharan Africa (SSA) will hit 3.78 billion people (Gu *et al.*, 2021). This population expansion causes land fragmentation and degradation (Henao & Baanante, 2006; Nagdeve, 2007; Pech & Sunada, 2008). Furthermore, Africa's soils are being depleted of nutrients at an alarming rate due to land pressure, and poor land management practices (Reich *et al*., 2019; Thapa & Diedrich, 2023). Moreover, deficiency in soil nutrients is recognized as the primary biophysical restriction on agricultural output in Africa (Omotayo & Chukwuka, 2009; Raimi *et al*., 2017; Tittonell & Giller, 2013). Although SSA is endowed with abundant land compared to other regions such as East Asia, arable land per capita has declined, and continues to shrink (Muyanga & Jayne, 2014; Lal, 2001; Otsuka & Place, 2015). The loss in size and quality of arable land in SSA has resulted into reduced productivity, making the region vulnerable to food insecurity (Van Ittersum *et al*., 2016; Zakari *et al*., 2014).

In the context of Uganda, loss in soil fertility has become a common phenomenon due to population pressure in many parts of the country and poor land management practices (Betty, 2013; Mubiru *et al.*, 2017). Generally, the loss in soil fertility has affected farm production as well as household welfare (Barrett & Bevis, 2015; Nkonya *et al*., 2008). Consequently, the declining land productivity requires a transition in farming methods towards more intensive agriculture where more prudent soil management practices, such as the use of fertilizer (Alimi, 2002; Diacono & Montemuro, 2011), are used to enhance productivity and eventually household welfare (Boahen, 2022; Eyhorn, 2007; Martey, 2018). Therefore, to stimulate production soil supplements are required (Bokhtiar *et al*., 2000; Zake *et al.*, 2010).

However, literature shows that agro-chemicals are environmentally hazardous (Salamat *et al*., 2021; Savci, 2012) and bear some health risks (Dhananjayan *et al*., 2020; Jayakumar *et al*., 2023) thus, putting organic supplements such as sludge manure in the limelight of enhancing farm production as well as improving farm household's welfare. And though literature (Abdoulaye *et al*., 2005; Martey, 2018; Yamano & Kijima, 2010) that relates organic supplements to household welfare does exist for other parts of the world it is lacking when it comes to the African continent. And though existing literature is based on the global south (Holmer, 2009; Landge, 2017; Zuo *et al*., 2021) studies covering Africa are limited (Andersson, 2015; Cofie *et al*., 2010) and when available they mainly look at faecal sludge impact on household crop incomes as a welfare measure.

Despite organic fertilizers having been proven to improve households' welfare, there is a lack of enough empirical evidence in Uganda on the impact of sludge manure as a potential resource for improved crop productivity and households' welfare. Therefore, the study on which the paper is based focused aimed at determining the impact of sludge manure adoption on Ugandan households' welfare. Specifically, the paper contributes to the body of knowledge in two main ways: first, it highlights the factors that influence farm households' adoption of sludge manure; second, it estimates the welfare impact of sludge manure on household welfare, focusing on per capita food expenditure, per capita household total expenditure and household food sufficiency.

The rest of the paper is structured as follows; the second section presents materials and methods. The third section presents the study findings and the relevant discussion. Finally, the fourth section presents the papers conclusions and recommendations.

Theoretical Framework

This paper follows Singh *et al.* (1986), in which a household is modelled as a utility maximizing entity. The study assumes three commodities that maximize household utility i.e. an agricultural staple food X_a, market purchased good X_m and leisure X_l. This study considers a subsistence farmer who aims at utility maximization. Such a farmer, is presumed to maximise his welfare through maximizing his utility. But utility is constraint by income as indicated in equation (1):

$$M=P_mX_m+P_a(Q-X_a)-w(L-F) \quad (1)$$

Where P_m and P_a are the prices of the market purchased commodities and staple, respectively. Q is the household's production of the staple food (so that $Q-X_a$ is the marketed surplus). Since this study considers a subsistence household, we take an assumption that its production depends on labour and other inputs purchased from the market and the funds from the farm sales are used to pay for labour and market goods. Hired labour is paid a market wage (w). total amount of labour used for farm production is given by L and F denotes family labour. The total payment to hired labour is given by w (L-F). using the langragean multiplier, the utility maximizing problem can be expressed as:

$$L=U(X_aX_mX_l)+\lambda(M-P_mX_m-P_a(Q-X_a+w(L-F)$$
(2)

From equation 2:

$$\frac{\partial l}{\partial X_a}=\frac{\partial u\,(X_a\,X_m\,X_l)}{\partial X_a}=P_a \quad (3)$$

$$\frac{\partial l}{\partial X_m}=\frac{\partial u\,(X_a\,X_m\,X_l)}{\partial X_m}=P_m \quad (4)$$

$$\frac{\partial l}{\partial (L-F)}=-\frac{\partial u\,(X_a\,X_m\,X_l)}{\partial (L-F)}=w \quad (5)$$

From equations 3,4 and 5 the utility maximizing bundle for each bundle of the commodity is given by equation 6.

$X_i = X_i\ (P_m P_a w) i =$ m*, a, and l.* (6)

Equation 6 shows that the farmer's welfare which is indicated by the bundles of the commodities consumed, depends on the price of staple food, marketed good and wage of the hired workers.

Methodology

Description of the study areas

The study was conducted in six districts in central Uganda i.e., Mpigi, Masaka, Mityana, Mukono, Luweero, and Wakiso. According to the information obtained from the international centre for tropical agriculture, these districts are situated in the Lake Victoria Crescent Agro-Ecological Zone (LVC-AEZ). The LVC-AEZ experiences annual rainfall that ranges between 1200 and 1450mm with annual temperature range of 15-30°C. In relation to altitude, the zone is located between 1000-1800M above sea level. Soils are characterised by clay, sandy clay and loam content. In some areas, the soils are acidic with low potassium, but with moderate levels of organic matter. Crop production is pre-dominantly carried out on slopes where the soil is generally deep. In terms of land use, the zone is an important agricultural area where 82% of the land is farmed. The cropping system is diverse with both perennial and annual crops. Bananas, maize, beans, sweet potatoes, cowpeas, cassava are the main food crops while coffee, tea and tobacco are the main cash crops (see UBOS, 2019). Due to the continuous depletion of the soil quality within LVC-AEZ, crop production has been supported through the use of both inorganic and organic supplements. Sludge manure is one of the agricultural supplements that have been used by farmers over the years though in an informal setting. In 2014, the government established Lubigi Sewerage Treatment Plant (LSTP) to reduce on pollution into Lake Victoria and improve on waste treatment. Through waste treatment mandate, LSTP started to formally process and distribute sludge manure.

Research design

The study employed a quasi-experimental research design. Data was collected between January and February 2023 from both adopters and non-adopters of sludge manure. Assessing the impact of an agricultural supplement like sludge manure would be appropriate through the use of a Randomized Control Trial (RCT). RCT requires baseline data and subsequent data waves. Due to absence of baseline data, we measure the impact of sludge manure on household welfare using a quasi-experimental setting. A number of studies have used a single data wave to assess the outcomes of various interventions (see Ntakyo & van den Berg, 2019; Melesse & Bulte, 2015; Melesse *et al.*, 2018).

Sampling techniques and sample size

The study used a mix of sampling techniques. To start with, the selection of the districts was purposively done basing on information obtained from Lubigi Sewerage Treatment Plant. Although, sludge manure provided by Lubigi has been used by farmers in over 15 districts, majority of adopters are located in Kampala, Wakiso, Mityana, Luweero, Mpigi, Mukono and Masaka districts[1]. A simple random sampling was used to select two sub-counties from each district and two parishes from each sub-county. The respondents were randomly selected from the list of adopters obtained from LSTP. We targeted 9 respondents per parish but some opted not to participate leading to 199 adopters in the sample. The selection of non-adopters was conducted using the village census books. The research team obtained these census books and dropped the adopters using the lists provided by LSTP. We used the remaining residents in the village census book to construct the parish census book. Thereafter, a probabilistic approach was used to select 14 households per parish and this would give a total of 336 households. However, a total of 323 households were interviewed due to non-compliance of 13 households[2].

[1] *For logistical reasons, we remained silent about districts with less than 75 adopting households. We also remained silent about Kampala because many adopters use sludge manure for supporting paspalum and flower growing in their compounds.*

[2] *The targeted sample for non-adopters exceeds adopters because our partner institution (LSTP) required some baseline information to guide scale up program.*

Data Collection

The population of interest constituted adopters and non-adopters of sludge manure in the selected districts. Data were collected through interviews guided by a well-structured questionnaire. The questionnaire was designed with various modules including a module on household socio-economic demographics, household production, household welfare, and a module on cost effectiveness of sludge manure visa a vie other supplements. A module on household welfare provides our dependent variables.

Variable definitions and their influence on sludge manure adoption

This section defines the variables used in the analysis of the adoption of sludge manure and

Table 1: Variables, variable description and expected influence

Variable	Variable description	Expected influence
Age household head	Age of household head in complete years.	-
household size	Average number of people in a household	+/-
Distance market	Distance to the market from a household in kilometres	¬¬-/+
Income household	Average monthly income of the household measured in Uganda shillings	+
Landsize_undercrop farm	Number of acres under crop production.	+
Hired_labor	Dummy =1 if household uses hired labour on crop production, 0 otherwise	+
Synthetic_fertilizer	Dummy =1 if household uses synthetic fertilizers, 0 otherwise	-
Compost_manure	Dummy =1 if household uses homemade compost manure, 0 otherwise	-
Hybrid_seeds	Dummy =1 if household used hybrid seeds in the last 12 months, 0 otherwise	+
Government_support	Dummy =1 if household received government support in the last 12 months, 0 otherwise	+
Credit_access	Dummy =1 if household accessed a loan in the last 12 months, 0 otherwise	+
Education_household head	Dummy =1 if household head attained at least a level of formal education, 0 otherwise	+
Pesticide use	Dummy =1 if household uses pesticide on the crops, 0 otherwise	+
Group member	Dummy =1 if household head is a member of at least a farmers' group	+
Irrigation	Dummy =1 if a household irrigated its crops regularly in the last 12 months, 0 otherwise	+
Main occupation	Dummy =1 if household head's main occupation is crop farming, 0 otherwise	+/-
Time spent farming	Time spent in crop farming in years	+
Distance input suppliers	Distance to the input suppliers from a household in kilometres	+/-
Married	Dummy =1 if household head is married, 0 otherwise	+
Male	Dummy =1 if household head is male, 0 otherwise	+

their expected influence on household welfare. The variables are based on the survey data we collected and the literature related to use of organic manure and households' welfare (Cofie *et al*., 2010; Martey, 2018; Manda *et al*., 2016). It is hypothesized that the impact of sludge manure on household welfare is determined by several factors, with varying directional influence. Table 1 provides the variable names, descriptions and expected influence on household welfare.

Model formulation

The theoretical foundation for technology adoption can be anchored on the random utility model in which farmers select the technology with the highest benefit among the available alternatives. However, this utility is not directly observed; rather, it is perceived through the farmers' choice. For example, if there are two options, (a) and (n), and Ua and Un represent the farm household utility of the two options, respectively. Then, the standard formulation of the linear random utility model is:

$$U_a = \beta_a X_i + \varepsilon_a \text{ and } U_n = \beta_n X_i + \varepsilon_n \quad (3)$$

The observed choice between the two options reveals which one provides the greater utility. Therefore, if the household chooses option (a) it means that the derived utility of adopting it is greater than the utility of not adopting it, let us say (n). Because of this, the observed indicator is equivalent to 1 when Ua >Un and 0 otherwise. Ua and Un are the perceived utility derived from options (a) and (n), respectively. Furthermore, Xi is a vector of explanatory variables influencing the perceived desirability of the technology, βa and βn are parameters to be estimated, εa and εn are residuals assumed to be IID (Greene, 2003).

Estimation Strategy

There are several econometric models for measuring the effect of agricultural innovations on crop yield. The most commonly used models and methodologies for cross-sectional surveys include simple mean comparisons of adopters and non-adopters, ordinary least squares regression with adoption as a binary variable, and propensity score matching (PSM). However, these models imply that adoption is exogenously determined, whereas it is endogenous (Di Falco & Veronesi, 2013; Khanal *et al*., 2018). If adoption was allocated randomly, the influence on yield can be simply determined by comparing adopters to non-adopters. However, if farmers who, for example, adopt sludge manure have different characteristics from non-adopters, the comparison between the two groups may be biased. If adopters are not assigned at random, the simple OLS estimate is likely to be biased. Furthermore, unobservable elements, such as farmer motivation, are typically difficult to model. It is extremely likely that motivated farmers will adopt and achieve higher yields; hence, the influence of adoption may be overstated due to this unobservable omission.

PSM is another approach that has been widely used in the literature. This approach requires no confounding, which means that all variables influencing treatment and outcome must be observed (Caliendo & Kopeinig, 2008), assuming no selection bias due to unobserved traits. However, unobservable abilities are inescapable in adoption and production contexts. Thus, matching only serves to control for observable differences. As a result, endogenous switching regression (ESR) is the most effective model for addressing selection bias. The ESR corrects the selection bias by allowing for an estimate of the influence of adoption on household welfare at the same time. Therefore, the study used both ESR and PSM because they outperform OLS in circumstances where unobservable factors influence both adoption decisions and farm household welfare. Furthermore, the impact evaluation literature frequently employs these two techniques (Becerril & Abdulai, 2010; Chiputwa *et al*., 2015; Ochieng *et al*., 2017).

The ESR model adjusts for unobserved heterogeneity, selection bias, and endogeneity in impact assessments (Kassie *et al*., 2018). Several studies have employed the ESR approach to address endogeneity problems in assessing the impacts of technology adoption in smallholder farming (Di Falco & Veronesi, 2013; Ochieng *et al*., 2017; Oyetunde-Usman *et al*., 2021). Moreover, based on literature (Awotide *et al*., 2015; Adebayo *et al*., 2018; Anang *et al*., 2020), the study employed the ESR to evaluate the influence of sludge manure adoption on the surveyed households' outcomes. With the ESR methodology, two stages are considered. First, the multinomial logit model is used to investigate the factors determining the adoption of sludge manure by rural farm households. Second, the effect of adopting sludge manure on the outcome variables is estimated (two-step model). The first stage identifies households' decisions to adopt sludge manure based on the observables augmented by a binary endogenous treatment variable as expressed below:

$$U_i^* = \alpha X_i + \beta W_i + \mu_i, \; U = \begin{cases} 1, if\ U_i^* > 0 \\ 0, otherwise \end{cases} \quad (4)$$

Where, *Wi* refers to the binary instrumental variables used for model identification in the ESR model estimation, and β is the parameter to be estimated. *Xi* is a vector of exogenous variables and μi is the error term. The inverse Mills' ratio is calculated from estimates of the multinomial logit model and included in the outcome equations to check for endogeneity issues.

Furthermore, the ESR model requires exclusion restrictions. Therefore, based on literature (Kraay, 2008: Verkaart *et al*., 2017), the study used an exclusion restriction test to determine whether the ESR model was adequately identified. Generally, the test operates by removing explanatory variables that are expected to have a direct impact on the selection equation (treatment equation) but not on the outcome equations (per capita total household expenditure and per capita household food expenditure). In addition, to ensure the model's suitability, the study used time spent farming, irrigation, pesticide use, compost manure and distance to the water source as instruments. The above-mentioned variables are endogenous to the adoption of farming technology (Manda *et al*., 2016; Martey *et al*., 2020).

Lastly, the ESR results robustly checked with PSM, and the parameter of interest for the study was the ATT, which allows us to assess the welfare level of adopters of sludge manure if they chose not to be in the treatment group. Therefore, following Imbens and Wooldridge (2009), the ATT is expressed as follows:

$$ATT = E\,[Y(1) - Y(0) \mid T = 1] \quad (5)$$

Where Y (1) and Y (0) are outcome indicators i.e., per capita total household expenditure and per capita food expenditure. T represents the treatment indicator, which equals 1 for adopters and 0 otherwise. However, the non-adoption status of adopters cannot be observed for E [Y (1) |T =0]; as only E [Y (1) |T =1] can be observed. Therefore, to observe the counterfactual status of the treated households, the PSM creates a comparable counterfactual of households for the treated group from the already matched observable characteristics of households, based on the assumption that there is no systematic difference between their unobservable characteristics.

Based on the given assumptions, the ATT can be computed as follows:

$$ATT=E\,[Y(1)|T=1, P(x)]–E[Y(0)|T=0, P(x)] \quad (6)$$

Results and discussion

Descriptive statistics

Table 2 shows the summary statistics of farm household characteristics and the mean difference between adopters and non-adopters. Table 2 shows that the average age of the household heads is 45 years, and the average household size is 6. In terms of farm characteristics, households cultivate on average (1.37 ha) of land. The Table 2 also shows that household heads on average have 18 years of farming experience, 43% use pesticides, 56% use hybrid seeds, 49% hire labour to work on gardens, 22% are members of farmers' groups, and on average, farmers are 4 kilometres away from input suppliers. As regards access to institutional services the Table shows that, on average, only 46% had access to credit, and 15% received government support.

Furthermore, Table 2 presents differences in the means of all covariates between adopters of sludge manure and non-adopters. The significant ($p \leq 0.005$) difference between adopters and non-adopters is evident in the covariates of hired labour (21%), compost manure use (20%), and farming experience (5.3 years). Pesticide use (46%), main occupation (40%) and marital status (15%). The surprising difference is for irrigation use (12%), where non-adopters irrigate more than adopters, and this may play a role in the crop yield. In terms of distance to

Table 2: Summary statistics of household attributes separating adopters from non-adopters.

	Total (n=522)	Adopters (n=199)	Non-adopters (n=323)	Mean Difference
Outcome variables				
Per-capita household food expend	498515.5	709073.8	368790.7	340283.2***
Per-capita total household expend	1224133	1540213	1029396	510817
Index[1]				
Welfare total expend[2]	-8.35e-10	0.263	-0.162	0. 425***
Independent variables				
Age_household head	45.92	44.41	46.86	-2.448*
Household size	6.295	6.432	6.210	0.221
Income_ month	378243.3	319598	414374.6	-94776.6*
Distance market	3.782	3.378	4.031	-0.653
Hired_labor	0.492	0.623	0.411	0.211**
Compost_manure	0.281	0.155	0.359	-0.203***
Hybrid_seeds	0.567	0.492	0.613	-0.120**
Government_support	0.151	0.155	0.148	0.007
Credit_access	0.461	0.402	0.498	-0.096*
Pesticide use	0.434	0.145	0.613	-0.467***
Main occupation	0.720	0.467	0.876	-0.408***
Group member	0.229	0.201	0.247	-0.046
Land size under crop	3.424	3.893	3.135	0.757
Distance water source	1.716	0.707	2.337	-1.629**
Distance input supplier	4.273	3.359	4.836	-1.477
Irrigation	0.201	0.125	0.247	0.122**
Time spent _farming	18.2911	14.954	20.3467	- 5.3919***
Married	0.766	0.859	0.709	0.150***
Males	0.708	0.869	0.609	0.259***

Source: Authors' computation from survey data; *** 1%, ** 5%, * 10% level of significance

[1] *The index has been calculated using Principal Component Analysis (CPA)*

[2] *This index is composed of household expenditure on health, education, and non-food. As used by Morratti and Natali (2012)*

the market, non-adopters are 0.6 km further than adopters, and the distance to input suppliers shows that non-adopters are further by 1.5 km. For the outcome variables, the mean difference between adopters and non-adopters is positive for per capita total household expenditure and positive and significant (p≤0.001) for per capita food expenditure. The findings highlight the importance of considering the potential confounding factors when assessing the impact of the adoption of sludge manure on the outcomes of interest. The paper sets the stage for a more rigorous analysis to establish the impact of sludge manure adoption and the outcomes.

To examine the household welfare effect of sludge manure household welfare was based on two variables, i.e., per capita total household expenditure and per capita household food expenditure[3]. In this case, per capita total household expenditure is the sum of expenditures

3 Following Morratti and Natali (2012) we constructed household welfare index, i.e., total household expenditure. We re-estimate our models using this constructed index and report the results as sensitivity checks.

on non-food items, food, medical bills and school expenses for a particular household in a year divided by the total number of household members. Second, per capita household food expenditure is measured by dividing total food expenditure for a particular household for a year by the total number of members in that household. The study considered household expenditures because they are less vulnerable to underreporting bias than income (Meyer & Sullivan, 2003), and it is in line with other impact studies (Abdoulaye *et al*., 2018; Wossen *et al*., 2017). Finally, the study used PSM to compute the ATT on food sufficiency between adopters and non-adopters. To get this the study included a question in the questionnaire that asked farmers whether the household always had enough food in the last 12 months. The treatment variable is the adoption of sludge manure measured by a dummy variable that takes the value of 1 if a farm household adopted sludge manure and 0 otherwise.

Table 3 shows the results of the endogenous treatment two-step model for both per capita household food expenditure and per capita total household expenditure. The estimates of the determinants of sludge manure adoption and the impact of adoption on household welfare are as presented in Table 3. As indicated earlier, the two-step approach estimates both the adoption and the outcome equations jointly. Thus, the selection equations, representing determinants of adoption, are given in the second and fourth columns of Table 3, providing two different sets of results due to slightly different specifications. Furthermore, given that these coefficients can be interpreted as normal Probit coefficients. The coefficient of the hired labour variable is positive and significantly different from zero (($p \leq 0.005$), suggesting that farm households that can hire labour are more likely to adopt sludge manure which is labour-intensive. The study's observation conforms to what has been reported by Chaudhary *et al*. (2022), that a positive association existed between number of workers and fertilizer adoption. The household size coefficient is positive but not significant in relation to the adoption of sludge manure. This is not surprising because some households use hired labour to handle sludge manure therefore, the support provided by family labour may not be significant.

The variable for access to credit is negative and significantly different from zero ($p \leq 0.010$), suggesting that farmers who are not liquidity constrained are less likely to adopt sludge manure. However, this contradicts our hypothesis that access to credit would be positively associated with a household's adoption of sludge manure. The reason for the above may be the fact that many smallholder farmers tend to diversify to nonfarm activities to hedge against risk in the case of crop failure, which is likely to affect adoption of sludge manure. The coefficient for the time spent in farming (experience) is negative and significant ($p \leq 0.001$). The results suggest that farmers who have been engaged in agriculture for a long time are less likely to adopt sludge manure, suggesting that experienced farmers tend to be risk averse and fear the unknown, which in turn affects adoption negatively. Furthermore, farm households with relatively higher monthly incomes are less likely to adopt sludge manure. This could be because richer households tend to hedge against risk by diversifying into other economic activities. This diversification affects sludge manure adoption since these activities are more of competitors than complements to farming.

The variable for compost manure use is negative and significant ($p \leq 0.001$) , indicating a lower likelihood of adopting sludge manure. This finding suggests that compost manure users may not want to replace their technology with a new technology for which they may not be certain how it works. This finding is in line with that of Zhang *et al.* (2022), which found that farmers with experience in manure use, composting and drying can easily make decisions for agricultural technology adoption. The coefficient for distance to the input supplier is positive but not significant. Farmers who live closer to the market are more likely to have access to agricultural information via various channels that aid in the adoption of modern technologies. This finding conforms to what was reported by Iresso and Abebe (2024), that in Ethiopia adopters of inorganic manure were closer to the market.

The results regarding the impact of adoption on per capita household food expenditure and per capita household total expenditure are presented in the third and fifth columns of Table 3. The estimates generally show the impact of individual, household and institutional factors on household welfare for adopters. As indicated before, the model used requires that there is at least one variable in the selection or adoption equation that does not appear in the outcome equations. In the per capita household food expenditure model specification, the variables; irrigation use, compost manure use, and pesticide use are used as instruments. And though these variables affect sludge manure adoption but do not affect household food expenditure directly. Similarly, the variables; time spent farming, pesticide use, compost manure use and distance to water source are also used to calculate the per capita total household expenditure because they are not expected to influence total expenditures under adoption or non-adoption.

The validity of ESR instruments was assessed by running a Probit model for adoption with instruments[4]. The instruments pesticide use, compost manure usage, time spent farming, irrigation are significant at $p \leq 0.001$ and distance to water sources variable is significant at $p \leq 0.005$) in predicting sludge manure adoption, although they do not directly affect farming households' welfare. The second validity test is the falsification test[5], which assesses whether the instruments influence the household welfare of non-adopters. It is worth noting that both tests were satisfactory.

Table 3 further shows that the surveyed households' monthly income is an important factor in explaining both household food and household total expenditure. The positive and significant coefficients of the variable ($p \leq 0.001$) suggest that higher incomes may increase household expenditures. This finding is in line with the study by Sekhampu, (2012) which looked at the impact of selected socio-economic characteristics on food expenditure patterns of a low-income township in South Africa. The findings showed that household income, household size, age, employment status, and the educational attainment of the household head were found to exert a strong positive impact on food expenditures. Furthermore, access to credit shows a positive effect on expenditures for households adopting sludge manure. This may be as a result of using borrowed money to purchase productivity-enhancing inputs that increase yield and hence crop income. The coefficients of government support have the expected positive sign and are significant, indicating that government support increases household welfare through its effect on household expenditure. Furthermore, the results show that male headed households experienced increased expenditure after adoption of sludge manure. The possible reason could be the households are more likely to cultivate a larger crop area than those headed by females. The observation is in line with that of Martey (2018), who reported that in Ghana male-headed households who had adopted organic fertilizer were more likely to increase their crop income compared female-headed households. Nonetheless, the findings in Table 3 indicate that spending decreases with a large household size and also if a household head is married. However, this is quite surprising as theory indicates that large household size (Donkoh *et al.*, 2014; Madudova & Corejova, 2023; Rashid *et al.*, 2024) and being married (Ndubueze-Ogaraku *et al.*, 2016) increases the chance of raising both food and total household expenses. Finally, our results show that age has a beneficial but insignificant impact on household expenditure. However, according to Chen and Chu, (1982) age of family head was found to have significant influence on expenditures, while Salam *et al.* (2022) report that age do not have significant impact on household food expenditure.

Robustness checks

The estimates for the average treatment effects (ATT), which show the impact of sludge manure adoption on household expenditure,

[4] *The study regressed the binary adoption variable on a set of excluded instruments (for details see appendix 1). Instruments are expected to significantly affect sludge manure adoption. Weakly correlated instruments with adoption variable, can lead to inconsistent and unreliable estimates.*

[5] *In this test, the welfare variable of non-adopters is regressed on all instruments. To be valid, all the instruments should be insignificant (Di Falco et al., 2011). For falsification test results, see appendix 2.*

Table 3: Endogenous treatment regression and two-step results (ESR model)

Variables	Treatment/ Selection Model	Outcome Model (Per capita household food Expenditure)	Treatment/ Selection Model	Outcome Model (Per capita household food Expenditure)
FS		698(107)***		120(274)***
Males		312(805)***		504(218)*
Married		-519(890)***		-537(241)*
Govrt_support		253(975)**		796(262)**
hh_size	0.016(0.024)	-877(122)***	0.015(0.025)	-173(334)***
Income	-0.000(0.000)*	0.352(0.063)***	-0.000(0.000)**	0.966(0.170)***
Credit_access	-0.274(0.152)*	287(717)***	-0.507(0.169)**	443(192)*
Hired_labor	0.788(0.154)***		0.740(0.165)***	
Time_spent _farming	-0.028(0.006)***		-0.014(0.006)*	
Irrigation	-0.632(0.196)***		-1.374(0.177)***	
Compost_manure	-1.421(0.166)***		-0.921(0.165)***	
Pesticide use	-1.132(0.158)***			
Distance input supplier	0.002(0.004)			
Distance water source			-0.185(0.071)**	
Main occupation			-1.126(0.180)***	
Age_household head				115(756)
Constant	0.580(0.212)**	657(108)***	1.425(0.261)***	693(439)
Inverse Mills ratio (Lambda)		-306***		-675***
Prob>Chi²		0.000		0.000
Obs		522		522

Source: Authors' computation from survey data
**** 1%, ** 5%, * 10% level of significance*

are presented in Table 4. Unlike the mean differences presented in Table 2, which may confound the impact of sludge manure adoption on expenditure with the influence of other characteristics, these ATT estimates account for selection bias arising from the fact that adopters and non-adopters may be systematically different. In this section, we perform robustness checks. First, the re-estimated the model with a welfare measure based on Morratti and Natali (2012), who built a welfare total expenditure index by adding health, education, non-food, and food expenditures. The generated index was used to re-estimate the influence of sludge manure on household welfare. The ATT findings show that adoption significantly ($p \leq 0.001$) increases household expenditure (Table 4).

Specifically, the causal effect of sludge manure adoption on total household expenditure is 0.485. This difference is statistically significant ($p \leq 0.001$), with a t-statistic of 3.94 and the findings support the preceding findings in the endogenous regression model about individual welfare outcomes.

Second, the study re-estimated the ESR model following the PSM algorithm. Table 5 presents the ATT results from the nearest neighbour matching specification. Table 5 shows

Table 4: Welfare impact of adoption of sludge manure based on the welfare index (NNM)

Variables	Parameters	Adopters	Non-adopters	Diff.	t.Stat
Welfare total expenditure	Unmatched	0.263163	-0.162213	0.425	4.82
	ATT	0.2833	-0.20180	0.485	3.94

Source: Authors' computation from survey data

that compared to non-adopters, adopters spend approximately 730,900 Ugandan Shillings (USD 192.3) more per person on food each year. And the difference was statistically significant ($p \leq 0.001$) with a t-statistic of 2.11. In terms of total spending per person, adopters also on average spend 398,900 Uganda Shillings (USD 105) more than non-adopters. It is important to highlight that despite supporting the idea that applying sludge manure enhances household well-being; study findings show that the increase in food expenses is generally twice as high as the total amount spent by the household. These PSM results are robustly similar to those of the ESR model. In summary, the results indicate a noteworthy increase in per capita food and per capita household spending overall for adopters.

Table 5: Welfare impact of adoption of sludge manure

Variables	Parameters	Adopters	Non-adopters	Diff.	t.Stat
Per-capita household food expenditure	Unmatched	1540212	1029395	510817	2.50
	ATT	1540212	809217	730995	2.11
Per-capita total household expenditure	Unmatched	709073	368790	340283	4.20
	ATT	709073	310135	398938	1.98

Moreover, to assess the food sufficiency component, the surveyed households were asked if they always had enough food in their households and based on the responses, the ATT results are shown in Table 6. The findings show that adopters had a greater level of welfare (7.4%) than non-adopters in terms of food sufficiency and the difference is statistically significant ($p \leq 0.005$).

The Conditional Independence Assumption (CIA) and Region of Common Support

Conditional independence assumption (CIA)

The matching quality was tested to confirm the efficacy of PSM in terms of reducing disparities in observables between adopters and non-adopters. The credibility of PSM is predicated on two distinct assumptions: the conditional independence assumption (CIA) and the condition of shared support. The study investigated whether the propensity score accurately balances the distribution of essential factors for CIA in matched adopter and non-adopter groups. Then the study compared the means of adopters and non-adopters on each observable before and after matching, using a two-sample t test, and we evaluate the joint significance of all variables in the logit model before and after matching, using a chi-square test. The results are presented in Table 7 below.

The chi-square test shows that all variables in the logit model are not jointly significant after matching (prob > x^2 = 0.405). In contrast, the same test is rejected before the match (prob > x^2 = 0.000). This is supported by the pseudo R^2 values of the model before and after matching.

Table 6: Propensity score matching: Welfare impact of the adoption of sludge manure

Variables	Parameters	Adopters	Non-adopters	Diff.	t.Stat
Food sufficiency	Unmatched	0.919	0.928	-0.009	-0.39
	ATT	0.921	0.846	0.074	1.98

Table 7: Chi-square test for joint significance of all variables before and after the match

Sample	Pseudo R^2	p> chi^2
Unmatched	0.257	0.000
Matched	0.023	0.405

Therefore, there were no systematic differences in the distribution of covariates between adopters and non-adopters after matching. Second, the pseudo R^2 is fairly low compared with its value before matching.

Region of common support

Table 8 shows that out of 199 adopters, only 12 observations are off support. This means that there is good overlap between adopters and non-adopters and that the study was comparing the comparable.

Furthermore, Figures 1 and 2 show the density distributions of the propensity scores for adopters and non-adopters thus, illustrating that there is considerable overlap in the distribution of both sludge manure users and nonusers. This shows that the condition for common support has been satisfied. The upper and bottom portions of the histogram depict the propensity score distributions of adopters and non-adopters, respectively.

Table 8: Region of common support

Treatment assignment	Off support	On support	Total
Untreated	0	323	323
Treated	12	187	199
Total	12	510	522

Conclusions

The study indicates for household welfare using per capita household food expenditure and per capita total household expenditure and the key findings show a positive and significant impact of sludge manure adoption on improving per capita household food and per capita total household expenditure. Specifically, the endogenous switching regression model results

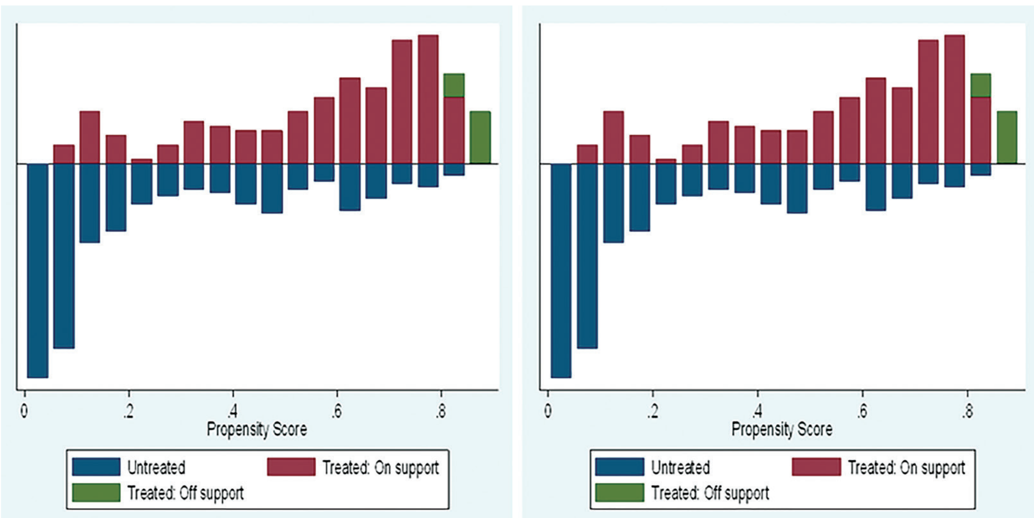

Figure 1: Households on common support: Per capita total household expenditure (left) and per capita household food expenditure (right)

Notes: "Treated: on support" indicates that sludge manure adopters constitute a suitable comparison group (non-adopters). "Treated: off support" indicates the sludge manure adopters that did not have a suitable comparison group (non-adopters) demonstrates that, on average, sludge manure adopters have higher per capita household food expenditure and per capita total household expenditures.

In terms of recommendation, government of Uganda should come up with effective policy measures that promote sludge manure adoption by smallholder farmers. In addition, the policy should include improvements in government support, access to credit and support for income-generating activities. It is also recommended that sludge manure awareness platforms need to be established to promote optimal and efficient sludge manure use by farmers. Moreover, based on the fact that sludge manure is an organic technology, encouraging and maintaining its use is vital for sustainable agricultural ecosystems, and this is critical for countries such as Uganda where more than 75% of the population derives its livelihood from peasant agriculture. It is further recommended that, there is a need of setting up agricultural funding platforms to ensure access to credit by resource constrained households hence, ensuring sustainable agricultural ecosystems. Lastly, since the current study faced financial limitations hence the collection of data from only six districts in central Uganda, it might affect the generalizability of our results. It is therefore recommended that another study should be conducted that collects more data across Uganda to provide a comprehensive understanding of the factors associated with households' adoption of sludge manure and how the same affects rural household's welfare.

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Declaration of conflict of interest

The authors have no conflict of interest to declare in the context of this study

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Appendices

Appendix 1: Instrument validation results

FS (adoption dummy)	Coefficient	t Values
Instruments		
Pesticide use	-0.405 (0.037)	-10.68
Compost_manure	-0.100 (0.042)	-2.34
Time spent_farming	-0.004 (0.001)	-3.39
Irrigation	-0.139 (0.462)	-3.01
Distance_water source	-0.005 (0.002)	-1.92
Constant	0.713 (0.035)	20.05
Observations	523	
R-squared	0.262	
Prob>F	0.000	

Notes: Values in parentheses are standard errors
All instruments are significant for the adoption dummy, which means that they pass the validation test.

Appendix 2: Falsification test results

	Per capita total household expenditure		Per capita household food expenditure	
Instruments	**Coeff.**	**t values**	**Coeff.**	**t values**
Pesticide use	123767 (135077)	0.92	-65461 (81991)	-0.80
Compost_manure	201294 (135110)	1.49	38114 (82094)	0.46
Time spent_farming	-5892 (4698)	-1.25		
Irrigation			130652 (91195)	1.43
Distance_water source	-3767 (8050)	-0.47		
Constant	958824 (159080)	6.03	353194 (78400)	4.51
Obs	323		323	
Prob>F	0.2317		0.3995	

Notes: Values in parentheses are standard errors. *All instruments are not significant for welfare variables, which mean that they pass the falsification test.*

Annex 1: Sludge manure making process at LSTP

The process of making sludge manure at the LSTP is explained in the following steps.

Step 1: Faecal sludge reaches the LSTP through two inlets. The first inlet consists of cesspool trucks that deliver faecal sludge from household pits and septic tanks to the LSTP. Cesspool trucks are emptied directly into screening/sedimentation tanks to remove grit, e.g., bottles, wood, clothes, etc. During the sedimentation process, liquids/effluents are separated from solids, and some solid particles can be pumped directly to the drying ponds. However, the remaining liquids with some solid particles are pumped to anaerobic ponds where they mix with faecal sludge from inlet 2. The second inlet (Inlet 2) is through national water and sewerage cooperation sewerage pipes, which are directly deposited into screening ponds to remove grit; thereafter, the effluent is pumped into anaerobic ponds.

Step 2: At this stage, the sludge is taken to anaerobic ponds. The primary function of anaerobic ponds is stabilization and to allow for the breakdown of the high concentrations of organic pollutants contained in sludge. This is done by removing oxygen from the affluent to encourage the growth of bacteria, which helps in the decomposition process. Another important function of anaerobic ponds is to reduce pathogens that are harmful to human life. After decomposition in anaerobic ponds, the sludge is pumped into facultative ponds to remove ammonia through a biological process. The use of sludge manure (2-3 weeks) in facultative ponds increases the efficiency of bacterial removal in these ponds.

Step 3: At this stage, the sludge manure is pumped out to drying ponds (beds), where it is allowed to dry and foster further decomposition for approximately five to six months. During this period, sludge manure reaches moisture content of 60%, and at this moisture content, pathogens (disease-causing organisms) are believed to be lifeless, protecting human life. When the sludge manure is dry enough, it is ready for use by farmers. This decomposition process at the LSTP converts faecal sludge into (sludge manure) which is an organic product that is largely safe for human use and the environment.