Agricultural and Food Economics

RESEARCH Open Access

Agricultural extension services and household welfare: evidence from Ghana socioeconomic panel survey

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Abstract

While agriculture is integral to the development plans of many developing countries, the sector and those who work in it face several challenges. Additionally, even though agricultural extension and advisory service (AEAS) is prescribed as essential to addressing some of these challenges, the evidence base is thin, especially in Ghana, where most existing studies are based on cross-sectional, regional, and small-sample analyses. The absence of rigorous and generalizable analyses limits evidence-informed advocacy, planning, and decision-making on AEAS. To address this evidence gap, we analyze the effects of AEAS on poverty, assets, per capita consumption, and dietary diversity based on three waves of the nationally representative Ghana Socioeconomic Panel Survey. We find that AEAS is associated with a 28.3% increase in household and farm assets, 20% increase in value of per capita food consumption, and a 4.2% increase in household dietary diversity. Disaggregated by provider type, we also find that households receiving extension service advice from farmer-based organizations show the highest increase across these welfare outcomes. Despite these positive effects, our results show that the uptake of AEAS is generally low and especially from service providers other than government sources. Furthermore, those who received AEAS show null or negative results for poverty. These findings add to the body of evidence on the positive effects of access to agriculture advisory. We recommend that the government further strengthen the extension service system, specifically by encouraging uptake of extension services from government and non-government providers.

Keywords: Agricultural education, Food security, Inverse probability weighted, Matching methods, Panel survey, Sub-Saharan Africa

JEL Classification: Q16, Q12, O13, I32, D12, O55

Introduction

The agricultural sector employs an estimated 26% of the global workforce (ILO, 2024) and contributes about 4% to the world's Gross Domestic Product (GDP). The relevance of the sector is more pronounced in developing countries, where about 3.4 billion rural people depend on agriculture and the food system for their livelihoods, and about 70% of total employment in some of these countries is agriculture-based

(Davis et al. 2023; Trentinaglia et al. 2023; Woodhill et al. 2022). In Ghana, 40% of the employed population works in agriculture (ILO 2024). Despite the sector's integral role in the global and local economy, agriculture workers struggle with food insecurity and low production (Pawlak and Kołodziejczak 2020). Yields are suboptimal (Anang et al. 2020; Danso-Abbeam et al. 2018) as key crops such as maize, rice, yam, cassava, and plantain yield less than half of their potential due to constraints such as primitive farming techniques, reliance on rain-fed production, limited adoption of modern agricultural equipment, constrained access to financial services, and inadequate agricultural services (Anang et al. 2020; Anang and Asante 2020; Danso-Abbeam et al. 2018; Asfaw et al. 2012).

Agricultural Extension and Advisory Services (AEAS) hold the potential to mitigate the highlighted agricultural challenges (Danso-Abbeam et al. 2018; Davis et al. 2020, Davis 2009; Ogundari and Bolarinwa 2019), as shown by scholars who investigate this vis-à-vis the productivity and well-being impact on farmers. However, the scholarship on the subject is inconclusive, given differing findings on AEAS's role in farmers' agricultural productivity and well-being (Emmanuel et al. 2016). Some strands of the literature, such as Abdoulaye et al. (2014), Emmanuel et al. (2016), Faborode and Ajayi (2015), Jones et al. (2023), Sodiya et al. (2007), and Wossen et al. (2017) suggest a significant correlation between agricultural extension services and increase in farmers' knowledge and adoption of new technologies. Beyond technology adoption, others also empirically accentuate the positive effect that receiving extension services has on farmers' productivity, yield, income, poverty reduction, dietary diversity, and food security (e.g., Aremu and Reynolds 2024; Azzari and Nico 2022; Brenya and Zhu 2023; Ehui and Pander 2005; Garbero & Jackering 2021; Hamilton and Hudson 2017, Ragasa and Mazunda 2018; Sibhatu et al. 2022; Yitayew et al. 2023). Previously, Asante et al. (2024) found that farmers who embraced agricultural services in the Brong Ahafo region of Ghana experienced an increase in maize yields, gross revenue, and per capita food consumption. Anang et al. (2020) showed a similar positive effect of AEAS on farmers' income in the northern region. Among farmers who received AEAS delivered by NGOs and religious-based organizations, Attipoe et al. (2021) and Danso-Abbeam et al. (2018), respectively, showed a positive impact on productivity and income.

In contrast, several studies have documented null or even adverse effects of AEAS on farmers' outcomes. In Argentina, Maffioli et al. (2011) find that publicly subsidized extension services negatively affected farm yields, attributing the decline to short-run adjustment costs as farmers adapted to new practices. In Nigeria, Aremu and Reynolds (2024) report a significant reduction in household assets among recipients of AEAS focused on animal care and marketing. However, their study also identifies a positive association between AEAS exposure and food insecurity, suggesting unintended welfare consequences. Beyond economic impacts, Kalogiannidis and Syndoukas (2024) raise environmental concerns, noting that some extension programs promote the increased use of inorganic fertilizers and other intensive farming practices, contributing to negative externalities. Not all evidence, however, points in the same direction. Ragasa and Mazunda (2018), examining AEAS in Malawi, find that access improves food security and farm productivity. By contrast, Sebaggala and Matovu (2020) finds no significant relationship between AEAS and crop yields. These mixed findings underscore the heterogeneity of AEAS effects across settings, delivery modalities, and outcome dimensions.

The conflicting interplay between AEAS and farmers' welfare necessitates more research on the benefits of agricultural extension services, especially new studies that are more representative and delves into specific subjects of agricultural advice to offer useful policy recommendations. Also, previous studies have been regionally skewed toward the North (Abdallah and Abdul-Rahaman 2016; Danso-Abbeam et al. 2018; Anang and Asante 2020; Anang et al. 2020; Danso-Abbeam 2018; Abdulai et al. 2023), with very few studies in the South (Jones et al. 2023; Asante et al. 2024; Attipoe et al. 2021). This geographical skewness is primarily due to data constraints, rendering such studies not generalizable. Many of these studies are also based on cross-sectional data. These two challenges affect the internal and external validity of previous research, with significant implications for extension policymaking in Ghana. To that end, our study empirically investigates the impact of AEAS on household welfare in Ghana and makes three significant contributions to the scholarship. Firstly, to the best of our knowledge, this study is the first to leverage a novel, nationally representative, micro-level panel dataset to assess the impact of AEAS on household welfare in Ghana thereby addressing validity limitations in previous studies. Secondly, beyond the binary variable of extension access, we also disaggregate the source of the advice into farmer-based, input dealers, and government-based extension services to provide deeper insights. We hypothesize that these channels differ not only in their modes of delivery but also in their underlying incentives, information quality, and reach. For instance, farmer-based extension services may prioritize peer to peer learning, while input based extension access may promote product specific advice and government-based extension services may promote national development initiatives. Lastly, our focal outcomes of interest are more comprehensive than previous studies, comprising poverty, household assets, per capita food consumption, and dietary diversity. This provides more comprehensive insights into the effect of AEAS on different proxies of welfare.

Our analysis offers evidence in support of a positive and statistically significant relationship between agricultural extension and advisory services and assets, household food consumption, and household dietary diversity, including advice received via farmer-based organizations and government personnel. We recommend that the government strengthen the extension advisory system, by paying attention to non-state providers to increase the benefits of AEAS to farmers in Ghana. The rest of the article is organized as follows. The next section briefly provides an overview of AEAS in Ghana before independence to the present. After that, we outline our methodological framework and describe the data used. In the Results Section, we present our findings on the effects of agricultural extension service on the different outcomes of interest. In Section 5, we discuss these findings, considering the implications and study limitations. Lastly, in Section 6, we conclude.

Agricultural extension and advisory service in Ghana

AEAS in Ghana dates to the early twentieth century, although as is the case in many other countries, it has undergone several reforms. Before Ghana's independence in 1957, missionaries and foreign-based companies delivered AEAS to enhance productivity and boost export production (MoFA 2002). After Ghana's independence, the existing AEAS structure was criticized for exacerbating food insecurity by prioritizing export crops at the expense of food crops, a trend that intensified during the 1970's global food insecurity crisis (Donkor 1984; Barzola Iza et al. 2020). This resulted in a review of the system to a Ministry-based general extension approach in 1978 and a shift in focus from promoting export crops to producing food crops for local consumption (Donkor et al. 1984).

In the early 1990s, the general extension approach was again criticized for being top-down, focusing on 'progressive farmers' while neglecting smallholder farmers and women, lacking well-trained extension personnel, and suffering from inadequate infrastructure and poor services (Hailu 1990; Amezah and Hesse 2002). Consequently, in 1992, the Unified Extension System (UES) was implemented alongside the Training and Visit (T & V) program to address the ineffectiveness of the previous general extension approach (Amezah and Hesse 2002; MoFA 2002). Nonetheless, the combined UES and T & V approach were also criticized for being rigid and non-responsive to farmers' needs and lacking linkage with research (MoFA 2002; DAES 2011).

Consequently, the Government of Ghana, through the Ministry of Food and Agriculture (MoFA), implemented a decentralization reform in 1996 by transferring the activities to the Metropolitan, Municipal, and District Assemblies (MMDAs) to improve AEAS and ensure these services reach those who need them (DAES 2011; Okorley et al. 2019; Anang et al. 2022). The decentralized system embodies the concept of demand-driven extension services to improve productivity, farm income, and farmers' welfare (Rivera 2004). Today, the Ghanaian AEAS services are made of a pluralistic extension approach, consisting of the leading actor, i.e., the Government through the Directorate of Agricultural Extension Services (DAES), non-governmental organizations (NGOs), private institutions, religious-based organizations, and cooperative institutions (Anang et al. 2022).

In Ghana, the effectiveness of agricultural extension programs is often limited by inadequate training and support provided to farmers beyond the initial AEAS. Danso-Abbeam et al. (2018) emphasize that these programs struggle to significantly enhance agricultural output without ongoing support and comprehensive training, underlining a critical gap in the extension services framework. Studies have also shown that inequitable implementation of AEAS results in widening income and gender disparities and increasing the poverty levels of farmers. Furthermore, the lack of inclusive and gender-responsive AEAS is detrimental to agricultural productivity and the welfare of farmers (Abdallah and Abdul-Rahaman 2016; Azzarri and Nico 2022).

Methods

Data

This study uses the three waves of panel data from the Ghana Socioeconomic Panel Survey. This dataset, consisting of information at the individual and household levels, is collected by the Institute of Statistical, Social and Economic Research (ISSER) at Legon in partnership with the Economic Growth Center at Yale University and the Global Poverty Research Lab at Northwestern University to address gaps in data quality and availability for evidence-informed decision making. The first wave was collected between 2009 and 2010, the second wave between 2010 and 2013, and the third wave between 2018 and

2019. The dataset is designed to be nationally representative and contains information on household demographic and health characteristics, farm characteristics, assets, consumption, expenditure, etc. Each wave consists of about 5,000 households.

For this analysis, we take advantage of relevant modules to obtain information on access to extension service, geographic characteristics (region), household head characteristics (age, gender, education), household durable goods (phone, television, refrigerator, fan, stove, etc.), cooking fuel, wall materials, and consumption expenditure. Gender is coded as 0 if male and 1 if female. The agricultural extension service variable is measured in various forms as a dichotomous variable where 0 indicates no access, and 1 indicates access. Extension service is first measured as having access to the service, regardless of the source (general). Then, we differentiate between the source of the extension service, i.e., services delivered by farmer-based organizations, input dealers, or government extension providers. At the end of data cleaning, we had a balanced panel size of 12,015 observations with 4,005 households in each wave.

Outcome variables

We test the effects of access to agricultural extension on four different outcomes, namely poverty, household assets, per capita food consumption, and dietary diversity. The first outcome variable, poverty, is based on the Innovation for Poverty Action-supported Poverty Probability Index (PPI score).[1] PPI score is a set of ten questions about household characteristics and assets assigned weights that sum up to a continuous index score ranging from 0 to100. While the score can be interpreted probabilistically, it is not inherently binary; rather, it provides a gradient of poverty risk, with 0 representing the highest likelihood of poverty and 100 the lowest (Cafiero et al. 2018). Thus, the likelihood of poverty decreases as the score increases from 0 to 100. For Ghana, the ten questions that make up this score are the region in which a household is located, the number of household members, purchase of chicken eggs, purchase of raw or corned beef, construction materials on the outer wall of the house, fuel for household cooking, ownership of gas stove, ownership of refrigerator, ownership of fan, and ownership of television.

For assets, we measure it as the monetary value of the sum of household and farm assets reported by households. For the third outcome, food consumption, we construct it as the monetary value of the sum of food produced and purchased by households less the amount given out as gifts in the last 30 days, then divided by the number of household members. Given the limited information in the dataset, we could not exclude the food produced for sale from the total household production to obtain the real amount of food produced for consumption. Also, we did not use a price deflator to account for spatial and temporal variation in the food value chain. Lastly, the dietary diversity is based on the household dietary diversity score, which is a score (from 0–12) computed using 12 classes of food (cereals, roots, pulses, oil, fruits, veggies, meat, eggs, milk, beverages, sugar, alcohol) consumed by households in the last 30 days (Ayenew et al. 2018; Hoddinott and Yohannes 2002).

[1] For more information on PPI Score, see https://www.povertyindex.org/about-ppi

Empirical strategy

To assess the association between access to extension services and household welfare outcomes, we draw on the panel dataset and employ a combination of propensity score matching (PSM), nearest neighbor estimation (NNE), and inverse probability weighted regression adjustment (IPWRA). These methods help improve comparability between households that did and did not receive extension advice by conditioning on observable characteristics. The panel structure of the dataset enables us to control for time-invariant household-level heterogeneity and to account for variation in treatment exposure over time. While these methods reduce bias from observable differences, the results should be interpreted as associations rather than causal estimates, as unobserved confounding may persist. In particular, assignment to extension services is not random and may correlate with unobserved household traits that also affect welfare outcomes.

To formalize this, we adopt the potential outcomes framework following Abadie and Imbens (2016), where treatment is binary and potential outcomes are defined accordingly. The setup for binary treatment is as follows. Let W represent the treatment variable (extension access), X represent the covariates, and Y represents the outcome variable (welfare indicators). We define the treatment as $W=1$ if farmers received extension services (treated group) and $W=0$ if they did not receive extension services (untreated group). Thus, we define the treatment effect in terms of potential outcomes: Y_1 (potential outcome under treatment) and Y_0 (potential outcome for the untreated). The average treatment effect (ATE) is given as follows:

$$\mathrm{ATE} = E[Y_1 - Y_0] \tag{1}$$

where the expectation is taken over the sample population. We estimate the average treatment effect for the treated (ATT) as:

$$\mathrm{ATT} = E[Y_1 - Y_0 | W = 1] \tag{2}$$

From Eq. (2), we can only observe $E[Y_1|W = 1]$ but the $E[Y_0|W = 1]$ is missing. This means we cannot observe the welfare effect of the treated, had they not been treated. According to Wossen et al. (2017), a simple comparison of the outcomes for those who received extension services and those who did not introduce self-selection bias and the magnitude of the bias is given as:

$$\mathrm{ATT} + E[Y_0|W = 1] - E[Y_0|W = 0] \tag{3}$$

A notable assumption of all treatment effects is the overlap assumption. Thus, after matching, we expect no systematic difference in unobservable characteristics between treated and untreated groups. However, this assumption is likely to be broken in the presence of model misspecification. Following Abadie and Imbens (2006) and Wooldridge (2010), the overlap assumption here implies that each farmer has a positive probability of receiving each treatment level. Another critical assumption is that the potential outcomes and treatment statuses of all other farmers in the population are independent. A problem with PSM is that it is not agnostic to model specification. PSM will produce biased results if the underlying model is mis-specified (Wooldridge 2010). Two potential solutions exist: the nearest neighbors approach, which uses a bias correction term when matching on one or more continuous covariates and does not require a functional form to be specified, and the inverse probability weighted regression adjusted (IPWRA) estimator. A problem with the nearest neighbor estimation approach is that it relies on global distance measures for matching; as such, it can be sensitive to outliers. According to Wooldridge (2010), the IPWRA estimator has double-robust property, which allows the model to be consistent and efficient even if one of the models is mis-specified. This means that even if one of the models (treatment or outcome) is mis-specified, the estimator is still consistent.

Empirically, Imbens and Wooldridge (2009) show that the IPWRA estimates selection to treatment, predicts treatments for all observations, assigns the inverse of the probability of treatment for treated individuals and the inverse probability of not being treated for control individuals, and finally re-estimates the outcome model using the new weights. Mathematically, we can derive the IPWRA from a logistic regression model as the propensity score.

$$e(X_i = P(W_i = 1|X_i) \tag{4}$$

Applying the inverse probability weight for each observation is:

$$\omega_i = \frac{W_i}{e(X_i)} + \frac{1 - W_i}{1 - e(X_i)} \tag{5}$$

Note that we have to fit the outcome for the treated and the untreated using the covariates X, as presented in Eqs. 6 and 7 as follows:

$$\widehat{Y_1}(X_i) = \mathrm{E}[Y_i|W_i = 1, X_i] = g_1(X_i) \tag{6}$$

$$\widehat{Y_0}(X_i) = \mathrm{E}[Y_i|W_i = 0, X_i] = g_0(X_i) \tag{7}$$

We can then combine the inverse probability weights and the regression adjustment for the outcome model for the treated and the untreated model as in Eqs. 8 and 9 as follows:

$$\hat{\mu}_1 = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{W_iY_i}{eX_i} - \left(\frac{W_i - e(X_i)}{e(X_i)}\right)g_1(X_i)\right] \tag{8}$$

$$\hat{\mu}_0 = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{(1 - W_i)Y_i}{1 - eX_i} - \left(\frac{(1 - W_i) - (1 - e(X_i))}{1 - e(X_i)}\right)g_0(X_i)\right] \tag{9}$$

where $\frac{W_iY_i}{eX_i}$ and $\frac{(1-W_i)Y_i}{1-eX_i}$ adjust to the treated and untreated, respectively, and $\left(\frac{W_i-e(X_i)}{e(X_i)}\right)g_1(X_i)$ and $\left(\frac{(1-W_i)-(1-e(X_i))}{1-e(X_i)}\right)g_0(X_i)$ respectfully adjust for the regression outcome. The difference between Eqs. 8 and 9 yields the ATE of the IPWRA. Formally we derive the ATE and the ATT as:

$$\widehat{\mathrm{ATE}}_{\mathrm{IPWRA}} = \hat{\mu}_1 - \hat{\mu}_0 \tag{10}$$

$$\widehat{\mathrm{ATT}}_{\mathrm{IPWRA}} = \hat{\mu}_1 - \hat{\mu}_0|W = 1 \tag{11}$$

Table 1 Summary statistics of panel sample

	count	mean	sd	min	max
Log of Assets (HH + Farm)	12,015	6.6827	1.6855	0	13.6204
Poverty Probability Index Score	12,015	45.507	22.3129	0	100
Log of Per capita Food Consumption	12,015	4.1780	1.0184	− 1.6095	9.1317
Household Dietary Diversity Score	12,015	5.2091	2.8419	1	11
Household head age	12,015	50.716	16.1161	18	111
Size of the household	12,015	3.7359	2.4092	1	20

Results

After providing a descriptive account of the sample, based on the three waves of panel data, we present the ATT of agricultural extension service (as a general dichotomous variable as well as disaggregated by sources of agricultural advice) on poverty, assets, per capita food consumption, and dietary diversity.

Descriptive statistics

While the panel dataset contains 12,015 household-wave observations across three survey rounds, some variables are not observed in every wave for all households due to item nonresponse, survey skip patterns, or variable-specific attrition. To address this, we used the *missRanger* algorithm in R to impute missing values and maintain a consistent sample across variables. Missingness was generally low: apart from *rural* and *HDDS*, which had 3.89 percent missing values, all other variables had less than 1 percent missingness. Table 1 presents the averages of the outcome variables and some continuous covariates. The mean Poverty Probability Index (*PPI*) score is 45.5. The average value for log of assets is 6.7, which corresponds to 812.41 Ghanaian cedis, while the mean for log of per capita food consumption is 4.2, equivalent to 66.69 cedis. The average Household Dietary Diversity Score (*HDDS*) is 5.2. Both asset and food consumption measures are log-transformed to reduce the influence of extreme values and account for the right-skewed distribution. The average age of household heads is 50 years, and the average household size is 4.

Summary statistics are based on a panel of 12,015 household-wave observations. Variable definitions are provided in the text.

Figure 1 shows the share of households with agricultural extension services access, disaggregated by provider type and survey wave. Across all three waves, access to extension remained limited. In each round, approximately 11 percent of households reported receiving any form of extension support, with the remaining 89 percent reporting no access. When disaggregated by provider types, government agencies accounted for the largest share of extension access. Around 7 to 9 percent of households reported receiving government-provided services in each wave. Access through input suppliers was more limited, at only 2 to 3 percent of households per wave. Farmer-based organizations were the least accessed provider, with under 2 percent of households reporting any engagement with this type across the survey period.

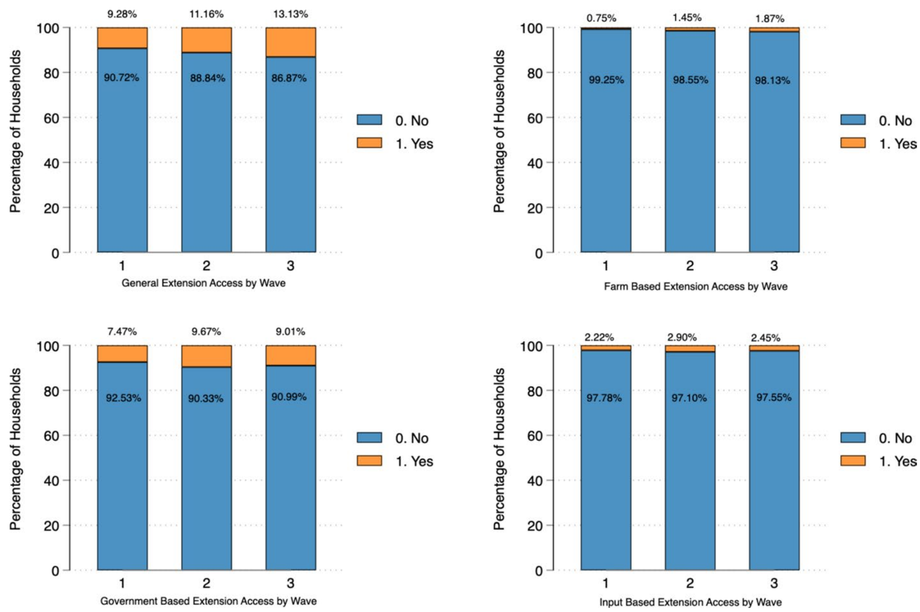

Fig. 1 Household access to agricultural extension services across survey waves, by provider type

Table 2 presents the demographic and socioeconomic characteristics of households in the panel, grouped by whether they received agricultural extension services.[2] Specifically, 79 percent of households receiving extension support were male-headed, compared to 60 percent among those with no access. Similarly, rural households comprised 85 percent of those who accessed extension services. Education attainment levels also differed: 45 percent of households who accessed extension had no formal education, compared to 40 percent among those who did not access extension. Ownership of phones and media (i.e., radio and television) was relatively balanced across groups, with about 70 percent of households reporting ownership of at least one communication device accessing extension services.

The table presents the distribution of household characteristics by whether the household received agricultural extension services. Values are frequencies with corresponding row percentages in parentheses. "Received Extension = Yes" refers to households that reported receiving extension services during the survey period. "HH head" stands for household head.

Propensity matching quality

Before presenting the main results, we assess the quality of the matching process that underpins both the matching and IPWRA models. As shown in Fig. 2 here and Fig. 3 in the appendix, the distribution of predicted propensity scores for treated (extension service access) and untreated (no extension service access) households overlaps substantially, with most observations concentrated between 0.1 and 0.3. This suggests that the positivity assumption is satisfied and that the estimates are likely to be credible within this common support. Both treated and untreated households are well

[2] That is, agricultural extension service without disaggregating by the provider type.

Table 2 Descriptive characteristics of households by access to agricultural extension services

	Received extension		Total
	No	Yes	
N (%)	8,703 (72.4%)	3,312 (27.6%)	12,015 (100.0%)
Household head gender			
0. Male	5,237 (60.2%)	2,626 (79.3%)	7,863 (65.4%)
1. Female	3,466 (39.8%)	686 (20.7%)	4,152 (34.6%)
Marital status of HH head			
0. Unmarried/betrothed	2,587 (29.7%)	954 (28.8%)	3,541 (29.5%)
1. Married/consensual	3,949 (45.4%)	1,874 (56.6%)	5,823 (48.5%)
2. Divorced/separated	1,019 (11.7%)	223 (6.7%)	1,242 (10.3%)
3. Widowed	1,148 (13.2%)	261 (7.9%)	1,409 (11.7%)
Education of HH head (ordered)			
0. No formal education	3,461 (39.8%)	1,499 (45.3%)	4,960 (41.3%)
1. Below tertiary	4,687 (53.9%)	1,688 (51.0%)	6,375 (53.1%)
2. Tertiary	555 (6.4%)	125 (3.8%)	680 (5.7%)
Locality of Residence			
0. Urban	3,609 (41.5%)	490 (14.8%)	4,099 (34.1%)
1. Rural	5,094 (58.5%)	2,822 (85.2%)	7,916 (65.9%)
Does HH have a phone			
0. No	2,449 (28.1%)	1,057 (31.9%)	3,506 (29.2%)
1. Yes	6,254 (71.9%)	2,255 (68.1%)	8,509 (70.8%)
Does HH have a radio/TV			
0. No	2,535 (29.1%)	905 (27.3%)	3,440 (28.6%)
1. Yes	6,168 (70.9%)	2,407 (72.7%)	8,575 (71.4%)

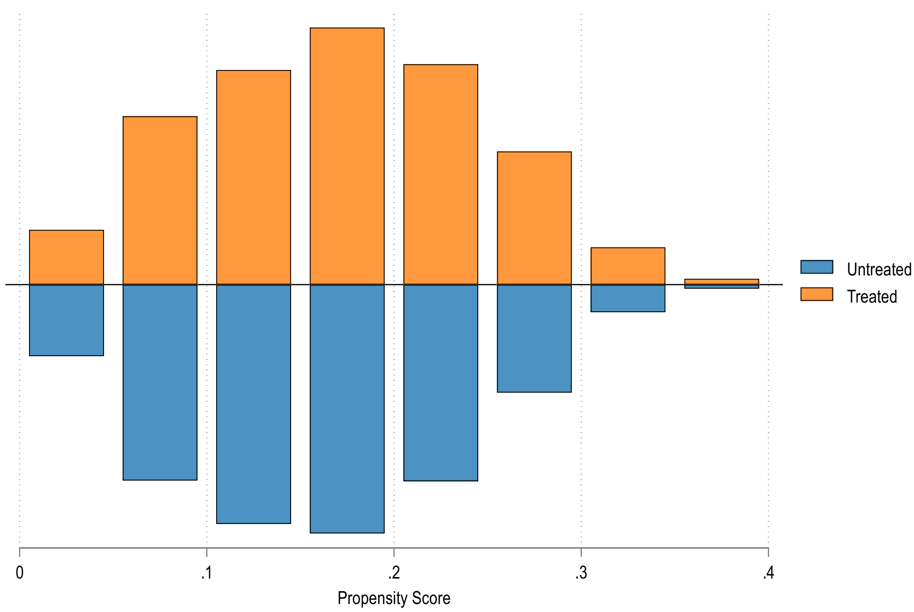

Fig. 2 Distribution of propensity score matching quality

represented across the score range, indicating that the reweighting and matching procedures are built on a strong foundation of overlap.

Table 3 Propensity score matching quality metrics

Sample	Unmatched	Matched
Pseudo R^2	0.074	0.002
Likelihood ratio chi^2	664.92	8.28
$p > chi^2$	0.00	0.996
Mean bias	14.7	1.7
Median bias	9.2	1.3
Percentage of Variance	100	50

Covariate balance

We also report the covariate balance table before and after weighting, using standardized differences and variance ratios (See Table 9 in the appendix). The unweighted sample exhibited notable imbalances in key covariates such as household size, gender of the household head, and location of household (rural/urban). After applying inverse probability weights, balance improved markedly across all covariates. Standardized differences fell near zero and variance ratios approached 1, indicating that the re-weighted control group closely resembled the treated group. The summary provides confidence in the quality of covariate adjustment.

Furthermore, Table 3 shows the result of matching quality tests by comparing metrics before and after matching. The lower proportion of variance explained by the covariates in predicting the treatment assignment (Pseudo R^2) after matching indicates a reduction in the ability of the covariates to predict treatment assignment and hence a better balance between treated and untreated households. Similarly, the test of joint prediction of treatment by covariates (LR χ^2) shows a significant reduction from the unmatched sample (664.92) to the matched sample (8.28), indicating a better balance. Lastly, the reduction in the mean and median bias – which measures the average and median standardized difference in covariates between treated and untreated groups – from before to after matching also points to improved balance after matching.

Effect of receiving extension on welfare outcomes

Table 4 presents the average treatment effects on the treated (ATT) of access to any form of agricultural extension services on four key welfare outcomes: household asset holdings, per capita food consumption, dietary diversity, and poverty likelihood. Across all three estimation strategies, namely, propensity score matching (PSM), nearest-neighbor estimation (NNE), and inverse probability weighted regression adjustment (IPWRA), we observe consistently positive and statistically significant effects on household assets, food consumption, and dietary diversity. Specifically, the log of household assets increases by 0.184 (or 20.2%) under PSM, 0.137 (or 14.7%) under NNE, and 0.249 (28.3%) under IPWRA, each significant at the one percent level. Food consumption effects are also tightly estimated across methods, ranging from 0.122 (or 13%) to 0.202 (or 22.4%). Extension access is associated with improvements in dietary diversity, with gains between 0.279 and 0.505 points, depending on the method. For the Poverty Probability Index (PPI), results vary more substantially. The estimates from PSM and NNE indicate significant reductions in

Table 4 ATT of general extension services on outcome variables

	PSM	NNE	IPWRA
Log of Assets	0.184***	0.137***	0.249***
	[0.062]	[0.051]	[0.035]
Log of Per capita Food Consumption	0.202***	0.122***	0.19***
	[0.037]	[0.028]	[0.019]
Household Dietary Diversity Score	0.492***	0.279***	0.505***
	[0.102]	[0.070]	[0.053]
Poverty Probability Index Score	−0.201**	−0.881**	−0.227
	[0.632]	[0.406]	[0.305]
N	12,015	12,015	12,015
Controls	Yes	Yes	Yes

Robust Standard errors in brackets.

*, **, and *** indicate significance at the 1, 5, and 10 percent levels, respectively.

The outcome variables are Log of Assets, Log of Per capita Food Consumption, Household Dietary Diversity Score, and Poverty Probability Index Score.

Table 5 ATT of extension service on assets

	PSM	NNE	IPWRA
Extension service (farmer-based organization)	0.254**	0.1868	0.276***
	[0.122]	[0.1369]	[0.090]
Extension service (input dealers)	0.128	0.0326	0.084
	[0.110]	[0.0990]	[0.073]
Extension service (government)	0.295***	0.1282**	0.260***
	[0.064]	[0.0580]	[0.041]
N	12,015	12,015	12,015
Controls	Yes	Yes	Yes

Standard errors in brackets.

*, **, and *** indicate significance at the 1, 5, and 10 percent levels, respectively.

the likelihood of poverty, with point estimates of −0.201 and −0.881, respectively. However, the corresponding estimate from IPWRA is -0.227 and not statistically significant.

Effect of extension access of different sources on welfare outcomes

Effect on household assets

The findings in Table 5 indicate that receiving agricultural extension advice is positively associated with household asset accumulation. This relationship is statistically significant for services received from farmer-based organizations and government providers, particularly in the PSM and IPWRA models. Specifically, access to advice from farmer-based organizations is associated with an increase in assets of approximately 28.9–31.8%. Government-provided extension services show a similarly strong and significant association, with increases in assets ranging from 13.7 to 29.7% across the different specifications. In contrast, advice from input dealers does not produce a statistically significant effect on household assets.[3]

[3] Note that here and after, the coefficients for the log-transformed outcome variables are exponentiated (1- e^x) to obtain the percentage values.

Table 6 ATT of extension service on per capita food consumption

	PSM	NNE	IPWRA
Extension service (farmer-based organization)	0.287***	0.1684**	0.258***
	[0.094]	[0.0845]	[0.059]
Extension service (input dealers)	0.178**	0.0677	0.096**
	[0.071]	[0.0561]	[0.042]
Extension service (government)	0.300***	0.1136***	0.221***
	[0.039]	[0.0321]	[0.022]
N	12,015	12,015	12,015
Controls	Yes	Yes	Yes

Standard errors in brackets.

*, **, and *** indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 7 ATT of extension service on household dietary diversity

	PSM	NNE	IPWRA
Extension service (farmer-based organization)	0.871***	0.6012***	0.684***
	[0.282]	[0.1963]	[0.147]
Extension service (input dealers)	0.515***	0.0666	0.316***
	[0.195]	[0.1504]	[0.115]
Extension service (government)	0.746***	0.2966***	0.591***
	[0.107]	[0.0813]	[0.060]
N	12,015	12,015	12,015
Controls	Yes	Yes	Yes

Standard errors in brackets.

*, **, and *** indicate significance at the 1, 5, and 10 percent levels, respectively.

Effect on food consumption

Table 6 shows the effects of various extension types on food consumption. The table shows a generally strong statistically significant and positive relationship between access to agricultural extension advice and per capita food consumption across provider types and model specifications. For households accessing services from farmer-based organizations, there is an increase of 18.3% to 29.4% in per capita food consumption. For households accessing services from input dealers, the increase is between 10.1 and 19.5% (NNE model is insignificant). Lastly, for households accessing services from government providers, the increase is between 12 and 35%.

Effect on dietary diversity

Table 7 shows that generally, receiving extension service shows a strong positive and statistically significant relationship with household dietary diversity across provider types and model specifications. For households accessing services from farmer-based organizations, there is an increase of between 0.60 and 0.87 points in dietary diversity. Receiving extension service from input dealers is associated with an increase of approximately between 0.32 and 0.52 points in the dietary diversity score (NNE model is insignificant). Government-provided extension, however, corresponds to an increase of between 0.30 and 0.75 points.

Table 8 ATT of extension service on PPI score

	PSM	NNE	IPWRA
Extension service (farmer-based organization)	1.887	0.8528	-0.145
	[1.702]	[1.2042]	[0.823]
Extension service (input dealers)	− 0.310	− 0.9901	− 1.703***
	[1.127]	[0.7750]	[0.571]
Extension service (government)	0.838	− 1.1536**	0.181
	[0.732]	[0.4818]	[0.355]
N	12,015	12,015	12,015
Controls	Yes	Yes	Yes

Standard errors in brackets.

*, **, and *** indicate significance at the 1, 5, and 10 percent levels, respectively.

Effect on poverty probability

Table 8 presents the ATT on the Poverty Probability Index (PPI) score across different types of extension services. The results are mixed across estimation methods. For farmer-based organizations, none of the models yield statistically significant estimates, and the direction of the effect varies. For input dealer-sourced extension services, the IPWRA model shows a statistically significant negative association with PPI score, suggesting that households who accessed extension advice from input dealers tend to have lower poverty probability, while the other models report null or imprecise effects. In contrast, government-provided extension services exhibit a statistically significant and negative association in the NNE specification, though this relationship is not robust across methods. These findings imply that the estimated association between extension access and household poverty is sensitive to both the type of service provider and the choice of estimation method.

Discussion and policy implications

Our study allows us to make important contributions to the literature on the benefits of receiving agricultural extension and advisory service, especially in Ghana. Firstly, we provide a nationally representative panel analysis that addresses external and internal validity concerns. This is important because previous studies, largely based on cross-sectional and limited size data, are not generalizable. We draw on a three-wave longitudinal dataset to examine the impact of AEAS on household welfare, measured across four dimensions: asset, food consumption per capita, and dietary diversity, and poverty. To estimate this relationship, we employ three treatment effects models: Propensity Score Matching (PSM), Nearest Neighbor Estimation (NNE), and Inverse Probability Weighted Regression Adjustment (IPWRA). Among these, IPWRA stands out for its doubly robust property, yielding consistently lower standard errors across estimates.

Studies on AEAS (e.g., Aremu and Reynolds 2024; Paul et al. 2023) suggest that the pathway from receiving extension service ends up with more income and consumption, reduced poverty, and improved food security and value of household assets.[4] The IPWRA model shows an increase of 28.3% in assets, 20.9% in the value of per capita food consumption, and 4.2% in dietary diversity score among households that received AEAS.

[4] See Aremu and Reynolds 2024 for a full graphical representation of this theoretical framework.

Disaggregating AEAS to the level of source, we further showed that receiving extension services from farmer-based organizations is associated with an increase of 31.8% in assets, 29.4% increase in per capita food consumption, and 5.7% increase in dietary diversity score. For households who received AEAS from input dealers, we found a null result for the effect on assets, 10.1% increase in per capita food consumption, and 2.6% increase in dietary diversity. Furthermore, households who received AEAS from government extension providers show 30% increase in assets, 24.7% increase in per capita food consumption, and 4.9% increase in household dietary diversity score. However, we found either null or statistically significant, negative results with poverty probability across all extension variables and model specifications. Our findings extend existing evidence for productivity and income (Anang et al. 2020; Asante et al. 2024; Danso-Abbeam et al. 2018) by showing that AEAS improves assets and food security (food consumption and dietary diversity).

The disaggregated extension source results provide new insights into how specific sources of agricultural advice influence household welfare. While previous studies have generally treated AEAS as a single, undifferentiated intervention (for example, Anang et al. 2020; Asante et al. 2024) or focused narrowly on services delivered by non-governmental or religious-based organizations (for example, Attipoe et al. 2021; Danso-Abbeam et al. 2018), our analysis distinguishes between AEAS received from government agents, input dealers, and farmer-based organizations. Among these, AEAS delivered by farmer-based organizations shows the largest positive effects across all welfare outcomes, followed by those administered by the government and input dealer services.

This finding aligns with a copious amount of literature highlighting the role of farmer-based organizations, such as cooperatives and producer associations, in improving agricultural outcomes among smallholder farmers in Ghana. These organizations have been found to enhance farmers' access to extension services, input markets, credit, and technical information, while also enabling collective action and bargaining power (Salifu et al. 2012; Asante et al. 2011; Buadi et al. 2013; Moore et al. 2015; Antwi-Agyei and Stringer 2021). For instance, Asante et al. (2011) report that membership increases access to farm machinery and market information, while Moore et al. (2015) emphasize the role of participatory approaches in facilitating technology adoption and productivity growth. Buadi et al. (2013) further find that farmers perceive extension services delivered by these organizations to be particularly effective due to their timeliness and contextual relevance.

While concerns remain about the economic sustainability of farmer-based organizations and the barriers to participation for resource-constrained farmers (Moore et al. 2015; Salifu et al. 2012), the evidence suggests that these groups serve as important institutional channels for scaling extension services and improving welfare. Our findings support this view and underscore the need for policies that strengthen the long-term viability and inclusiveness of such organizations, especially for a context currently dominated by government-based extension advice. One option would be for the government to train lead farmers or private input sellers to provide basic agricultural advisory services, especially in areas underserved by public agents. As mobile technology becomes more accessible, digital channels for extension, including mobile messaging, radio, and television, offer further opportunities to expand reach. The growing potential of artificial intelligence also presents a promising avenue for delivering personalized and context-sensitive advice to remote farming communities.

The null or negative result of AEAS on poverty reduction could be because receiving advice on good practice or new technology alone is not enough to lift people out of poverty, especially when many farmers in the country are subsistent, poor, and grow for their own consumption (Alexander 2019, pp. 1). Future studies may explore this relationship using income as an outcome measure which is supposed to be a direct measure. Indeed, most rural income in many African countries are currently agriculture-based (Davis et al. 2017, 2023). However, other studies argue that there is potential in crop and labor diversification to not only adapt to different shocks but also improve food security, income, and poverty, especially among smallholder and most vulnerable households (Asfaw et al. 2018, 2019; Birthal et al. 2015; Sánchez et al. 2022). Thus, if extension services will contribute to poverty reduction, policies may need to focus on encouraging diversification, particularly among poor and smallholder households. Moreover, policies that support market access, infrastructure development, and value chain integration can complement extension services to improve household welfare.

Finally, our study has limitations. Even though there are differences in the growing conditions, decision making, and poverty status between the north and south of Ghana, which often influence the use of agricultural extension services (Alexander 2019), our analysis did not discuss these geographical dynamics and how this influences access/use of extension service and subsequently recipient farmers' welfare. Do farmers who live in certain regions, own certain sizes of land, grow certain types of crops, or are within certain quartiles of wealth have better access to and/or use extension service than others and is there a difference in the effect of extension services on these sub-populations? We also acknowledge the potential role of input subsidies in shaping both access to extension services and household welfare. Disentangling these confounding influences remains an important task for future research. We hope that such questions can be answered in future studies.

Conclusion

While governments in developing countries rely on the potential of agriculture to drive development in their countries, this sector faces challenges that limit such potential (Asante et al. 2024; Danso-Abbeam et al. 2018). Additionally, the AEAS system that could potentially help farmers is poorly serviced, is mired in inconclusive evidence or is advocated for with non-generalizable evidence. Our study provides evidence in support of the role of AEAS in livelihood improvements in Ghana, particularly for asset, food consumption, and dietary diversity. Given currently low levels of overall adoption of extension services and the domination by government sources, policies should focus on supporting alternative sources such as those by farmer-based organizations and input dealers.

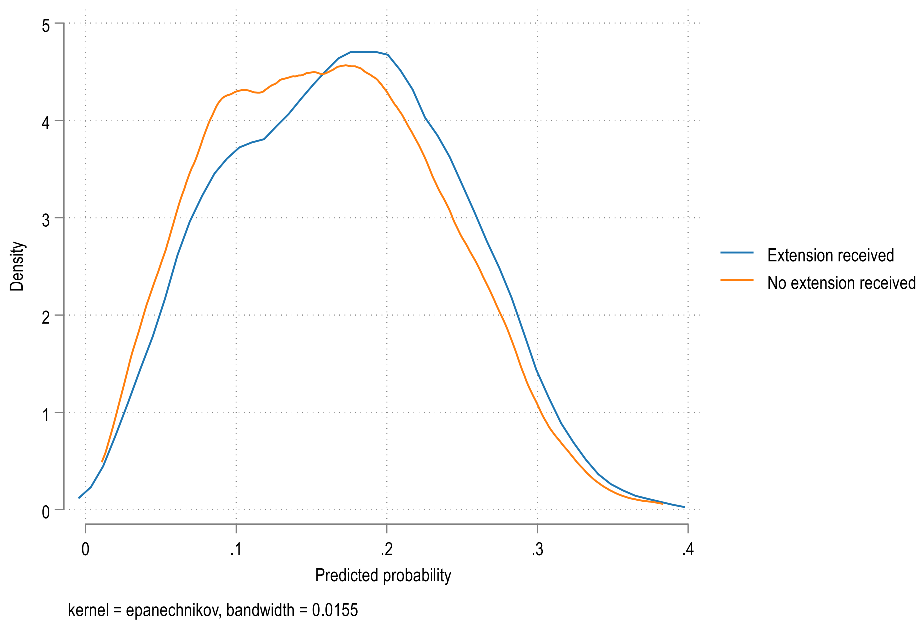

Fig. 3 Density of propensity score matching quality

Table 9 Covariate balance summary

Covariate	Standardized diff (Raw)	Standardized diff (Weighted)	Variance ratio (Raw)	Variance ratio (weighted)
household age	0.0465	−0.0036	0.9025	0.9354
Household size	0.3479	−0.0038	1.3599	0.9966
Household gender (1. Female)	−0.4065	0.0028	0.66	1.0045
Household marital status (Married)	0.1403	0.0011	0.9944	0.9998
Household marital status (2. divorced/separated)	−0.1351	0.0014	0.6732	1.0046
Household marital status (3. widowed)	−0.1928	−0.0001	0.5806	0.9997
Household education (1. Below tertiary)	−0.0078	0.0042	1.0015	0.9996
Household education (2. Tertiary)	−0.0638	0.0004	0.7705	1.0018
Location (1. Rural)	0.4779	−0.0012	0.5839	1.0021
Phone (1. Yes)	−0.0066	−0.0028	1.0066	1.0025
Radio and/ or TV (1. Yes)	0.141	−0.006	0.8591	1.0077
wave (2)	−0.0805	0.0082	0.9399	1.0072
wave (3)	0.0468	−0.0007	1.0324	0.9996
region (2. Brong Ahafo)	0.0892	−0.0111	1.2443	0.9758
region (3. Central)	−0.12	0.0039	0.6782	1.0145
region (4. Eastern)	0.0897	0.0036	1.2268	1.0076
region (5. Greater Accra)	−0.3204	−0.0014	0.3336	0.9933
region (6. Northern)	0.2266	0.0003	1.5136	1.0005
region (7. Upper East)	−0.0911	0.0036	0.6769	1.0178
region (8. Upper West)	0.0624	−0.0001	1.3037	0.9998
region (9. Volta)	0.0454	0.0005	1.1349	1.0012
region (10. Western)	−0.0937	−0.002	0.741	0.9931

Table 10 Full model estimation for general extension access

	Log asset	PPI score	Log food	HDDS
ATT				
r1vs0.extension	0.249***	−0.227	0.190***	0.505***
	[0.035]	[0.305]	[0.019]	[0.053]
POmean				
0.extension	6.696***	38.664***	3.980***	5.218***
	[0.030]	[0.515]	[0.019]	[0.061]
OME0				
_cons	6.696***	38.664***	3.980***	5.218***
	[0.030]	[0.515]	[0.019]	[0.061]
OME1				
_cons	6.945***	38.437***	4.170***	5.724***
	[0.039]	[0.548]	[0.024]	[0.072]
TME1				
hh_age	0.006***	0.006***	0.006***	0.006***
	[0.002]	[0.002]	[0.002]	[0.002]
hhsize	0.072***	0.072***	0.072***	0.072***
	[0.012]	[0.012]	[0.012]	[0.012]
1.hh_gender	−0.659***	−0.659***	−0.659***	−0.659***
	[0.085]	[0.085]	[0.085]	[0.085]
1.hh_mar	−0.169*	−0.169*	−0.169*	−0.169*
	[0.102]	[0.102]	[0.102]	[0.102]
2.hh_mar	−0.065	−0.065	−0.065	−0.065
	[0.135]	[0.135]	[0.135]	[0.135]
3.hh_mar	−0.142	−0.142	−0.142	−0.142
	[0.147]	[0.147]	[0.147]	[0.147]
1.hh_edu	0.210***	0.210***	0.210***	0.210***
	[0.075]	[0.075]	[0.075]	[0.075]
2.hh_edu	−0.060	−0.060	−0.060	−0.060
	[0.147]	[0.147]	[0.147]	[0.147]
1.rural	0.976***	0.976***	0.976***	0.976***
	[0.080]	[0.080]	[0.080]	[0.080]
1.phone	0.074	0.074	0.074	0.074
	[0.072]	[0.072]	[0.072]	[0.072]
1.radio_tv	0.371***	0.371***	0.371***	0.371***
	[0.072]	[0.072]	[0.072]	[0.072]
2.wave	−0.245***	−0.245***	−0.245***	−0.245***
	[0.075]	[0.075]	[0.075]	[0.075]
3.wave	−0.078	−0.078	−0.078	−0.078
	[0.106]	[0.106]	[0.106]	[0.106]
2.region	0.248**	0.248**	0.248**	0.248**
	[0.108]	[0.108]	[0.108]	[0.108]
3.region	−0.330**	−0.330**	−0.330**	−0.330**
	[0.132]	[0.132]	[0.132]	[0.132]
4.region	0.157	0.157	0.157	0.157
	[0.104]	[0.104]	[0.104]	[0.104]
5.region	−0.736***	−0.736***	−0.736***	−0.736***
	[0.155]	[0.155]	[0.155]	[0.155]
6.region	0.245**	0.245**	0.245**	0.245**
	[0.104]	[0.104]	[0.104]	[0.104]

Table 10 (continued)

	Log asset	PPI score	Log food	HDDS
7.region	−0.622***	−0.622***	−0.622***	−0.622***
	[0.161]	[0.161]	[0.161]	[0.161]
8.region	0.051	0.051	0.051	0.051
	[0.149]	[0.149]	[0.149]	[0.149]
9.region	0.130	0.130	0.130	0.130
	[0.115]	[0.115]	[0.115]	[0.115]
10.region	−0.439***	−0.439***	−0.439***	−0.439***
	[0.130]	[0.130]	[0.130]	[0.130]
_cons	−3.308***	−3.308***	−3.308***	−3.308***
	[0.190]	[0.190]	[0.190]	[0.190]
N	12,015	12,015	12,015	12,015

Appendix

See Appendix Fig. 3 and Tables 9, 10, and 11

Author contributions

T. A. and R. S. B conceptualized the paper and worked on the results. T. A., R. S. B, and K.O worked on the formal analysis. T. A. obtained and cleaned the data, led the writing of results and discussion and edited the manuscript. R. S. B. led the methodology and visualization. K. O. and P. P. A. wrote the introduction and literature review. All the authors discussed the results and implications and agreed on the final manuscript draft.

Funding

No funding was received for this work.

Data availability

The datasets used for this analysis are publicly available on the African Centre of Excellence for Inequality Research (ACEIR-GH) website (DOIs: Wave 1 - https://dataportal.isser.edu.gh/index.php/catalog/2, Wave 2 - https://dataportal.isser.edu.gh/index.php/catalog/3, Wave 3 - https://dataportal.isser.edu.gh/index.php/catalog/4).

Declarations

Ethics approval and consent to participate

Not applicable.

Competing Interests

The authors declare no competing interests.

Received: 14 March 2025 Revised: 28 August 2025 Accepted: 1 September 2025
Published online: 29 September 2025

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Table 11 Full model for disaggregated extension services

	Farm based org. Extension service				Input dealer-based extension service				Government extension service			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
	Log Asset	PPI Score	Log Food	HDDS	Log Asset	PPI Score	Log Food	HDDS	Log Asset	PPI Score	Log Food	HDDS
ATT												
r1vs0.extension_fbo	0.276***	−0.145	0.258***	0.684***								
	[0.090]	[0.823]	[0.059]	[0.147]								
r1vs0.extension_input					0.084	−1.703***	0.096**	0.316***				
					[0.073]	[0.571]	[0.042]	[0.115]				
r1vs0.extension_gov									0.260***	0.181	0.221***	0.591***
									[0.041]	[0.355]	[0.022]	[0.060]
POmean												
0.extension_fbo	7.062***	31.930***	4.065***	5.733***								
	[0.068]	[1.552]	[0.045]	[0.171]								
0.extension_input					6.842***	32.235***	3.982***	5.222***				
					[0.055]	[1.105]	[0.040]	[0.123]				
0.extension_gov									6.731***	36.984***	4.000***	5.230***
									[0.035]	[0.582]	[0.022]	[0.071]
OME0												
_cons	7.062***	31.930***	4.065***	5.733***	6.842***	32.235***	3.982***	5.222***	6.731***	36.984***	4.000***	5.230***
	[0.068]	[1.552]	[0.045]	[0.171]	[0.055]	[1.105]	[0.040]	[0.123]	[0.035]	[0.582]	[0.022]	[0.071]
OME1												
_cons	7.338***	31.785***	4.323***	6.417***	6.926***	30.531***	4.078***	5.538***	6.991***	37.164***	4.221***	5.820***
	[0.111]	[1.715]	[0.076]	[0.218]	[0.086]	[1.091]	[0.055]	[0.146]	[0.046]	[0.620]	[0.029]	[0.084]
TME1												
hh_age	−0.002	−0.002	−0.002	−0.002	−0.011**	−0.011**	−0.011**	−0.011**	0.007***	0.007***	0.007***	0.007***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]	[0.004]	[0.002]	[0.002]	[0.002]	[0.002]
hhsize	0.082***	0.082***	0.082***	0.082***	0.080***	0.080***	0.080***	0.080***	0.086***	0.086***	0.086***	0.086***

Table 11 (continued)

	Farm based org. Extension service				Input dealer-based extension service				Government extension service			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
	[0.030]	[0.030]	[0.030]	[0.030]	[0.022]	[0.022]	[0.022]	[0.022]	[0.014]	[0.014]	[0.014]	[0.014]
1.hh_gender	−0.655**	−0.655**	−0.655**	−0.655**	−0.415**	−0.415**	−0.415**	−0.415**	−0.796***	−0.796***	−0.796***	−0.796***
	[0.274]	[0.274]	[0.274]	[0.274]	[0.192]	[0.192]	[0.192]	[0.192]	[0.107]	[0.107]	[0.107]	[0.107]
1.hh_mar	0.417	0.417	0.417	0.417	0.388*	0.388*	0.388*	0.388*	0.076	0.076	0.076	0.076
	[0.295]	[0.295]	[0.295]	[0.295]	[0.221]	[0.221]	[0.221]	[0.221]	[0.123]	[0.123]	[0.123]	[0.123]
2.hh_mar	−0.069	−0.069	−0.069	−0.069	−0.129	−0.129	−0.129	−0.129	0.015	0.015	0.015	0.015
	[0.529]	[0.529]	[0.529]	[0.529]	[0.369]	[0.369]	[0.369]	[0.369]	[0.167]	[0.167]	[0.167]	[0.167]
3.hh_mar	−0.143	−0.143	−0.143	−0.143	−0.577	−0.577	−0.577	−0.577	0.178	0.178	0.178	0.178
	[0.566]	[0.566]	[0.566]	[0.566]	[0.412]	[0.412]	[0.412]	[0.412]	[0.177]	[0.177]	[0.177]	[0.177]
1.hh_edu	0.212	0.212	0.212	0.212	−0.11	−0.11	−0.11	−0.11	0.304***	0.304***	0.304***	0.304***
	[0.220]	[0.220]	[0.220]	[0.220]	[0.153]	[0.153]	[0.153]	[0.153]	[0.089]	[0.089]	[0.089]	[0.089]
2.hh_edu	0.362	0.362	0.362	0.362	−0.507	−0.507	−0.507	−0.507	−0.173	−0.173	−0.173	−0.173
	[0.357]	[0.357]	[0.357]	[0.357]	[0.320]	[0.320]	[0.320]	[0.320]	[0.190]	[0.190]	[0.190]	[0.190]
1.rural	0.817***	0.817***	0.817***	0.817***	0.845***	0.845***	0.845***	0.845***	1.121***	1.121***	1.121***	1.121***
	[0.244]	[0.244]	[0.244]	[0.244]	[0.183]	[0.183]	[0.183]	[0.183]	[0.102]	[0.102]	[0.102]	[0.102]
1.phone	0.153	0.153	0.153	0.153	0.285*	0.285*	0.285*	0.285*	−0.049	−0.049	−0.049	−0.049
	[0.220]	[0.220]	[0.220]	[0.220]	[0.151]	[0.151]	[0.151]	[0.151]	[0.083]	[0.083]	[0.083]	[0.083]
1.radio_tv	0.641***	0.641***	0.641***	0.641***	0.617***	0.617***	0.617***	0.617***	0.365***	0.365***	0.365***	0.365***
	[0.222]	[0.222]	[0.222]	[0.222]	[0.154]	[0.154]	[0.154]	[0.154]	[0.084]	[0.084]	[0.084]	[0.084]
2.wave	0.636***	0.636***	0.636***	0.636***	0.234	0.234	0.234	0.234	0.263***	0.263***	0.263***	0.263***
	[0.244]	[0.244]	[0.244]	[0.244]	[0.149]	[0.149]	[0.149]	[0.149]	[0.088]	[0.088]	[0.088]	[0.088]
3.wave	1.322***	1.322***	1.322***	1.322***	0.399*	0.399*	0.399*	0.399*	0.361***	0.361***	0.361***	0.361***
	[0.325]	[0.325]	[0.325]	[0.325]	[0.229]	[0.229]	[0.229]	[0.229]	[0.127]	[0.127]	[0.127]	[0.127]
2.region	0.935**	0.935**	0.935**	0.935**	0.394	0.394	0.394	0.394	0.380***	0.380***	0.380***	0.380***
	[0.393]	[0.393]	[0.393]	[0.393]	[0.266]	[0.266]	[0.266]	[0.266]	[0.121]	[0.121]	[0.121]	[0.121]

Table 11 (continued)

	Farm based org. Extension service				Input dealer-based extension service				Government extension service			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
3.region	−0.947	−0.947	−0.947	−0.947	−2.711***	−2.711***	−2.711***	−2.711***	−0.14	−0.14	−0.14	−0.14
	[0.764]	[0.764]	[0.764]	[0.764]	[1.014]	[1.014]	[1.014]	[1.014]	[0.147]	[0.147]	[0.147]	[0.147]
4.region	1.233***	1.233***	1.233***	1.233***	0.535**	0.535**	0.535**	0.535**	−0.024	−0.024	−0.024	−0.024
	[0.362]	[0.362]	[0.362]	[0.362]	[0.252]	[0.252]	[0.252]	[0.252]	[0.124]	[0.124]	[0.124]	[0.124]
5.region	−1.657	−1.657	−1.657	−1.657	−2.616***	−2.616***	−2.616***	−2.616***	−2.731***	−2.731***	−2.731***	−2.731***
	[1.047]	[1.047]	[1.047]	[1.047]	[1.015]	[1.015]	[1.015]	[1.015]	[0.457]	[0.457]	[0.457]	[0.457]
6.region	1.890***	1.890***	1.890***	1.890***	1.213***	1.213***	1.213***	1.213***	0.284**	0.284**	0.284**	0.284**
	[0.352]	[0.352]	[0.352]	[0.352]	[0.228]	[0.228]	[0.228]	[0.228]	[0.120]	[0.120]	[0.120]	[0.120]
7.region	0.257	0.257	0.257	0.257	−0.415	−0.415	−0.415	−0.415	−0.482***	−0.482***	−0.482***	−0.482***
	[0.556]	[0.556]	[0.556]	[0.556]	[0.415]	[0.415]	[0.415]	[0.415]	[0.182]	[0.182]	[0.182]	[0.182]
8.region	1.378***	1.378***	1.378***	1.378***	0.084	0.084	0.084	0.084	−0.399**	−0.399**	−0.399**	−0.399**
	[0.442]	[0.442]	[0.442]	[0.442]	[0.374]	[0.374]	[0.374]	[0.374]	[0.194]	[0.194]	[0.194]	[0.194]
9.region	0.592	0.592	0.592	0.592	1.333***	1.333***	1.333***	1.333***	−0.006	−0.006	−0.006	−0.006
	[0.438]	[0.438]	[0.438]	[0.438]	[0.235]	[0.235]	[0.235]	[0.235]	[0.134]	[0.134]	[0.134]	[0.134]
10.region	0.251	0.251	0.251	0.251	0.052	0.052	0.052	0.052	−0.342**	−0.342**	−0.342**	−0.342**
	[0.468]	[0.468]	[0.468]	[0.468]	[0.297]	[0.297]	[0.297]	[0.297]	[0.148]	[0.148]	[0.148]	[0.148]
_cons	−7.602***	−7.602***	−7.602***	−7.602***	−5.441***	−5.441***	−5.441***	−5.441***	−4.331***	−4.331***	−4.331***	−4.331***
	[0.676]	[0.676]	[0.676]	[0.676]	[0.426]	[0.426]	[0.426]	[0.426]	[0.232]	[0.232]	[0.232]	[0.232]
N	12,015	12,015	12,015	12,015	12,015	12,015	12,015	12,015	12,015	12,015	12,015	12,015

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