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Does Adopting the Bean Technology Bundle Enhance Food Security Access and Resilience for Smallholder Farmers in Ethiopia?

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Abstract: We assess simultaneous adoption and impacts of multiple improved technologies promoted as a bundle and recommended for legumes intensification systems for smallholder farmers in Ethiopia. We use DNA fingerprinting data to precisely identify our key treatment - "adoption to improved bean varieties" in the study. The results show significant positive impacts of adopting bundled interventions on, agricultural incomes and household food security but vulnerability to food insecurity persists. We find that growing improved varieties with fertilizers increased household agricultural revenue, allowing for more legume consumption and enhancing their likelihood of achieving adequate food consumption and food security outcomes. However, the vulnerability to food insecurity of the adopters remains high due to pre-existing resource degradation issues. Given similarity in production contexts in Sub Saharan Africa, our results provide perspective for similar development interventions. We use the results of our analysis to discuss potential policy implications and programmes to support technology intensification among small holder farmers.

Keywords: adoption; bundled technologies; Ethiopia; common beans; household welfare

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1. Introduction

In Sub-Saharan Africa (SSA), people's health, productivity, and survival are threatened by food insecurity and poverty. Smallholder agriculture is the main source of income for many of the poor, but it suffers from low productivity (Collier & Dercon, 2014; Diao et al., 2010). The rapidly increasing population in SSA strains landholdings and exacerbates the impacts of climate change, which reduces available cropland (FAO, 2009). This underscores the need to improve modern intensive farming systems in the region. Developing technologies that boost output per area (intensification) and improving farmers' skills through effective extension services (Waceke & Kimenju, 2007) for crucial for better crop management and resource use efficiency.

Access to agricultural technological bundles, developed, and promoted by crop improvement research, can improve food security for smallholders. These technologies can mitigate the effects of population growth and climate change, as demonstrated by previous studies. For example, Biru et al. (2020) found that adopting various technologies simultaneously increased consumption, reduced poverty, and improved food security for Ethiopian smallholders. Likewise, Mujeyi et al. (2021) found that climate smart agriculture technological bundles improved food security and incomes for households in Zimbabwe's crop-livestock systems. Khonje et al. (2018) in Zambia and Gebremariam (2018) in Northern Ghana also examined the welfare benefits of technological packages. While these studies indicate that technological bundles can enhance household welfare, the effects can vary in magnitude and distribution depending on the characteristics and level of adoption (Ogundari and Bolarinwa, 2018). This variation is due to factors such as resources, education, and markets, which

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influence how these technological bundles are adopted and their effectiveness. Although much is known about differential impacts of improved technologies, the impact of adopting agricultural technological bundles on household welfare is less understood when considering adoption intensity.

Our study aimed to examine the simultaneous adoption of multiple improved technologies for common bean (Phaseolus vulgaris), their adoption intensity and how this influences their food security outcomes using several indicators selected along the innovation-to- food security impact pathways. The food security impacts are assessed among smallholder bean producing households in Ethiopia, accounting for partial adoption of improved varieties. Improved varieties of common beans were developed with a focus on high yielding potential and resistance to numerous diseases. Consequently, their adoption could bolster welfare by boosting production, mitigating yield loss, or minimizing pesticide usage, ultimately resulting in better food security outcomes. Similarly, resource management strategies like the use of fertilizers, planting in a timely manner, and row planting could be associated with improvements in household welfare via comparable pathways. However, common bean is usually grown on less fertile parts of the farm which may affect the adoption intensity and effectiveness of recommended technological packages.

The study was conducted in Ethiopia, one of the top ten bean producing countries in SSA. Ethiopia is highly populous with about 115 million people in 2019, a number expected to grow to 150 million by 2030 (https://www.fao.org/countryprofiles). Small scale agriculture is the mainstay of the country's economy, covering 38,190, 000 hectares of land and accounting for half of GDP, 83.9% of export, and 80% of employment (https://www.usaid.gov/agriculture and food security . More than 290,000 ha of land in Ethiopia are planted with common bean, which makes up about 3% of all grain crops (Habte et al., 2021). The crop is important for both export and food security, as it provides about 10% of the total agricultural export value (FAO, 2021) and helps to ease liquidity constraints with early cash income when other crops are not yet harvested (Legesse et al., 2006). Climatic variations, which may cause 13% of farmers to abandon bean production in a season (Habte et al., 2021), are among the biotic and abiotic factors that reduce the crop's productivity. Other factors include small landholdings due to high population density and limited access to improved technologies. Therefore, many interventions have focused on providing better technologies to enhance crop productivity, which is vital.

The bean program of Ethiopian Institute of Agriculture Research (EIAR) and the International Centre for Tropical Agriculture (CIAT) collaborated from 2007 to 2016 under the tropical legumes (TL) project to address the obstacles to bean productivity in the country by improving smallholder farmers' access to better bean technologies. The collaboration resulted in the distribution of 30 varieties to smallholder farmers across the country, including seven new ones. The intervention also trained implementers in good agricultural practice, such as weed control, fertilizer, and row planting, to combine these practices with the varieties and deliver a comprehensive technology package to farmers. Advanced technologies, such as better varieties and management practices, can help farmers boost productivity and grow more beans for consumption and sale. The income from bean sales can buy things that improve welfare, like healthy food, clothing, or other goods. With higher yields, farmers may switch some land from beans to other crops. Both pathways increase household food supply for consumption and/or sale.

This paper contributes to literature in the following ways. First, we measure improved crop variety adoption differently from previous studies, by separating full and partial use in a multi valued treatment framework (e.g Biru et al., 2020, Khonje et al., 2018 and Gebremariam,2018). This allows us to assess how adoption intensity of technological bundles affects the impacts of technology use. It is crucial to split the adopters by adoption intensity in impact evaluation, as it can reveal the reasons for the weak adoption to impact relations in SSA (Ogundari and Bolarinwa, 2018). It also emphasizes the need to address the technological access barriers that may influence adoption intensity. Second, many studies have shown the causal link between technology adoption and food security dimensions, such as availability, access, and utilization, but not food security stability. Some

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evidence shows that hunger and starvation affect many Africans[1], which makes it crucial to assess how research can help improve food security resilience. There are few studies that have looked at food security resilience in an impact evaluation framework (Tsegaye Mulugeta Habtewold & Almas Heshmati. 2023). We use indicators that show food availability (i.e. agricultural income (ETB), access (e.g consumption expenditure, food consumption groups) and food insecurity vulnerability (food expenditure share, and Household Food insecurity Assessment score index). Third, we identify our varieties by DNA fingerprinting, which ensures accurate variety classification and reliable outcome estimates of improved bean technology adoption.

Our analysis is based on data from a nationally representative sample of 972 bean-growing households collected after the meher agricultural season of 2016. This is more reliable than farmer's recall, which can cause variety misclassification (Maredia et al., 2016), as previously used in ex-post impact studies of improved bean varieties adoption (Katungi et al., 2018; Letaa et al., 2020; Vaiknoras & Larochelle, 2021). We use the Multinomial Endogenous Treatment Effect (METE) model proposed by Deb and Trivedi (2006) to analyze the adoption and impacts of improved bean technological bundles of varieties and fertilizers. The METE model has been used in a few empirical studies with multiple treatments by other researchers (e.g., Khonje et al., 2018; Manda, 2017; Tufa et al., 2019).

The rest of the paper is structured as follows. Section 2 describes data sources and definition of key variables whereas section 3 deals with the conceptual framework and estimation strategy. Section 4 presents and discusses results, and the paper concludes with a discussion of key findings and policy recommendations.

2. The Data Source and Variable Definition

2.1. Data Sources

We used primary data collected from a nationally representative sample of common bean growers in Ethiopia. Using Central Services Agency (CSA) data on study site characteristics, and geographical administrative boundaries, a three-stage stratified probability proportional to size (PPS) sampling design was employed to draw samples from each stratum. The strata included the four major common bean producing regions of the country: Oromia, SNNPR, Amhara, and Benishangul-Gumuz, which accounted for about 98% of the national area under common bean in the 2016 production season. From the four major bean growing regions, a total of 275 common bean producing districts (Weredas) were identified using the 2002/03 agricultural census report, the most recent agricultural census at the time. From these, a total of 1122 bean producing households were sampled and were allocated proportionately to each region using the regions share of bean area cultivated as the probability weights. However, due to missing observations in some variables, the final sample size used in analysis was 972. The second (kebele) and the third (household) stage sampling were conducted when the team visited the sites to collect data. The list of kebeles was obtained from district offices based on a simple random sampling technique after dropping non-bean growing Kabeles. Respondents were selected from the kebele (village) list of households using a random starting point and then selecting every nth household.

Data for the study was collected at three levels: Kebele, household and plot level. Community level data were collected using key informants (extension agents, model farmers, and community chairperson) interviews. Household heads, and if missing a knowledgeable senior member of the household, provided household and plot level data. Experienced and trained enumerators collected data using Computer Assisted Personal Interviewing (CAPI) techniques on the ODK platform. Data collection took place from April to June 2017, immediately after the completion of the Meher (main cropping) agricultural season of 2016.

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[1] About 346 million people in Africa are undernourished. In 2021 alone, East Africa faced 7.2 million people at risk of hunger and 26.5 million with acute food insecurity (Verner et al., 2021; Wudil et al., 2022)

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2.2. Definition and Measurement of Treatment and Outcome Variables

2.2.1. Treatment Variables:

Variety and Management Practice Adoption

A household was defined as an adopter of an improved common bean variety if any improved common bean variety was planted during the 2016 meher as a season of the study. We used DNA fingerprinting to classify farmer varieties as: Landraces and improved varieties. We found a challenge in defining adoption of management practices since farmers tend to change the agronomic techniques upon application. Researchers recommend: (1) weeding beans twice to keep the crop free of weeds up to the flowering stage, (2) row planting at a spacing of 40 cm x 10 cm and seeding rate of 80-100 kg/ha depending on the seed size, and (3) application of fertilizers at rates of 150kg/ha for NPK. However, fertilizer performance depends on the soil and variety, with some varieties responding to fertilizers better than others. Furthermore, fertilizer use in Ethiopia is positively correlated with row planting while adoption of weeding was very high. In the final estimation, we used only variety adoption and fertilizer adoption since row planting and weeding count were collinear. Although adoption of improved varieties was high, only 53.5% adopted fully while 21% were partial adopters. Approximately 34.8 percent of bean growing households used fertilizer in the main season (meher). Among the adopters of fertilizers, approximately 71.5% applied it on improved varieties while 23.9% applied it on either improved varieties or landraces, thus being partial adopters of the technology package. A farmer was defined as a full adopter if he/she planted only improved bean varieties on land reallocated to bean production and managed them with fertilizers.

Combined, there are six treatments: (0) growing land race varieties without fertilizer (LV only), the control group, (1) growing improved varieties and landraces without fertilizer (partial variety adopters only (PVO)), (2) growing only improved varieties without fertilizer (IV only), (3) growing landraces with fertilizer (LVF), (4) growing improved varieties and landraces with fertilizer (PV+F) and (5) growing improved varieties with fertilizer (FIV+F). The non-adopters who applied fertilizers were too few (only 10 households) to stand alone as a category. This category was merged with the control group and coded zero. Additionally, the intensity of fertilizer use among this category was very low, at about 19.3 kg/ha, making it indistinguishable from non-adopters in terms of productivity. Overall, the rate of fertilizer application was minimal, averaging 84kg per hectare among those who adopted the technology. Estimates from a two-step endogenous Tobit tests confirmed that there was no notable statistical difference between the full (FIV+F) and partial adopters (PV +F) of improved varieties in terms of fertilizer application rate. This finding rules out any potential simultaneity in the adoption of the two technologies to justify complex models like simultaneous Tobit (Appendix A.1).

2.2.2. Food Security Outcome Variables

According to the 1996 World Food Summit, food security is defined as a state where all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life (worldbank.org). Food security requires food availability and accessibility (Mahmudiono et al., 2020). We use indicators of availability, accessibility, and vulnerability to measure food security for Ethiopian bean farmers.

a.1 Food availability indicators

We measured food availability by agricultural income, defined as total revenue from crops grown during the observed agricultural season. To calculate total agricultural crop revenue, we multiplied output produced by adjusted prices and summed the value of all crops produced. Data were collected on quantities of output for all crops produced by the household during the season and market prices of commodities were collected at community level. We accounted for spatial differences in commodity prices by dividing each price with the price index, which was calculated using the same procedure applied in adjusting consumption expenditure estimates as described below.

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a.2 Food access and utilization indicators

Household access to food was defined as the ability to acquire a sufficient quality and quantity of food to meet all household members' nutritional requirements for productive lives (worldbank.org). In the study, household food access was represented by: 1) food consumption expenditure and dietary diversity (measured by food consumption groups). We calculated the household total expenditure from data on food, non-durable, and durable spending, using recall periods of 7, 30, and 365 days, respectively. We converted all consumption spending into annual per capita levels, adjusted by the household adult equivalent and used the food price index to standardize prices across locations. The price index (P^h) was: $P^h = w_k^h(\frac{P_k^0}{P_k^h})$, where P_k^h is the price for good k faced by household, P_k^0 is the price of good k in the reference community, and w_k^h is the share of expenditure a household devotes to good k. We analyzed food and nonfood spending separately to see how productivity gains affect household food consumption. While food expenditure indicates how much food a household can afford, it does not show the variety of foods they have access to or how they feel about their food situation. Therefore, we also included the food consumption score (FCS) an indicator of food dietary diversity. The FCS is computed based on a 7-day recall of food groups, weighted by consumption frequency and nutritional value, thus reflecting the diversity, frequency, and quality of food intake by households.

a.3 Food insecurity vulnerability indicators

The household vulnerability to food insecurity was measured by three indicators: the food expenditure share, quantity of grain in storage at end of main season and household food insecurity assessment score (HFIAS). We computed the share of food expenditure as: $Share\ of\ food\ expenditure = \frac{food\ expenditure}{Total\ expenditure}$. We used this to test the impact of technology adoption on household food security poverty. The share of household income spent on food is a measure of economic access to food and vulnerability to shocks (Humanitarian Global, 2021). We classified households into four food security groups based on humanitarian global indicators: very high (vulnerable) if expenditure ≥ 0.75%, high if 65% ≤ expenditure < 75%, medium if 50% ≤ expenditure < 65%, and low if expenditure < 50% (Humanitarian Global, 2021). The data showed that nearly 66% of the households could be classified as vulnerable based on the food expenditure share, while only 9% were rate as low in terms of vulnerability. We used the continuous expenditure share in the analysis directly to ensure variation in the data.

To accounts for temporal changes in food security (Kennedy et al., 2011) that FCS score could potentially miss, we collected data on household behaviors indicating inadequate food quality and quantity, as well as food supply anxiety and uncertainty. This data was used to compute the household food insecurity assessment score (HFIAS) based on the methods outlined Coasters et al., (2007). According to these authors, HFIAS uses a set of questions on three domains: Domain I addresses food supply anxiety and uncertainty. Domain II covers food quality intake in three sub-domains, and Domain III focuses on food quantity intake. Respondents rate each question as 1=1 to 2 times; 2=3 to 10 times; or 3= more than 10 times, based on the frequency of the problem in the last four weeks. The HFIAS ranges from 0 to 27, with higher scores indicating greater severity.

Finally, the quantity of grain (q) stored at the end of the main season was determined based on the collected data on crop utilization. For each crop, we gathered information on production, the amount stored at the beginning of the season, the quantity consumed and/or sold, and the quantity received as gifts or purchased from the market. The stock at the end of the season (q) was calculated as follows: q = quantity in store at the start of the season + quantity produced + quantity received (in gifts or purchased) - (quantity sold + consumed). The remaining grain at the end of observed main season (meher) served as a measure of household food security resilience.

3.0. Conceptual Framework and ESTIMATION STRATEGY

3.1. Conceptual Framework

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In Ethiopia, smallholder farmers grow beans in remote locations characterized by low-quality road infrastructure (Worku, 2011), poor access to credit, limited off farm employment opportunities (Schmidt & Bekele, 2016) and high population density (CSA & ICF, 2012). A significant proportion of production is consumed on farms, while much of the input used in production are owned by the farmers. These circumstances prompt bean farmers to engage in both production and consumption decisions concurrently (de Janvry et al., 1991; Sadoulet & De Janvry, 1995; Singh et al., 1986a). In situations where farmers' production and consumption decisions occur simultaneously, a non-separable household model, where the chosen technology is a result of utility optimization, is a suitable framework for analyzing the adoption of improved bean technology in Ethiopia (de Janvry et al., 1991; Singh et al., 1986b). In a non-separable household model, household resource allocation, including off-farm labor supply, is determined simultaneously rather than recursively (Brown et al., 2015).

Therefore, technology adoption depicts a farmer's decision-making process regarding whether to adopt or refrain from adopting a particular technology. The transfer of technology from researchers to farming communities introduced new varieties of beans, bundled with a set of best agricultural practices including weed control, fertilizer application, and row planting. Farmers had the liberty to adopt the entire technological package or select components of it. We follow a random utility model, positing that a household will choose a technology option if the perceived utility from it exceeds that of other alternatives. Factors, such as socio-demographic characteristics and resource endowments influence a household's utility and its decisions regarding technology adoption. The assets a household holds, including natural, human, financial, physical, and social resources, shape its consumption preferences and production choices.

Since multiple improved bean technologies in the form of better varieties and good management practices have higher yielding potential than traditional ones, their adoption is expected to increase the productivity of land pre-allocated to beans. Higher productivity affects crop production enabling the household to harvest more—thereby plays an important role in the generation of household income through direct consumption and the sale of surplus crops (De & Sadoulet, 2001). The resulting income from bean sales can be used to relax cash constraints to finance consumption of welfare enhancing items including nutritious foods, or non-food items. An increase in bean production could potentially allow households to allocate some land previously used for bean cultivation to other crops. This could lead to either a diversified crop portfolio and/or an expansion of land for other crops. Consequently, the overall agricultural income of the households would increase. Thus, household outcomes depend on the choice of technology used, t_{ij}, besides other factors such as socioeconomic characteristics of the farmer, their managerial ability, other production inputs, and land characteristics, and climatic conditions.

3.2. The Identification Strategy, Model Specification, Estimation.

The choice to adopt a technology bundle is a voluntary decision, leading to the potential for self-selection. This means that farm households who choose to adopt a particular technology may differ systematically from those who do not. For instance, enhanced technologies are often aimed at highly productive areas or adopted by farms with distinct observable and unobservable traits, such as those seeking substantial expected returns from modern technology. This could be a possibility in this study, given the absence of a controlled experiment. The issue with self-selection into adoption and non-adoption categories is that the decision to adopt may be influenced by unobservable household characteristics, which could correlate (the endogeneity problem) with outcome variables. In this scenario, estimating impact under the assumption of exogeneity of adoption may be inconsistent and biased. Without controlled randomization, quasi-experimental methods have been employed to estimate the effects of improved technology adoption on household economic wellbeing (Khonje et al., 2018; Manda, 2017; Smale et al., 2018). However, this necessitates meticulous modeling of adoption, the treatment variable, to control potential endogeneity in the outcome functions.

First, we estimate a general model assuming exogenous adoption decisions as our base model (Eq.2):

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$$y_{jic} = \alpha + \beta_j t_{ij} + \tau X_i' + \varepsilon_{ij} \quad (2)$$

where y_{jic} is the outcome variable, c (c: per capita household food consumption expenditure, agricultural income, FSC, amount of food in storage, share of total expenditure allocated to food and HFIAS) from adoption of option j made by household i. Each outcome equation is estimated separately. The variable t_{ij} is the observed adoption indicator for technological component j (i.e., treatment). It takes a value of 1 if the household was treated (i.e., an adopter of option j) and 0 otherwise. Here, the choice of treatments is mutually exclusive. The parameter β_j captures the effect of interest for treatment option j. The vector X_i consists of covariates included as controls in the model while ε_{ij} is the random error term assumed to be independently and identically distributed. Because we suspect an endogeneity problem, we estimated the Multinomial Endogenous Treatment Effects (METE) Model to estimate the treatment effects.

3.3. Multinomial Endogenous Treatment Effect (METE) Model specification

The METE model, introduced and described by (Deb & Trivedi, 2006), uses a joint framework to examine how a technological choice affects outcomes such as agricultural income, and food security (Khonje et al., 2018; Manda, 2017; Tufa et al., 2019). The model estimates and incorporates a latent factor structure to adjust for potential selection bias (Bourguignon et al., 2007). This method has the benefit of assessing the impact of a single practice and a combination of practices, while considering the interdependence among adoption of different options and potential selection bias. Following Deb & Trivedi, (2006), let EV_{ij}^* denote the indirect utility to the household for selecting the j^{th} technological option such that,

$$EV_{ij}^* = Z_i'\alpha_j + \delta_j l_{ij} + \pi_{ij} \quad (3)$$

Where, technological option, $j = 0,1 \dots ,5$ represents six adoption decisions as defined in section 3.2.1, while Z_i denotes a vector of exogenous covariates with associated coefficient parameters in vector, α_j. Exogenous variables hypothesized to influence adoption of improved bean technology include household & farm-level characteristics (i.e., socio-demographics, household wealth assets) as well as contextual characteristics of the physical location, and market environment that affect the returns from technology use (Feder et al., 1985; Takahashi et al., 2019; Teklewold et al., 2013). The vector,π_{ij} includes the error terms that are assumed to be independently and identically distributed[2]. The latent factor l_{ij} incorporates unobserved characteristics common to individual household $i's$ technology choice and associated outcomes with δ_j capturing the coefficient of correlation between the two. Given that each individual household adoption decision is observed as a binary choice, the probability of adopting the improved bean technology bundle or any of its sub-component becomes:

$$\Pr\left(\mathbf{t}_{ij} \middle| Z_i, \mathrm{I}_i\right) = \boldsymbol{g}\left(Z_i'\alpha_1 + \delta_1 l_{i1}, Z_i'\alpha_2 + \delta_2 l_{i2} \dots, Z_i'\alpha_J + \delta_J l_{iJ}\right) \quad (4)$$

where, $\boldsymbol{g}$ is a multinomial probability distribution function of choice. In this study, we assume $\boldsymbol{g}$ to follow a mixed multinomial logit structure, defined as:

$$\Pr\left(\mathbf{t}_{ij} \middle| Z_i, \mathbf{I}_i\right) = \frac{\exp(Z_i'\alpha_j + \delta_j l_{ij})}{1 + \sum_{k=1}^{J} \exp(Z_i'\alpha_k + \delta_j l_{ik})} \quad (5)$$

The second stage estimates the impact of adopting a technology option, j, on specific welfare outcome indicator relative to the counterfactual groups. The expected welfare outcome equation for household $i, i = 1, \dots, N$ is:

$$E(y_{jic} | \mathbf{t}_{ij}, X_i, \mathbf{I}_i) = X_i'\beta + \sum_{j=1}^{J} \gamma_j t_{ij} + \sum_{j=1}^{J} \rho_j l_{ij} \quad (6)$$

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[2] Also, l_{ij} is assumed to be independent of π_{ij}. The control group, $j = 0$, has $EV_{i0}^* = 0$. Also, denote $\mathbf{I}_i = l_{i1}, l_{i2}, \dots, l_{iJ}$

where; $E(y_{jic}\ )$ represents the expected value of the welfare outcomes, c, that household, i obtains from adopting technological option, t_j. Vector X_i consists of exogenous covariates within vector Z_i with β being the associated parameters and the parameter of interest γ_j denotes treatment effects relative to the control group of no adoption status. The expected outcome, E (y_{jic}), is a function of each latent factor l_{ij} when affected by unobserved characteristics that also affect selection into the any of treatment options. The factor loading parameters in vector ρ_j are the coefficients of correlation between the treatment and outcome. It is positive (negative) if there is positive (negative) correlation between selection into the treatment and the outcome through unobserved characteristics.

We follow a Gaussian distribution function to obtain the parameters of interest, γ_j,. Estimation uses a maximum simulated likelihood techniques based on the joint distribution[3] of the outcome and treatment variables (Deb & Trivedi, 2006). Using the simulation approach, with a total of S Halton draws, to ensure that the simulated log likelihood is equivalent to maximizing the log likelihood, the parameters of interest for this data are recovered by estimating Eq. 7.

$$\ln l(\left(y_{jic}, \mathbf{t}_i \middle| X_i, Z_i,\right) \approx \sum_{i=1}^{N} \ln \left[\frac{1}{S}\sum_{S=1}^{S}\{\boldsymbol{f}((X'_i\beta + \mathbf{T}_{\mathrm{i}}'\gamma + \tilde{\mathbf{I}}_{is}'\rho)\right.$$

$$\left. * \boldsymbol{g}\left(Z_i'\alpha_1 + \delta_1 l_{i1s}, \dots, Z_i'\alpha_J + \delta_5 \tilde{l}_{iJs}\right)\}\right] \quad (7)$$

Even though the model is identified when $Z_i = X_i$, we included additional variables in Z_i as instrumental variables for different outcome models to improve robustness of estimates, also recommended by Deb & Trivedi, (2006).

The consistency of estimates requires that instrumental variables (IV) be statistically correlated with t_j, the endogenous regressor, but uncorrelated with random variables that may affect our outcomes in the structural equation, omitted from X_i. Because we had multiple equations to estimate given that we had different outcomes, we also needed several IV's that suit different indicators. As IVs for improved variety adoption, we used a) village level access to extension services; b) village level number of farmers talked to prior to adopting (as a proxy for stocks of information); c) village level dummy on whether there is group dealing with input distribution as this particularly decrease transactions that hinder adoption of fertilizers communities.

Access to extension services and information influence adoption of production technologies (Ragasa et al., 2013; Donkor et al., 2016). We constructed village level access to extension services following the approach used by Manda et al (2021) to ensure that IV is not directly correlated with our food security indicators. For each household, the dummy for access to extension in the sampled households within each village was summed up while excluding the household in question. Then after summation, we divided the total by the number of sampled households in the village to get the village level proportion of household with access to extension. Similarly, we calculated the average number of farmers consulted before adopting by the sampled households within the same village, excluding the household itself. This represents the stock of information on new improved varieties and complementary management practices within a village. We assumed that this variable does not directly affect household outcomes such as agricultural income, but only through the adoption of the improved varieties.

To test for validity of our instruments, we followed (Di Falco and Veronesi, 2013) falsification methods and included IVs in the respective outcome equations (Eq. 1), as additional regressors, estimated on a subsample of only the control group (i.e. non-adopters). A variable is considered a valid selection instrument, if it affects adoption decisions, but it is not correlated with outcome

[3] The joint distribution of treatment and outcome variables, conditional on the common latent factors is the product of the marginal density of treatment and the conditional density, and is specified as: $\Pr(\mathbf{t}_{ij}|X_i, Z_i, \mathbf{I}_i) = \boldsymbol{g}\left(Z_i'\alpha_1 + \delta_1 l_{i1}, Z_i'\alpha_2 + \delta_2 l_{i2} \dots, Z_i'\alpha_J + \delta_J l_{iJ}\right) * f((X'_i\beta + \mathbf{T}_i'\gamma + \mathbf{I}_i'\rho)$

indicators of households that do not adopt. In all models, the instruments were neither individually or jointly significant from zero (appendix A.2). Furthermore, to make sure that the various treatment alternatives we use in the study are relevant, we tested the assumption of Independence of Irrelevant Alternatives (IIA). The Hausman test of IIA showed that the assumption of IIA is not violated, thus the appropriateness of MNL model[4].

4. Empirical Result and Discussion

4.1. Descriptive Analysis

The Table 1 presents the summary statistics of the chosen socioeconomic characteristics of the sample in the study. For brevity, we do not go into a detailed explanation. The bivariate comparisons of sample means indicated significant differences between adopters and non-adopters in terms of agro-ecological condition (such as rainfall amounts and altitude) and demographic, farm & social attributes of the household (such as size of landholdings and access to market conditions). Adopters were less likely to be in warm or hot humid environments and more likely to be found in tepid moist environments. Additionally, farmers who fully adopted improved varieties with fertilizers had significantly lower landholding and were more likely to be situated nearer to paved roads than non-adopters or most of other adoption categories. These structural factors have been shown to motivate or enable adoption of land intensification technologies such as fertilizers and improved seed (Jones-Garcia and Krishna, 2021). On the contrary, farmers who partially adopted improved varieties managed with fertilizers, had higher household assets index, agricultural assets, and land holding. This group of adopters also had access to relatively higher contacts from agriculture extension and had larger social networks compared to other adoption categories. It was unexpected to find that partial adopters resided in villages with greater access to extension services, both partial and full adopters who used fertilizers were, on average, cultivating newer varieties compared to other adoption categories. In general, adoption was more likely in villages that were part of the seed distribution program. These descriptive results suggest that partial adoption of improved varieties cannot be attributed to technology access constraints but rather other factors that need to be identified through econometric estimation. These differences mean that observed and probably unobserved characteristics determine selection into adoption and non-adoption categories.

Table 1. Mean descriptive statistics of welfare indicators, and socioeconomic characteristics of the sample by adoption category.

Outcome variable	**Full sample**	**LV only**	**PIV only**	**FIV only**	**PIV+F**	**FIV+F**
	(N=865)	**(n=207)**	**(n=120)**	**(n=266)**	**(n=69)**	**(n=204)**
Adoption indicator		23.93	13.87	30.75	7.86	23.58
Outcome variables						
Non-food consumption expenditure/Capita (000ETBirr	1.88(2.11)	1.65(1.86)	1.77(1.09)	1.85(2.35)	3.1 (3.12(	2.00(1.78)
Food consumption expenditure/Capita (000ETBirr)	4.89(5.89)	4.10(1,86)	4.69(3.05)	5.47 (9.02)	5.21 (4.13)	5.14(5.06)
bean yield ('000/ha)***	1.00 (0.824)	0.962 (0.775)	0.947(0.628)	0.865(0.759)	**1.0 (0.671)**	**1.15 (0.953)**
Net bean income (000ETBirr)	4.24(4.87)	5.36(4.69)	4.56(3.98)	3.93(3.95)	3.944.46)	3.19(4.69)

[4] chi2(51) = (b-B)'[(V_b-V_B)^(-1)](b-B)= 13.63: Prob > chi2 = 1.0000

Agricultural income (000ETBirr)	45.38(128.70)	64.64 (54.19)	36.00(54.19)	37.65(88.89)	75.82(129.56)	31.90(48.02)
Food consumption groups**						
1	1.94	2.42		2.63		2.45
2	7.97	9.18	1.79	7.89	3.28	11.27
3	90.09	88.41	98.21	89.47	96.72	86.27
Food expenditure share**	70.12(17.91)	70.45(18.73)	70.18(16.38)	71.25(18.43)	64.16(17.54)	68.93(17.08)
Kg of grain store at end of meher season	27.85(63.96)	31.32(56.90)	32.20(42.73)	22.14(59.89)	115.81(152.33)	19.36 (38.91)
HFIAS ***	4.84(5.26)	4.21 (4.89)	3.46(4.19)	4.98(5.49)	3.13(4.01)	6.29(5.51)
Explanatory variables						
HH Age (Years)	42.93(11.90)	42.67(11.32)	44.08(14.24)	43.72(12.62)	47.26(9.41)	41.04(11.20)
HH head education (base category=none)						
primary education only (%)**	30.25 (45.94)	50.24 (50.12)	22.5 (41.92)	40.23 (0.49)	39.71 (49.29)	48.04(11.21)
above primary education (%)	41.4 (49.27)	14.01 (34.79)	23.33 (42.47)	9.02 (28.7)	22.06(41.77)	15.2 (35.98)
Household size	6.14(2.18)	6.26(2.20)	5.76(1.94)	6.02(2.14)(2.09)	6.27(1.68)	6.11(2.02)
HH gender (1=male)	0.93 (0.26)	0.93(0.22)	0.98(0.13)	0.91(0.29)	0.85(0.36)	0.92(0.27)
HH asset index	0.14(1.39)	0.05 (1.31)	0.26(1.70)	-0.0776	1.07(1.78)	0.02(1.27)
Agricultural index	-1.72(2.34)	-4.0296	-2.9388	-1.72(2.46)	0.003(3.47)	-1.73(2.54)
Credit in cash (1=yes)	0.16(0.37)	0.17(0.38)	0.21(0.41)	0.21(0.41)	0.25(0.44)	0.21(0.41)
Credit in kind (1=yes)	0.23(0.42)	0.30(0.47)	0.20(0.41)	0.24(0.43)	0.29(0.45)	0.30 (0.46)
Off farm income**	0.33(0.47)	0.35(0.48)	0.31(0.46)	0.28(0.45)	0.37(0.48)	0.35(0.47)
Farm characteristics						
Seed rate (Kg/Ha)	55.54(45.52)	52.52(46.02)	61.32(46.70)	52.48(42.60)	59.37(40.09)	60.50(54.08)
Bean area (Ha) all farms	0.27(0.27)	0.31(0.30)	0.24(0.25)	0.28(0.22)	0.21(0.18)	0.26(0.25)
Total landholding (Ha)	2.44 (4.90)	2.99(3.19)	2.51(4.40)	2.58(8.28)	3.24	1.58(1.60)
Precipitation (000 mm)	1.15 (0.31)	1.26(0.33)	1.13(0.28)	1.08 (0.28)	1.17(0.36)	1.07(0.25)
Soil PH	6.52 (0.75)	6.13(0.76)	6.64(0.71)	6.70(0.66)	6.66(0.83)	6.73(0.69)
temperature	19.56(1.87)	20.38(1.39)	18.85(1.72)	19.26(2.19)	19.24 (2.07)	19.43(1.81)
Labour/Ha(man days)***	586.94 (1891.7)	393.26(1223.8)	404.49(947.4)	425.55(2187.8)	315.70(475.84)	958.98(2464.7)
Climbing bean (1=Yes)**	0.33(0.48)	0.29(0.46)	0.50(0.50)	0.32(0.47)	0.46(0.50)	0.35(0.50)
Irrigation (1=Yes)***	0.51(0.50)	0.570.49)	0.58(0.50)	0.48(0.50)	0.59(0.50)	0.39(0.46)
mean soil fertility poor	0.12(0.24)	0.09 (0.22)	0.10(0.16)	0.14(0.25)	0.08 (0.18)	0.14(0.28)
Distance to town (km)***	19.03 (12.57)	22.59(14.94)	23.74(17.24)	19.14(13.88)	18.70(16.71)	14.18(9.62)
Located <10km tarmac road	0.34(0.47)	0.52(0.50)	0.44(0.50)	0.45 (0.50)	0.411 (0.50)	0.53(0.50)
Located >10km tarmac road	0.11 (0.31)	0.24(0.43)	0.26(0.44)	0.16(0.37)	0.16(0.38)	0.05(0.23)

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Means village extension contact freq	28.79(15.18	25.28(11.86)	32.84(7.62)	25.49(12.12)	40.22(23.64)	28.27(15.38)
mean village level social network	4.92 (6.10)	2.87(4.62)	7.62(7.59)	6.37(6.44)	6.55(5.03)	3.67(5.11)
Total Livestock Units	4.10(19.51)	7.18(52.16)	3.70(4.32)	3.15(2.69)	4.49(4.51))	2.63(2.08)
Regions ***						
Benshangul_Gumuz	0.04	0.03	0.05	0.06	0.07	0.005
Oromya	0.52	0.71	0.43	0.34	0.62	0.54
SNNPR	0.22	0.18	0.07	0.13	0.15	0.37
Amhara	0.22	0.08	0.45	0.47	0.16	0.098
aez_id3	11.95	7.25	0.25	0.17	0.09	0.25
aez_id4	8.5	11.11	0.1	0.09	0.21	0.17
aez_id5	18.32	6.76	0.25	0.31	0.26	0.41
aez_id6	6.76	18.36	0.05	0.04	0.13	0.05
aez_id8	11.75	42.03	0.15	0.09	0.15	0.02

Notes: ***, ** represent a significant difference between treated groups. Figures in parenthesis are standard deviations. aez_id1cool sub-moist mid highlands; aez_id2; Hot semi-arid lowlands aez_id3=tepid moist mid highland; aez_id4=tepid semi-arid lowland; aez_id5; tepid sub moist mid highlands, aez_id6=warm humid lowlands; aez_id7; Warm moist lowlands and aez_id8=warm sub humid lowlands.

The summary statistics of the outcome means are reported in the upper part of **Table 1** On average, the annual per capita expenditure for food is approximately ETBirr 1880, while for non-food items it is about ETBirr 4889. An average household generates **ETBirr 45380** of revenue from agricultural activities and earns net income of **ETBirr 4170** from beans (**Table 1**). The bivariate analysis revealed variation in the food consumption score, food expenditure share, and food storage across sampled households. The Food Consumption Score (FCS) ranged from 14 to 110, and it was lowest among the full adopters of improved varieties only. The same households also had the highest food expenditure share, suggesting that this group could be more vulnerable to food insecurity. On the other hand, the average kilograms of grain (cereals and legumes) in storage at the end of observed season was 28, with approximately 60.3% of households reporting no grain in storage for future consumption (Table 1). Households that combined improved varieties with local ones and managed with fertilizers had the greatest volume of grain in storage, while other adoption categories were not statistically distinguishable in terms of grain in storage.

Figure 1 displays a strip plot of outcome data that reveals some systematic differences among adoption categories. Farmers who used fertilizers (treatment category 3 and 4) had higher productivity levels than those who did not. Additionally, farmers who used new improved varieties and those who used fertilizer (for any variety type) had higher per capita food consumption expenditure and crop income compared to those in the counterfactual group. Net bean income did not vary much across adoption groups. These differences justify use of the METE for more robust econometric analysis, which is presented in the following sections.

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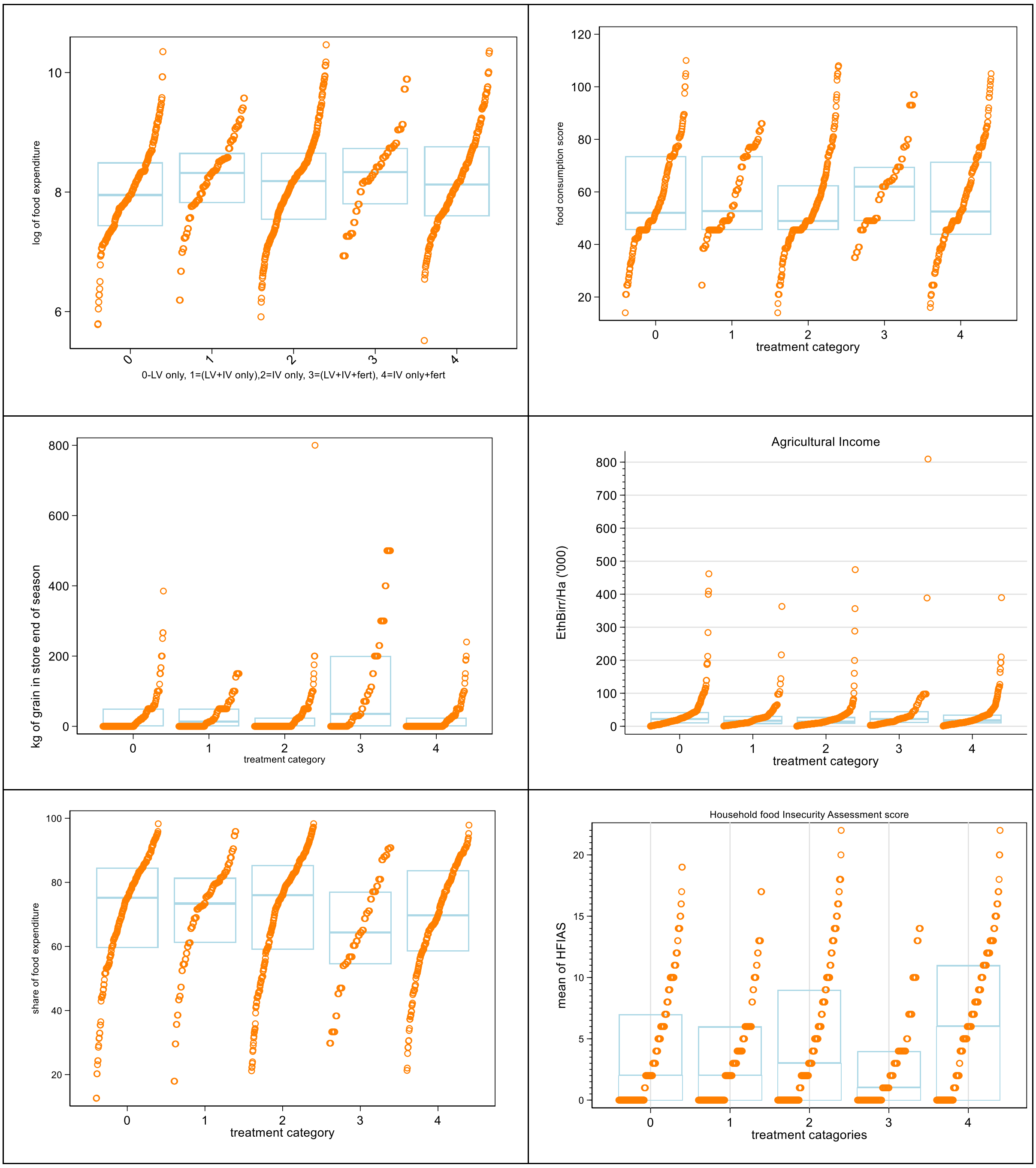

Figure 1. Distribution of outcome variables by adoption category.

4.0. Econometric Results

4.1. Multinomial Logit Estimates of the Determinants of Technology Adoption.

Results of the first stage (i.e marginal effects from a multinomial logit model of adoption), with non-adoption serving as the base category, are presented in Table 2. The diagnostic test results [Wald chi2 (100) = 2642.52] showed that explanatory variables included in the empirical model jointly determine adoption. The model estimates a higher probability (41%) of bean-producing households fully adopting the improved varieties subcomponent of the package. Additionally, 19% of the bean-growing households were predicted to fully adopt improved varieties with fertilizers. However, the partial adoption of improved varieties was lower, at 20% with fertilizers and only 5% without fertilizers.

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Table 2. Marginal Effects from Multinomial Logit Regression Estimates of the Technology Adoption.

	PIV only		FIV only		PIV+F		FIV+F	
	(n=120)		(n=266)		(n=69)		(n=204)	
	me	Se	me	Se	me	Se	me	Se
Predicted prob	0.139 ***	.031	0.411***	0.033	0.049***	0.0126	0.194***	0.028
HH Age (Years)	0.000	0.001	0.002	0.002	0.001	0.001	-0.003**	0.001
HH head education (base category=none)								
primary education only	-0.073**	0.034	0.083**	0.038	0.015	0.030	-0.003	0.033
above primary education	0.017	0.026	0.037	0.030	-0.023	0.021	0.010	0.025
Household size	-0.007	0.010	-0.003	0.009	0.007	0.006	0.003	0.007
HH gender (1=male)	0.194*	0.109	-0.103*	0.064	-0.057	0.043	-0.009	0.057
HH asset index	0.020*	0.011	0.005	0.017	0.007	0.008	0.018	0.012
Agricultural index	-0.014*	0.008	0.009	0.009	0.011***	0.004	0.005	0.008
Credit in cash (1=yes)	-0.010	0.037	-0.071*	0.041	0.027	0.028	0.035	0.036
Credit in kind (1=yes)	-0.001	0.035	-0.071*	0.039	0.012	0.029	0.059*	0.034
Off farm income**	-0.004	0.035	-0.042	0.036	-0.002	0.028	-0.021	0.032
Farm characteristics								
altitude	0.161	0.225	-0.220	0.222	-0.035	0.178	0.192	0.167
Total landholding (Ha)	-0.005	0.020	-0.019	0.022	0.022	0.019	-0.003	0.019
temperature	-0.096	0.223	-0.428	0.290	0.085	0.213	0.393*	0.239
Climbing bean (1=Yes)**	0.028	0.029	-0.103***	0.034	0.015	0.021	0.041	0.030
Irrigation (1=Yes)***	-0.002	0.045	0.000	0.040	0.014	0.029	-0.079**	0.033
Soil fertility (base-good)								
mean soil fertility poor	-0.084	0.067	0.066	0.063	-0.025	0.048	0.044	0.057
mean soil fertility medium	0.042	0.046	-0.037	0.044	-0.054*	0.0312	-0.036	0.037
Distance to town (km)***	0.030	0.020	0.030	0.024	-0.026	0.020	-0.049*	0.028
Located <10km tarmac road	0.026	0.071	0.022	0.055	-0.004	0.049	-0.139***	0.046
Located >10km tarmac road	0.083	0.073	0.043	0.071	0.058	0.058	-0.292***	0.069
Means village extension	0.004***	0.001	-0.002	0.002	0.004***	0.001	0.000	0.001
village level social network	-0.002	0.004	-0.007	0.005	0.000	0.003	0.010**	0.005
Total Livestock Units	0.003	0.002	-0.001	0.007	0.002	0.001	-0.008	0.006
Regions *** (Base=Amhara)								
Benshangul_Gumuz	-0.035	0.129	0.311*	0.172	-0.070	0.110	0.007	0.248
Oromya	-0.110	0.091	-0.332***	0.080	-0.037	0.064	0.354***	0.079

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SNNPR	-0.159	0.144	-0.302***	0.098	-0.059	0.059	0.435***	0.080
agroecological zones (base=1/2)								
aez_id3	0.056	0.104	-0.103	0.078	0.011	0.068	0.142**	0.059
aez_id4	0.170**	0.085	-0.151**	0.071	0.096*	0.053	-0.020	0.063
aez_id5	0.053	0.117	-0.044	0.076	0.035	0.056	0.199***	0.063
aez_id6	0.162	0.165	-0.212**	0.105	0.124**	0.059	-0.146*	0.079
aez_id8	0.163	0.124	-0.280**	0.128	-0.010	0.068	-0.144	0.117

Notes: Log pseudolikelihood=- -893.38938; Wald chi2(130) = 655.12; Prob >Chi2 = 0.000; Pseudo R2= 0.2991; N = 846. Std. Err. adjusted for 624 clusters at village level. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% level. The base category is growing only landraces. aez_id1cool sub-moist mid highlands; aez_id2; Hot semi-arid lowlands aez_id3=tepid moist mid highland; aez_id4=tepid semi-arid lowland; aez_id5; tepid sub moist mid highlands, aez_id6=warm humid lowlands; aez_id7; Warm moist lowlands and aez_id8=warm sub humid lowlands. Study Key: 0=Landrace only, 1=Old improved variety, 3=New improved variety, 4=landrace & fertilizer 5=Old improved variety & Fertilizer, 6=New improved variety & Fertilizer". PCE is Per Capita Consumption Expenditure, NBI is Net Bean Income.

Variables included as instruments (i.e., village-level average frequency of extension contact, village-level average size of social networks for farming) to improve identification could be considered valid based on a simple falsification test (Appendix A.2) and their significance in adoption models (see Table 2). The average frequency of extension village visits was positively and significantly associated with categories of partial adopters (i.e., those adopting improved varieties with or without fertilizers), but it is not significant for full adopters. For the latter category, adoption was linked to the size of social networks, implying that these households source their information and technology from their social networks. This is consistent with the descriptive results showing that full adopters were generally in a worse position than partial adopters.

We also observed spatial differences in the intensity of adoption. The full adoption of improved varieties was more prevalent in the tepid moist and semi-moist mid-highland regions of the country, with rates of 14.2% and 19.9%, higher than in cool environments. Agro-ecological temperature appears to have a more significant impact on the adoption of improved varieties. A marginal increase of one percent in the temperature was associated with a 39% likelihood of full adoption. On the other hand, the chance of partially adopting improved varieties was higher in warm or hot agro-ecological environments (i.e., tepid semi-arid and warm humid lowlands) compared to cool environments. In these warmer environments, the likelihood of fully adopting improved varieties was 15% higher than in cool sub humid highlands. This suggests that the adaptation of beans to less favourable environments in Ethiopia, such as drier areas, could have focused more on these regions and less in cool environments.

Our findings further indicate that the adoption of improved technologies (improved varieties + fertilizer) in bean cultivation is significantly influenced by market access conditions. Consistent with the findings of Asfaw et al., 2012, and Minten et al., 2013, our results demonstrate that the likelihood of adopting fertilizers decreases with increasing distance from a tarmac road, which serves as a proxy for transaction costs that hinder economic development and access to extension services. Households situated more than 10 km away from the tarmac roads were 13.9% less likely to fully adopt improved varieties in conjunction with fertilizers (Table 2). An additional distance beyond 10 km further reduced the probability of adopting the same combination by 29.2%. However, this variable did not influence the adoption of improved varieties when fertilizers were not considered. Finally, bean-growing households in Oromia and SNNR are more inclined to use fertilizers exclusively on improved varieties and dedicate all the land pre-allocated for bean cultivation to these improved varieties, compared to their counterparts in the Amhara region. On the other hand, full adoption without fertilizer was 31% higher in Benshangul_Gumuz than in Amhara region.

The analysis further indicates that full adopters own relatively smaller landholdings, implying that their adoption decisions are motivated by the potential for increased yield from beans that can

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offset the impact of decreasing land availability. Results also show that the variation in the adoption of the improved bean production package was partially attributed to other resources available to the household. For instance, a positive correlation was observed between the household's agricultural assets and the likelihood of partially adopting improved varieties managed with fertilizers. Similarly, the possession of durable goods by the household was positively linked to the partial adoption of improved varieties without the use of fertilizers. The coefficients were however small at 1% for agricultural index and 2% for durable goods.

Among the demographic factors considered, education, age, and gender significantly influenced the likelihood of adopting the improved bean technology package or its components. The findings indicate that with each additional year of age, the probability of a household fully adopting improved varieties combined with fertilizers decreases by 0.3%. This could be because older bean growers might be more risk-averse or conservative due to a lack of trust in new technology, as suggested by Bezu et al. (2014). Male-headed households were 10.3% less likely than female-headed households to fully adopt improved varieties without fertilizers, but they were 19% more likely to partially adopt improved varieties without fertilizers.

In line with existing studies, our findings indicate that primary education plays a pivotal role in the adoption of technology in bean farming, affecting both the probability and extent of adoption. When compared to uneducated farmers, those with primary education are 8.3% more likely to fully adopt improved varieties without the use of fertilizers, while the chance of them being partial adopters decreases by 7.3% (Table 2). Education enhances an individual's capacity to comprehend and utilize new technologies, and shapes their attitudes towards technology, making them more receptive to new innovations. However, once primary education is accounted for, further education does not significantly correlate with the adoption of improved bean varieties.

4.2. METE Results on the Effect of Technology Adoption on Food Security Indicators.

The results for each of the five food security outcome variables are presented in Table 3. Per capita food expenditure, non-food expenditure, and agricultural income were transformed into natural logarithm to normalize their distribution in the data. We used ordinary regression followed by the multinomial endogenous treatment effects (METE) model to check and address the possibility of endogeneity. Ordinary Least Squares (OLS) results were presented under the assumption that the decisions to adopt improved bean technologies are exogenous in the outcome equations.

Table 3. Estimated coefficients of OLS and METE models: Impact of technology adoption on Household food security and vulnerability to food insecurity.

	PIV only	FIV only	PIV +F	FIV +F
OLS				
agricultural income	0.188	0.180*	0.277*	0.395***
	0.124	0.105	0.149	0.113
per capita food consumption expenditure	0.012**	-0.005	0.074	0.023
	0.077	0.066	0.093	0.071
Non food expenditure	0.110	-0.030	0.355***	0.247***
	0.098	0.083	0.118	0.090
Food consumption score	6.029***	3.096*	1.217	6.109***
	2.123	1.804	2.562	1.951
Food expenditure share	-0.872	-0.083	-6.330***	-4.855***
	2.257	1.918	2.724	2.074
Food in store	20.235	-7.217	94.837	1.027748**
	14.613	12.917	16.805	13.982
Household food insecurity assessment score	-2.142**	-0.184	-1.401	0.88
	0.889	0.714	1.073	0.785

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METE				
agricultural income	-0.215	0.396***	0.502**	0.211***
	0.199	0.15	0.529	0.175
per capita food consumption expenditure	0.384***	-0.115	0.095	-0.076
	0.109	0.111	0.116	0.115
Nonfood expenditure	0.110	-0.030	0.355***	0.247***
	0.098	0.083	0.118	0.090
Food consumption score	-0.054	0.084**	0.134*	0.083*
	0.052	0.043	0.072	0.046
Food expenditure share	-0.013	-0.01	-0.100***	-0.073***
	0.036	0.03	0.043	0.033
Food in storage	0.455*	0.056	1.094***	0.249
	0.256	0.206	0.261	0.241
Household food insecurity assessment score	-0.206	0.111	-0.363	0.152
	0.203	0.142	0.240	0.150

Note: The base (control group) is landrace without fertilizer. Standard errors in parentheses are clustered at village level. 100 Halton sequence-based quasirandom draws were performed per observation. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the (10%, 5%, 1%) level. The outcome model in METE is linear and the treatment Multinomial.

In table 3, we also present the results derived from the estimation under exogeneity assumption methods in conjunction with those from the Multinomial Endogenous Treatment Effects (METE) model for the purpose of comparison and robustness. Due to concerns about endogeneity and/or omitted variable bias, our discussion centers on the findings from a robust multinomial endogenous treatment regression. Coefficient estimates in the METE outcome models are presented in Table 3, and second stage estimates for each treatment model are reported in Appendix B.1-B.3 in the supplementary online Appendix. Due to space limitations, we will briefly discuss the results of the METE model diagnostic tests. It is worth noting that the METE model was significant from zero in all outcomes with Wald statistics significant at 1%[5]. The reference category is the non-adoption (coded as zero) of any technological component by a household.

Our results from the Multinomial Endogenous Treatment Effects (METE) model show that most of the factor loadings (ρ_j) provide evidence of selection bias across all equations, suggesting that assuming exogeneity would likely result in biased estimates. The sign and nature of selection bias varied across the adoption categories and outcome equations. In the equations for agricultural income and food consumption expenditure, full adopters of the improved variety with fertilizers exhibited a negative and statistically significant factor loading. This suggests that unobserved factors that increase the likelihood of full adoption with fertilizers also reduce household food security compared to a random assignment. Conversely, most of the latent factors associated with the adoption of improved varieties or the category of adoption without fertilizers were positive. This indicates that, on average, unobserved factors that deter the use of fertilizers tend to improve food security. While there is limited evidence of endogeneity in the vulnerability to food insecurity across various adoption categories, these diagnostic results overall confirm the presence of endogeneity in the decision to adopt in the context of food availability and utilization (i.e., Agricultural income, food expenditure and consumption frequency).

Test results showed that the factor loading for the partial adoption of improved varieties was negative and statistically significant in the equation for the proportion of the household budget

[5] Wald (126) = 1607.28 for agricultural income, Waldchi2 (122) = 19187.8 for food expenditure, Wald chi2 (122) = 17153.9 for food consumption score, Waldchi2 (111) =20974.1 for non-food expenditure and Wald chi2 (126) =12869.07 for grain in storage respectively

allocated to food. Conversely, fully adopting improved varieties had a positive factor loading for the quantity of grain stored at the end of the Meher season. Furthermore, the factor loading for the partial adoption of improved varieties with fertilizer showed a positive correlation with the Household Food Insecurity Assessment.

4.2.1. Average Effect of Adoption on Food Availability

Food availability for the household was measured by agricultural income in the estimation. Table 3 illustrates the effect of adopting improved varieties and/or fertilizers on household agricultural income, accounting for observed and unobserved heterogeneity. Generally, farmers who adopted improved varieties in conjunction with fertilizers obtained a significant increase in their agricultural income compared to non-adopters, regardless of the adoption intensity. For instance, farmers that partially adopted improved varieties with fertilizers saw their agricultural income increase by 50% compared to non-adopters. This figure rose to approximately 53% for households that fully adopted improved varieties with fertilizers. Similar findings have been observed among cultivators of other legume crops (Manda et al., 2019).

When considering the full adoption of improved varieties without the use of fertilizers, there is an average gain of about 39.5% in agricultural income compared to non-adopters. However, those who partially adopted improved varieties without using fertilizers saw a 39% higher agricultural income than the counterfactual group. Our results align with those of Ogundari and Bolarinwa (2018), who suggested that the impact of agricultural technology in Sub-Saharan Africa varies significantly based on the characteristics and extent of adoption. A comparison of the anticipated yield per 0.25 hectare across different adoption categories also revealed that households expecting higher yields per 0.25 hectare were those that had adopted both improved varieties and fertilizers (Appendix B.4. This suggests that the prospect of increased productivity motivates the adoption of the bean technology bundle.

4.2.2. Average Effect of Adoption on Food Access and Utilization

In assessing the impact of adopting improved bean varieties and fertilizer bundles, or their subcomponents, on food access and utilization, we used per capita food consumption expenditure and food consumption score as indicators of food security. The results indicated that partial adoption of improved varieties, without the use of fertilizers, is associated with a 32% higher food expenditure compared to non-adopters. Other categories of adoption did not make any significant change in food expenditure, as additional income was allocated to non-food consumption items (Table 3). This finding suggests that while the adoption of improved bean varieties can enhance household food security, the impacts vary among different adoption categories. It appears that greater intensification is more likely to affect non-food consumption as opposed to food consumption. This finding aligns with the results from Kaliba and Kizito (2021), which revealed that the effects of adopting sorghum seeds in Tanzania differed based on the region and the specific household groups.

Regarding the food consumption score, the results indicate that adopting improved varieties, on average, leads to a 19% and 16% increase for partial and full adoption, respectively, when the varieties are grown with fertilizers. These findings align with results from Rwanda where the impacts of improved bean varieties were more pronounced when cultivated with fertilizers (Larochelle and Alwang, 2022). However, unlike in Rwanda, our study indicates that when improved varieties are adopted, whether partially or fully, without the use of fertilizers, gains in food consumption score were positive but not statistically significant.

Like its effect on availability, the influence of improved bean technology adoption on access was likely through the income effect, as also observed in the Rwandan study on the impact of improved varieties on household dietary diversity (Larochelle and Alwang, 2022). From the descriptive analysis (Table 2), it is revealed that adopters had a higher consumption frequency of legumes and sugar when compared with non-adopters. This could be linked to their greater dietary diversity. Consequently, the enhanced dietary diversity among adopters was probably due to the inclusion of

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more economically viable foods. This might account for the result that their influence on food expenditure, despite being positive, was not statistically significant.

4.2.3. Average Effects on Household Vulnerability to Food Insecurity

To assess the effects of the improved bean technology bundle on the vulnerability of households to food insecurity, we employed three indicators: the share of expenditure, the quantity of food stock, and the Household Food Insecurity Access (HFIA) score. As outlined in Table 3, all variables in the METE models were jointly non-zero, with the Wald chi-square statistic being significant at the 1% level. Our research suggests that the joint adoption of improved varieties and fertilizers is negatively correlated with the overall share of food expenditure. Specifically, there is a 7.2% decrease, significant at the 5% level, when the technology package is fully adopted. Similarly, households that partially adopted improved varieties with fertilizers experienced a food expenditure share that was 10% lower than non-adopters, also significant at 5%. These findings imply that the combination of improved varieties and fertilizer mitigates household vulnerability more effectively than when improved varieties are used in isolation, but the context matters.

Even if a household was not experiencing food insecurity at the time of the survey, it could still be classified as food insecure if it experiences periodic inadequacies in food access. Therefore, we further explored the impacts of improved bean technology packages on food insecurity vulnerability using the quantity of grain in storage and the Household Food Insecurity Assessment (HFIA) score. Consistent with the findings from the food expenditure share, we found that the impact of improved bean technology on the quantity of food stored at the end of the Meher season is context-dependent, showing a higher effect among partial adopters who also have larger agricultural income. By the end of the meher season, those who partially adopted improved varieties and fertilizers had, on average, an increase of one kilogram in their grain storage compared to non-adopters. Meanwhile, partial adopters who did not use fertilizer saw a smaller increase, with their grain in storage increasing by half a kilogram. The amount of grain stored at the end of the meher season was not significantly influenced by other adoption categories.

The household food insecurity assessment score estimation yielded comparable outcomes. Overall, the causal effect of adopting improved varieties with or without fertilizer on food security resilience was less pronounced (for example, the coefficient was small and not statistically significant), which could be because these households may have had very low resilience to food insecurity before adoption. Our results align with the conclusion drawn by Ogundari, K. and Bolarinwa, O.D. (2018) that while the correlation between agricultural technologies and welfare is positive, it is relatively weak.

5. Conclusions and Implications

The research assessed the adoption of an enhanced bean technology bundle or its components and its impact on food security mechanisms (i.e., food availability, access, and food insecurity vulnerability) using a multi-valued endogenous treatment regression. The findings revealed a notable disparity in the intensity of adoption, with most farmers likely to adopt only the improved varieties without fertilizers due to the high transaction costs of accessing fertilizers in rural areas. Adoption of improved varieties occurred in seven out of eight agro-ecological zones, supporting the conclusion that bean improvement efforts have successfully adapted the crop to various environments, thereby broadening the overall usage of improved varieties.

By breaking down the adoption of improved varieties into full and partial adopters, our study offers valuable insights into impact pathways. The complete introduction of the improved bean varieties is driven by population growth, yet their impact is diminished due to the low intensity of fertilizer usage and pre-adopt low soil quality. We observed intensive adoption of improved varieties on farms with relatively low soil fertility rating and found no correlation between the intensity of variety adoption and bean productivity. These findings highlight the fact that the full adoption of improved varieties does not always lead to more significant benefits than partial adoption, as impact depends on the context.

Therefore, when promoting improved variety seed bundled with fertilizer among households with limited land, it is crucial to convey clear messages about the benefits of applying fertilizers at the recommended rates. A breeding strategy that does not intentionally include soil management interventions, such as promotion of fertilizers along with varieties, is a less effective approach to food security in Ethiopia. Additionally, it is essential to advocate for policies that can eliminate market access barriers and enhance the resilience of smallholder farmers against climate variations. Evidence from the data used in this study suggests the presence of market access barriers. For instance, in almost all the villages surveyed, price was identified as a major obstacle to the adoption of fertilizers, with over 85% of the villages indicating that fertilizers are never timely available in their communities.

The impacts of adopting improved varieties and fertilizers differ across adoption categories. For approximately eight percent of growers who partially adopt improved varieties along with fertilizers, which enhance land productivity, their food availability, access, and resilience are augmented. Their additional income from adoption is then used for non-food items, and diversifying their diets which bolsters their resilience against food insecurity. Conversely, for about 24 percent of bean growers, the intensive adoption of improved varieties along with fertilizers enables them to slightly increase their agricultural income, allowing for more legume consumption and enhancing their likelihood of achieving adequate food consumption. Despite these benefits, their vulnerability to food insecurity remains high due to pre-existing soil fertility issues. The benefits are further diminished for the 31% who fully adopt improved varieties but do not use fertilizers at all.

In line with the findings of Ogundari, K. and Bolarinwa, O.D. (2018), we deduce that while the present usage of improved varieties and fertilizers boosts food availability and access for most adopters, it does not significantly bolster their resilience to food insecurity. This implies that as resources for agricultural production become increasingly scarce, focusing solely on investments in breeding and seed systems without addressing the soil fertility issues of less affluent farmers will not ensure food security in countries like Ethiopia**.**

Finally, a limitation of our study is the inability to evaluate the differences among farmers based on their resource endowments such as size of their holdings. We attempted this analysis, but the disaggregation of data with already multiple treatment groups led to a failure in achieving model convergence. Future research could explore the heterogeneity effect among farmers with different resource endowments to identify customer segments and improved bean technology bundles for each segment for higher impacts and efficiency.

Authors Contribution: Katungi Enid (KE) and Habte Endeshaw (HE) led the study and field survey tool design. HE oversaw data collection and conducted initial data processed and preparation for analysis. KE and Aseete Paul (AP) conducted data analysis and manuscript write up and discussion of results. RJC contribute on resource mobilization, manuscript review and editing.

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Appendices

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Appendix A.1. Tobit Estimates of Variety and Fertilizer Adoption: Testing for Simultaneity of Variety and Fertilizer Adoption

	Fertilizer application rate		Improved variety adoption	
	Coefficient	Std. err.	Coefficient	Std. err.
Qty of improved variety seed per hectare	3.76	7.47		
quantity of fertilizer per hectare			-0.09	0.09
HH head education (base category=none)				
primary education only	8.54	47.24	-3.29	2.70
above primary education	-44.65	31.54	1.34	4.11
Household size	1.20	6.73	-0.34	0.60
HH Age (Years)	-1.24	0.94	-0.11	0.12
HH gender (1=male)	67.70	87.46	-2.46	4.58
HH asset index	10.07	22.79	2.77***	1.04
Agricultural index	-2.26	5.02	-0.08	0.61
Total Livestock Units	-0.51	3.97	-0.66	0.42
log total landholding (Ha)	18.62	22.70	-0.33	1.64
climbing bean	5.07	32.47	-1.11	2.50
village number of input groups	15.36	20.12	1.08	2.66
Credit in cash (1=yes)	77.83**	39.44	0.18	3.89
Credit in kind (1=yes)	41.10*	23.28	1.83	3.56
log distance to town (km)***	-30.38	24.48	3.27**	1.55
Located <10km tarmac road	-41.78	33.71	-1.09	4.11
Located >10km tarmac road	-76.84*	42.40	-0.25	5.24
Regions *** (Base=Amhara)				
Benshangul_Gumuz	-131.96	196.94	19.98**	8.89
Oromya	102.13**	43.19	-12.18**	5.66
SNNPR	214.36	165.04	-30.73***	5.63
agroecological zones (base=1)				
aez_id3	9.28	134.87	7.29	4.90
aez_id4	53.37	132.46	-11.10	9.80
aez_id5	13.26	101.38	9.03*	5.14
aez_id6	-62.47	55.54	-1.05	5.86
aez_id8	34.76	67.13	-19.90***	6.85
Soil fertility (base-good)				
mean soil fertility medium	-3.29	55.63	1.01	3.21
mean soil fertility poor	-3.71	66.21	1.81	4.99
Means village extension	1.82**	0.86	0.03	0.12
village level social network	1.02	3.57	-0.32	0.33
average distance to most plots	-1.10*	0.60	0.01	0.06
was rainfal amount poor (1=yes)	-38.90	76.57		
was rainfal benging poor (1=yes	-24.83	30.23		
drough_seed			-4.77	3.81
village level dummy for seed distribution	0.31	87.25	9.88***	3.70
constant	-179.40	134.17	0.89	10.31
Number	655		774	
Wald chi2(33)	95.63		140.14	
Prob	0		0	
exogeneity: chi (1)	0.45	1.52		
Prob chi2	>.5029		0.2174	

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Appendix A.2: Falsification Test for Instrumental Variables Used in METE Results

	_Ag_income		**FCSET**		**Food expenditure**		**cropstore2 (kg)**		**HFIA_SCORE**		**_foodexp share (%)**		**per_ad_nonfood_exp~**	
	Coef	**Std. err.**	**Coef**	**Std. err.**	**Coef**	**Std. err.**	**Coef**	**Std. err.**	**Coef**	**Std. err.**	**Coef**	**Std. err.**	**Coef**	**Std. err.**
d_educ HH	0.24	0.16	-0.10	2.76	-0.7**9	0.09	-17.55	17.40	0.27	1.18	0.83	3.30	0.223	0.144
d_educ HH2	0.15	0.23	3.85	4.09			-17.29	24.84	0.04	1.79	-8.16^	4.86	0.662**	0.211
hhsize_innumbr	0.01	0.03	-0.78	0.56	0.01	0.01	4.52	3.64	0.02	0.25	0.51	0.70	-0.08**	0.031
hh_age	-0.01	0.01	-0.14	0.11	-0.01**	0.00	-1.24^	0.73	0.04	0.05	0.01	0.13	-0.009	0.006
Gender	0.07	0.28	-3.98	4.83	0.14	0.13	5.43	31.37	-0.74	2.06	0.36	5.67	0.219	0.243
HH_assetindex	0.26**	0.06	2.59*	1.12	0.09**	0.03	10.83	6.81	-1.61	0.57	-3.02*	1.41	0.138*	0.061
agric_equiindex	0.07*	0.03	0.17	0.57	0.02	0.02	-0.48	3.56	-0.40**	0.25	0.33	0.68	0.021	0.029
l_land_cult_ha	0.39*	0.08	3.20*	1.44	-0.04	0.04	24.37*	10.06	-1.60	0.68	-0.65	1.92	0.101	0.085
d_offINC	0.16	0.14	-2.21	2.47	0.02	0.07					-1.28	2.92	0.110	0.126
credit_d1	-0.26	0.19	-0.86	3.24	0.21**	0.09	18.02^	19.48	3.56*	1.37	3.81	3.77	-0.356*	0.163
credit_d2	0.17	0.16	-9.56**	2.76	0.06	0.07	31.70**	17.48	4.97**	1.17	-5.93^	3.26	0.028	0.142
irrg	-0.03	0.15	-5.16*	2.59	0.05	0.07	47.67	17.12	3.04**	1.10	4.68	3.04	-0.220	0.135
ddist_km10	-0.17	0.22	3.06	3.82	0.26**	0.10	20.90	24.86	2.66	1.64	-4.12	4.57	0.221	0.205
ddist_kmhigh10	-0.09	0.27	11.12*	4.64	0.25*	0.12	1.28	29.74	4.93*	2.06	-8.47	5.81	0.316	0.258
BG											-18.08^	10.47	0.498	0.540
Oromya											-2.98	7.64	0.071	0.375
SNNPR											-5.36	7.35	-0.026	0.361
aez_id3	0.04	0.32	-10.83*	5.57	0.14	0.15	22.63	37.89	-3.86	2.47	-5.73	6.97	-0.021	0.321

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aez_id4	0.69**	0.32	14.36**	5.51	0.12	0.15	21.08	35.53	3.47	2.25	-3.83	6.90	0.349	0.307
aez_id5	0.58^	0.34	-0.59	5.86	0.04	0.16	-28.5**	39.23	0.78	2.46	-3.69	6.91	-0.420	0.306
aez_id6	0.95**	0.23	8.15*	4.09	0.08	0.11	63.00	25.40	-4.78**	1.79	1.13	5.15	-0.513	0.228
aez_id8	1.36**	0.29	9.20^	5.01	0.19	0.13	-17.72*	32.31	-1.57	2.22	-0.20	6.40	-0.650*	0.277
subplt_bn_var_climbing	0.03	0.16	-1.99	2.80	-0.07	0.07	42.49	17.52	2.67*	1.18	0.27	3.42	0.034	0.149
mean_soil_fert_p	-0.79**	0.32	-0.61	5.49	-0.06	0.15	-56.24	38.15	5.58*	2.31	-0.02	6.38	0.164	0.257
mean_soil_fert_m	-0.19	0.18	3.73	3.13	0.00	0.08	-6.41	19.48	1.86	1.35	1.13	3.69		
meanVsocionetwork	0.01	0.02	0.42	0.31	-0.01	0.01	-0.76	1.86	-0.03	0.13	-0.17	0.43	0.024	0.020
meanext_v2	0.00	0.01	0.19	0.14	0.00	0.00	0.84	0.85	-0.02	0.06	0.22	0.17	-0.005	0.007
_cons	2.66**	0.49	59.46**	8.58	0.49*	0.23	-41.89	58.42	-10.68	7.85	69.50**	11.58	9.701	8.692
Number of obs	207		207		207		204		204		204		204	
F(24, 182)/LR chi2 (25	10.79		5.09		5.15		50.06		70.56		1.26		3.26	
Prob > F	0		0		0		0.0009		0		0.19		0	
R-squared	0.587		0.4015		0.3927						0.167		0.3611	
Adj R-squared	0.533		0.3226		0.3164						0.034		0.2503	

**, * &^ denote significant level at 1%, 5% and 10% respectively. aez_id1cool sub-moist mid highlands; aez_id2; Hot semi-arid lowlands aez_id3=tepid moist mid highland; aez_id4=tepid semi-arid lowland; aez_id5; tepid sub moist mid highlands, aez_id6=warm humid lowlands; aez_id7; Warm moist lowlands and aez_id8=warm sub humid lowlands.

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