



FACULTY OF AGRONOMY AND FORESTRY ENGINEERING

IMPACT OF BUNDLED IMPROVED AGRICULTURAL TECHNOLOGIES ON
FOOD SECURITY AMONG MAIZE FARMERS IN UGANDA

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Declaration

I Namuyima Shamira, declare that this dissertation has never been submitted for the purpose of obtaining any degree or in any other field and that it is the result of my individual effort. This dissertation is presented in partial fulfilment of the requirements for obtaining a degree of Master of Science in Agricultural Economics, from the University of Eduardo Mondlane

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List Of Abbreviations and Acronyms

UBOS	Uganda Bureau of Statistics
UNHS	Uganda National Household Survey
UNPS	Uganda National Panel Survey
LSMS-ISA	Living Standards Measurement Study and Integrated Surveys on

Agriculture

CAI	Composite Adoption Index
MAAIF	Ministry of Agriculture, Animal Industry and Fisheries
HH	Household
FES	Food Expenditure Share
FCS	Food Consumption Score
GHI	Global Hunger Index
WFP	World Food Program

Abstract

Food security is put at risk by the fragmented and poor adoption of improved agricultural technology among Uganda's smallholder maize farmers, despite their potential for rising agricultural output. To examine the effect of the extent of adopting complementary technology packages on household food security, this study extends beyond a binary adoption analysis. The study uses a Markov process to characterize adoption trends, a fractional probit model to identify drivers of adoption intensity, and panel fixed models to quantify causal impacts on food security using a three-wave panel dataset (2015/16, 2018/19, 2019/20) from the Uganda National Panel Survey. Key findings show major rates of dis-adoption, path dependency, and a persistent condition of non-adoption (almost 90% of families). Access to extension services, irrigation access and male-headed households all have a positive effect on adoption intensity while exposure to shocks showed a negative effect on adoption intensity. Research results show that increasing the use of technology bundles improves food security in a significant way. Adoption of complementary bundles increased the Food Consumption Score and lowered the Food Expenditure Share. The study concludes that to achieve significant improvements in food security for Ugandan smallholders, it is crucial to promote the increased and continuous adoption of complementary technology bundles rather than isolated inputs.

Keywords: Uganda, Technology Bundles, Adoption Intensity, Food Security

CHAPTER I: INTRODUCTION

1.1 Background

Food insecurity is a global problem with an estimated 673 million individuals facing hunger in 2024 globally based on the statistics from the FAO state of food and agriculture report (Food and Agriculture Organization, 2025). Although there is enough food produced worldwide, millions of people lack access to it because of the differences in food distribution and access (FAO, 2013). Population growth, violent conflicts, economic recessions, and climate change all increase food insecurity by interrupting global systems of agriculture (World Bank, 2025). Food insecurity hence remains a serious worldwide issue that calls for serious policies to address it. Food insecurity is highest in Africa, where 307 million people which represents over 20 percent of the continent's population, experienced hunger in 2024 (FAO, 2025). According to the World Bank (2025), the continent is still vulnerable to economic unrest, violence, and climate shocks, all of which limit the gradual growth of food security by interfering with food production and market access.

Uganda's food insecurity situation remains similar to that of the African continent and the world at large, and this is shown by the 27.3 score achieved by the country in 2024 on the Global Hunger Index (GHI)¹. Around three in every ten Uganda homes experience severe food insecurity, and 46 percent of homes are moderately food insecure as reported by the National Population and Housing Census in 2024 (UBOS, 2025). Poverty remains a key driver to this food insecurity as 20.3 percent of the general population lived below the national poverty line, which has been defined as the minimum amount required to meet basic food and non-food needs estimated at about UGX 3,600 per person per day (about US\$1) according to the Uganda National Household Survey (2019/20)

Since agriculture is the main source of food and income for most households, especially those in rural areas where poverty and food insecurity are most common, agriculture is important to Uganda's food security. The agriculture sector is the base of Uganda's economy, employing over 70% of the workforce and contributing an average of 24.12% to GDP between 2019/20 and 2023/24 (UBOS, 2024). Most of Uganda's food is produced by smallholder farmers, making agriculture the foundation of the country's food security (Kikafunda, 2010).

Within the agricultural sector, maize is Uganda's most important food security crop, supporting households across its value chain (Daly et al., 2016). Maize contributes over 40

¹ The scale that runs from 0 to 100, with 0 indicating no hunger and 100 showing the worst possible hunger scenario. Nations with scores between 20.0 and 34.9 are taken to have serious hunger levels and Uganda's score is within this range (Global Hunger Index, 2024)

percent of national calorie intake, making it the staple food for many low-income households (NAADS, 2021). Agricultural productivity growth is highly dependent on the adoption of modern techniques and improved practices in developing countries, making their dissemination and uptake essential for reducing hunger and poverty amid rapidly rising food costs (Mulugeta Habtewold & Heshmati, 2023; Smith & Glauber, 2020). Adoption of modern agricultural technologies stays so low despite Uganda's strong natural endowments. However, the Government of Uganda introduced input subsidy programmes through Operation Wealth Creation to increase adoption and improve productivity by distributing agricultural inputs (Operation Wealth Creation, 2013)

1.2 Problem statement

While modern agricultural technologies such as improved seeds, fertilizers, and pesticides have the potential to improve food security among smallholder households (Amankwah & Gwatidzo, 2024; Mulugeta & Heshmati, 2023; Walusimbi et al., 2024), their uptake in Uganda remains low, and farmers often use these technologies in isolation rather than as integrated bundles (Miehe et al., 2025b; Mpuuga et al., 2023; UBOS, 2023). Because these technologies are complementary in nature, adopting them individually may limit the potential productivity and food security benefits (Mpuuga et al., 2023).

Numerous studies on the adoption of improved agricultural technologies in Sub-Saharan Africa have examined the use of individual technologies such as improved seeds, fertilizers, and pesticides and their effects on household food security (Abebe & Debebe, 2019; Aryal et al., 2021; Effendy et al., 2021; Gumindoga et al., 2024; Oluwatoyin, 2021). Some studies have also looked at the combined use of multiple technologies (Amankwah & Gwatidzo, 2024; Mulugeta & Heshmati, 2023; Tilaye et al., 2023; Falconnier et al., 2023), showing the potential for greater productivity gains and improved food security outcomes. While these studies provide valuable insights, limited attention has been given to the intensity with which farmers use multiple technologies together, leaving a gap in understanding their full impact on food security.

Understanding the drivers of adoption intensity of agricultural technology bundles and their effect on household food security is essential for designing strategies that enhance technology use and improve food security. Therefore, this study provides a thorough examination of the determinants of the intensity of adoption of improved agricultural technology bundles among smallholder maize farmers in Uganda. The research offers actionable findings for policy formulation, enabling the government and development agencies to plan programs that promote the complementary use of improved seeds, fertilizers, and

pesticides. Additionally, this study serves as a practical tool for agricultural extension services to strategically guide farmers in intensifying the use of integrated technology packages, thereby improving household food security and strengthening the resilience of smallholder households in Uganda.

1.3 Research Objectives

General Objective

This study aims to examine the adoption trends and use-intensity of bundled improved agricultural technologies and their subsequent contribution to household food security.

1.3.1 Specific Objectives

- i) To describe trends in the adoption of improved agricultural technology bundles over multiple agricultural seasons
- ii) To determine the factors affecting adoption intensity of improved agricultural technology bundles.
- iii) To estimate the impact of the intensity of adoption of improved agricultural technology bundles on household food security outcomes.

CHAPTER II: LITERATURE REVIEW

2.1 Overview of the food security situation in Uganda

According to the World Food Programme (WFP), Uganda's food security condition is rated as serious on the 2024 Global Hunger Index, indicating continued issues in food access, availability, and use (GHI,2024; WFP,2025). In addition, chronic malnutrition remains a concern, with one in every four children being stunted, showing long-term inadequacies in dietary quality and nutrition, according to the World Food Programme's country update report (WFP, 2025). National data indicate that about 23 percent of households faced severe food insecurity between 2021 and 2023 while 71.2 percent were moderately food insecure for the same period (FAO, 2024) . Approximately three in every ten households are reported to skip meals or go an entire day without food, reflecting serious access constraints driven by poverty and limited purchasing power (UBOS, 2024). Earlier estimates from the World Food Programme hunger map show that 18 million Ugandans live with insufficient food consumption (WFP, 2026). Food insecurity in Uganda is unevenly distributed across regions, with the semi-arid Karamoja sub-region consistently identified as the most vulnerable(Okidi et al., 2022). Similarly, food insecurity is prevalent in refugee-hosting districts, where pressure on resources and services worsens existing vulnerabilities(Kamugisha et al., 2024.)

2.2 Current status of technology adoption in Uganda

The adoption of agricultural technology in Uganda remains generally low, despite the country's favourable agricultural potential(World Bank, 2025). According to the World Bank Uganda Economic Update 2025, agricultural growth has largely been driven by the expansion of cultivated land rather than improvements in productivity through modern technologies (World Bank, 2025). Statistics from Uganda Bureau of Statistics (UBOS) show that only about 10 percent of farming households apply fertilizers, with average application rates ranging between 3 and 8 kg per hectare which is far below the Sub-Saharan Africa average of approximately 60 kg per hectare (UBOS, 2023). This low adoption is partly attributed to high input costs and farmers' misperceptions about soil fertility where many farmers believe their soils are sufficiently fertile and therefore do not require fertilizer application (Nakiyemba et al., 2024). However, evidence shows that only 30 percent of farmers can accurately assess soil quality, while the majority lack reliable knowledge of soil fertility conditions (Nakiyemba et al., 2024). The adoption of other modern technologies is similarly limited. Only about 4 percent of crop farmers use improved seed varieties, and adoption rates remain below 10 percent for most crops, except for maize and cotton (World Bank, 2025). In addition, irrigation remains highly underutilized and this is because out of an estimated 3.03 million hectares of irrigable

land, less than 2 percent is currently used, and irrigation coverage has remained below 1 percent for decades (World Bank, 2025).

2.3 Agriculture's Role in Uganda's Economy and Food Security

Agriculture has served as Uganda's economic backbone for decades, shaping livelihoods and driving economic activity (Bamwesigye, 2016). In recent years, the sector has remained important, accounting for 24.09% in 2023 and growing slightly to 24.67% in 2024 (UBOS, 2024). Agriculture currently employs about 70% of Uganda's labour force, with most of them working in rural areas and accounts for approximately 42% of export revenues and supplies raw materials to agro-based industries (UBOS, 2024). Smallholder rain-fed farming still dominates the sector, and it faces persistent barriers, including poor adoption of irrigation, modern inputs such as fertilizers, improved crop varieties, herbicides, and mechanization, all which limit production (Bamwesigye et al., 2020).

Agriculture is the foundation for improving household food security (Wegren & Elvestad, 2018). However, higher agricultural production does not always lead to improved food security (Wekesa et al., 2025) This is because food security encompasses more than just the amount of food produced; it includes four key pillars: availability, access, utilization, and stability (FAO, 2008). While greater agricultural production is most times connected to improved household food security, the relationship is not direct since many smallholder farmers consume a large amount of their harvest, restricting their ability to make income for other food needs or necessity services (Pawlak & Kołodziejczak, 2020; Kaini, 2020). The foundation of food security is sustainable food production, according to Swaminathan & Bhavani (2013), showing the value of smart and productive use of natural resources (Kaini, 2020) . Although increasing food production might reduce food shortages, many developing nations suffer with knowledge and technology constraints (Pawlak & Kołodziejczak, 2020)

Research constantly confirms that increased food security is mostly driven by strong agricultural performance, especially when it relates to productivity growth (V. H. Smith & Glauber, 2020). This connection is most evident in developing nations that depend heavily on agriculture, where many people depend on farming for both income and sustenance (V. H. Smith & Glauber, 2020). The mechanism explaining this link is twofold: first, increased productivity directly boosts food availability at the national and household level, and second, it raises the incomes of rural households, hence improving their economic access to food (Steensland & Zeigler, 2020). However, evidence also indicates that: while vital, production alone is not synonymous with full food security (Sunderland et al., 2013.). The ultimate outcomes are mediated by a country's specific socioeconomic context, including the quality of

its infrastructure, the effectiveness of its institutions, and its ability to close the gap between the designing and execution of policies (Pawlak & Kołodziejczak, 2020). Hence, sustainable agricultural productivity is established not as a standalone solution, but as a necessary and powerful engine for achieving better food security, which must be coupled with policies that ensure stability, access, and equitable distribution (Fanzo, 2023)

2.4. Review of Food security concepts and common indicators used for its measurements.

The 1996 World Food Summit defines food security as a state when everyone consistently has economic and physical access to abundant, safe, and healthy food that meets dietary needs for an active, healthy life (FAO, 1996). Based on the definition by Food and Agriculture Organization, food security lies on four connected components: access, availability, utilization and stability (FAO, 2008). These dimensions also operate at different functional levels of society. Availability operates at the regional and national levels and is based on food supply from domestic production, stocks, and trade. Access acts mostly at the level of household because it relies on household income, spending patterns, and physical and economic ability to get food from markets. Utilization acts at the individual level, showing how food eaten turns into sufficient nutrition, determined by dietary diversity, food safety, health, and intra-household distribution. Stability crosscuts all the other levels since as time passes, shocks like price or climate instability can affect the other three dimensions (FAO, 2008).

Researchers use accepted indicators to do assessments of food security outcomes, most especially on improved agricultural technologies. The most used ones are the Calorie Adequacy Indicator, the Food Expenditure Share (FES), the Household Dietary Diversity Score (HDDS), and the Food Consumption Score (FCS). Because it is frequently expensive and difficult to measure the four aspects of food security directly, these indicators function as proxies. These measures, on the other hand are affordable and function as useful proxies that may be gathered using household survey data. They are widely used since they are approved by international bodies (World Food Program, World Bank, Food and Agriculture Organization), enable cross-country comparability, and have been proven valid in various contexts, making them useful for both policy monitoring and research (Carletto et al., 2013; FAO, 2016; WFP, 2008).

Table 1: Common Food security Indicators

Indicator	Description	Pros and Cons	Food Security Pillars
Food Consumption Score (FCS)	Weighted score combining food frequency, dietary diversity, and nutritional value of food groups over 7 days (WFP, 2008).	It is simple to calculate, widely used, and reflects nutritional quality, but ignores intra-household distribution, portion sizes, and long-term diet adequacy (WFP, 2008; FAO, 2023).	Access: Measures what households obtain and eat., Utilization: Nutritional weighting reflects diet quality and nutrient absorption
Household Dietary Diversity Score (HDDS)	Counts the number of different food groups consumed over a reference period of 24hours or 7 days (Swindale & Bilinsky, 2006).	It is easy to collect, requires minimal data, and proxies nutrient adequacy, but does not capture food frequency or nutritional weighting (Kennedy et al, 2011)..	Utilization: More food groups consumed means higher likelihood of meeting micronutrient needs
Food Expenditure Share (FES)	Percentage of household income spent on food. Higher shares indicate higher vulnerability (FAO, 2016; WFP, 2018; Smith & Subandoro, 2007).	It shows economic access and is easy to compute from survey data, but assumes spending equals adequate food access and is sensitive to price changes (Smith & Subandoro, 2007).	Access: Higher share of income spent on food indicates greater economic vulnerability
Calorie Adequacy Indicator	Compares household caloric intake to age- and gender-adjusted dietary energy requirements (Carletto et al., 2013).	It measures energy sufficiency and is useful for targeting safety-net programs, but assumes equal intra-household distribution, ignores micronutrient adequacy, and needs detailed consumption data(Carletto et al., 2013).	Availability: Measures sufficient food energy presence., Access: Captures whether households' ability to meet energy requirements

2.5 Empirical Evidence on the Factors Influencing Adoption Intensity

Empirical evidence from previous studies shows both consistent patterns and notable deviations in the determinants of adoption intensity (Awuni et al., 2018; Mahama et al., 2017a; Ghimire et al., 2015; Misango et al., 2022; Murage et al., 2015). A key finding is that the factors influencing the initial adoption decision can differ significantly from those affecting the subsequent intensity of use (Ghimire et al., 2015). For instance, in their study of improved maize varieties (IMVs) in Nepal, Ghimire et al. (2015) found that while age and education of the household head were important for the adoption decision, they became insignificant in determining how much land was allocated to the technology. This demonstrates that after a decision to adopt is made, economic and institutional reasons take precedence over fundamental demographic traits.

Among the most consistently significant factors is access to information and social capital, particularly through extension services and farmer groups. The positive and significant influence of extension contact on adoption intensity is well-documented. Ghimire et al. (2015) found that access to extension services was a strong positive determinant of the intensity of IMV adoption in Nepal, a result mirrored by Chepchirchir et al. (2017) for the push-pull technology (PPT) in Uganda and by Mahama et al. (2020) for improved soybean technologies in Ghana. Extension services provide important technical advice and facilitate access to inputs, hence encouraging farmers to commit more land to a new technology (Chepchirchir et al. 2017; Mahama et al. 2020; Ghimire et al. 2015). Closely related is the role of social networks and group membership. Engagement in farmer groups was shown to significantly increase adoption intensity for both IMVs in Nepal (Ghimire et al., 2015) and PPT in Rwanda (Misango et al., 2022). Chepchirchir et al. (2017) similarly showed that membership in community organizations and attendance at field days facilitated information gathering and intensified PPT adoption in Uganda.

Access to physical resources and markets also plays a critical role. The availability of key inputs, such as improved seed, is fundamental; Ghimire et al. (2015) reported that better access to maize seeds directly correlated with a larger area being planted with IMVs. Conversely, distance to markets consistently acts as a barrier to intensification. Both Ghimire et al. (2015) and Mahama et al. (2020) found a significant and negative relationship between the distance from a farm to the nearest market and the intensity of adoption for IMVs in Nepal and soybean technologies in Ghana, respectively. Farms located farther from input and output markets face higher transaction costs, which demotivates farmers from investing a larger share of their land in a new technology. The effect of farm size itself can be complex. Ghimire et al.

(2015) reported a significant and negative relationship, implying that farmers with larger landholdings might diversify into other crops, while Chepchirchir et al. (2017) found a positive relationship between land size and PPT intensity in Uganda, showing that resource endowment can enable greater commitment to a technology.

Livestock ownership, serving as a proxy for wealth and providing complementary benefits, was found to positively influence the intensity of adoption for PPT in both Rwanda (Misango et al., 2022) and Uganda (Chepchirchir et al., 2017), as the technology provides valuable animal fodder. While Murage et al. (2015) in Kenya found that male farmers allocated larger portions of land to PPT, attributing this to men's greater control over resources, Chepchirchir et al. (2017) observed that being female increased the intensity of PPT adoption in Uganda, possibly because the technology's characteristics aligned with women's preferences. Mahama et al. (2020) added another dimension, finding that age positively influenced adoption intensity in Ghana, as older farmers sought to improve yields for their families, while farming experience had a negative effect, with experienced farmers potentially being more comfortable with traditional practices. Farmers' perceptions of a technology's performance are crucial. Both Ghimire et al. (2015) and Misango et al. (2022) reported that positive perceptions of a technology's superiority drive intensification. The perceived yield potential and pest resistance of IMVs significantly increased the area allocated to them by farmers in Nepal (Ghimire et al., 2015). Similarly, in Rwanda, farmers who believed PPT was effective in increasing maize yields and controlling Fall Armyworm showed significantly higher adoption intensities (Misango et al., 2022).

2.6. Empirical link between agricultural input adoption and food security.

A growing body of literature examines the influence of adopting improved agricultural technologies on household food security (Amankwah & Gwatidzo, 2024; Mulugeta & Heshmati, 2023; Tilaye et al., 2023; Walusimbi et al., 2024). While many of these studies focus on the impact of individual technologies (e.g., Tilaye et al., 2023; Walusimbi et al., 2024), a few explored the combined impact of adopting multiple technologies as a bundle (Amankwah & Gwatidzo, 2024; Mulugeta & Heshmati, 2023; Katungi et al., 2024). This distinction is critical because farmers typically adopt complementary packages of technologies rather than single components in isolation. Consequently, research centred solely on individual technologies may understate the true impact of adoption on food security. For instance, Katungi et al. (2024) found that the full adoption of a bean technology bundle (improved varieties and fertilizer) in Ethiopia significantly reduced household vulnerability measured by food

expenditure share to food insecurity, an effect that was not as pronounced when improved varieties were used in isolation. Beyond the issue of technology bundling, the literature is often limited by its treatment of adoption as a binary state. Studies (for example Tilaye et al., 2023; Aweke et al.,2021; Hailu et al., 2021; Mulugeta & Heshmati, 2023) categorize farmers simply as users or non-users of improved technologies, hence ignoring the intensity of adoption. This binary classification therefore misses the relationship between the level of technology uptake and the extent of food security outcomes.

Furthermore, many studies on this topic, such as those by Manda et al. (2018), Tilaye et al. (2023), and Hailu et al. (2021), rely on cross-sectional data, which captures information at a single point in time. This approach limits the ability to assess the long-term and dynamic impacts of technology adoption, especially as farmers learn, adapt, and expand their use of technologies over time. A static snapshot can hence provide an incomplete of the true impact of adoption. Exceptions like Mulugeta and Heshmati (2023) demonstrate the value of panel data in capturing these dynamics.

This study aims to fill these gaps in the literature, offering perspectives, particularly for the Ugandan setting. First, unlike previous studies that depend on cross-sectional data, this research uses a panel dataset from Uganda's LSMS-ISA surveys. This enables an examination of the changing nature of technology adoption, recognizing that as adoption evolves through farmer learning and adjustment, its effect on food security is better understood over time. Second, the study accounts for the intensity of technology adoption.

CHAPTER III: METHODOLOGY

3.1 Theoretical and Conceptual Framework

This study is grounded in the Use-Diffusion (UD) theory proposed by Shih & Venkatesh (2004) which explores decision-making process of farmers on whether to use or not a new technology and how much of it to use (Hu, 2007; Shih & Venkatesh, 2004). The UD theory extends the Rodgers' (1995) adoption diffusion (AD) theory, which primarily focuses on how an innovation gains widespread acceptance, how its dissemination is accelerated, and the conditions under which it is considered successful (Mahajan, et al., 1990; Rodgers, 1995). The UD theory delves deeper into post-adoption behaviour by explaining both the rate (high or low frequency of use) and variety (the range of applications or intensity) of technology use. This makes it particularly useful for predicting not only the factors that influence initial adoption but also the subsequent effects of that adoption. Based on these two dimensions, the UD theory classifies users into four distinct patterns: a) intense users who combine a high usage rate with high variety; b) specialized users who use a specific application frequently but with little variety; c) non-specialized users who apply the technology in many ways but not frequently; and d) limited users who are low on both dimensions.

To operationalize the concept of use intensity, Shih and Venkatesh (2004) employs two distinct measures: the rate of use and the variety of use. The rate of use refers to the amount of time an individual uses a product over a specified period, while the variety of use indicates the different ways in which the product is used. Empirical studies have successfully applied the UD framework; for instance, Misango et al. (2022) used it to model the determinants of adoption intensity for push-pull technology in Rwanda, and Hu (2007) applied it in an empirical test of a use-diffusion model for mobile digital TV in Taiwan.

The UD model is composed of three critical components: 1) UD determinants, 2) UD patterns and 3) UD outcomes. According to the theory, factors influencing the variety and rate of usage are the UD determinants which are categorized into four dimensions; 1) household social-context, 2) personal aspect, 3) technological aspect, and 4) external elements. The conceptual framework of the UD theory, which forms the basis of this thesis, is shown in Figure 1.

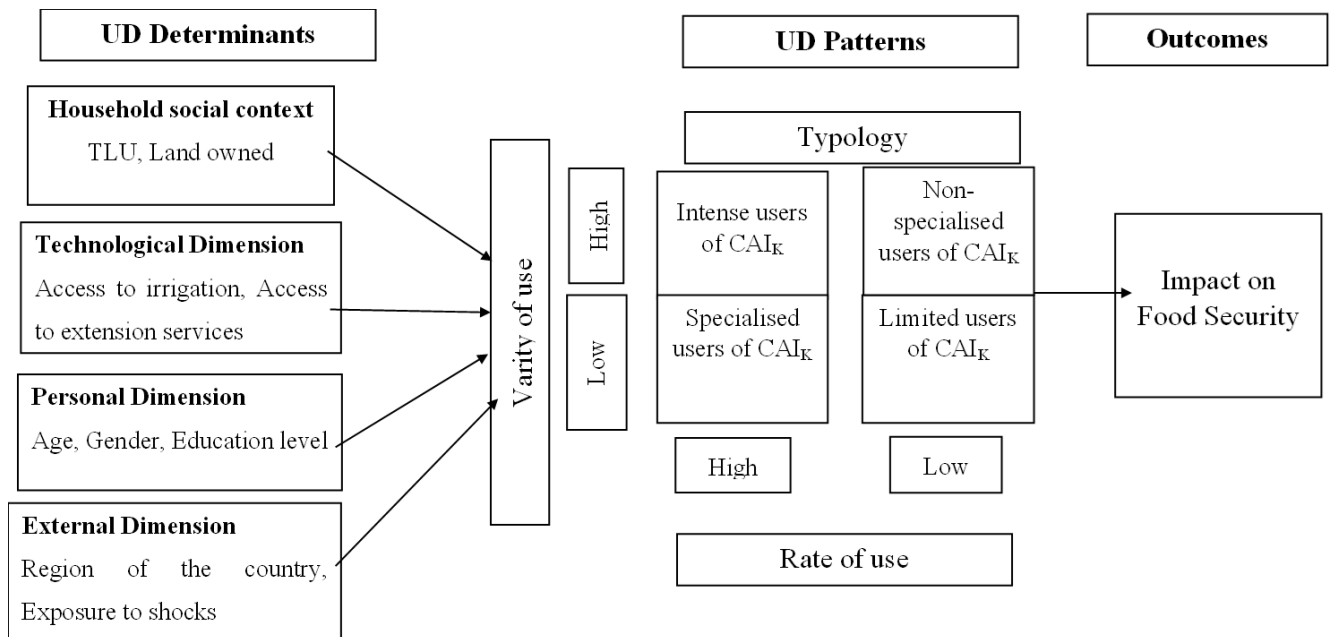


Figure 1: UD model adapted from Shih and Venkatesh (2004)

Consistent with the Use-Diffusion (UD) model, which emphasizes the rate and variety of technology use, this study focuses on the intensity of agricultural technology use among farm households. The intensity of adoption is measured using a Composite Adoption Index (CAI) constructed from key agricultural technologies. Because CAI is a fractional variable bounded between 0 and 1, linear regression models may give projected values that are outside of the practical range and do not sufficiently reflect the nonlinear connection between the dependent and explanatory factors. Several empirical models have been used to analyse adoption and intensity of technology use, including binary choice models (logit and probit)(Greene, 2003.) for adoption decisions and Tobit(Murage et al., 2015), Poisson(Awuni et al., 2018; Mahama et al., 2017a), and fractional response models for adoption intensity (Papke and Wooldridge, 1996; Misango et al., 2022). However, when the dependent variable represents a proportion bounded between zero and one, the fractional response model (FRM) is considered more appropriate. The fractional probit model ensures that predicted values remain within the unit interval and directly models the conditional expectation of the fractional outcome given the predictors(Papke & Wooldridge, 2008; Papke & Woolridge, 1996).

Therefore, this study employs a fractional probit model estimated using the Generalized Estimating Equations (GEE) approach (Liang & Zeger, 1986) to estimate the determinants of adoption intensity among farm households.

3.2. Empirical model for objective 1: Trends in the adoption of improved agricultural technology

Markov transition probabilities were used to describe trends in enhanced agricultural technology adoption over time (Bazzi et al., 2014 ; Miller et al., 2017). Based on the combinations of inputs, four adoption states were identified: State 1 (non-adoption) reflects households that did not use any of the improved inputs. State 2 (Only improved seeds) includes households that only used improved seeds. State 3 (Partial adoption) includes households that have adopted either fertilizer and improved seeds or pesticides and improved seeds, but not both. State 4 (Full adoption) represents households that have adopted fertilizer, improved seeds, and pesticides all at the same time.

Household's adoption state in each season is the dependent variable in the Markov model, denoted as Z_{it} , where i indexes households and t indexes seasons. It is a discrete variable that can take one of four mutually exclusive states:

$$Z_t \in \{1,2,3,4\} \dots \dots (1)$$

The probability of moving from one adoption state to another was estimated with a one-step Markov chain. The key assumption is that a household's adoption state in season t is solely determined by its previous state in season $t - 1$. The transition probability from state i in season $t - 1$ to state j in season t is:

$$P(Z_t = j | Z_{t-1} = i) = \pi_{ij}, \quad i, j \in \{1,2,3,4\} \dots \dots (2)$$

All transitions are summarized in a 4×4 transition matrix π , where diagonal elements capture persistence and off-diagonal elements show switching or upgrading or dis-adoption: and this is shown in equation 3:

$$\pi_{ij} = \begin{pmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \pi_{14} \\ \pi_{21} & \pi_{22} & \pi_{23} & \pi_{24} \\ \pi_{31} & \pi_{32} & \pi_{33} & \pi_{34} \\ \pi_{41} & \pi_{42} & \pi_{43} & \pi_{44} \end{pmatrix} \dots \dots (3)$$

Observed transitions between adoption states (n_{ij}) were tabulated as counts of households moving between states i and j . Maximum likelihood estimates of the transition probabilities were obtained as (Anderson & Goodman, 1957)

$$\pi_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \quad i, j \in \{1,2,3,4\} \dots \dots (4)$$

3.2.1 Model validity tests

To validate the Markov transition framework, standard tests were performed as it is a common practice in the applied economics literature (e.g., Iacono et al., 2015; Bazzi et al., 2014; Stokey et al., 1989). The stationarity assumption that transition probabilities remain

constant over time was tested by regressing the elements of a subsequent period's transition matrix on those of a base period (Iacono et al., 2015). The slope coefficient was evaluated using a Wald test and a 95% confidence interval; a coefficient not significantly different from one indicates stable transition probabilities, supporting the use of the Markov chain model.

The null hypothesis that adoption at a given time t is statistically independent of adoption in the previous period $t - 1$ was tested to ensure validity of our Markov framework. This test was conducted using contingency table techniques for cross-classified categorical data. Observed and expected transitions between adoption states were tabulated and Pearson's chi-square statistic was then computed to evaluate whether deviations between observed and expected transitions are statistically significant. A significant chi-square indicates dependence between successive adoption states, supporting the use of a Markov chain framework for modelling adoption dynamics (Iacono et al., 2015) (see appendix 2).

3.3 Empirical model for objective 2: Determinants of the Level of Use of Complementary Improved Technologies

3.3.1 Model estimation

A fractional probit model proposed by Papke & Wooldridge (2008) was estimated to determine the factors influencing adoption intensity. The model ensures that predicted values of adoption intensity CAI_{it} fall within the unit interval: The fractional probit is presented below:

$$E(CAI_{it} | X_{it}, c_i) = \Phi(\beta_0 + \beta_1 Age_{it} + \beta_2 Gender_{it} + \beta_3 Education_{it} + \beta_4 HHsize_{it} + \beta_5 Landownership_{it} + \beta_6 Region_{it} + \beta_7 Extension_{it} + \beta_8 Irrigation_{it} + \beta_9 TLU_{it} + \beta_{10} Shock_{it} + \beta_{11} Household\ income_{it} + c_i) \dots \dots (5)$$

where CAI_{it} represents the composite adoption index for household i in agricultural season t and lies between $0 \leq CAI_{it} \leq 1$, i and t denote the household and agricultural season, respectively. $\Phi(\cdot)$ shows the cumulative distribution function (CDF) of the standard normal distribution, while β_{1-11} are parameters to be estimated and β_0 is the intercept.

Equation 5 was estimated using the generalized estimating equation (GEE) approach (Liang & Zeger, 1986) The use of a Probit link function that is, the standard normal CDF rather than a logistic one poses no conceptual or theoretical difficulties (Papke & Wooldridge 2008).

3.3.2 Construction of the dependent variable

To measure adoption intensity, a Composite Adoption Index (CAI) was constructed following approaches used in agricultural technology adoption studies (Kavitha et al., 2021;

Manaswi et al., 2019, 2020; Misango et al., 2022) . The index captures the degree to which farmers adopt multiple technologies simultaneously and at varying intensities.

First, the Adoption Intensity Index (AI) for each individual technology was computed by normalizing actual use relative to recommended agronomic rate.

For fertilizers (AI₁).

$$AI_{1it} = \frac{\text{Actual fertilizer applied (Kg per acre)}}{\text{Recommended fertilizer application rate (Kg per acre)}} \dots \dots \dots (6)$$

For Pesticides (AI₂)

$$AI_{2it} = \frac{\text{Actual pesticides applied (litres per acre)}}{\text{Recommended pesticide application rate (litres per acre)}} \dots \dots \dots (7)$$

For improved seeds (AI₃).

$$AI_{3it} = \frac{\text{Actual improved maize seed planted (kg per acre)}}{\text{Recommended improved maize seed rate (kg per acre)}} \dots \dots \dots (8)$$

Recommended agronomic rates were obtained from official extension guidelines issued by Ministry of Agriculture Animal Industry and Fisheries (MAAIF) and pesticide application techniques from FAO. The recommended NPK fertilizer application rate was 50 kg per acre, the recommended improved seed rate was 10 kg per acre, and for pesticides, a standard label recommended field dose of 1.5 Liters per acre was applied as a benchmark, consistent with common herbicide application rates for maize (MAAIF, 2019; FAO, 1998)

Principle Component Analysis (PCA) was applied for computing weight for different technologies(Kavitha et al., 2021; Manaswi et al., 2019, 2020; Thakur et al., 2024) . The principal components from the analysis were used to determine the weights. The highest principal component for each technology was chosen based on the results, and the ratio of each maximum principal component to the total was used to compute the weight (Thakur et al., 2024).

The resulting indices for the different technology bundles were defined as follows:

Bundle 1 (fertilizers and improved seeds)

$$CAI_{1it} = W_1AI_{1it} + W_3AI_{3it} \dots \dots \dots (9)$$

Bundle 2 (pesticides and improved seeds)

$$CAI_{2it} = W_2AI_{2it} + W_3AI_{3it} \dots \dots \dots (10)$$

Bundle 3 (fertilizers, pesticides and improved seeds)

$$CAI_{3it} = W_1AI_{1it} + W_2AI_{2it} + W_3AI_{3it} \dots \dots \dots (11)$$

Where CAI indicates composite adoption index score for a farmer, AI₁, AI₂, AI₃ represents adoption intensity indices for fertilizer, pesticide, and improved seeds, respectively.

W_1, W_2, W_3 are the corresponding PCA derived weights. The resulting CAI values ranged between 0 and 1.

3.3.3. Model validity checks.

To ensure the validity and robustness of the estimated fractional probit models, the generalized estimating equation (GEE) approach was applied with robust standard errors to account for potential heteroskedasticity and serial correlation in the panel data (Papke & Wooldridge, 2008). Second, alternative working correlation structures were tested, including the exchangeable and unrestricted correlation matrices, to examine the sensitivity of coefficient estimates to assumptions about within-household correlations. (Papke & Wooldridge, 2008). The consistency of estimated coefficients and significance levels across these specifications shows that the results are robust.

3.3.4 Definition of variables and expected signs of parameters

Table 2 shows the description and measurement of the variables used with their expected signs. The choice of independent variables was informed by the use-diffusion model and previous studies (e.g Chepchirchir et al., 2017; Ghimire et al., 2015; Langyintuo & Mungoma, 2008; Awuni et al., 2018; Mahama et al., 2017b; Miruts, 2016).

Table 2: Description of Variables and Expected Effects on Technology Adoption

Variable	Measurement	Expected Sign (Adoption)
Dependent Variable		
Adoption Intensity (CAI)	proportion	N/A
Explanatory Variables		
Household head age	Years	+
Household head sex	Dummy (1=Male, 0=Female)	+
Education level	Levels of Education (categorical)	+
Region of the country	Categorical (Central, Eastern, Northern, and Western)	+/-
Access to extension services	Household access to extension services (1 if yes, 0 otherwise)	+
Access to Irrigation	Household used irrigation Dummy (1=Yes, 0=No)	+
Total Livestock Units (TLU)	continuous (Livestock ownership)	+

Land Ownership	Size of parcel owned in acres (GPS - measurements)
Exposure to shocks	Dummy (1 = Yes, 0 = No)

Age measured in years was used as a proxy of farmers' experience. This was expected to be positive as it is believed that older farmers take more responsibility for themselves and their household and tend to have a strong desire to adopt a combination of technologies that will increase their yields and allow them to provide for their families (Fitsum, 2016; Mahama et al., 2017b). Land owned was expected to have a negative relationship with adoption intensity as research suggests that additional land increases are normally diverted to other crops other than maize varieties (Chepchirchir et al., 2017; Ghimire et al., 2015; Langyintuo & Mungoma, 2008; Awuni et al., 2018). Education defined by the levels of education was expected to have a positive impact on adoption intensity as more years of schooling come with the understanding of the gains from using sustainable techniques in production (Awuni et al., 2018; Mahama et al., 2017a). Extension access was expected to be positive. Farmers with access to extension services or have extension contacts have higher adoption intensities (Awuni et al., 2018; Mahama et al., 2017a; Ghimire et al., 2015).

Gender was expected to be positive if the household head was male because studies show that men have more control and access over resources as opposed to women since men are the main decision makers in homes hence tend to intensively adopt the technologies (Awuni et al., 2018; Misango et al., 2022; Murage et al., 2015). Livestock ownership was anticipated to be positive and this is because livestock ownership is a proxy of a farmer's wealth status which is a crucial component of technology adoption (Ghimire et al., 2015; Misango et al., 2022; Murage et al., 2015). Region was expected to have mixed effect on adoption intensity. Studies indicate that this shows the unobserved regional disparities between the agro-climatic regions (Awuni et al., 2018; Chepchirchir et al., 2017; Ghimire et al., 2015). Access to irrigation was predicted to have a positive impact on the intensity of technology use. In the technological dimension of the UD model, technologies frequently operate in clusters where complementing technologies support one another. Irrigation boosts water availability and the efficacy of other agricultural technology, such as improved seeds, fertilizers, and pesticides (Shih & Venkatesh, 2004). Exposure to shocks was expected to be negative. Shocks reduce households' competency and capacity to adopt new agricultural innovations (Gebremariam & Tesfaye, 2018a). In this study, shocks included both climate-related and socio-economic events such as floods, drought, irregular rains, landslides, and erosion, as well as unusually high levels of crop

pests and diseases, livestock diseases, high costs of agricultural inputs, and low prices for agricultural outputs. Household-level shocks were also considered, including loss of employment or reduced earnings of household members, serious illness, among others.

3.4 Technology Adoption impact on Food Security

3.4.1 Model estimation

To estimate the impact of agricultural technology adoption intensity on food security outcomes, the study used a fixed effects panel data model was specified:

$$Y_{it} = \beta_0 + \beta_1 CAI_{it}^* + X_{it}\beta_k + v_{it} + u_i + \mu_i \dots \dots (12)$$

Where:

Y_{it} – Indicates the outcome variable (food security in terms of FCS and FES) for household i at time t . CAI_{it}^* shows adoption intensity in terms of the Composite Adoption Index for household i at time t . β_1 is the impact of adoption intensity on food security to be estimated. X_{it} represents the vector of household characteristics to be included. β_k shows the parameters for the household characteristics to be estimated. i indexes households, t indexes agricultural seasons, and k indexes control variables. v_{it} indicates the season effects while μ_i shows the random error and u_i shows unobserved household effects.

3.4.2 Addressing endogeneity.

Since adoption intensity may be influenced by unobserved household characteristics that also affect food security, it is possible that CAI is endogenous. To address this, the study plans to test for endogeneity using a control function approach (Wooldridge, 2010). If endogeneity is detected, the model will be estimated with the generalized residual included as an additional regressor.

3.4.3 Diagnostic Tests

To test for groupwise heteroskedasticity, the Modified Wald test was applied:

$$H_0: \sigma_i^2 = \sigma^2 \forall i$$

$$H_1: \sigma_i^2 \neq \sigma^2 \text{ for some } i$$

In the presence of heteroskedasticity, inference was made using cluster-robust standard errors at the household level.

Multicollinearity was tested using standard variance inflation factors (VIFs) .

3.4.4 Robustness check

The Mundlak correlated random effects (CRE) approach was used as a robustness check of the baseline model (Mundlak, 1978). This approach relaxes the strict random effects

assumption by allowing for potential correlation between the explanatory variables and unobserved household-specific effects. It augments the random effects model by including household-specific means of all time-varying covariates, thereby controlling for unobserved heterogeneity and decomposing the effects into within- and between-household components (Mundlak, 1978). Following Wooldridge (2019), in the presence of an unbalanced panel, the model was further extended to include household-level means of the time dummies to account for differential time exposure across households. Under this specification, the estimated coefficients on the time-varying variables are expected to be numerically identical to those obtained from the fixed effects estimator (Wooldridge, 2019). The close correspondence between the coefficients from the fixed effects model and the Mundlak specification confirms the validity of the approach and indicates that the results are correlation between regressors and unobserved effects, providing additional support for the preferred specification.

Table 3: Model Variables and Their Anticipated Impact on Food Security

Variable Name & Measurement Description	FCS	FES
Outcome of interest		
Food Consumption Score (FCS) Count of food groups eaten over the past 7 days	N/A	N/A
Food Expenditure Share (FES) Ratio of food expenditure to total household expenditure (%)	N/A	N/A
Main Explanatory Variables of interest		
Improved maize seeds Area under improved maize varieties in acres	+	-
CAI ₁ Bundle 1: Fertilizers and improved seeds (fractional)	+	-
CAI ₂ Bundle 2: Pesticides and improved seeds (fractional)	+	-
CAI ₃ Bundle 3: Fertilizers, pesticides, and improved seeds (fractional)	+	-
Control Variables		
Household head sex Dummy (1=Male, 0=Female)	+	-

Total Livestock Units	Continuous (Tropical Livestock Units)	+	-
Household income	Amount in Uganda shillings	+	-
Region of the country	Categorical (Central, Eastern, Northern, and Western)	+/-	+/-

3.3 Data sources

This study utilizes the Uganda National Panel Survey (UNPS) secondary data, implemented by the Uganda Bureau of Statistics (UBOS) under the World Bank’s Living Standards Measurement Study (LSMS) program. The data were collected through household, agriculture, and community modules, with each wave spanning a 12-month period. To account for Uganda’s two agricultural seasons, enumerators visited each household twice each visit covering six months to capture both completed and ongoing season data. For this study, data from the 2015/2016, 2018/2019, and 2019/2020 survey waves were used, yielding household-season level observations across three waves and six agricultural seasons per household across the three waves. Household is the unit of observation, and planting season is the time unit.

Table 4: Definition of variables and descriptives statistics

Variable	Description	Min	Max	Mean	Std. Dev
Food Consumption Score (FCS)	Count of food groups eaten over past 7 days	0	108.5	46.66	17.61
Food Expenditure Share (FES)	Ratio of food expenditure to total household expenditure (%)	0.07	82.29	8.94	8.79
CAI1	Bundle 1: Fertilizers and improved seeds (fractional)	0	0.74	0.041	0.070
CAI2	Bundle 2: Pesticides and improved seeds (fractional)	0	0.40	0.040	0.065
CAI3	Bundle 3: Fertilizers, pesticides, and improved seeds (fractional)	0	0.74	0.043	0.072
Household head age	Years	18	99	48.48	15.12
Household head sex	1 = Male, 0 = Female	0	1	0.66	0.47
Education Level – Primary	Dummy	0	1	0.689	0.463
Education Level – Junior	Dummy	0	1	0.024	0.152
Education Level – Ordinary	Dummy	0	1	0.170	0.376
Education Level – Advanced	Dummy	0	1	0.016	0.125
Education Level – Tertiary	Dummy	0	1	0.081	0.273
Education Level – Degree+	Dummy	0	1	0.011	0.104
Education Level – Do not know	Dummy	0	1	0.009	0.095
Household size	Members in the home	1	16	4.81	2.63
Land ownership	Acres owned	0	158	0.35	2.91
Access to extension services	1 = Yes, 0 = No	0	1	0.113	0.316
Access to irrigation	1 = Yes, 0 = No	0	1	0.003	0.056

Total Livestock Units (TLU)	Livestock ownership	0	11.4	0.761	1.865
Exposure to shocks	1 = Yes, 0 = No	0	1	0.551	0.497
Region – Central	Dummy	0	1	0.293	0.455
Region – Eastern	Dummy	0	1	0.315	0.464
Region – Northern	Dummy	0	1	0.200	0.400
Region – Western	Dummy	0	1	0.192	0.394
Household income	Uganda shillings per year	0	9,760,000	313,634.7	1,067,705
Fertilizer adoption	1 if the farmer adopts, and 2 otherwise	1	2	1.98	0.14
Pesticide adoption	1 if the farmer adopts, and 2 otherwise	1	2	1.95	0.21
Improved seeds adoption	1 if the farmer adopts, and 0 otherwise	0	1	0.11	0.31

CHAPTER IV: RESULTS AND DISCUSSION

4.1 Descriptive statistics

The data shows that the extensive use of traditional farming methods is still the mainstay of the Ugandan maize farmers' agricultural practices. Non-adopters consistently constituted the majority representing 88.42% of households in 2015/16, 90.63% in 2018/19, and 91.19% in 2019/20. This reveals a persistent and substantial barrier to uptake of improved agricultural technologies. The use of Only Improved Seeds decreased from 10.81% of households in 2015/16 to 6.64% in 2019/20. On the other hand, the adoption of partial and full bundles, while very low, revealed a bit of a positive trend. Full adoption, though starting from a negligible base of 0.1% in 2015/16, increased to 0.54% by 2019/20. This implies that while moving farmers from non-adoption to initial adoption of only improved seeds is very difficult, those who have started adopting may gradually intensify their use of technologies over time.

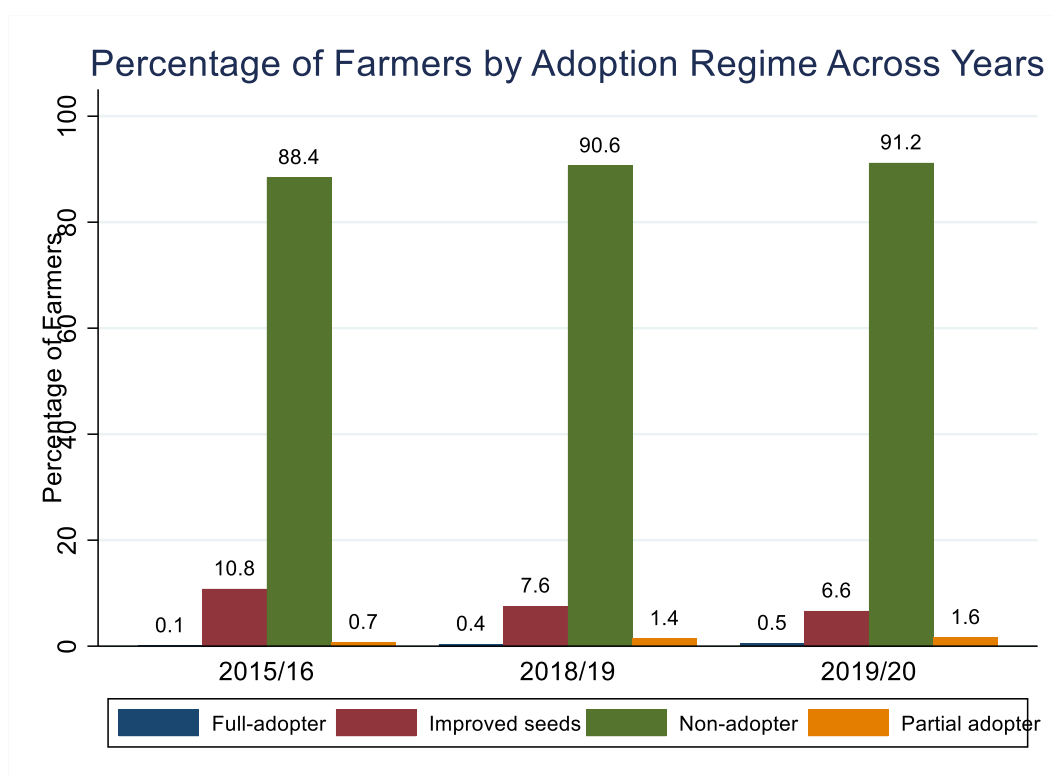


Figure 2: Trends in Maize Technology Adoption in Uganda (2015/16–2019/20)

Household food security, as measured by the Food Consumption Score (FCS), showed a positive trend over the study period. The mean FCS increased from 43.3 in 2015/16 to 50.4 in 2018/19 then dropped to 48.8% in 2019/20. On the contrary, the mean Food Expenditure Share (FES) reduced from 9.2% in 2015/16 to 8.2 % in 2019/20 and the overall mean was 8.94%, which, based on Engel's law, means that the sample households were not severely economically vulnerable in terms of food access.

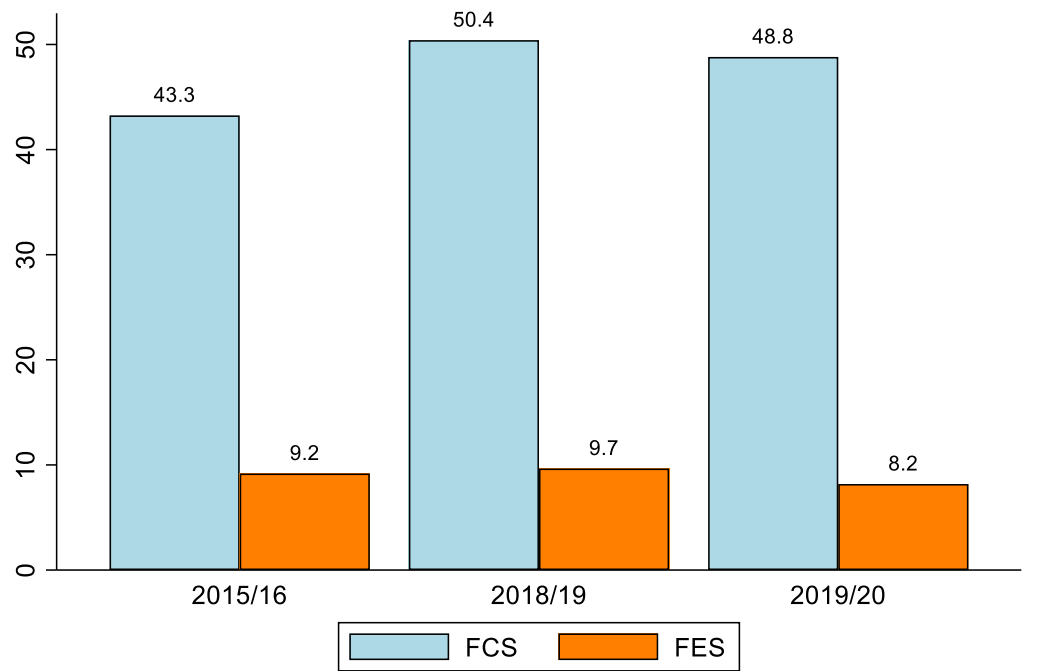


Figure 3: Trends in Household Food Security overtime (2015/16- 2019/20)

4.2 Trends in Technology Bundle Adoption

4.2.1. Observed Transitions Across Survey Waves

The findings in table 5 and 6 show that non-adoption remains the most persistent state among Ugandan maize farmers, while transitions to higher adoption regimes especially full adoption of improved agricultural technology bundles are rare. From 2015/16 to 2018/19, only 5.11% of non-adopters moved to improved seeds alone, 0.43% to partial adoption, and 0.14% to full adoption. Among households using only improved seeds in 2015/16, 68.12% moved to non-adoption, while 27.54% remained. 4.35% moved to partial adoption. No household maintained or reached full adoption. This pattern continued in 2018/19–2019/20. Among non-adopters, 94.27% remained in the same category. Of those using only improved seeds, 74.65% returned to non-adoption, 18.31% persisted, and 7.04% moved to partial adoption. Among partial adopters, 42.86% reverted to non-adoption and 35.71% switched to seeds only, while 21.43% remained in partial adoption. Among full adopters, 60.00% reverted to non-adoption, 20.00% moved to seeds only, 0.00% moved to partial adoption, and 20.00% remained in full adoption. These patterns show substantial evidence of state dependence in adoption decisions, implying that a farmer's previous experiences with technology have a considerable impact on their future choices. This result aligns with dynamic models of technology adoption, showing that farmers modify their choices based on insights acquired in earlier periods (Miller et al., 2017; Vivas et al., 2023)

While improved seeds may serve as an entry point, few farmers adopt complementary inputs like fertilizer or pesticides. Adoption decisions for seeds and fertilizer are often joint and interdependent, without complementarity, uptake stalls (Ogada et al.,2014). The high state reliance seen in our study aligns with research of African indigenous vegetables in Kenya, where earlier adoption primarily influenced current adoption decisions (Vivas et al., 2023) Behavioural influences can help to clarify this path dependency pattern. According to Miede et al.(2025) farmers frequently have "miracle seed" ideas, expecting improved seeds to grow even without extra inputs such as fertilizer or pesticides. When yields inevitably fall short, many return to non-adoption, creating the exact state dependence recorded in our study and others. This behavioural mechanism directly explains the high regression rates from improved seed adoption back to non-adoption observed in our data. In addition, Bold et al.(2015) link non adoption to the poor quality of inputs available in local retail markets, which makes the use of modern inputs with average quality unprofitable. Additionally, substantial variation in input quality and uncertainty in expected yields limit farmers' ability to learn about the effectiveness of fertilizer and hybrid seeds, thereby reducing their willingness to sustain adoption Bold et al.(2015)

Table 5:Transitions in Technology Adoption (2015/16 - 2018/19)

Adoption Year 1 (2015/16)	Adoption Year 2 (2018/19)			
	Non-adopter	Only Improved Seeds	Partial Adopter	Full Adopter
Non-adopter	665 (94.33%)	36 (5.11%)	3 (0.43%)	1 (0.14%)
Only improved seeds	47 (68.12%)	19 (27.54%)	3 (4.35%)	0 (0.00%)
Partial adopter	4 (50.00%)	0 (0.00%)	3 (37.50%)	1 (12.50%)
Full adopter	—	—	—	—

Table 6:Transitions in Technology Adoption (2018/19–2019/20)

Adoption Year 2 (2018/19)	Adoption Year 3 (2019/20)			
	Non-adopter	Only Improved Seeds	Partial Adopter	Full Adopter
Non-adopter	839 (94.27%)	41 (4.61%)	4 (0.45%)	6 (0.67%)
Only improved seeds	53 (74.65%)	13 (18.31%)	5 (7.04%)	0 (0.00%)
Partial adopter	6 (42.86%)	5 (35.71%)	3 (21.43%)	0 (0.00%)

Full adopter	3 (60.00%)	1 (20.00%)	0 (0.00%)	1 (20.00%)
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Note: Column totals for the 2015/16–2018/19 transition period do not perfectly match the corresponding row totals for the 2018/19–2019/20 period due to the use of an unbalanced panel. Transitions are calculated strictly for households with valid, non-missing technology adoption data in consecutive waves (t and $t - 1$). Consequently, households that missed the 2015/16 baseline but re-entered the sample in 2018/19 are excluded from the first transition table (Table 5) due to a missing lag but are successfully captured as starting observations in the second transition table (Table 6).

4.2.2 Transition Probability Matrix and State Dependence

Table 7 shows the transition probability matrix which summarizes the dynamics of technology adoption over time. Conditional on their previous adoption state, 93.6% of non-adopters remain non-adopters, 5.8% adopt only improved seeds, 0.36% adopt partially, and 0.32% achieve full adoption. Households that had previously adopted only improved seeds have a 68.9% probability of shifting back to non-adoption, 27.3% remaining in the same state, 3.83% adopting partially, and 0.00% achieving full adoption. Partial adopters show a 42.9% chance of reverting to non-adoption, 25.0% shifting to improved seeds only, 28.6% remaining partial adopters, and 3.6% moving to full adoption. Full adopters show a 50.0% probability of reverting to non-adoption, 33.3% shifting to improved seeds only, no probability of partial adoption, and a 16.7% chance of maintaining full adoption. This pattern demonstrates that past adoption behaviour strongly influences future decisions, consistent with Birhanu & Jensen (2023) finding of state dependence in enhanced maize variety adoption. The high probability of farmers reverting to non-adoption, even after partial or full adoption, implies that past adoption alone does not ensure sustained use of improved technologies. Literature indicates that high dis-adoption rates are due to limitations such as input availability, perceived risk, high labour demands and lack of complementary knowledge (Habanyati et al., 2020; Taylor & Bhasme, 2024).

Table 7: Transition Probability Matrix of Adoption Regimes

Previous Adoption Status	Non-adopter	Only Improved Seeds	Partial Adopter	Full Adopter
Non-adopter	0.9356	0.0576	0.0036	0.0032
Only Improved Seeds	0.6890	0.2727	0.0383	0.0000

Partial Adopter	0.4286	0.2500	0.2857	0.0357
Full Adopter	0.5000	0.3333	0.0000	0.1667

4.2.3 Long-Run (Stationary) Distribution of Adoption Regime

The stationary distribution data (Table 8) reveal long-term adoption patterns. If present transition probabilities continue as they are, most families (91.06%) are anticipated to remain non-adopters in the long term. Approximately 7.68% are likely to adopt solely better seeds, 0.87% to partially adopt, and 0.38% to fully embrace the entire technological bundle. This suggests that, despite considerable experimentation, the adoption of whole technology packages is extremely limited over time. This pattern of low sustained adoption aligns with findings from other contexts in Sub-Saharan Africa. For example, the dynamics of technology adoption study in Ethiopia also found that while initial adoption of improved maize seeds occurs, long-term persistence is low, with significant rates of dis-adoption preventing a widespread shift away from non-adoption in the long run (Birhanu & Jensen, 2023a)

Table 8: Stationary (Long-Run) Distribution of Adoption Regimes

Adoption Status	Long-run Probability
Non-adopter	0.9106
Only improved seeds	0.0768
Partial adopter	0.0087
Full adopter	0.0038

4.2.4 Model Validity results

The results revealed that the slope coefficient for the regression of follow-up transition probabilities on the base period is 0.9155 ($t = 7.13$, $p < 0.001$) with an R-squared of 0.8355. A formal test of whether the slope equals one yielded $F(1,10) = 0.43$, $p = 0.5255$, indicating that transition probabilities remain constant over time. This confirms the stationarity assumption. The Pearson chi-square test for the dependence of current adoption states on previous states produced a value of 444.35 ($p < 0.001$), showing that adoption at time t is significantly associated with the previous period $t - 1$. Observed and expected frequencies closely matched for most categories, indicating meaningful dependence between successive adoption states (see appendix). Together, these results provided strong evidence supporting the validity of the Markov transition framework for modelling adoption dynamics.

4.3 Technology Adoption Intensity Determinants

Table 9 reports the fractional probit model estimates and marginal effects for the determinants of the adoption intensity of improved agricultural technology bundles. The results show that household head sex shows a consistent and statistically significant positive association with adoption intensity across all technology bundles. Male-headed households revealed higher adoption intensity across all the technology bundles. This finding is in line with the a priori expectation of positive relationship and supports Misango et al.(2022) and Fitsum.(2016). This result shows gender-based variations in access to productive resources like land, credit, and labour, which are often more readily available to male-headed households in many rural settings. In addition, male farmers may face less socio-cultural restrictions in accessing extension services and input markets, enabling them to adopt and combine multiple technologies more intensively.

The results reveal a non-linear, quadratic relationship between the age of the household head and adoption intensity, as evidenced by the positive coefficient for head age and the negative coefficient for age squared across the models. This concave relationship indicates that adoption intensity initially increases with the age of the household head, reaches an optimal peak, and subsequently declines among much older heads of households. Younger to middle-aged farmers may accumulate experiential knowledge, resources, and social capital over time, which improves their capacity to intensify technology use. However, as household heads advance past a certain age threshold, human capital constraints, shorter planning horizons, and risk aversion typically set in, causing a drop-off in adoption intensity. This lifecycle effect strongly contradicts the findings of Awuni et al.(2018) , who reported that age had no significant influence on adoption intensity.

Farmers with access to extension services access had a positive effect on adoption intensity, and this shows the role played by extension services in distributing improved agricultural technologies. Beyond simple information dissemination, extension services reduce uncertainty allied with new technologies, improve farmers' technical capacity, and enhance confidence in combining multiple technologies. This is mostly important for bundled technologies, where complementarities need proper knowledge for effective use. This finding is consistent with the results of Awuni et al.(2018), who reported that extension contacts had a positive and significant impact on the intensity of adoption, as well as Ghimire et al.(2015) who found that extension access had a significant and positive effect on the intensity of improved maize varieties adoption. In a similar study, Mahama et al.(2017b) found a

significant and positive influence of extension visits on the adoption intensity of enhanced soybean production technologies.

Exposure to shocks had a negative and significant impact on adoption intensity across all the bundles. This result shows that when households face shocks such as drought, pests and diseases, health crises, they may reallocate resources thus reducing their ability to intensify the use of improved technologies. This aligns with findings of Gebremariam & Tesfaye (2018) found that shocks reduce households' competency and capacity to adopt new agricultural innovations. The northern and western region showed a negative and significant impact on adoption intensity relative to the central region. This is due to the variation in climatic and agricultural conditions across these regions and this shows the unobserved regional disparities between the agro-climatic regions (Awuni et al., 2018; Chepchirchir et al., 2017; Ghimire et al., 2015)

Table 9: Determinants of the adoption Intensity (Marginal Effects of Fractional Probit estimation)

Variables	CAI1 Fractional Estimates	Marginal Effects	CAI2 Fractional Estimates	Marginal Effects	CAI3 Fractional Estimates	Marginal Effects
HH head Gender (male = 1)	0.299*** (0.064)	0.0117*** (0.0024)	0.235*** (0.056)	0.0095*** (0.0021)	0.284*** (0.060)	0.0131*** (0.0026)
HH head age	0.025* (0.013)	0.0011* (0.0006)	0.024** (0.011)	0.0011** (0.0005)	0.031** (0.012)	0.0016** (0.0006)
Age squared	-0.00025** (0.00012)	-0.000011** (0.000006)	-0.00026*** (0.00010)	-0.000012*** (0.000005)	-0.00031*** (0.00011)	-0.000016*** (0.000006)
Access to extension services	0.257*** (0.096)	0.0113** (0.0045)	0.146* (0.075)	0.0065* (0.0034)	0.255*** (0.090)	0.0131*** (0.0048)
Tropical Livestock Units	0.016 (0.011)	0.0007 (0.0005)	0.010 (0.010)	0.0005 (0.0005)	0.013 (0.011)	0.0007 (0.0006)
Access to irrigation	0.388 (0.313)	0.0171 (0.0138)	0.341 (0.298)	0.0152 (0.0133)	0.400 (0.327)	0.0205 (0.0167)
Land Owned	-0.002 (0.004)	-0.00007 (0.00018)	-0.001 (0.003)	-0.00004 (0.00013)	0.0002 (0.003)	0.00001 (0.00014)
Shocks exposure	-0.224* (0.129)	-0.0099* (0.0058)	-0.162* (0.092)	-0.0072* (0.0042)	-0.183* (0.104)	-0.0094* (0.0054)
Education Level (Ref: Primary)						
Junior Secondary	0.164 (0.213)	0.0081 (0.0122)	0.003 (0.107)	0.0001 (0.0047)	0.140 (0.183)	0.0079 (0.0117)

Ordinary Secondary	0.075 (0.096)	0.0034 (0.0046)	0.054 (0.076)	0.0025 (0.0036)	0.082 (0.086)	0.0044 (0.0048)
Advanced Secondary	-0.148 (0.214)	-0.0054 (0.0068)	-0.237 (0.165)	-0.0081* (0.0045)	-0.219 (0.206)	-0.0087 (0.0067)
Tertiary (Diploma/Cert.)	0.065 (0.111)	0.0029 (0.0052)	0.072 (0.101)	0.0033 (0.0050)	0.045 (0.109)	0.0023 (0.0058)
University Degree+	-0.005 (0.348)	-0.0002 (0.0145)	-0.226 (0.267)	-0.0078 (0.0073)	-0.108 (0.335)	-0.0048 (0.0134)
Education Not Reported	0.318* (0.170)	0.0183 (0.0126)	0.293 (0.183)	0.0170 (0.0135)	0.180 (0.182)	0.0106 (0.0124)
Region (Ref: Central)						
Eastern	0.044 (0.081)	0.0022 (0.0041)	-0.059 (0.065)	-0.0030 (0.0034)	-0.141* (0.075)	-0.0086* (0.0046)
Northern	-0.301** (0.117)	-0.0110*** (0.0040)	-0.411*** (0.093)	-0.0153*** (0.0032)	-0.455*** (0.109)	-0.0210*** (0.0045)
Western	-0.170** (0.078)	-0.0071** (0.0034)	-0.197*** (0.068)	-0.0090*** (0.0032)	-0.305*** (0.071)	-0.0161*** (0.0040)
Observations	1,397		1,397		1,397	
Number of households	643		643		643	
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes

Parenttheses indicate robust standard errors (* p<0.10, ** p<0.05, *** p<0.01). Seasonal dummies included to control for time-specific effects.

4.4 Technology Adoption Intensity Impact on Food Security

The Modified Wald test for groupwise heteroskedasticity revealed heteroskedasticity presence in all models hence all preferred specifications were estimated at the household level using cluster-robust standard errors to ensure consistent inference in the presence of heteroskedasticity. While robust standard errors correct for heteroskedasticity and within-household correlation, conducting the test remains necessary to justify their use and to show that the classical homoskedasticity assumption is violated in the data. Model 1 represents improved seeds, model 2 shows CAI1 (fertilizers + improved seeds), model 3 indicates CAI2 (pesticides + improved seeds), model 4 shows CAI3 (fertilizers + pesticides + improved seeds). To account for potential skewness and enable interpretation in percentage terms, the Food Consumption Score (FCS) and Food Expenditure Share (FES) were transformed into their natural logarithmic forms, denoted as $\log(\text{FCS})$ and $\log(\text{FES})$.

4.4.1 Effect on Food Consumption Score (FCS)

Results in table 10 show that adoption intensity has a positive and significant impact on Food Consumption Score (FCS). Increasing the area under improved maize seeds by one acre leads to a marginal effect of 4.59% increase in FCS (coefficient = 0.0459, $p < 0.10$). Higher adoption intensity of technology bundles produces larger improvements in FCS compared only improved seeds. Specifically, a 0.1 increase in adoption intensity (10 percentage-point increase) is associated with an increase in Food Consumption Score of about 4.51%, 7.11%, and 4.16% for CAI1, CAI2, and CAI3 respectively, holding other factors constant. These results show that higher intensity and combining of complementary technologies improves dietary diversity compared. This finding aligns with evidence from Ethiopia, where adopting a bundle of improved bean varieties and fertilizers significantly increased food availability and enabling more diverse consumption, hence improving smallholder food security (Katungi et al., 2024). Similarly, in rural Zimbabwe, joint adoption of improved seeds and inorganic fertilizers increased dietary diversity, raising the number of food groups consumed by 23% (Amankwah & Gwatidzo, 2024). The present results extend this evidence by showing that not only the decision to adopt but also the degree or intensity of adoption are important for improving dietary diversity and food security, with complementary use of improved seeds, fertilizers, and pesticides producing combined effects.

Table 10: Technology Adoption Intensity Impact on Food Consumption Score

	Model 1	Model 2	Model 3	Model 4
Improved seeds	0.0459* (0.0243)			
CAI1		0.4511* (0.2490)		
CAI2			0.7112** (0.2872)	
CAI3				0.4155** (0.2016)
Head sex (male = 1)	0.0135 (0.0367)	-0.0224 (0.0559)	-0.0258 (0.0558)	-0.0234 (0.0558)
Total livestock Unit	0.0308*** (0.0048)	0.0284*** (0.0041)	0.0282*** (0.0041)	0.0284*** (0.0041)
Income	0.0102*** (0.0033)	0.0121*** (0.0040)	0.0122*** (0.0040)	0.0122*** (0.0040)
Region (ref: Central)				
Eastern	-0.0305 (0.0431)	-0.0379 (0.0666)	-0.0332 (0.0657)	-0.0341 (0.0659)
Northern	-0.0994* (0.0533)	0.0131 (0.0934)	0.0216 (0.0929)	0.0168 (0.0931)
Western	0.1132** (0.0535)	0.0959 (0.0697)	0.1015 (0.0690)	0.0995 (0.0693)
Period dummies	Yes	Yes	Yes	Yes
Constant	3.500*** (0.0697)	3.630*** (0.0477)	3.627*** (0.0474)	3.627*** (0.0475)
Observations	4,666	3,012	3,012	3,012
Number of households	1,238	1,064	1,064	1,064
Within R ²	0.064	0.057	0.058	0.057

Parentheses indicate robust standard errors (* p<0.10, ** p<0.05, *** p<0.01). Seasonal dummies included to control for time-specific effects

4.4.2 Effect on Food Expenditure Share (FES)

Table 11 shows that adoption intensity has a negative relationship with the share of household income spent on food. The results show that higher adoption intensity of technology bundles is linked to a lower percentage of household income spent on food. A 0.1 increase in adoption intensity reduces food expenditure share by approximately 8.95%, 10.13%, and 7.14% for CAI1, CAI2, and CAI3 respectively. This suggests that increased adoption intensity improves household welfare by reducing the proportion of income spent on food. These findings align with Katungi et al. (2024) who reported that the joint adoption of fertilizers and improved varieties had a negative correlation with the share of food expenditure reducing household vulnerability. In a similar study Amankwah & Gwatidzo (2024) showed that adoption of improved seed reduced the food expenditure share of poor households by 16 percent.

Other variables included in the outcome models (FCS and FES) showed an effect on food security. Livestock ownership is highly and positively associated with FCS but negatively associated with FES. This shows livestock's significance as both a direct source of food (via products like milk and meat) and a buffer asset that boosts household resilience and economic welfare, decreasing the amount of money spent on food purchases. Household income correlates strongly negatively with FES and positively with FCS. This result is consistent with Engel's law, which states that wealthier households spend a lesser portion of their income on food as their purchasing power and consumption diversification increase. Households in the Northern region show a positive effect on food expenditure share compared to central region meaning they spend more on food while Eastern and western regions spend less on food compared to those in central region. This is consistent with national poverty and vulnerability trends that identify the North as more economically unstable.

Table 11: Technology Adoption Intensity Impact on Food Expenditure Share

	Model 1	Model 2	Model 3	Model 4
Improved seeds	-0.0569 (0.0407)			
CAI1		-0.8946** (0.4512)		
CAI2			-1.0127* (0.5324)	
CAI3				- -0.7142 (0.4229) *
Head sex (male = 1)	0.0120 (0.0520)	0.0159 (0.0624)	0.0177 (0.0628)	.0161 (0.0624)
Total livestock Unit	-0.0351*** (0.0070)	-0.0261*** (0.0076)	-0.0261*** (0.0076)	-0.0262*** (0.0076)
Income	-0.0133** (0.0045)	-0.0083 (0.0055)	-0.0084 (0.0055)	-0.0084 (0.0055)
Region (ref: Central)				
Eastern	-0.0726 (0.0617)	-0.2006*** (0.0760)	-0.2077*** (0.0764)	-0.2074*** (0.0762)
Northern	0.2345*** (0.0698)	0.0514 (0.1055)	0.0432 (0.1056)	0.0467 (0.1054)
Western	-0.1631** (0.0712)	-0.2501*** (0.0865)	-0.2556*** (0.0870)	-0.2552*** (0.0869)
Period dummies	Yes	Yes	Yes	Yes
Constant	3.528*** (0.0845)	2.109*** (0.0697)	2.113*** (0.0697)	2.112*** (0.0697)
Observations	4,666	3,012	3,012	3,012
Number of households	1,238	1,064	1,064	1,064
Within R ²	0.064	0.040	0.040	0.039

Parentheses indicate robust standard errors (* p<0.10, ** p<0.05, *** p<0.01). Seasonal dummies included to control for time-specific effects

4.4.3 Robustness results

The results show that the estimated coefficients from the Mundlak model are highly consistent with those from the fixed effects model in terms of sign, magnitude, and statistical significance (see appendix). The adoption intensity indices remain positive and statistically significant in the food consumption model, while they remain negative and significant in the food expenditure share mode. Key control variables such as livestock holdings and income maintain their anticipated effects across specifications. This close correspondence verifies the estimates' stability and indicates that the primary conclusions are not influenced by model specification. This observation supports the argument by Wooldridge (2019) that, provided the Mundlak model is correctly described, the coefficients on time-varying variables should be identical to those derived from the fixed effects estimator, even in unbalanced panels.

On the endogeneity test, the results showed that the generalised residuals were statistically insignificant ($pvalue > 0.05$) across all specifications hence adoption intensity was treated as exogenous.

CHAPTER V: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

The findings paint a clear picture of both the agricultural industry's potential and its challenges. Over 91% of households are anticipated to remain non-adopters in the long run across all panel waves, indicating that non-adoption is dominant. There are challenges to taking on complementary inputs, as seen by the extremely low adoption of partial or full technology bundles, with full adoption expected to reach only 0.4% in the long run.

The analysis indicates that technology adoption is a path-dependent process. Households' previous adoption status is a powerful predictor of future behaviour, with high rates of dis-adoption reported. The significant dis-adoption rate was worrying, especially for households who had previously only accepted improved seeds. About 68.9% of these households returned to not adopting, while 42.9% of partial adopters and 50% of complete adopters also dropped to non-adoption. The stationary distribution indicates that, if current trends continue, approximately 91% of households will remain non-adopters. This shows the urgent need for interventions that not only initiate adoption but also ensure its sustainability, directing farmers in the line of combined technology packages that can improve productivity and food security.

Male-headed households and those with extension access consistently showed higher adoption intensity across all technology bundles, reflecting gender disparities and the significance of agricultural information. Irrigation also showed a positive and significant impact on adoption intensity indicating the complementarity in inputs. Shocks also reduced adoption intensity of technologies. The study shows that increasing the usage of improved agricultural technology bundles significantly improves household food security. Higher adoption intensities of complementary technologies are associated with proportional increases in dietary diversity, as reflected in higher Food Consumption Scores (FCS), and reductions in the share of income spent on food (FES), showing improved economic welfare. In addition, socioeconomic and contextual characteristics also influence food security. Livestock ownership and household income support higher food security outcomes. The value of local context in influencing the impact of technology adoption is also shown by regional variations.

5.2 Policy Implications and Recommendations

The following policy measures and suggestions are proposed in response to the study's findings to boost Uganda's adoption and long-term use of improved agricultural technologies.

Promotion of Complementary Technology Bundles: Agricultural policies and extension messages should actively shift from promoting isolated inputs and instead focus on the deployment of complementary technology bundles. Demonstrations and training packages should emphasize the overall agronomic and economic benefits of these full packages, which based on the findings in this study result in significantly larger improvements in household dietary diversity (FCS) and welfare (FES) than the adoption of improved seeds alone.

Sustaining Adoption Paths and Preventing Reversion. Given the exceptionally high regression rates and state dependence documented in the Markov transition analysis (where the majority of initial or partial adopters revert to traditional farming methods), policy interventions must look beyond initial promotion. The Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) and local governments must strengthen output market connections to ensure production profitability, guarantee the local availability of verified, high-quality inputs to counter "miracle seed" letdowns, and provide continuous, season-long extension support to help farmers effectively manage the technical complexities of input mixing

Gender-Responsive Extension and Resource Access: The strong, consistent positive association between male-headed households and adoption intensity shows persistent structural differences in rural settings. To bridge this gap, extension programs should be deliberately restructured to accommodate the domestic responsibilities, mobility limitations, and labor constraints faced by female farmers.

Resilience Building: Because exposure to shocks (droughts, pests, and health crises) exerts a statistically significant negative drag on adoption intensity by forcing households to reallocate scarce resources away from production, technology dissemination must be paired with safety nets. The government should integrate weather-indexed crop insurance and community-level safety nets directly with input delivery systems. This ensures that an adverse seasonal shock does not compromise household liquidity or trigger a permanent dis-adoption spiral back to traditional, low-yielding practices.

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APPENDIX A

A.1 Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
headage	4,692	48.47613	15.12009	18	99
headsex	4,692	.6611253	.4733776	0	1
headhsize	5,588	4.811382	2.627497	1	16
landowners~p	6,734	.3504128	2.909069	0	158
extension_~s	5,604	.1127766	.3163477	0	1
irrig_access	5,134	.0031165	.0557438	0	1
TLU_s	6,734	.7613306	1.865068	0	11.4
shocks	3,812	.5514166	.4974146	0	1
Householdi~e	6,734	313634.7	1067705	0	9760000
FCS	5,572	46.66009	17.6147	0	108.5
FES	5,572	8.94038	8.792076	.0708137	82.29305
CAI1	4,171	.0413685	.0699555	0	.7439438
CAI2	4,171	.0400067	.0649821	0	.3982134
CAI3	4,171	.0434933	.0723053	0	.7439438

Variable	Obs	Mean	Std. dev.	Min	Max
binaryfert~s	4,434	1.979251	.1425582	1	2
binarypest~s	4,433	1.954433	.2085684	1	2
binaryimpr~s	5,233	.1075865	.309887	0	1
education_~1					
Primary	5,326	.6890725	.4629167	0	1
Junior	5,326	.0236575	.151994	0	1
Ordinary_~1	5,326	.1704844	.3760931	0	1
Advanced_~1	5,326	.0157717	.1246028	0	1
Tertiary	5,326	.0811115	.2730319	0	1
Degree+	5,326	.01089	.103795	0	1
Don't know	5,326	.0090124	.0945137	0	1
headregion					
Central	5,596	.2934239	.4553717	0	1
Eastern	5,596	.3145104	.4643621	0	1
Northern	5,596	.1997856	.3998748	0	1
Western	5,596	.1922802	.3941272	0	1

A.2 Variance Inflation Factor (VIF) output

. vif

Variable	VIF	1/VIF
education_~1	1.16	0.860836
Householdi~e	1.14	0.879008
headage	1.10	0.911294
headhsize	1.09	0.919634
headsex	1.09	0.919679
shocks	1.07	0.936680
headregion	1.06	0.939553
irrig_access	1.05	0.955614
TLU_s	1.04	0.959625
extension_~s	1.03	0.971887
landowners~p	1.01	0.987593
Mean VIF	1.08	

.

A.3 Stationarity test of the Markov model using transition probabilities 2015/16-2018/19 as the base

. reg follow base

Source	SS	df	MS	Number of obs	=	12
Model	.913841395	1	.913841395	F(1, 10)	=	50.80
Residual	.179881375	10	.017988138	Prob > F	=	0.0000
Total	1.09372277	11	.099429343	R-squared	=	0.8355
				Adj R-squared	=	0.8191
				Root MSE	=	.13412

follow	Coefficient	Std. err.	t	P> t	[95% conf. interval]
base	.9155025	.128445	7.13	0.000	.6293092 1.201696
_cons	.0211244	.0503005	0.42	0.683	-.0909522 .133201

. test base = 1

(1) base = 1

F(1, 10) = 0.43
 Prob > F = 0.5255

2

A.4 Testing independence between current and previous adoption state

² The estimated slope coefficient was 0.916 with a 95% confidence interval of [0.629, 1.202]. A Wald test could not reject the null hypothesis that the slope equals one ($p = 0.526$). These results suggest that the transition probabilities are relatively stable across periods, supporting the stationarity assumption of the Markov chain model.

<i>frequency</i> <i>expected frequency</i>

adopt_prev	adopt_regime				Total
	1	2	3	4	
1	2,064 2,002.4	127 173.8	8 21.6	7 8.1	2,206 2,206.0
2	144 189.7	57 16.5	8 2.0	0 0.8	209 209.0
3	12 25.4	7 2.2	8 0.3	1 0.1	28 28.0
4	3 5.4	2 0.5	0 0.1	1 0.0	6 6.0
Total	2,223 2,223.0	193 193.0	24 24.0	9 9.0	2,449 2,449.0

Pearson chi2(9) = 444.3480 Pr = 0.000

A.5 Modified wald heteroskedasticity test output

Dependent Variable	Adoption Intensity	Chi-squared (χ^2)	p-value	Decision
logFCS	CAI1	92,639,091.68	0.0000	Reject H ₀
logFCS	CAI2	63,774,301.23	0.0000	Reject H ₀
logFCS	CAI3	101,904,143.91	0.0000	Reject H ₀
logFES	CAI1	249,781,161.42	0.0000	Reject H ₀
logFES	CAI2	152,163,985.87	0.0000	Reject H ₀
logFES	CAI3	522,892,823.75	0.0000	Reject H ₀

A.6 Principal component analysis Weights for technology

```
. pca AI_fertilizer AI_pesticide AI_seed
```

```
Principal components/correlation      Number of obs   =    4,171
                                      Number of comp. =     3
                                      Trace            =     3
Rotation: (unrotated = principal)    Rho             =    1.0000
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.26821	.286701	0.4227	0.4227
Comp2	.981512	.231237	0.3272	0.7499
Comp3	.750275	.	0.2501	1.0000

```
Principal components (eigenvectors)
```

Variable	Comp1	Comp2	Comp3	Unexplained
AI_fertili~s	0.6928	-0.0708	-0.7177	0
AI_pestici~s	0.6456	-0.3827	0.6609	0
AI_seed_s	0.3215	0.9211	0.2195	0

```
.
. local w1 = 0.6928/1.6599
. local w2 = 0.6456/1.6599
. local w3 = 0.3215/1.6599
.
. display "Weight 1: " `w1'
Weight 1: .41737454
. display "Weight 2: " `w2'
Weight 2: .38893909
. display "Weight 3: " `w3'
Weight 3: .19368637
```

APPENDIX B

B.1 Mundlak approach output

B.1.1 For FCS Outcome

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFCS	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
area_improved_maize_seed_s	.0485885	.0245766	1.98	0.048	.0004192	.0967578
headsex	-.0271184	.0372589	-0.73	0.467	-.1001444	.0459076
TLU_s	.0311005	.0040181	7.74	0.000	.0232252	.0389757
lnincome	.0115274	.0037592	3.07	0.002	.0041595	.0188953
m_imseeds	.0794427	.0564513	1.41	0.159	-.0311998	.1900852
m_TLU	.0360154	.0100789	3.57	0.000	.0162612	.0557697
m_lnlincome	-.0055001	.0056398	-0.98	0.329	-.016554	.0055537
headregion						
Eastern	-.0339254	.0467103	-0.73	0.468	-.1254758	.0576251
Northern	-.048915	.0627286	-0.78	0.436	-.1718608	.0740308
Western	.1116342	.0500553	2.23	0.026	.0135276	.2097407
period						
2	-.020502	.0040107	-5.11	0.000	-.0283627	-.0126413
3	.2226908	.0608043	3.66	0.000	.1035164	.3418651
4	.1973796	.0602815	3.27	0.001	.0792301	.3155292
5	.0737715	.0419552	1.76	0.079	-.0084592	.1560022
6	.1132518	.0450069	2.52	0.012	.0250399	.2014637
m_p_1	-.6481493	.5998822	-1.08	0.280	-1.823897	.5275982
m_p_2	.5261212	.586382	0.90	0.370	-.6231663	1.675409
m_p_3	-.3936963	.2731227	-1.44	0.149	-.9290069	.1416143
m_p_4	.3934615	.276312	1.42	0.154	-.1481	.9350231
m_p_5	-.104496	.1605381	-0.65	0.515	-.4191449	.2101528
m_p_6	0 (omitted)					
_cons	3.671336	.129057	28.45	0.000	3.418389	3.924283
sigma_u	.42806157					
sigma_e	.42885372					
rho	.49907558	(fraction of variance due to u_i)				

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFCS	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
CAI1	.3768865	.2448932	1.54	0.124	-.1030954	.8568683
headsex	-.0296416	.0373799	-0.79	0.428	-.1029048	.0436216
TLU_s	.0310508	.0040071	7.75	0.000	.0231971	.0389045
lnincome	.0114691	.0037393	3.07	0.002	.0041402	.018798
m_CAI1	.4035041	.6579689	0.61	0.540	-.8860912	1.693099
m_TLU	.0360951	.0100497	3.59	0.000	.016398	.0557922
m_lnlincome	-.0059742	.0056632	-1.05	0.291	-.0170739	.0051254
headregion						
Eastern	-.0293101	.0468051	-0.63	0.531	-.1210465	.0624262
Northern	-.0407526	.062618	-0.65	0.515	-.1634816	.0819764
Western	.1110273	.0495037	2.24	0.025	.0140018	.2080528
period						
2	-.0206933	.0040185	-5.15	0.000	-.0285694	-.0128172
3	.2124524	.0600462	3.54	0.000	.0947641	.3301407
4	.1869418	.0594639	3.14	0.002	.0703948	.3034889
5	.0675234	.0408306	1.65	0.098	-.012503	.1475499
6	.1066446	.0438644	2.43	0.015	.0206719	.1926173
m_p_1	-.518882	.5035314	-1.03	0.303	-1.505785	.4680214
m_p_2	.424414	.4857363	0.87	0.382	-.5276117	1.37644
m_p_3	-.3475924	.2719468	-1.28	0.201	-.8805983	.1854134
m_p_4	.3498338	.2698198	1.30	0.195	-.1790033	.8786708
m_p_5	-.0927909	.162501	-0.57	0.568	-.411287	.2257051
m_p_6	0 (omitted)					
_cons	3.662902	.1300768	28.16	0.000	3.407957	3.917848
sigma_u	.42839068					
sigma_e	.42882118					
rho	.49949779	(fraction of variance due to u_i)				

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFCS	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
CAI2	.5789595	.2892833	2.00	0.045	.0119747	1.145944
headsex	-.0284032	.0372306	-0.76	0.446	-.1013738	.0445673
TLU_s	.0308753	.0040043	7.71	0.000	.0230271	.0387235
lnincome	.0114792	.0037305	3.08	0.002	.0041676	.0187909
m_CAI2	-.6550567	.8772421	-0.75	0.455	-2.37442	1.064306
m_TLU	.0376277	.0101914	3.69	0.000	.0176529	.0576024
m_lincome	-.0057207	.0056229	-1.02	0.309	-.0167415	.0053
headregion						
Eastern	-.0263247	.046228	-0.57	0.569	-.11693	.0642806
Northern	-.0392051	.0624844	-0.63	0.530	-.1616722	.083262
Western	.1116238	.0493286	2.26	0.024	.0149415	.2083061
period						
2	-.021146	.0040901	-5.17	0.000	-.0291625	-.0131295
3	.2077091	.0602488	3.45	0.001	.0896236	.3257946
4	.1823291	.0596246	3.06	0.002	.0654671	.2991912
5	.0642201	.0406049	1.58	0.114	-.0153641	.1438042
6	.1040041	.043742	2.38	0.017	.0182714	.1897369
m_p_1	-.5609453	.4862202	-1.15	0.249	-1.513919	.3920288
m_p_2	.4122323	.4696861	0.88	0.380	-.5083355	1.3328
m_p_3	-.3236281	.2779755	-1.16	0.244	-.8684501	.2211938
m_p_4	.3164712	.2729749	1.16	0.246	-.2185497	.8514922
m_p_5	-.1031675	.1609354	-0.64	0.521	-.4185952	.2122601
m_p_6	0	(omitted)				
_cons	3.694326	.1273029	29.02	0.000	3.444817	3.943835
sigma_u	.42829112					
sigma_e	.42848756					
rho	.49977072	(fraction of variance due to u_i)				

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFCS	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
CAI3	.3371168	.2015308	1.67	0.094	-.0578763	.73211
headsex	-.0284174	.0372588	-0.76	0.446	-.1014433	.0446085
TLU_s	.0310549	.0040018	7.76	0.000	.0232115	.0388983
lnincome	.0114979	.0037319	3.08	0.002	.0041835	.0188122
m_CAI3	-.0668737	.6488863	-0.10	0.918	-1.338668	1.20492
m_TLU	.0368238	.0101331	3.63	0.000	.0169632	.0566844
m_lincome	-.0058621	.0056478	-1.04	0.299	-.0169316	.0052074
headregion						
Eastern	-.0265187	.0463337	-0.57	0.567	-.117331	.0642937
Northern	-.0402518	.0625476	-0.64	0.520	-.1628429	.0823392
Western	.1117259	.0495124	2.26	0.024	.0146833	.2087684
period						
2	-.0210433	.0040521	-5.19	0.000	-.0289852	-.0131014
3	.2142894	.0603449	3.55	0.000	.0960155	.3325632
4	.1891546	.0597617	3.17	0.002	.0720238	.3062855
5	.0684871	.0409985	1.67	0.095	-.0118685	.1488428
6	.1076801	.0441077	2.44	0.015	.0212306	.1941295
m_p_1	-.5325945	.4876167	-1.09	0.275	-1.488306	.4231167
m_p_2	.4122843	.4702613	0.88	0.381	-.5094109	1.33398
m_p_3	-.3348341	.2762721	-1.21	0.226	-.8763175	.2066493
m_p_4	.3287471	.2698381	1.22	0.223	-.2001259	.8576201
m_p_5	-.0988398	.1609926	-0.61	0.539	-.4143796	.2167
m_p_6	0	(omitted)				
_cons	3.677188	.1264156	29.09	0.000	3.429418	3.924958
sigma_u	.42844212					
sigma_e	.42878305					
rho	.49960229	(fraction of variance due to u_i)				

B.1.2 For FES Outcome

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFES	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
area_improved_maize_seed_s	-.0653583	.0434415	-1.50	0.132	-.1505021	.0197855
headsex	.0072825	.0458268	0.16	0.874	-.0825365	.0971014
TLU_s	-.0274456	.0075472	-3.64	0.000	-.0422377	-.0126534
lnincome	-.0100176	.0051438	-1.95	0.051	-.0200992	.0000641
m_imseeds	-.1272412	.0770536	-1.65	0.099	-.2782635	.0237812
m_TLU	-.0525212	.0173764	-3.02	0.003	-.0865783	-.0184641
m_lnlncome	-.0042394	.0073407	-0.58	0.564	-.018627	.0101482
headregion						
Eastern	-.1755263	.0538237	-3.26	0.001	-.2810188	-.0700338
Northern	.086833	.0790706	1.10	0.272	-.0681426	.2418086
Western	-.1916455	.0638118	-3.00	0.003	-.3167144	-.0665766
period						
2	.0171538	.0058304	2.94	0.003	.0057263	.0285813
3	-.0305706	.0784693	-0.39	0.697	-.1843677	.1232264
4	-.0120904	.0791708	-0.15	0.879	-.1672623	.1430814
5	-.0093904	.0519969	-0.18	0.857	-.1113025	.0925217
6	-.0156331	.0537577	-0.29	0.771	-.1209963	.0897301
m_p_1	.6449402	1.846154	0.35	0.727	-2.973456	4.263336
m_p_2	-.6130709	1.835772	-0.33	0.738	-4.211117	2.984975
m_p_3	.805477	.6835953	1.18	0.239	-.5343452	2.145299
m_p_4	-.4338795	.6670754	-0.65	0.515	-1.741323	.8735643
m_p_5	.0552029	.2021299	0.27	0.785	-.3409645	.4513703
m_p_6	0 (omitted)					
_cons	2.111489	.1519078	13.90	0.000	1.813755	2.409223
sigma_u	.57564917					
sigma_e	.55745525					
rho	.51605256	(fraction of variance due to u_i)				

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFES	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
CAI1	-.9372365	.4399088	-2.13	0.033	-1.799442	-.0750311
headsex	.020425	.0459821	0.44	0.657	-.0696982	.1105481
TLU_s	-.0268295	.0075084	-3.57	0.000	-.0415458	-.0121133
lnincome	-.0101576	.0051083	-1.99	0.047	-.0201698	-.0001455
m_CAI1	-2.002451	.8881147	-2.25	0.024	-3.743124	-.2617781
m_TLU	-.0501494	.0171999	-2.92	0.004	-.0838606	-.0164381
m_lnlincome	-.0027442	.0073091	-0.38	0.707	-.0170699	.0115815
headregion						
Eastern	-.1813186	.0535471	-3.39	0.001	-.2862689	-.0763682
Northern	.0638188	.0787809	0.81	0.418	-.0905888	.2182265
Western	-.1991479	.0637632	-3.12	0.002	-.3241215	-.0741743
period						
2	.0174964	.0061201	2.86	0.004	.0055014	.0294915
3	-.0049363	.078557	-0.06	0.950	-.1589052	.1490326
4	.0132128	.0792954	0.17	0.868	-.1422033	.1686289
5	.0099711	.0518468	0.19	0.847	-.0916468	.1115891
6	.003414	.053596	0.06	0.949	-.1016323	.1084603
m_p_1	.414432	1.75243	0.24	0.813	-3.020267	3.849131
m_p_2	-.4986789	1.741516	-0.29	0.775	-3.911988	2.91463
m_p_3	.778292	.6420633	1.21	0.225	-.4801289	2.036713
m_p_4	-.4317928	.6211859	-0.70	0.487	-1.649295	.7857091
m_p_5	.0179642	.1993838	0.09	0.928	-.3728208	.4087492
m_p_6	0	(omitted)				
_cons	2.171338	.1520716	14.28	0.000	1.873284	2.469393
sigma_u	.57426238					
sigma_e	.55658775					
rho	.51562569	(fraction of variance due to u_i)				

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFES	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
CAI2	-1.086395	.5209234	-2.09	0.037	-2.107386	-.0654042
headsex	.0213673	.0461719	0.46	0.644	-.0691279	.1118624
TLU_s	-.0270015	.0075248	-3.59	0.000	-.0417498	-.0122532
lnincome	-.0102146	.0051055	-2.00	0.045	-.0202212	-.000208
m_CAI2	-2.180798	.9328402	-2.34	0.019	-4.009131	-.3524647
m_TLU	-.0478499	.0172466	-2.77	0.006	-.0816526	-.0140472
m_lnlincome	-.0030212	.0073104	-0.41	0.679	-.0173492	.0113068
headregion						
Eastern	-.1898612	.0538395	-3.53	0.000	-.2953847	-.0843377
Northern	.0545063	.0787966	0.69	0.489	-.0999321	.2089448
Western	-.2034444	.0639602	-3.18	0.001	-.3288042	-.0780846
period						
2	.0184062	.0061504	2.99	0.003	.0063517	.0304607
3	-9.09e-06	.0796548	-0.00	1.000	-.1561297	.1561115
4	.0183965	.0804713	0.23	0.819	-.1393243	.1761173
5	.0128986	.0527207	0.24	0.807	-.0904321	.1162293
6	.0048545	.0540762	0.09	0.928	-.101133	.110842
m_p_1	.4483228	1.778556	0.25	0.801	-3.037582	3.934228
m_p_2	-.5390463	1.767695	-0.30	0.760	-4.003665	2.925573
m_p_3	.7499104	.6487291	1.16	0.248	-.5215753	2.021396
m_p_4	-.4065465	.6283311	-0.65	0.518	-1.638053	.8249599
m_p_5	.0251695	.1986091	0.13	0.899	-.3640972	.4144361
m_p_6	0	(omitted)				
_cons	2.178994	.152875	14.25	0.000	1.879364	2.478623
sigma_u	.57390415					
sigma_e	.5566857					
rho	.51522609	(fraction of variance due to u_i)				

(Std. err. adjusted for 1,064 clusters in hhid_num)

logFES	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
CAI3	-.7835527	.4126255	-1.90	0.058	-1.592284	.0251784
headsex	.0212841	.0459702	0.46	0.643	-.0688158	.1113839
TLU_s	-.0270033	.0075201	-3.59	0.000	-.0417423	-.0122642
lnincome	-.0102789	.0051023	-2.01	0.044	-.0202792	-.0002787
m_CAI3	-1.836115	.7823802	-2.35	0.019	-3.369553	-.3026784
m_TLU	-.049435	.0171687	-2.88	0.004	-.0830851	-.015785
m_lincome	-.0023963	.0073094	-0.33	0.743	-.0167226	.0119299
headregion						
Eastern	-.1907465	.0537988	-3.55	0.000	-.2961901	-.0853028
Northern	.0573293	.0787547	0.73	0.467	-.097027	.2116856
Western	-.204818	.0641251	-3.19	0.001	-.330501	-.0791351
period						
2	.0183333	.0061693	2.97	0.003	.0062417	.0304248
3	-.0098774	.078588	-0.13	0.900	-.1639072	.1441523
4	.007583	.0792944	0.10	0.924	-.1478311	.1629971
5	.0076541	.0519259	0.15	0.883	-.0941187	.109427
6	.0006684	.0535365	0.01	0.990	-.1042611	.105598
m_p_1	.4270848	1.765237	0.24	0.809	-3.032716	3.886886
m_p_2	-.5011039	1.754492	-0.29	0.775	-3.939845	2.937637
m_p_3	.7720975	.6436946	1.20	0.230	-.4895207	2.033716
m_p_4	-.4169849	.6225892	-0.67	0.503	-1.637237	.8032675
m_p_5	.02202	.1993021	0.11	0.912	-.368605	.412645
m_p_6	0	(omitted)				
_cons	2.172776	.1519257	14.30	0.000	1.875007	2.470544
sigma_u	.57339038					
sigma_e	.55681841					
rho	.5146596	(fraction of variance due to u_i)				

B.2 Control Function Approach Results (CFA)

B.2.1 First Stage results

```
. reg CAI1 extension_access headsex TLU_s lnincome i.headregion i.period, cluster(hhid_num)
```

Linear regression

```
Number of obs   =   3,019
F(12, 1063)     =   21.83
Prob > F        =   0.0000
R-squared       =   0.0936
Root MSE       =   .04373
```

(Std. err. adjusted for 1,064 clusters in hhid_num)

CAI1	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
extension_access	.0168902	.0044636	3.78	0.000	.0081318	.0256487
headsex	.0111519	.0017324	6.44	0.000	.0077525	.0145512
TLU_s	.0014794	.000479	3.09	0.002	.0005395	.0024193
lnincome	-.0000264	.000165	-0.16	0.873	-.0003502	.0002974
headregion						
Eastern	-.000294	.0025291	-0.12	0.907	-.0052566	.0046687
Northern	-.0184113	.0029209	-6.30	0.000	-.0241427	-.0126798
Western	-.0103302	.0022668	-4.56	0.000	-.014778	-.0058824
period						
2	.0000812	.0020606	0.04	0.969	-.0039622	.0041246
3	.0243902	.0036161	6.74	0.000	.0172948	.0314856
4	.0227166	.0032102	7.08	0.000	.0164175	.0290157
5	.0215581	.0023195	9.29	0.000	.0170068	.0261094
6	.0212181	.002733	7.76	0.000	.0158553	.0265808
_cons	.0036576	.002337	1.57	0.118	-.0009281	.0082433

```
. reg CAI2 extension_access headsex TLU_s lnincome i.headregion i.period, cluster(hhid_num)
```

Linear regression

```
Number of obs   =   3,019
F(12, 1063)     =   25.25
Prob > F        =   0.0000
R-squared       =   0.1073
Root MSE       =   .03746
```

(Std. err. adjusted for 1,064 clusters in hhid_num)

CAI2	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
extension_access	.0103736	.0033862	3.06	0.002	.0037292	.0170181
headsex	.0103012	.0016085	6.40	0.000	.007145	.0134574
TLU_s	.0014286	.0004138	3.45	0.001	.0006167	.0022406
lnincome	-.0001052	.0001498	-0.70	0.483	-.0003992	.0001888
headregion						
Eastern	-.0054006	.0021497	-2.51	0.012	-.0096188	-.0011824
Northern	-.0213957	.0025958	-8.24	0.000	-.0264892	-.0163021
Western	-.0124838	.0022861	-5.46	0.000	-.0169696	-.007998
period						
2	.0008957	.0017003	0.53	0.598	-.0024407	.004232
3	.0245827	.003345	7.35	0.000	.0180191	.0311462
4	.0231877	.0030758	7.54	0.000	.0171525	.029223
5	.0212359	.0020061	10.59	0.000	.0172996	.0251723
6	.0196081	.0022059	8.89	0.000	.0152796	.0239366
_cons	.0073893	.0020987	3.52	0.000	.0032713	.0115074


```

. xtreg logFES CAI1 CAI1_hat headsex TLU_s lnincome i.headregion i.period, fe vce(cluster hhid_num)

```

```

Fixed-effects (within) regression      Number of obs   =    3,004
Group variable: hhid_num              Number of groups =    1,062

```

```

R-squared:                            Obs per group:
  Within = 0.0435                      min =          1
  Between = 0.0410                     avg =          2.8
  Overall = 0.0395                      max =          6

```

```

corr(u_i, Xb) = 0.0053                 F(13,1061)     =    3.03
                                        Prob > F        =    0.0002

```

(Std. err. adjusted for 1,062 clusters in hhid_num)

logFES	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CAI1	-8.960553	5.743114	-1.56	0.119	-20.2297	2.308599
CAI1_hat	8.152432	5.77211	1.41	0.158	-3.173616	19.47848
headsex	.1063063	.0928631	1.14	0.253	-.07591	.2885225
TLU_s	-.0137616	.0120036	-1.15	0.252	-.037315	.0097919
lnincome	-.0087485	.0055202	-1.58	0.113	-.0195802	.0020832
headregion						
Eastern	-.2057796	.0766404	-2.69	0.007	-.3561635	-.0553957
Northern	-.0863179	.1489811	-0.58	0.562	-.378649	.2060131
Western	-.343361	.1079201	-3.18	0.002	-.5551221	-.1315999
period						
2	.0178669	.0061088	2.92	0.004	.0058803	.0298536
3	.1975266	.1681069	1.18	0.240	-.1323331	.5273863
4	.2003687	.1595806	1.26	0.210	-.1127606	.5134981
5	.1743132	.1338185	1.30	0.193	-.0882657	.4368922
6	.1632028	.132449	1.23	0.218	-.0966889	.4230944
_cons	2.160368	.0762569	28.33	0.000	2.010737	2.31
sigma_u	.69375455					
sigma_e	.55635768					
rho	.60859583	(fraction of variance due to u_i)				

logFES	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CAI2	-14.5965	9.319899	-1.57	0.118	-32.88403	3.691023
CAI2_hat	13.66128	9.339265	1.46	0.144	-4.664248	31.98681
headsex	.1581146	.1183935	1.34	0.182	-.0741975	.3904266
TLU_s	-.0063362	.0159831	-0.40	0.692	-.0376984	.0250259
lnincome	-.0100187	.005636	-1.78	0.076	-.0210777	.0010403
headregion						
Eastern	-.2837073	.0911613	-3.11	0.002	-.4625842	-.1048304
Northern	-.2359508	.2258023	-1.04	0.296	-.6790205	.207119
Western	-.4352937	.1491216	-2.92	0.004	-.7279004	-.1426869
period						

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2	.0301514	.0101147	2.98	0.003	.0103044	.0499985
3	.3389642	.2490902	1.36	0.174	-.1498011	.8277295
4	.3365848	.2364139	1.42	0.155	-.1273071	.8004766
5	.2910854	.2038433	1.43	0.154	-.1088965	.6910672
6	.259313	.1894566	1.37	0.171	-.1124392	.6310651
_cons	2.235606	.1054883	21.19	0.000	2.028617	2.442596
sigma_u	.69347817					
sigma_e	.55638843					
rho	.60837964	(fraction of variance due to u_i)				

Fixed-effects (within) regression
 Group variable: **hhid_num**

Number of obs = **3,004**
 Number of groups = **1,062**

R-squared:
 Within = **0.0427**
 Between = **0.0405**
 Overall = **0.0389**

Obs per group:
 min = **1**
 avg = **2.8**
 max = **6**

corr(u_i, Xb) = **0.0043**

F(13,1061) = **2.98**
 Prob > F = **0.0003**

(Std. err. adjusted for **1,062** clusters in **hhid_num**)

logFES	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CAI3	-7.590215	4.883554	-1.55	0.120	-17.17274	1.992307
CAI3_hat	6.961254	4.908654	1.42	0.156	-2.670519	16.59303
headsex	.1068155	.0930303	1.15	0.251	-.0757287	.2893598
TLU_s	-.0150467	.0113795	-1.32	0.186	-.0373757	.0072823
lnincome	-.0091555	.0055372	-1.65	0.099	-.0200206	.0017097
headregion						
Eastern	-.2632551	.0849384	-3.10	0.002	-.4299215	-.0965887
Northern	-.1212563	.1650545	-0.73	0.463	-.4451267	.2026141
Western	-.380174	.1226632	-3.10	0.002	-.620864	-.1394839
period						
2	.0273171	.0088011	3.10	0.002	.0100475	.0445866
3	.1572628	.1470398	1.07	0.285	-.131259	.4457847
4	.1532024	.1356361	1.13	0.259	-.112943	.4193478
5	.151171	.1210046	1.25	0.212	-.0862645	.3886065
6	.1331834	.1156061	1.15	0.250	-.0936592	.3600261
_cons	2.202538	.090583	24.32	0.000	2.024796	2.380281
sigma_u	.69390094					
sigma_e	.55658795					
rho	.6084992	(fraction of variance due to u_i)				

Note: The generalized residuals are statistically insignificant across all specifications ($p > 0.05$), indicating no evidence of endogeneity. Therefore, the Composite Adoption Indices (CAI1–CAI3) are treated as exogenous.