
Volume 3 No: 4 (2018)

# Agricultural Extension Service and Technology Adoption for Food and Nutrition Security: Evidence from Ethiopia

Tigabu Degu Getahun and Gebeyehu Manie Fetene

July 2018

EDRI Ethiopian Development Research Institute (EDRI)

PARI

FARA Forum for Agricultural Research in Africa

Zentrum für Entwicklungsforschung
Center for Development Research
University of Bonn
ZEF Bonn

ISSN 2550-3359

**Citation**

Tigabu D. G., Gebeyehu M. F. (2018). Agricultural Extension Service and Technology Adoption for Food and Nutrition Security: Evidence from Ethiopia. FARA Research Report 3(4):30

**Corresponding Author**

Tigabu Degu (tigyget14@gmail.com)



**Forum for Agricultural Research in Africa (FARA)**
12 Anmeda Street, Roman Ridge PMB CT 173, Accra, Ghana Tel: +233 302 772823 / 302 779421
Fax: +233 302 773676 Email: info@faraafrica.org Website: www.faraafrica.org



**ISSN: 2550-3359**

## About FARA

The Forum for Agricultural Research in Africa (FARA) is the apex continental organisation responsible for coordinating and advocating for agricultural research-for-development. (AR4D). It serves as the entry point for agricultural research initiatives designed to have a continental reach or a sub-continental reach spanning more than one sub-region.

FARA serves as the technical arm of the African Union Commission (AUC) on matters concerning agricultural science, technology and innovation. FARA has provided a continental forum for stakeholders in AR4D to shape the vision and agenda for the sub-sector and to mobilise themselves to respond to key continent-wide development frameworks, notably the Comprehensive Africa Agriculture Development Programme (CAADP).

**FARA's vision is;** "Reduced poverty in Africa as a result of sustainable broad-based agricultural growth and improved livelihoods, particularly of smallholder and pastoral enterprises" its **mission is the** "Creation of broad-based improvements in agricultural productivity, competitiveness and markets by strengthening the capacity for agricultural innovation at the continental-level"; its **Value Proposition is the** "Strengthening Africa's capacity for innovation and transformation by visioning its strategic direction, integrating its capacities for change and creating an enabling policy environment for implementation". FARA's strategic direction is derived from and aligned to the Science Agenda for Agriculture in Africa (S3A), which is in turn designed to support the realization of the CAADP vision.

## About FARA Research Result (FRR)

FARA Research Report (FRR) is an online organ of the Forum for Agricultural Research in Africa (FARA). It aims to promote access to information generated from research activities, commissioned studies or other intellectual inquiry that are not structured to yield journal articles. The outputs could be preliminary in most cases and in other instances final. The papers are only published after FARA secretariat internal review and adjudgment as suitable for the intellectual community consumption.

**Abstract**

The objective of this paper is twofold. First, using a three rounds panel data of 7110 households, we investigate the adoption decisions and the complementarities among the four labor-intensive technologies (agricultural extension service, irrigation, soil conservation and planting seeds in a row) and a comprehensive use of four modern inputs (improved seed variates, inorganic fertilizer, pesticides, organic fertilizer) which have been frequently adopted by smallholder farmers. Second, controlling for the dynamic effects of wealth, previous technology adoptions and other cofounders, we estimate the impact of agricultural extension services and other multiple technology adoptions on food and nutrition security of the smallholder farmers in Ethiopia. The estimation results indicate that a significant complementarity between modern inputs and labor-intensive technologies. This suggests that the adoption of modern inputs induces farmers to adopt labor-intensive technologies and vice versa. In addition, our finding suggests that farmers who adopt technologies once are more likely to adopt the technologies again, reflecting the profitability of agricultural technology adoption. Our finding also indicates that agricultural extension services and technology adoption have a statistically significant and positive impact on nutrition and food security.



**Keywords**

Agricultural technologies adoption; input complementarity; food and nutrition security.

## Introduction

The prevalence of undernourishment is increasing and around 815 million of the world population has been undernourished in 2016 (FAO, 2017). The prevalence of undernourishment is the highest in Africa where agriculture is the dominant sector and where there is huge yield-gap (FAO, 2017; Luan et al., 2013). A review by de Graaff et al. (2010) of the food security and agricultural trends in the past 40 years in Sub-Sahara Africa shows that achieving food security remains a challenging issues and food aid is still indispensable. Moreover, the rural households in most developing countries remain disproportionally poor. As a result, the primary goal of many of the developing countries remains producing sufficient food (de Graaff et al., 2011; Garrity et al., 2010; Luan et al., 2013).

Since the seminar work of Griliches (1957) and the formal adoption and diffusion models applied by Mansfield (1963), Feder et al. (1985) and Green & Ng'ong'ola (1993), agricultural technology adoption is considered as one means of securing food and nutrition by increasing productivity and rural income. A number of studies empirically investigated the adoption decisions and the contributions of agricultural technologies for improving the income of the stallholder farmers. For instance, in Tanzania, Magrini & Vigani (2016) found among maize that adoption of improved seed and inorganic fertilizer increased the availability of food. In Ethiopia, Jalet et al. (2015) found that adoption of improved maize varieties increases consumption per capita while Kassie et al. (2008) found that soil conservation mechanisms increases land productivity in semi-arid areas of Ethiopia. In India, Mahanta & Rai (2008) found that inorganic fertilizer increases productivity and is profitable in soybean and wheat production. In Kenya, Suri (2011) found a mixed effect of adoption of hybrid maize, Mucheru-Muna et al. (2014) found that adoption of both organic and inorganic fertilizers increased productivity in maize production while Duflo et al. (2008) found that optimal application of inorganic fertilizer is profitable, but not other levels of fertilizer use including the combination of fertilizer and hybrid seed. In Uganda, Pan et al. (2015) found that adoption of agricultural extension services that focused on improving the cultivation method increased agricultural production, savings and wage income. There are also a number of studies that investigate adoption decisions of various agricultural technologies (see, e.g., Abate et al. (2016), Abiy et al. (2017); Ahmed et al. (2017), Beaman et al. (2015), Duflo et al. (2011), Magrini et al. (2014), Teklewold et al. (2013), Zeweld et al. (2017)).

However, most of these studies analyzed the adoption decisions of a single technology or joint adoption of only few of the many technologies that farmers practically use. Emerging studies found that studies based on single or only few joint technologies adoption decisions suffer from endogeneity and simultaneity problems and provide incomplete picture of the reality since practically farmers choose among and use multiple technologies (Abay et al., 2017; Feder, 1982; Nyangera and Juma, 2014; Teklewold et al., 2013; Yu et al., 2012). For instance, Abay et al. (2017) find a 0.7, 0.23 and 0.06 correlation coefficients respectively between fertilizer use and improved seed adoption, inorganic fertilizer and extension service use and between improved seed adoption and extension service use. Even studies that investigated multiple technologies adoption have not comprehensively addressed technologies that farmers usually adopt. Some of these studies investigate the adoption decisions of modern technologies only (see, e.g., Abay et al. (2017), Duflo et al. (2008), Mahanta and Rai (2008), Zeweld et al. (2016)) and their effects on farmers' welfare (see, e.g., Goshu et al. (2012), Manda et al. (2016)). Others have investigated adoption decisions of labor-intensive technologies only (see, e.g., Kassie et al. (2008)). Indeed, there are studies that analyzed adoption decisions of modern and labor-intensive technologies and their effects on farmers' welfare, (e.g., Ahmed et al. (2017), Magrini et al. (2014), Mucheru-Muna et al. (2014) and Teklewold et al. (2013). However, these studies considered only few of the many technologies that the smallholders practically adopt, as evidently presented in the later section of this paper, with the obvious implication of inaccurate estimates. Moreover, previous studies that investigated the effects of technologies on the welfare of farmers do not control for the dynamic effects of income and technology adoptions. Studies that did not address the dynamic effect of wealth on food and nutrition security may suffer methodological flaws resulting in inaccurate estimates. This paper aims to contribute to this literature gap.

Using multivariate probit model, we analyze the farmers' multidimensional technology adoption decisions of a comprehensive of four modern inputs and four labor-intensive technologies including improved seed varieties, inorganic fertilizer, chemicals (that includes pesticides, herbicides, fungicides and others), extension service, organic fertilizer, irrigation, soil conservation and planting seeds in a row. These are the main technologies that farmers at least in Ethiopia usually adopt. Then, we investigate the determinants of the eight agricultural technologies adoption decisions. Finally, we investigate the effects of these technologies on food and nutrition security of the households after three and five years of the adoptions after controlling for the dynamic effect of wealth and controlling for the endogeinity problem between technology adoption and income. Adoption of technologies may affect food and nutrition security by increasing productivity and quality of the products (Manda et al., 2016; Mangisoni, 2008; Pan et al., 2015). However, studies show that adoption of modern inputs may not be profitable for some farmers (Burke et al., 2017; Marenya & Barrett, 2009; Suri, 2011). Thus, it is essential to investigate the effects of multiple technologies that farmers usually adopt on food and nutrition security.

We use a unique panel dataset of 7110 farm-households that were collected in 2011, 2013 and in 2017 by the Central Statistics Authority (CSA) of Ethiopia in collaboration with the International Food Policy Research Institute (IFPRI) and the Ethiopian Development Research Institute (EDRI). The dataset covers most important agricultural zones in Ethiopia and is reach contenting detailed household and plot characteristics, livestock ownership and production, crop varieties harvested and harvesting methods, agricultural technologies access and use, information and factor market access, shock variables, food and nutrition security and dietary diversity and agro-climate information.

The paper has at least the following contributions to the adoption of agricultural technologies literature including to Abay et al. (2017), Duflo et al. (2008), Kassie et al. (2008), Mahanta and Rai (2008), Suri (2011), Teklewold et al. (2013), etc. as well to the effects of the adoptions on farmers' welfare literature including to Abate et al. (2016), Magrini et al. (2014), Mucheru-Muna et al. (2013), Qaim (2014), Tesfaye et al. (2016), etc. First, by considering most of the technologies that have been adopted by smallholders, at least, in Ethiopia, we better control for the complementarities between labor-intensive technologies and modern inputs as well as among modern inputs and among labor-intensive technologies. Second, we examine the effects on food and nutrition security of the adoptions of the technologies after three and five years of the adoption after controlling for the dynamic effect of wealth and controlling for the endogeinity problem between technology adoption and income. Third, we use four indicators of food and nutrition security to better distinguish the behavioral and socio-religious reasons from the economic reasons for food and nutrition security. Fourth, we consider the adoptions of the eight technologies for all of the crops that the farmers harvested instead of considering only the adoption for a single crop in that households who didn't adopt technologies for the crop of interest but adopted technologies for other crops have been considered as "non-adopters" in most previous studies. Finally, we use a rich data that have detailed information well suited for the study. Indeed, Abay et al. (2017) also used the 2011 and 2013 dataset that we use. However, we also used the 2017 data as well in addition to addressing five more technologies and investigating the effects of the adoptions on food security that were not addressed by Abay et al.

The remaining section of the paper is organized as follows. Section two presents the data collection method, a brief about the dependent variables, trends of adoption and the unconditional complementarity among technologies. Section three presents the empirical specification followed by section four presenting the results from econometric models. Section five concludes the paper.

## Sampling Design, Data and Description of Variables

### Sampling design

Our analysis is based on a large panel dataset collected from major crop producing four regions in Ethiopia, namely Amhara, Oromia, Southern People, nations and Nationalities (SNNP) and Tigray. The data were collected to evaluate the performance of the Agricultural Growth Program. Multistage sampling technique was used to collect the data. First, 93 woredas (districts) were selected from the four regions. Then, three enumeration areas were randomly selected from each woreda, and finally, a total of 7927 households were randomly selected from the enumeration areas in 2011. Out of the 7927 households, 7503 and 7110 households were re-interviewed in 2013 and 2017 respectively, implying a 10% overall attrition rate. We used these 7110 panel households for our analysis.

Covering the most important agricultural zones in Ethiopia, the dataset has rich information and covers a large geographical and ecological area that is well-suited for this study. The dataset has detailed plot and household characteristics as well as socio-economic variables and households' participation in meetings and trainings. Moreover, the dataset contents information on market existence and access such as whether the household has media access and whether the household follows price information, whether the households have access to credits and factor markets, distance to the markets and towns, whether there are training and demonstration centers, etc.

**Dependent variables**

**A. Agricultural Technologies**

We choose the eight agricultural technologies that have been mostly practiced in Ethiopia. The first variable that we consider is agricultural extension service that provides consultation and training about land preparation, planting fertilizer and seeds, harvesting, soil conversation, irrigating and about the importance of modern inputs for farmers (Abay et al., 2017). Following previous studies (e.g., Abay et al. (2017)), we consider DAs' service as a "knowledge input" and a decision variable for farmers to choose (or not choose) to have it since it is usually their choice to participate in the trainings that the DAs call for as well as the decision to seek private consultation from the DAs. Our second and third dependent variables are irrigation and soil conservation, which increase productivity (Barbier, 1990; Kassie et al., 2008; Teklewold et al., 2013). Our fourth technology that we consider is the type of planting of seeds since planting in a row increases yield when compared to broadcasting method (Caliskan et al., 2004). Adoption of inorganic fertilizer is our fifth dependent variable. Several studies have shown that inorganic fertilizer increases productivity even though it may not be profitable for some farmers depending on timeliness and amount of application and plot type (Mahanta and Rai, 2008; Suri, 2011). Adoption of improved seed varieties are the six agricultural technologies that we analyze. Improved seed varieties could improve food security by improving productivity (Byerlee, 1994 and Shiferaw et al. (2012)). Organic fertilizer (manure or compost) is the seventh dependent variable that we investigate. Organic fertilizers are considered as a sustainable means of increasing productivity and maintaining the soil fertility (Mucheru-Muna et al., 2014). The last agricultural technology that we consider is adoption of chemicals including pesticides, insecticides, herbicides and fungicides used to protect the crops against pests, insects, weeds and fungi. Empirical studies about the relevance of adopting chemicals is mixed in that, on the one hand, they increase yield, and, on the other hand, they negatively impact farmers' health, the environment, agricultural land and the biodiversity (Antle et al., 1994, 1997; Crissman et al., 1994; Wilson and Tisdell, 2000). Literature about adoption of chemicals in Ethiopia is limited.

Table 1 presents the adoption rates of the eight agricultural technologies over the three survey periods. For instance, the percent of households who used DA service in 12 months preceding the surveys were 48% in 2011, 51% in 2013 and 53% in 2017; whereas the percent of households who practiced soil conservation in five years preceding the surveys were around 71% in 2011, 53% in 2013 and 60% in 2017. The share of the households who irrigated their land was below 10% in all survey years while about half of the households planted the seeds in a row in all the three survey years. While adoption of some of the technologies increased overtime (e.g., improved seed, DA service and inorganic fertilizer), adoption of other technologies declined (e.g., soil conservation and irrigation). One potential reason for the lower percentage of households responding that they did not adopt soil conservation practices in 2013 and 2017 than in 2011 could be that, once adopted, most of the soil conservations last long time in that the farmers may not need to adopt the technology gain on the same plot within the five years of the surveys period.

The table further presents that more than half of the households who adopted the technologies in 2011 continued adopting the technologies in 2013. For instance, 29% of the households which used DA service in 2011 also used in 2013 while 22% of households who did not use DA service in 2011 used in 2013. Similarly, more than half of the households who adopted the technologies in 2011 or in 2013 continued adopting the technologies in 2017. For instance, 42% of households who adopted improved seeds in 2011 or in 2013 also adopted in 2017while only 11% of the households who did not adopt improved seeds in 2011 and 2013 adopted the technology in 2017.

Table 1 presents also the correlations among the eight agricultural technologies. The complementarities among the technologies imply that the (perceived) productivity of one technology depends on the adoption of another technology in that the farmers have to adopt the technologies together. The results show that there are statistically significant correlations among the eight technologies and between modern and labor intensive technologies.

**Table 1: Technology adoption rates, trends and correlation among adoption of technologies over the survey periods**

| **Technology types** | **N** | **2011 (%)** | **2013 (%)** | | | **2017 (%)** | | |
|---|---|---|---|---|---|---|---|---|
| | | | **Continued adopting** | **New adopters** | **Total** | **Continued adopting** | **New adopters** | **Total** |
| Households received DA advice | 7,073 | 48 | 29 | 22 | 51 | 42 | 11 | 53 |
| Households adopted improved seed | 6,161 | 24 | 12 | 9 | 21 | 20 | 19 | 39 |
| Households adopted chemicals | 6,207 | 40 | 19 | 8 | 27 | 28 | 10 | 38 |
| Households adopted inorganic fertilizer | 7,110 | 59 | 45 | 13 | 58 | 55 | 9 | 64 |
| Households practiced soil conservation | 7,089 | 71 | 44 | 9 | 53 | 53 | 7 | 60 |
| Households planted the seed in a row | 6,580 | 50 | 35 | 13 | 48 | 44 | 10 | 54 |
| Households irrigated (part/all of) plot(s) | 6,694 | 10 | 3 | 2 | 5 | 5 | 4 | 9 |
| Households adopted organic fertilizer | 7,110 | 66 | 14 | 4 | 18 | 34 | 8 | 42 |
| Correlation between seeding in a row and: | | | | | | | | |

| | | | |
|---|---|---|---|
| DA advice | 0.0783*** | 0.146*** | 0.1802*** |
| Soil conservation | 0.0009 | 0.0144 | -0.0283** |
| Improved seed | 0.3236*** | 0.3319*** | 0.3741*** |
| Irrigation | 0.1081*** | 0.0945*** | 0.0730*** |
| Chemicals | 0.1418*** | 0.0534*** | 0.0624*** |
| Inorganic fertilizer | 0.2516*** | 0.1961*** | 0.2877*** |
| Organic fertilizer | 0.1488*** | 0.1092*** | 0.0892*** |
| Correlation between DA visit and: | | | |
| Soil conservation | 0.1541*** | 0.1638*** | 0.1914*** |
| Improved seed | 0.2378*** | 0.2293*** | 0.2243*** |
| Irrigation | 0.0835*** | 0.0769*** | 0.0613*** |
| Chemicals | 0.0289** | 0.1287*** | 0.066*** |
| Inorganic fertilizer | 0.2434*** | 0.3147*** | 0.3738*** |
| Organic fertilizer | 0.0975*** | 0.0959*** | 0.1514*** |
| Correlation between improved seed adoption and: | | | |
| Soil conservation | 0.1255*** | 0.1066*** | 0.0515*** |
| Irrigation | 0.0994*** | 0.1177*** | 0.0387*** |
| Chemicals | 0.1206*** | 0.0740*** | 0.1122*** |
| Inorganic fertilizer | 0.3962*** | 0.3564*** | 0.3189*** |
| Organic fertilizer | 0.0833*** | 0.1016*** | 0.0734*** |
| Correlation between irrigation use and: | | | |
| Chemicals | 0.0357*** | 0.0016 | 0.019 |
| Soil conservation | 0.1229*** | 0.0990*** | 0.0591*** |
| Inorganic fertilizer | 0.1224*** | 0.1067*** | 0.104*** |
| Organic fertilizer | 0.0273** | 0.0618*** | 0.0344*** |
| Correlation between chemical use and: | | | |
| Inorganic fertilizer | 0.3357*** | 0.3211*** | 0.2129*** |
| Soil conservation | 0.0787 *** | 0.1138*** | 0.0761*** |
| Organic fertilizer | 0.0957*** | 0.0294** | 0.0586*** |
| Correlation between organic and inorganic fertilizer adoption | 0.1306** | 0.0684*** | 0.1147*** |
| Correlation between soil conservation & inorganic fertilizer | 0.2288*** | 0.2182*** | 0.2137*** |

| | | | |
|---|---|---|---|
| Correlation between soil conservation & Organic fertilizer | 0.0815*** | 0.0457*** | 0.0737*** |

Notes: *, ** and *** respectively indicate that the pairwise correlations are statistically significant at < 10%, 5<% & <1% levels of significance.

### B. Food and nutrition security

The second dependent variables is food and nutrition security. We use four indicators of food and nutrition security. The first measure is the number of months that households experienced food shortage problem in 12 months preceding the surveys. This measure could show the year-long food security conditions of the households. Table 2 presents the number of months and the corresponding percentage of households who were food insecure within a year. The percentage of households who reported that they were not food insecure increased from 45% in 2011 to 72% in 2017. On the other hand, the percentage of households who reported that they were food insecure throughout the year increased from 0.92% in 2011 to 1.06% in 2017. The rest of the households reported between one to eleven months of food insecurity.

**Table 2. The number of months with food insecurity during the last 12 months, over the survey years**

| **The No. of months with food insecurity problem** | **Percentage of households** | | |
|---|---|---|---|
| | **2011** | **2013** | **2017** |
| 0 (food secure) | 45.22 | 33.71 | 71.64 |
| 1 | 7.25 | 44.69 | 3.77 |
| 2 | 19.25 | 15.57 | 8.35 |
| 3 | 12.46 | 2.96 | 6.85 |
| 4 | 6.98 | 1.07 | 3.08 |
| 5 | 3.27 | 0.72 | 1.61 |
| 6 | 2.23 | 0.59 | 1.75 |
| 7 | 0.80 | 0.14 | 0.37 |
| 8 | 0.65 | 0.11 | 0.75 |
| 9 | 0.36 | 0.03 | 0.11 |
| 10 | 0.46 | 0.10 | 0.59 |
| 11 | 0.12 | 0.08 | 0.06 |
| 12 | 0.92 | 0.23 | 1.06 |

**Note. Computed from the data**

The second measure we use is if the households experienced food shortage problem in summer. We include this as one indicator of food security since summer is the main season that households usually experience food shortage problem; summer occurs at the middle of the previous and the next harvesting periods in that some households may have left with only limited food from previous season while food from the coming harvesting season is yet to come. For example, our data show that the months that the largest percentage of households reported serious food shortage problem are August (23%), September (21%) and July (17%) while only 1% of the household reported food insecurity problem in December and January.
The third indicator of food and nutrition security is household dietary diversity score (HDDS) that consists of 10 food groups namely (i) cereals, (ii) root and tubers, (iii) pulses/legumes/nuts, (iv) vegetables, (v) milk and milk products, (vi) fruits, (vii) meat, poultry, offal (viii), sugar/honey (xi), eggs and (x) miscellaneous. Besides dietary diversity, HDDS is considered as one indicator of food security (IFPRI, 2002; Swindale and Bilinsky, 2006). In our data, households were asked about whether any of the household members consumed the above-mentioned food groups in seven days preceding the surveys. Table 3 presents the percentage of households under each of the ten scores (food groups).

**Table 3. Household dietary diversity score**

| No. of food groups consumed during the last 7 days, HDDS | Percentage of households | | |
|---|---|---|---|
| | **2011** | **2013** | **2017** |
| Only one | 0.69 | 3.11 | 1.06 |
| Two | 3.91 | 7.00 | 4.71 |
| Three | 11.42 | 15.75 | 15.36 |
| Four | 20.3 | 22.77 | 23.29 |
| Five | 25.75 | 22.03 | 28.23 |
| Six | 22.67 | 15.99 | 17.26 |
| Seven | 11.64 | 8.23 | 6.56 |
| Eight | 2.94 | 3.45 | 2.54 |
| Nine | 0.55 | 1.4 | 0.78 |
| Ten | 0.13 | 0.27 | 0.21 |
| **Mean** | **5.00** | **4.62** | **4.70** |

The last indicator of food and nutrition indicator that we consider is whether the households had only few kinds of food to eat because of inability to afford more varieties, which could complement the last two indicators that we discussed before. While HDDS indicates the dietary diversity, they do not indicate the reasons why the households eat few varieties of food, which could be, for example, because of inability to afford or because of lack of awareness about the benefits of diet diversity even though the households can afford. The fourth indicator fills this gap since households were asked whether the reason for eating few varieties of food is lack of access of the food.

**C. Independent variables**

Table 4 presents some brief descriptive statistics of our explanatory variables for the aforementioned two functions. We select these explanatory variables considering the local context and following the pioneer literatures in the area such as Abay et al. (2017), Antle and Pingali (1994), Duflo et al. (2011), Teklewold et al. (2013). These includes household characteristics and socio-economic indicators, plot characteristics, factor market existence and access, access for information, timely access of inputs, households' participation at meetings and trainings and distance to markets.

To investigate the effects of the adoption of technologies on food security, we included the number of technologies that households adopted in addition to including each of the eight technologies independently. Moreover, we use lagged values of extension service as covariate because empirical studies show that the extension services provide consultation services about the importance of adopting modern technologies for farmers in Ethiopia (Abay et al., 2017; Bachewe et al., 2014). We use the lagged value instead of the contemporaneous value to curtain the endogeneity problem of the potential reverse causality between extension service use and adoption of other technologies (Abay et al., 2017). We used also lagged values of the dependent variables to control for any dynamic effect even though this may reduce the explanatory power of other covariates.

**Table 4. Description of variables**

| Variable | Description | Mean | SD |
|---|---|---|---|
| ***Household characteristics*** | | | |
| Mean age of the HH members | Mean age of the HH members | 27.76 | 12.07 |
| Male HH head | Dummy = 1 if the HH head is male | 0.70 | 0.46 |
| HH size | Number of HH members | 8.70 | 9.39 |
| Age of the HH head | Age of the HH head | 44.97 | 15.06 |
| Mature head | Dummy = 1 if the HH head was older than 34 years | 0.72 | 0.45 |
| Illiterate head | Dummy = 1 if the HH head cannot write and read | 0.63 | 0.48 |
| Job of head | Dummy = 1 if agriculture was the primary job of the HH head | 0.87 | 0.33 |
| Married head | Dummy = 1 if the HH head was married | 0.77 | 0.42 |
| ***Wealth and social status*** | | | |
| Model farmer | Dummy = 1 if the HH was ever chosen as model farmer | 0.07 | 0.25 |

| | | | |
|---|---|---|---|
| Relatively poor | Dummy = 1 if the HH feels that it is poorer than the average HH in the village | 0.44 | 0.50 |
| Poor well-being | Dummy = 1 if the HH feels that its well-being is poor | 0.36 | 0.48 |
| Livestock number | Average number of livestock owned | 10 | 11.50 |
| Value of total crop and livestock ownership | Average value of crops harvested and livestock owned in Birr | 52,191 | 1,053,683 |
| ***Cultivated plot characteristics*** | | | |
| Cultivated area | Cultivated area in hectare during the last 12 months | 1.72 | 1.50 |
| Fertile soil | Percent of fertile soil cultivated land | 59.60 | 41.31 |
| Semi-fertile soil | Percent of semi-fertile soil cultivated land | 29.47 | 37.53 |
| Not fertile | Percent of infertile soil cultivated land | 10.93 | 24.62 |
| Flat sloped | Percent of flat slopped cultivated land | 68.33 | 38.33 |
| Gently sloped | Percent of gently sloped cultivated land | 31.90 | 38.28 |
| Steep slopped | Percent of steep slopped cultivated land | 1.98 | 10.15 |
| ***Shock variables*** | | | |
| Natural shock | Dummy = 1 if the HH experienced natural shocks such as drought, flooding etc. during the last 12 months | 0.36 | 0.48 |
| Market shock | Dummy = 1 if the HH experienced high and rising input price or low & declining output price during the last 12 months | 0.15 | 0.36 |
| ***Information & market access*** | | | |
| Price information | Dummy = 1 if the HH follows price information from various sources | 0.22 | 0.41 |
| Community participation | Dummy = 1 if the HH | 0.41 | 0.49 |
| Distance to Agri. office | Distance in minutes to agricultural offices | 53.43 | 87.35 |
| Labor hired out | Dummy = 1 if the HH hired out labor | 0.40 | 0.49 |
| Labor hired in | Dummy = 1 if the HH hired in labor | 0.23 | 0.42 |
| Media access | Dummy = 1 if the HH has access to media such as radio, TV, bulletins and newspapers | 0.23 | 0.42 |
| Market distance | Distance in minutes to the nearest market centre | 82.07 | 78.99 |

Note: Authors' compilation from the three surveys.

## Econometrics Specification

### Multiple Technology Adoption Decisions: The Multivariate Probit Model

As discussed before, one of the main objectives of this study is to investigate multiple technologies adoption decisions. Table 5 presents that most of the households have been adopting more than one technology in each of the survey years, indicating that single input adoption decision analysis could be inaccurate because of the potential correlations as we saw before. Around 3%, 9% and 8% of the households did not adopt any of the eight technologies in 2011, 2013 and in 2017, respectively. On the other hand, 0.75%, 0.15% and 0.51% of the households adopted all eight technologies in 2011, 2013 and in 2017 respectively. The rest of the households adopted from two to seven technologies at a time.

**Table 5: Number of technologies adopted by households over the survey period**

| No. of technologies adopted | Percentage of households | | |
|---|---|---|---|
| | 2011 | 2013 | 2017 |
| 0 | 3.24 | 9.20 | 7.61 |
| 1 | 11.81 | 16.61 | 12.07 |
| 2 | 16.13 | 19.04 | 13.22 |
| 3 | 17.73 | 20.37 | 17.17 |
| 4 | 17.99 | 16.86 | 18.26 |
| 5 | 15.30 | 11.24 | 15.99 |
| 6 | 11.53 | 5.22 | 10.11 |
| 7 | 5.53 | 1.31 | 5.06 |
| 8 | 0.75 | 0.15 | 0.51 |
| **N** | ***7110*** | ***7110*** | ***7110*** |

The results in Tables 1 & 3 clearly show that households have been adopting technologies complementarily in that multivariate probit model is preferred to a simple probit model to analyze multiple technology adoption decisions. We next present the empirical model used to analyze the multiple technology adoption decision.

A household, i, adopts a technology, k (where k ∈ {DA visit, soil conservation practice, irrigation, seeding in a row, Improved seed, inorganic fertilizer, organic fertilizer, chemicals}), at time, t, if the expected net benefit of adoption, $y_k$*, is positive. That is,

$$y_{itk} = \begin{cases} 1 \; if \; y^*_{itk} > 0 \\ 0 \; if \; y^*_{itk} \leq 0 \end{cases} \quad (1)$$

The expected net benefit, *yk**, is a latent (unobserved) variable that is determined by observable variables and unobserved factors, and given by:

$$y_{itk}^{*} = \alpha_i + y_{ih}\beta + X_{it}\delta + \varepsilon_{ikt},\ k = 1,\ 2,\ldots,\ 8 \qquad (2)$$

Where $\alpha_i$ is the time-invariant household-specific latent variable that are assumed to be common across the eight adoption decisions. These unobserved time-invariant variables may include agro-ecological factors, behavioral factors and time-invariant plot characteristics. $y_{ih}$ is a vector of lagged covariates including past adoption decisions. $X_{it}$ is a vector of exogenous covariates. The last term denotes the error terms, $\varepsilon_{ikt}$, which are assumed to be identically and independently distributed, but the $\varepsilon_{ikt}$ are allowed to correlate across the eight equations. The error terms jointly follow a multivariate normal distribution with zero conditional mean, variance normalized to unity (for identification) and a symmetric covariance given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} & \rho_{15} & \rho_{16} & \rho_{17} & \rho_{18} \\ \rho_{21} & . & & & & & & . \\ \rho_{31} & & . & & & & & . \\ . & & & . & & & & . \\ . & & & & . & & & . \\ . & & & & & . & & . \\ . & & & & & & . & . \\ . & & & & & & . & . \\ \rho_{81} & . & . & . & . & . & . & 1 \end{bmatrix} \qquad (3)$$

A key issue in the multiple agricultural technologies adoption decision is that the adoption decision of a technology correlates with the adoption decision of other technologies. That is, the net benefit of adopting a technology depends on the net benefit of adopting other technologies. Thus, the probabilities of adopting technologies could be correlated, in that the off-diagonal coefficients in equation 3 will be statistically different from zero.

The computation of the estimation of adoption decisions involves an eight-dimensional integration problem. The integrals are evaluated using Maximum Simulation Likelihood approach, where the Geweke–Hajivassiliou–Keane (GHK) smooth recursive conditioning simulator is used for efficiency gain.

**The technologies effect on food and nutrition security: Ordered probit model**

As we saw before, the four dependent variables take different forms where two of them are binary variables for which we use binary outcome models, and two of them are count variables for which we use count outcome models.

We use the Ordered Probit model for the estimation of the number of months that the households experienced food shortage problem in 12 months preceding the surveys since the dependent variable is an ordered count variable. Order probit model is specified as

$$
\Pr(y_i = j) = \begin{cases} \text{j if } y*_i \le 0, \\ \text{j+1 if } 0 < y*_i \le \mu_1, \\ . \\ . \\ \text{j+n} \end{cases}, \quad (4)
$$

$$
\text{where } y_i^* = \alpha_i + y_{is}\beta + X_i\delta + \varepsilon_i,
$$

where j = 1 and n = 12 representing the 12 months in a year that the households experienced food shortage problem, $y_i$* is the unobserved food security status of household i, $y_{is}$ is a vector of past years values of the dependent variables for household i, X is a vector of exogenous covariates, α, β and δ are vectors of population parameters of interest to be estimated and $e_i$ is a standard normally distributed error term independent of the covariates.

Following literature (e.g., Bellon et al., 2016; Dillon et al, 2015; Hirvonen and Hoddinott, 2016), we use instrumental variable general method of moments (GMM) framework of Poisson model to estimates the effects of adoptions on HHDS. We use the instrumental variable approach to control for the endogeneity problem between HDDS and production diversity arising from inseparable production and consumption decisions. As instrument, we use covariates including cultivation area size, on-time arrival of rain, sufficiency of the rain during the beginning and growing seasons of the crops and on-time stoppage of the rain (Bellon et al., 2016; Hirvonen & Hoddinott, 2017). Mathematically, the Poisson model is specified as

$$
HDDS_i = exp(HDDS_{is}\theta + X_i\tau + IV(PD)) + \varepsilon_i, \quad (5)
$$

where IV is HDDSi is the DD score of household i in 2017, $HDDS_{is}$ is DD score of household i in 2011 and 2013, X denotes a vector of exogenous covariates affecting HDDS, IV(PD) denotes the estimated values from first-stage estimation of production diversity using instruments including cultivated land size and weather indicator variables, and the lest term is the error term independent of covariates.

On the other hand, we use Probit model for the estimation of the dummy variables of whether the households experienced food shortage in summer and if the households ate only few varieties of food due to income constraint to buy more varieties.

$$
y_{itk} = \begin{cases} 1 \; if \; y^*_{itk} > 0 \\ 0 \; if \; y^*_{itk} \le 0 \end{cases}, \quad (6)
$$

$$
y_i^* = \alpha_i + y_{is}\beta + X_{ih}\,\delta + e_i,
$$

where $y_i$ denotes the two binary dependent variables regressed independently for household i, $y_{is}$ is a vector of past years, s, values of the dependent variables, X is a vector of exogenous covariates, α, β and δ are vectors of population parameters of interest to be estimated and $e_i$ is a standard normally distributed error term independent of the covariates. To investigate the effects of the adoption of technologies on food security, we included the number of technologies that households adopted in addition to including each of the eight technologies individually. We used also lagged values of the dependent variables to control for any dynamic effect even though this may reduce the explanatory power of other covariates (Achen, 2000).

## Results and Discussion

### Adoption Decisions of Multiple Technologies

Table 6 presents the regression results from the multivariate probit model. Most of the estimates for each of the equations have the expected sign and are jointly statistically significant. Similarly, the hull hypothesis that the covariance coefficients among the error terms of the eight technologies are jointly zero is also rejected, indicating that there is indeed complementarity among adoption of the technologies. Most of the contemporaneous error correlations are positive and statistically significant individually as well.

Interestingly, the results show that there are statistically significant complementarities between modern inputs and labor-intensive technologies. For instance, we find strong complementarity between improved seeds adoption and three of labor-intensive technologies including with seeding in a row (0.41), organic fertilizer use (0.134), and with irrigation (0.094). In fact, our data show that around 77% of the households seeded their improved seed in a row, around 47% of the households seeded their adopted improved seeds on plots they applied organic fertilizer and around 10% of the households seeded their improved seeds on irrigated plot in 2017. Though weak, we also find input complementarity between DA visit and all the four labor-intensive technologies and between adoption of conventional fertilizer and labor-intensive technologies, except with organic fertilizer expectedly. These input complementarities between modern inputs and labor-intensive technologies may have either of the following two implications. The complementarities may indicate that the farmers are choosing better plots (where they adopted labor-intensive technologies) for the adoption of expensive modern inputs in that studies that do not control for this implication may overestimate the net-benefits of modern inputs. On the other hand, the complementarities may also indicate that adoption of modern inputs induces farmers to adopt labor-intensive technologies to increase the productivity of modern inputs and, thereby to pay for the input costs. In this case, studies that do not control for the modern inputs' inducing effect on adoption of labor-intensive technologies may underestimate the net-benefits of modern inputs.

Consistent to previous evidence (e.g., Abay et al, 2017; Emerick et al., 2016; Teklewold et al., 2013), we find also input complementarity among adoption of labor-intensive technologies and among modern inputs. For instance, extension service (DA visit) has a statistically significant complementarity with improved seed (0.306) and inorganic fertilizer adoptions (0.221) as well as with labor-intensive and sustainable technologies including with irrigation (0.071), soil conservation (0.072), seeding in a row (0.073) and with organic fertilizer adoption (0.059). However, the degree of complementarities between DAs visit and sustainable technologies is weaker than the degree of complementarity between the DAs visit and modern inputs, perhaps indicating that farmers do not much need the consultation of DAs to implement sustainable and labor-intensive technologies as most of these technologies are well known among farmers. Moreover, the relatively weaker between DAs visit and labor-intensive technologies may also indicate that the DAs visit primarily aims at consulting farmers to adopt modern inputs. As expected, strong complementarity exists between inorganic fertilizer and improved seed adoptions. However, the degree of complementarity we find (0.45) is less than that Abey et al. (2017) found (0,7) using the first two of the three surveys we used, perhaps because we use the 2017 survey as well and because we control for five more technologies that were not addressed by them. For example, while they found only 2% of the households who adopted improved seed without inorganic fertilizer, we find that 10% of the households who adopted improved seed did not adopt inorganic fertilizer in 2017.

The results further reveal farmers who adopt technologies once are more likely to adopt the technologies again. For instance, we find for all the eight technologies that households who adopted the technologies in previous years (in 2011 & 2013) continued adopting the technologies in 2017. This result has a plausible policy implication: once farmers choose (are persuaded) to use the technologies, they are most likely to continue using the technologies, perhaps due to learning behavior about the net-benefits of the technologies (Besley and Case, 1993). We also find that past extension services have statistically significant effects on improved seed adoption, soil conservation and on organic fertilizer use even though we included lagged value of the dependent variables that may reduce the explanatory power of other covariates (Achen, 2001). However, we find also unexpected result that past extension service has statistically significant negative effect on adoption of irrigation.

Concerning the remaining determinants of adoption, the results reveal that the effects of other covariates on the adoption propensity of the technologies are generally consistent with previous evidence. For instance, households headed by mature persons are more likely to seek extension service, to plant the seeds in a row, and to adopt improved seeds, inorganic and organic fertilizer. Adoption of soil conservation, irrigation, inorganic and organic fertilizers decreases as the proportion of fertile plots increases, consistent with previous evidence (see, eg., Abay et al., 2017; Teklewold et al., 2013). Adoption propensity of most technologies increases with the percentage increase in the value of total crop harvest and the value of livestock owned, possible because relatively rich households are able to afford to buy the technologies and the inputs used to adopt the technologies, are less risk averse and perhaps reflecting economies of scale (Khanna, 2001; Knight, 2003; Zerfu and Larson, 2010). The results also reveal that experiencing natural shocks such as drought, flooding and storm, and market shocks such as input price inflation or output price deflation negatively affect the propensities of adoption. Table 6 further reveals that access to fertilizer credit, participation in community trainings and meetings, distance to the market and timely access of the inputs affect the propensity of adoption of most of the eight technologies. Moreover, we find that the households substitute adoption of chemicals by hiring-in labor for weeding.

**Table 6. Multivariate Probit estimates of joint technology adoption decisions**

| Covariates | Adopted Technology Type | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Extension service | Seeding in a row | Soil conservation | Irrigation | Improved seed | Chemicals | Inorganic fertilizer | Organic fertilizer |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ***Past adoption decisions*** | | | | | | | | |
| Adoption of the technology in 2013 | 0.270*** | 0.698*** | 0.363*** | 1.135*** | 0.480*** | 0.0604 | 0.717*** | 0.343*** |
| | (7.34) | (17.88) | (9.02) | (15.22) | (11.58) | (0.85) | (15.08) | (8.87) |
| Adoption of the technology in 2011 | 0.420*** | 0.811*** | 0.415*** | 0.887*** | 0.633*** | 0.280*** | 0.750*** | 0.39*** |
| | (11.58) | (20.83) | (10.40) | (11.95) | (15.55) | (3.93) | (16.43) | (10.29) |
| Extension service in 2013 | 0.270*** | 0.0598 | 0.0667+ | -0.128* | 0.0875* | -0.00742 | -0.0330 | 0.0702+ |
| | (7.34) | (1.56) | (1.70) | (-2.39) | (2.08) | (-0.11) | (-0.71) | (1.89) |
| ***Household characteristics*** | | | | | | | | |
| Male HH head | 0.0630 | -0.150* | 0.300*** | 0.232* | -0.0233 | 0.0314 | -0.0829 | 0.0485 |
| | (1.06) | (-2.39) | (4.90) | (2.43) | (-0.35) | (0.28) | (-1.15) | (0.82) |
| Mature HH head | 0.150** | 0.128* | -0.0217 | 0.0691 | 0.0965* | -0.0732 | 0.125* | 0.23*** |
| | (3.61) | (2.96) | (-0.48) | (1.14) | (2.10) | (-0.92) | (2.46) | (5.56) |
| Illiterate HH head | -0.0252 | -0.111* | 0.114* | -0.0976+ | -0.111* | 0.0544 | -0.200*** | -0.002 |
| | (-0.62) | (-2.60) | (2.56) | (-1.68) | (-2.47) | (0.71) | (-3.96) | (-0.04) |
| ***Plot characteristics*** | | | | | | | | |
| Cultivation area, hectare | -0.00215 | -0.0124 | -0.0628*** | -0.0157 | -0.0116 | 0.0405 | -0.0142 | -0.0117 |
| | (-0.17) | (-0.96) | (-4.88) | (-0.90) | (-0.85) | (1.57) | (-0.90) | (-0.94) |
| Proportion of fertile plot | -0.00078 | 0.00006 | -0.00367*** | -0.0015* | -0.000443 | 0.000997 | -0.0019* | -0.0013* |
| | (-1.61) | (0.11) | (-7.01) | (-2.09) | (-0.81) | (1.10) | (-3.25) | (-2.74) |
| Proportion of flat-slopped plot | 0.00068 | 0.0009 | -0.00008 | 0.00240* | 0.003*** | -0.0017+ | 0.00120+ | -0.0013* |
| | (1.26) | (1.62) | (-0.15) | (2.85) | (4.87) | (-1.65) | (1.87) | (-2.47) |
| ***Wealth & social status, real and perceived*** | | | | | | | | |
| Total value of crops & livestock, log | 0.109*** | 0.135*** | 0.122*** | 0.117** | 0.322*** | -0.120* | 0.330*** | -0.0002 |
| | (5.28) | (6.12) | (5.63) | (3.77) | (13.07) | (-2.93) | (12.39) | (-0.01) |
| The HH is poor | -0.0519 | 0.0874* | -0.0330 | 0.0681 | -0.00511 | -0.232* | -0.0639 | - |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (-1.29) | (2.06) | (-0.76) | (1.17) | (-0.11) | (-3.02) | (-1.31) | 0.0851* |
| | | | | | | | | (-2.09) |
| Chosen as model farmer | 0.475*** | 0.0367 | 0.0839 | 0.181* | 0.183* | 0.158 | 0.164+ | 0.110 |
| | (6.63) | (0.52) | (1.12) | (2.14) | (2.61) | (1.14) | (1.89) | (1.60) |
| ***Shocks experienced*** | | | | | | | | |
| Experienced natural shock | 0.122* | -0.086* | 0.116* | -0.0137 | 0.0229 | -0.0144 | 0.0283 | 0.19*** |
| | (3.22) | (-2.17) | (2.84) | (-0.25) | (0.55) | (-0.20) | (0.62) | (5.07) |
| Experienced market shock | -0.176*** | 0.0982* | -0.0261 | -0.00971 | -0.0541 | 0.267* | 0.188** | 0.19*** |
| | (-4.32) | (2.33) | (-0.60) | (-0.16) | (-1.21) | (3.19) | (3.79) | (4.54) |
| ***Information and market access*** | | | | | | | | |
| Had credit access for fertilizer | | | | | 0.290*** | -0.232* | 1.016*** | 0.0819+ |
| | | | | | (6.65) | (-3.14) | (16.57) | (1.93) |
| Follow price information | -0.0678 | -0.0518 | 0.210* | 0.132 | -0.0761 | -0.0136 | -0.145 | 0.0506 |
| | (-0.87) | (-0.64) | (2.39) | (1.21) | (-0.90) | (-0.09) | (-1.49) | (0.65) |
| Participate in meetings/trainings | 0.595*** | 0.193*** | 0.264*** | 0.177* | 0.0718+ | 0.0777 | 0.151* | 0.0847* |
| | (15.55) | (4.76) | (6.32) | (3.14) | (1.66) | (1.07) | (3.20) | (2.17) |
| Have media access | 0.0907 | 0.00660 | -0.158+ | -0.0873 | 0.0599 | 0.158 | 0.0996 | -0.0424 |
| | (1.15) | (0.08) | (-1.80) | (-0.79) | (0.71) | (1.03) | (1.01) | (-0.54) |
| Distance to the nearest market | -0.00044+ | -0.001*** | -0.0007* | -0.00009 | -0.001*** | 0.00085+ | -0.0019*** | -0.00005 |
| | (-1.81) | (-5.73) | (-2.78) | (-0.25) | (-4.16) | (1.74) | (-6.79) | (-0.21) |
| Reside in AGP *woreda* | -0.00369 | 0.00172 | -0.109* | 0.144* | 0.0752+ | 0.157* | 0.0522 | -0.0593 |
| | (-0.10) | (0.04) | (-2.57) | (2.49) | (1.75) | (2.18) | (1.11) | (-1.51) |
| Timely access of the input | | | | | 0.730*** | 0.0989 | 0.849*** | |
| | | | | | (18.45) | (1.16) | (19.75) | |
| Hired-in labor for weeding | | | | | | -0.0006* | | |
| | | | | | | (-2.49) | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Constant | -1.812*** | -1.82*** | -0.801** | -2.97*** | -4.422*** | 2.666*** | -4.009*** | 0.0653 |
| | (-8.38) | (-7.95) | (-3.52) | (-9.11) | (-17.27) | (6.33) | (-14.62) | (0.31) |

***Correlations (complementarities)***

| | | | |
|---|---|---|---|
| $\rho_{21}$ (DA visit & row seeding) | 0.0732* | $\rho_{43}$ (soil cons. & irrigation) | 0.231*** |
| | (2.97) | | (5.59) |
| $\rho_{31}$ (DA visit & soil cons.) | 0.0719* | $\rho_{53}$ (soil cons. & improved seed) | 0.0449 |
| | (2.82) | | (1.58) |
| $\rho_{41}$ (DA visit & irrigation) | 0.0707* | $\rho_{63}$ (soil cons. & chemicals) | -0.0334 |
| | (2.06) | | (-1.24) |
| $\rho_{51}$ (DA visit & improved seed) | 0.306*** | $\rho_{73}$ (soil cons. & conv. fertilizer) | 0.111** |
| | (11.22) | | (3.72) |
| $\rho_{61}$ (DA visit & chemicals) | -0.0313 | $\rho_{83}$ (soil cons. & org. fertilizer) | 0.0953** |
| | (-1.22) | | (3.73) |
| $\rho_{71}$ (DA visit & conv. fertilizer) | 0.221*** | $\rho_{54}$ (irrigation & improved seed) | 0.0901* |
| | (7.59) | | (2.48) |
| $\rho_{81}$ (DA visit & org. fertilizer) | 0.0594* | $\rho_{64}$ (irrigation & chemicals) | 0.0322 |
| | (2.47) | | (0.86) |
| $\rho_{32}$ (Row seeding & soil. Conv.) | -0.00151 | $\rho_{74}$ (irrigation & conv. fertilizer) | 0.0944* |
| | (-0.06) | | (2.25) |
| $\rho_{42}$ (Row seeding & irrigation) | 0.171*** | $\rho_{84}$ (irrigation & org. fertilizer) | 0.0726* |
| | (4.85) | | (2.11) |
| $\rho_{52}$ (Row seeding & improved seed | 0.410*** | $\rho_{65}$ (Chemicals & improved seed) | 0.273*** |
| | (13.75) | | (9.34) |
| $\rho_{62}$ (Row seeding & chemicals) | 0.186*** | $\rho_{75}$ (Chemicals & conv. fertilizer) | 0.887*** |
| | (6.87) | | (21.38) |
| $\rho_{72}$ (Row seeding & conv. fertilizer) | 0.352*** | $\rho_{85}$ (Chemicals & org. fertilizer) | -0.0267 |
| | (11.83) | | (-1.01) |
| $\rho_{82}$ (Row seeding & org. fertilizer) | 0.149*** | $\rho_{76}$ (improved seed & conv. fertilizer) | 0.450*** |
| | (5.95) | | (14.22) |
| $\rho_{86}$ (improved seed & org. fertilizer) | 0.134*** | $\rho_{87}$ (Conv. & organic fertilizer) | 0.0261 |
| | (5.21) | | (0.92) |

| | |
|---|---|
| *N* | 5355 |

*t* statistics in parentheses
+ p<0.10, * p<0.05, ** p<0.001, *** p<0.0001

**The Effects of Technology Adoption on Food and Nutrition Security**

As we observed in Table 5, around 80% of the households adopted at least two technologies in 2017. This section presents the effects after three and five years of the adoptions of the eight technologies on food and nutrition security. As we discuss before, we measure food and nutrition security using four indicators. Table 7 presents the regression results from the probit and ordered probit models where the 2011 and 2013 values of the dependent variables are included to control for the dynamics effects. The estimates for each of the four equations are jointly significant and most of the coefficients have the expected sign and are consistent to previous studies.

The results show that there is strong tenacity in food and nutrition insecurity, perhaps indicating the cycle of poverty with the implication of the need for intervention to break the cycle. We find that the households who were food insecure in 2011 and/or in 2013 are more likely to be also food insecure in 2017. Specifically, households who had only few varieties of food to eat in 2011/13 are more likely to have few varieties of food to eat in 2017 as well. Experiencing food shortage problem in 2017 summer season is more likely for households who did also experience food shortage problem in 2011 and/or in 2013 summer seasons. Similarly, the number of months with food security problem is higher in 2017 for households who experienced longer months of food shortage problem in 2011/2013. Households who had diverse diet in 2013 have also diverse diet in 2017. Moreover, household dietary diversity score is higher in 2017 for households who had a higher HDDS in 2013.

Coming to the main aim of this study, the effects of technology adoption on food and nutrition security, the results reveal that the higher the number of technologies that the households adopted, the less likely that they experience food shortage problem during summer and the higher the HDDS of the households. This result may indicate that adoption of complementary technologies is essential to increase agricultural productivity and thereby to secure food.

In addition to the joint effects of the technologies, most of the eight technologies have also statistically significant effects individually. For instance, the results reveal that households who adopted improved seeds in 2011 are less likely to experience food shortage problem during summer and the lower the number of months that they experience food shortage problem in 2017. This could be because improved seeds increase agricultural productivity and thereby improve food security (Emerick et al., 2016; Jaleta et al., 2015; Tesfaye et al. 2016). Even after controlling for the adoption rate in 2011, we also find that households who adopted improved seeds in 2013 are less likely to experience food shortage problem in summer, more likely to experience lower number of months of food shortage problem and less likely that they have only few kinds of food to eat. We get similar results when we consider the 2011 and the 2013 adoptions effects separately.

Similarly, households who adopted organic and conventional fertilizers, irrigation and soil conservation mechanisms are less likely to experience food insecurity and are more likely to have higher HDDS. The results further reveal that households who adopted chemicals are less likely to have only few varieties of food and are more likely to have a higher HDDS, perhaps because chemicals increase agricultural production and productivity despite the negative externalities on health, environment and on sustainability (Antle & Pingali, 1994; Wilson & Tisdell, 2001). Moreover, households who visited by DAs in 2011 are more likely to have fewer months of food shortage problem within a year.

On the other hand, we find that households who planted the seed in a row are more likely to be food insecure and less likely to have diet diversity, perhaps indicating that seeding in a row may not be a profitable technology because of the high labor-hour it demands. Another unexpected result is that households who were visit by DAs in 2013 are more likely to experience food shortage problem in summer and to experience more months of food insecurity (at 10% level of significance). One potential reason for the observed negative effect could be that once the households received DAs' service in 2011 and we control for the technologies that the DAs provide consultation service about, the 2013 DAs coefficient shows the time that the farmers waste attending trainings and visiting demonstration plots again which could negatively impact food security.

The results regarding the remaining explanatory variables have generally the expected sign. For instance, households with better economic standing, measured by the total value of agricultural production, landholding and being chosen as model farmer, are more likely to be food secure. Households who followed price information are more likely to be better-off in terms of all the four indicators of food and nutrition security, perhaps indicating that information access is one of the key factors that farmers need to improve their living standard. Moreover, the results show that, while households who hired-in labor are more likely to have more varieties of food and higher HDDS, household who hired-out family labor are more likely to experience food shortage in summer. This could be because while farmers who hire-in labor increase their agricultural production (the farmers do not hire-in labor if they do not expect higher labor return), poor farmers hire-out family labor to curtain their short-run food shortage problem at the expense of fewer-labor time than the required amount allotted to own production. Expectedly, farmers who experienced natural shocks such as drought and flooding as well as death or illness of a spouse are more likely to be food insecure.

**Table 7: The effects of technology adoption on food & nutrition security**

| **Covariates** | **Dynamic Probit Model** | | **Dynamic Ordered Probit model** | **GMM IV Poisson** |
|---|---|---|---|---|
| | **Experienced food shortage in summer** | **Had only few food varieties** | **Months of food shortage problem** | **HDDS** |

| | | | | |
|---|---|---|---|---|
| ***Dynamics (past food security)*** | | | | |
| Food security in 2013 | 0.203*** | 0.175* | 0.0494* | 0.0240*** |
| | (3.89) | (3.28) | (2.49) | (5.03) |
| Food security in 2011 | 0.147* | 0.176*** | 0.0390** | 0.00819 |
| | (3.06) | (4.20) | (3.39) | (1.12) |
| ***Technologies effect*** | | | | |
| No. of technologies adopted | -0.0467* | -0.0201 | -0.0226 | 0.0158* |
| | (-3.01) | (-1.37) | (-1.31) | (2.87) |
| Adopted improved seed in 2013 | -0.137* | -0.121* | -0.209* | -0.0483+ |
| | (-2.36) | (-2.18) | (-3.16) | (-1.88) |
| Adopted improved seed in 2011 | -0.138* | -0.0869 | -0.129* | -0.0235 |
| | (-2.49) | (-1.62) | (-1.96) | (-1.32) |
| Adopted con. fertilizer in 2013 | 0.0452 | -0.0511 | 0.0813 | -0.00556 |
| | (0.87) | (-1.08) | (1.41) | (-0.30) |
| Adopted con. fertilizer in 2011 | 0.0865 | -0.0272 | -0.0534 | 0.0581* |
| | (1.55) | (-0.51) | (-0.87) | (2.36) |
| Adopted chemicals in 2013 | -0.0247 | -0.0487 | -0.0643 | 0.0266 |
| | (-0.47) | (-1.03) | (-1.08) | (1.61) |
| Adopted chemicals in 2011 | -0.0454 | -0.0908* | 0.0437 | 0.0300+ |
| | (-0.92) | (-1.99) | (0.83) | (1.79) |
| Visited by DA in 2013 | 0.0920* | 0.0597 | 0.0921+ | -0.0221 |
| | (1.96) | (1.48) | (1.82) | (-1.32) |
| Visited by DA in 2011 | -0.0674 | -0.0313 | -0.106* | 0.00633 |
| | (-1.42) | (-0.73) | (-1.99) | (0.43) |
| Adopted irrigation in 2013 | 0.00780 | -0.112 | 0.0846 | 0.0277 |
| | (0.08) | (-1.08) | (0.62) | (0.90) |
| Adopted irrigation in 2011 | 0.0180 | -0.0348 | -0.102 | 0.0451+ |
| | (0.22) | (-0.47) | (-1.06) | (1.92) |
| Adopted organic fertilizer in 2013 | -0.137* | -0.0247 | -0.0766 | 0.0339+ |
| | (-2.41) | (-0.48) | (-1.33) | (1.79) |
| Adopted organic fertilizer in 2011 | -0.00231 | 0.0758+ | 0.0351 | -0.0466* |
| | (-0.05) | (1.80) | (0.67) | (-2.56) |

| | | | | |
|---|---|---|---|---|
| Adopted soil cons. practice in 2013 | -0.00896 | -0.0543 | -0.156** | -0.0140 |
| | (-0.20) | (-1.29) | (-3.32) | (-1.00) |
| Adopted soil cons. practice in 2011 | -0.0179 | -0.0751 | -0.138* | -0.0132 |
| | (-0.36) | (-1.58) | (-2.48) | (-0.62) |
| Planted seeds in a row in 2013 | 0.239*** | 0.251*** | 0.170* | -0.0340+ |
| | (4.79) | (5.24) | (2.97) | (-1.72) |
| Planted seeds in a row in 2011 | -0.0341 | 0.0863+ | 0.0186 | -0.0668* |
| | (-0.70) | (1.88) | (0.33) | (-2.94) |
| ***Wealth and social status*** | | | | |
| Cultivated area in hectare | -0.110*** | -0.120*** | -0.0901** | 0.0382** |
| | (-5.08) | (-6.00) | (-3.88) | (3.58) |
| Chosen as model farmer | -0.296** | -0.168* | -0.364* | 0.0331 |
| | (-3.32) | (-2.20) | (-3.27) | (0.71) |
| Value of total production in 2016, log | -0.272*** | -0.248*** | -0.227*** | 0.130*** |
| | (-12.86) | (-11.66) | (-9.23) | (8.54) |
| ***Information and market access*** | | | | |
| Agricultural revenue, log | | | | -0.00206 |
| | | | | (-0.46) |
| Have media access | -0.0711 | 0.0279 | -0.0681 | 0.0423 |
| | (-1.30) | (0.52) | (-1.04) | (1.58) |
| Follow price info | -0.151* | -0.128* | -0.238** | 0.0411 |
| | (-3.02) | (-2.73) | (-3.88) | (1.44) |
| Hired in labor in 2011 | -0.0537 | -0.125* | 0.0816 | -0.00618 |
| | (-1.05) | (-2.40) | (1.26) | (-0.17) |
| Hired in labor in 2013 | -0.00877 | -0.00224 | -0.0355 | 0.0296+ |
| | (-0.18) | (-0.05) | (-0.60) | (1.78) |
| Hired out family labor in 2013 | 0.139* | 0.0746 | 0.0885 | 0.0317 |
| | (2.02) | (1.13) | (1.15) | (1.64) |
| ***Shock variables, community participation*** | | | | |
| Experienced natural shock in 2013 | 0.384*** | 0.287*** | 0.330*** | -0.0225 |

| | | | | |
|---|---|---|---|---|
| | (6.59) | (5.34) | (4.82) | (-1.49) |
| Experienced market shock in 2013 | -0.0849 | -0.0488 | -0.121 | -0.0136 |
| | (-0.76) | (-0.49) | (-1.07) | (-0.57) |
| Sick or dead spouse | 0.333*** | 0.360*** | 0.296*** | 0.00319 |
| | (7.61) | (8.13) | (5.69) | (0.17) |
| Participated in meetings/trainings in 2011 | 0.128* | 0.130* | 0.189** | 0.0538* |
| | (2.95) | (3.29) | (3.72) | (3.28) |
| Resides in AGP woreda | 0.00607 | -0.122* | 0.0546 | -0.102* |
| | (0.10) | (-2.20) | (0.83) | (-2.71) |
| Production diversity | | | | 0.0297* |
| | | | | (2.84) |
| Household characteristics | Yes | Yes | Yes | Yes |
| Constant | 1.771*** | 1.917*** | | 0.138 |
| | (8.11) | (8.77) | | (0.74) |
| *Log likelihood* | -2492.762 | -2871.2128 | -3500.4522 | |
| *N* | 5,652 | 5,649 | 3,263 | 2,912 |

*t* statistics in parentheses from bootstrapping
+ p<0.10, * p<0.05, ** p<0.001, *** p<0.0001

## Conclusion

We investigate whether the technologies that farm households adopted three and five years ago have effects on food and nutrition security of the adopters. We measure food and nutrition security using four variables including the number of months that households experienced food shortage problem during the last 12 months, if the households experienced food shortage problem in summer, household dietary diversity score (HDDS) and if the households had only few varieties of food to eat because of inability to afford more varieties. Secondly, using multivariate probit model on a large panel data of 7110 farm households in Ethiopia, we analyze the adoption decisions of a comprehensive of eight modern inputs and labor-intensive technologies including improved seed varieties, inorganic and organic fertilizer, chemicals, extension service, irrigation, soil conservation and planting seeds in a row. Finally, we analyze the determinants of the adoptions of the eight technologies.

We find that adoption of technologies reduces food insecurity and increases dietary diversity. Specifically, we find that the higher the number of technologies that the households adopted, the more likely that they are food secured and have diversified diet. This has an interesting policy implication that policies should aim at encouraging multiple technologies adoptions by, for example, providing credit for the rural poor who cannot afford joint adoption of multiple technologies. In addition to the joint effects of the technologies, most of the eight technologies have also statistically significant effects individually. For instance, the results reveal that households who adopted improved seed, chemicals, irrigation, organic fertilizer, extension service, and soil conservation mechanisms are less likely to experienced food insecurity and are more likely to have higher HDDS.

Consistent with previous studies, we also find complementarity between modern inputs and labor-intensive technologies, perhaps indicating that adoption of modern inputs induces farmers to complement the modern input with labor-intensive technologies or that farmers adopt modern inputs on plots where they invested in labor to increase the productivity of the expensive modern inputs. The results further reveal that farmers who adopt technologies once are more likely to adopt the technologies again, perhaps indicating that adoption of these technologies is profitable on average.

The paper has at least the following contributions to the literature about the adoption of agricultural technologies and their effects on farmers' welfare. First, by considering four modern inputs and four labor-intensive practices, we better control for the complementarities among various technologies. Second, we investigate whether the households who adopted the technologies have improved food and nutrition security after three and five years of adopting the technologies. Finally, we use a rich panel data that allow for control for the dynamics effects. Yet the scope of the study is limited and have the following caveats. First, we do not investigate the dosage effects of technology adoption though it is expected that the amount of modern inputs adopted matters for food and nutrition security. Second, we do not control for the effects on food and nutrition security of the technologies that the households adopted between survey rounds.

## Reference

Abate, G. T., Rashid, S., Borzaga, C., & Getnet, K. (2016). Rural Finance and Agricultural Technology Adoption in Ethiopia: Does the Institutional Design of Lending Organizations Matter?. *World Development*, *84*, 235-253.

Achen, C. H. (2000). Why lagged dependent variables can suppress the explanatory power of other independent variables. Ann Arbor, 1001(2000), 48106-1248.

Ahmed, M. H., Geleta, K. M., Tazeze, A., Mesfin, H. M., & Tilahun, E. A. (2017). Cropping systems diversification, improved seed, manure and inorganic fertilizer adoption by maize producers of eastern Ethiopia. *Journal of Economic Structures*, *6*(1), 31.

Antle, J. M., & Pingali, P. L. (1994). Chemicals, productivity, and farmer health: A Philippine case study. *American Journal of Agricultural Economics*, *76*(3), 418-430.

Ashraf, N., Giné, X., & Karlan, D. (2009). Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya. *American Journal of Agricultural Economics*, *91*(4), 973-990.

Barrett, C. B., Carter, M. R., & Timmer, C. P. (2010). A century-long perspective on agricultural development. *American Journal of Agricultural Economics*, *92*(2), 447-468.

Besley, T. J. and Case, A. 'Modeling technology adoption in developing countries', American

Economic Review, Vol. 83, (1993) pp. 396–402.

Burke, W. J., Jayne, T., & Black, J. R. (2017). Factors explaining the low and variable profitability of fertilizer application to maize in Zambia. *Agricultural Economics*, *48*(1), 115-126.

Byerlee, D. 1994. *Moden! Varieties, Productivity,* Il/ld *Sustaiuability: Recent Experience and*

*Emergiug Challenges.* Mexico, D.F.: OMMYT.

Charles C. Crissman, Donald C. Cole and Fernando Carpio (1994). Pesticide Use and Farm Worker Health in Ecuadorian Potato Production. American Journal of Agricultural Economics, Vol. 76, No. 3 (Aug., 1994), pp. 593-597.

Croppenstedt, A., Demeke, M., & Meschi, M. M. (2003). Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. *Review of Development Economics*, *7*(1), 58-70.

de Graaff, J., Kessler, A., & Nibbering, J. W. (2011). Agriculture and food security in selected countries in Sub-Saharan Africa: diversity in trends and opportunities. Food Security, 3(2), 195-213.

Emerick, K., de Janvry, A., Sadoulet, E., & Dar, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, *106*(6), 1537-61.

Feder, G. (1982). Adoption of interrelated agricultural innovations: Complementarity and the impacts of risk, scale, and credit. *American Journal of Agricultural Economics*, *64*(1), 94-101.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, *33*(2), 255-298.

Green, D. A., & Ng'ong'ola, D. H. (1993). Factors Affecting Fertilizer Adoption in Less Developed Countries: An Application of Multivariate Logistic Analysis in Malaŵi. *Journal of Agricultural Economics*, *44*(1), 99-109.

Griliches, Zvi (1957). "Hybrid Corn: An Exploration in the Economics of Technological Change." Econometrica *(1957), Vol.* 25, pp. 501-522.

Goshu, D., Kassa, B., & Ketema, M. (2012). Is food security enhanced by agricultural technologies in rural Ethiopia. *African Journal of Agricultural and Resource Economics*, *8*(1), 58-68.

FAO, IFAD, UNICEF, WFP and WHO (2017). The State of Food Security and Nutrition in the World. Building resilience for peace and food security. Rome, FAO.

FAO (2017). The future of food and agriculture – Trends and challenges. Rome.

Garrity, D. P., Akinnifesi, F. K., Ajayi, O. C., Weldesemayat, S. G., Mowo, J. G., Kalinganire, A., ... & Bayala, J. (2010). Evergreen Agriculture: a robust approach to sustainable food security in Africa. Food security, 2(3), 197-214.

Hanna, R., Mullainathan, S., & Schwartzstein, J. (2014). Learning through noticing: Theory and evidence from a field experiment. *The Quarterly Journal of Economics*, *129*(3), 1311-1353.

IFPRI (2002). Dietary Diversity as A Food Security Indicator. FCND Discussion Paper No. 136.

Jaleta, M., Kassie, M., & Marenya, P. (2015). Impact of improved maize variety adoption on household food security in Ethiopia: an endogenous switching regression approach. In *Paper presented on Int. conference of agricultural economists*(Vol. 29).

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, *129*(2), 597-652.

Luan, Y., Cui, X., Ferrat, M. (2013). Historical Trends of Food Self-Sufficiency in Africa. Food Security. Volume 5, Issue 3, pp 397- 405.

Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., & Mulugeta, E. (2008). Estimating returns to soil conservation adoption in the northern Ethiopian highlands. *Agricultural Economics*, *38*(2), 213-232.

Kennedy, G., Ballard, T., & Dop, M. C. (2011). Guidelines for measuring household and individual dietary diversity. Food and Agriculture Organization of the United Nations.

Mahanta, D., & Rai, R. K. (2008). Effects of sources of phosphorus and biofertilizers on productivity and profitability of soybean (Glycine max)-wheat (Triticum aestivum) system. *Indian Journal of Agronomy*, *53*(4), 279.

Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and impacts of sustainable agricultural practices on maize yields and incomes: evidence from Rural Zambia. *Journal of agricultural* economics, *67*(1), 130-153.

Mangisoni, J. H. (2008). Impact of treadle pump irrigation technology on smallholder poverty and food security in Malawi: a case study of Blantyre and Mchinji districts. *International Journal of Agricultural Sustainability*, *6*(4), 248-266.

Mansfield E, 1963. The speed of response of firms to new techniques. Quarterly Journal of

Economics 77: 290–311.

Magrini, Emiliano; Vigani, Mauro (2014) : Technology adoption and the multiple dimensions of food security: The case of maize in Tanzania, LICOS Discussion Paper Series, No. 352.

Mansfield, E. (1963). The speed of response of firms to new techniques. *The Quarterly Journal of Economics*, *77*(2), 290-311.

Marenya, P. P., & Barrett, C. B. (2009). State-conditional fertilizer yield response on western Kenyan farms. *American Journal of Agricultural Economics*, *91*(4), 991-1006.

Minten, B., & Barrett, C. B. (2008). Agricultural technology, productivity, and poverty in Madagascar. World Development, 36(5), 797-822.

Mucheru-Muna, M., Mugendi, D., Pypers, P., Mugwe, J., Kung'u, J., Vanlauwe, B., & Merckx, R. (2014). Enhancing maize productivity and profitability using organic inputs and mineral fertilizer in central Kenya small-hold farms. *Experimental Agriculture*, *50*(2), 250-269.

Pan, Y., Smith, S. C., & Sulaiman, M. (2015). Agricultural extension and technology adoption for food security: Evidence from Uganda (No. 9206). IZA Discussion Papers.

Qaim, M. (2014). *Evaluating nutrition and health impacts of agricultural innovations* (No. 46). GlobalFood Discussion Papers.

Shiferaw, Bekele, Menale Kassie, Moti Jaleta and Chilot Yirga (2014). Adoption of improved wheat varieties and impacts on household food Security in Ethiopia. *Food Policy* (Elsevier Ltd.) 44: 272-284.

Suri, T. 'Selection and comparative advantage in technology adoption', Econometrica, Vol. 79,

(2011) pp. 159–209.

Swindale, Anne, and Paula Bilinsky (2006). Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access: Indicator Guide (v.2). Washington, D.C.: FHI 360/FANTA.

Tesfaye, S., Bedada, B., & Mesay, Y. (2016). Impact of improved wheat technology adoption on productivity and income in Ethiopia. *African Crop Science Journal*, *24*(s1), 127-135.

Wilson, C., & Tisdell, C. (2001). Why farmers continue to use chemicals despite environmental, health and sustainability costs. *Ecological economics*, *39*(3), 449-462.

Yao Pan, Stephen C. Smith, Munshi Sulaiman (2015). Agricultural Extension and Technology Adoption for Food Security: Evidence from Uganda. IZA Discussion Paper No. 9206.

Zeweld, W., Van Huylenbroeck, G., Tesfay, G., & Speelman, S. (2017). Smallholder farmers' behavioural intentions towards sustainable agricultural practices. *Journal of environmental management*, *187*, 71-81.