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The Impact of Improved Seed Adoption on Nutrition Outcome

A Panel Endogenous Switching Regression Analysis

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Keywords: Technology adoption; Food security; Nutrition; Vulnerability; and Ethiopia

JEL Codes: C33; C34; D6; D13

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Abstract

A large body of literature in development economics has investigated the impact of improved agricultural technologies on productivity and the welfare of smallholder farmers. This paper studies the impact of new technologies on a relatively under-researched outcome variable of interest, nutrition security. We use a two-step panel Endogenous Switching Regression (ESR) on two rounds of household panel data from rural Ethiopia and show that improved seed adoption resulted in a significant increase in households' protein, fat, and iron consumption. Improved seed adopter households also exhibit a significantly larger household diet diversity index, implying that they consume a wide range of nutritious food items. The results suggest that the impact of the adoption of improved agricultural technologies may be significantly larger than what has been documented by previous studies.

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1. Introduction

Modern agricultural technologies, such as fertilizers and improved seeds, pesticides and herbicides have potential to improve the productivity and welfare of poor rural communities, but their adoption and diffusion rate has been very low. The key factors that hinder adoption and diffusion identified by previous literature includes liquidity constraint (Giné et al., 2008), uninsured risk (Lamb, 2003; Alem et al., 2010; Dercon and Christiaensen, 2011), lack of experimentation and inefficient communication (Foster and Rosenzweig, 1995; Sseruyange and Bulte, 2018; Shikuku et al., 2019; BenYishay and Mobarak, 2019), imperfect information (Anderson and Feder, 2004; Abdulai and Huffman, 2005; Magruder, 2018) and marketing & supply chain constraints (Pan et al., 2018). In programs where these constraints have been addressed, modern agricultural technologies have been shown to have a positive impact on yield and welfare of farm households, which are often the primary outcome variables of interest (Abate et al., 2017; Alwang et al., 2019). In this paper, we investigate the impact of adoption of improved seeds on household nutritional intake, a key indirect outcome variable which did not receive sufficient attention in previous studies.

We use two rounds of panel data from rural Ethiopia - the Ethiopian Socioeconomic Survey (ESS) and investigate the impact of adoption of improved seeds on nutritional outcomes of household members. ESS is a nationally representative household data collected by the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA), in collaboration with the Ethiopian Central Statistics Agency (CSA) with the key objective of understanding agriculture and its role in household wellbeing. The survey collects detailed information on socio-economic variables, agricultural technology adoption and production, and food and non-food consumption from which we constructed our key nutritional outcome variables - per capita protein, fat, iron, and calorie intake. Availability of rich panel data collected from adopter and non-adopter households enables us to control for household unobserved time-invariant heterogeneity and estimate the impact of adoption on our outcome variables using the panel Endogenous-Switching-Regression estimator.

The results suggest that adoption of improved seeds increases consumption of protein, fat, iron, calorie intake and household diet diversity. Panel ESR results show that if adopting households had not adopt improved seed, their protein, fat, and iron consumption would have decreased by about 2.89, 1.35, and 2.85 mg, respectively. If non-adopting households had adopt, their protein, fat, and iron consumption would have increased by about 5.45, 0.49, and 2.60 mg, respectively. Similarly, adopting improved seed increases the diet diversity of farm households. Housedold Diet Diversity Score (HDDS) and Food Consumption Score (FCS) of adopting households would have decreased by about 0.22 and 2.35 score if they fail to adopt improved seed, respectively. On the other hand, if non-adopting households adopt improved seed their HDDS and FCS would have increased by about 0.12 and 1.00 score, respectively. As anticipated, adopting improved seed increases rural households' calorie consumption.

If the adopting household had not adopt, their calorie consumption would have been reduced by approximately 79.96 calories. While non-adopting households' calorie consumption would have increased by about 91.22 calories if they had adopt. Results also suggest that, adoption of improved seed reduces rural households' food insecurity and economic vulnerability to food insecurity. If adopting households had not adopt, their economic vulnerability to food insecurity and likelihood of being food insecure would have increased by about 2% and 3%, respectively. While non-adopting households' economic vulnerability to food insecurity and likelihood of food insecurity would have decreased by about 1% and 5%, respectively, if they had adopt. Our results therefore confirm that the impact of adoption of productivity-enhancing agricultural inputs on adopting households extends far beyond improving productivity.

This paper contributes to the technology adoption literature in developing countries. Almost all previous studies that investigated the impact of adoption of improved seeds (Tufa et al., 2019; Wossen et al., 2019; Kassie et al., 2018; Feleke et al., 2016; Manda et al., 2019; Arouna et al., 2017; Verkaart et al., 2017; Martey et al., 2020; Bezu et al., 2014; Shiferaw et al., 2014; Jaleta et al., 2018) focus on the primary outcome variables of interest, yield and welfare of farm households. The only exceptions are Zeng et al. (2017); Biru et al. (2020); Teklewold et al. (2019); Larochelle and Alwang (2014); Magrini and Vigani (2016) which investigate the impact on nutrition and economic vulnerability to food insecurity. Adoption of modern technologies in general and adoption of agricultural technologies in particular possibly have other unanticipated positive effects on households. In addition, all these studies, except (Teklewold et al., 2019) use nutrition indicators constructed from aggregate data. All these studies use crossectional data, which doesn't allow controlling for household unobserved heterogeneity in a credible manner. In this paper, we use the panel-endogenous-switching-regression estimator on detailed nutritional intake indicator variables and show that adoption of improved seeds has a significant positive impact. The results therefore imply that the returns to modern technologies, such as improved seeds, are clearly larger than what previous studies document.

This paper also contributes to the literature on nutrition and health in developing countries. In addition to hunger, a large population in developing countries suffer from lack of important nutrients, such as protein, iron, vitamin A, and iodine (Welch et al., 2001). Micronutrient deficiencies have been documented to have short and long-term negative effects, such as stunting, impaired cognitive abilities, and susceptibility to other non-communicable diseases on people in general and children in particular (Kennedy et al., 2003). Understanding the extent of nutritional deficiency and the impact of modern technologies on farm households using rich data from a Sub-Saharan African context will significantly improve our understanding of the issue and help policymakers design effective social support and safety net programs.

The rest of the paper is structured as follows. Section 2 presents the data and variable construction. Section 3 describes econometric methods used to analyze the impact of agricultural technology adoption on food and nutrition security. Section 4 presents results and robustness checks. Section 5 concludes.

2. Data and Variable Construction

2.1. Household Data Source

This study made use of two recent waves of the Ethiopian Socioeconomic Survey (ESS) conducted in 2013/14 and 2015/16. (henceforth 2014 and 2016, respectively). The ESS is a component of the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) project, which was carried out in collaboration with Ethiopia's Central Statistics Agency (CSA). The data was gathered from 433 enumeration areas (EAs), of which 290 are rural, 43 are small towns, and 100 are medium and large towns. ESS began in 2011/12 as ERSS (Ethiopia Rural Socioeconomic Survey), with a total sample of 333 EAs or 3,776 households, encompassing only rural and small-town areas. In 2014 and 2016, ERSS data was recollected as ESS, including urban areas, to ensure that the data could provide nationally representative estimates. Now ESS covers 433 EAs, up from 333 previously. The total number of households increased from 3,776 to 5,262. The survey used five separate questionnaires to collect a wide range of information (i.e., household, post-plant, post-harvest, livestock, and community).

In general, attrition between ESS waves is minimal. For instance, attrition between the first and second waves of ESS is about 4% and leaves a total sample of 3323 rural households in the 2014 survey. Again, the level of attrition between the 2014 and 2016 waves is about 1.9%. However, it is challenging to generate main variables for all observations in the selected sample. Generally, landholding and food consumption are reported in local units, for a small number of which no plausible conversion method exists. Subsequently, the final sample used in this study contains balanced data of 2045 households from 9 regions and one city administration and 268 enumeration areas between the 2014 and 2016 waves after removing urban sample households and those households with missing information for main variables.

Among other information, the household questionnaire gathers detailed data about the consumption and expenditure of 26 food commodities commonly consumed in Ethiopia over the last seven days. Moreover, the household questionnaire asks households to report the source of their consumption as market purchases, in-kind transfers, and home production, which provides a complete image of the household's food consumption. Also, households were asked about how many days they had consumed any of food aggregates[1] in the past seven days.

[1]In ESS food aggregate data is collected by classifying foods consumed in 16 groups as: enjera (teff); other cereals (such as rice, sorghum, millet, maize, wheat bread, etc); potatoes; Pasta, Macaroni and Biscuits; Sugar or sugar products (honey, jam); Beans, lentils, nuts; vegetables; fruits; Beef, sheep, goat, or other red meat and pork; Poultry; eggs; fishes; Oils or fats or butter; Other condiments (Spice, Salt, Pepper, etc); and Kocho or Bula.

2.2. Food and Nutrition Security Indicators

"Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, 2008). Food security encompasses four dimensions: availability, access, utilization, and stability. Availability states the physical existence of food; access denotes the ability of households to obtain food, which is mainly influenced by market access, income, and prices. Utilization discusses the ability of individuals to process nutrients and energy from food. And finally, stability refers to how other three factors are stable over time (FAO, 2008). Using information from the household questionnaire, we construct different measures of food and nutrition.

For this study, different dimensions of food and nutrition indicators (food utilization, food access, and household's economic vulnerability) are considered to analyze the impact of improved agricultural technology adoption. Food utilization is represented in two different ways; 1) nutrient intake constructed from food consumption data (i.e., daily per capita protein, daily per capita fat, and daily per capita iron)[2] and 2) diet diversity indicators constructed from food aggregate data (i.e., HDDS and FCS). Daily per capita calorie and percentage of people who are food energy deficit relate food access. Share of food from total household expenditure relates to economic vulnerability of households to food insecurity.

To construct daily per capita protein, fat, iron, and calorie intake: First, local (nonstandard) units are converted into standard units. Then, total calories consumed in the household are determined by taking the quantity consumed per household for each food item multiplied by its perspective (protein, fat, iron, and energy (calories)) values using Ethiopia Food composition table (EHNRI, 1997). Then, average daily consumption is calculated by dividing total protein, fat, iron, and calories consumed in the household by the reference period during which the food was consumed. Finally, average daily per capita consumption is computed by dividing per day consumption by the number of household members, adjusting for age and sex[3].

For several reasons, food consumption reported in ESS may not represent household members' actual food intake. First, members of the household may eat meals outside the home, and capturing the nutritional content of these meals is challenging due to a lack of data. Second, non-household members may be fed by households. Third, the nutritional value of meals is determined by how they are prepared and cooked, as well as the quantity of waste produced. The first concern is addressed, if the cost of meals eaten outside the home is reported. The amount of money spent on meals consumed outside of the home is reported in the ESS data. Thus, price per calorie of food acquired for consumption in the home is used as an adjustment to

[2]For this study, we used the per adult equivalent approach because ih has an advantage over the per capita approach as it takes into account the fact that individual food needs vary by age and gender and it improves precision in estimating household food and energy requirements.

[3]Adult equivalence conversion factors are obtained from the Ethiopia Socioeconomic Survey Wave 1 consumption aggregates construction guideline.

consider food consumed outside. However, we failed to account for meals provided to the non-household member, nutrients lost in food preparation, and food wastage. Therefore such aspects are treated as measurement errors. To determine the percentage of individuals who are food energy deficit, we followed Smith and Subandoro (2007) & UNU, WHO and FAO (2004) and classified households as food secure and insecure using the minimum requirement of 2,550 kilocalories per adult equivalent as cutoff criteria.

HDDS and FCS are used to measure household dietary diversity. Both diet diversity indicators are constructed from food aggregate data. As indicated in (Ruel, 2003), in developing countries, there is a strong positive relationship between diet diversity measures and nutritional adequacy. FAO Kennedy et al. (2011) guideline is used to construct HDDS. HDDS is constructed by classifying food items into twelve food groups[4]. FCS is a frequency weighted diet diversity score computed using the frequency of households food consumed from nine different groups during the seven days before the survey[5]. FCS can be used as an alternative measure for HDDS. FCS is an aggregate score based on the food diversity, frequency, and relative nutritional content of different food groups consumed. The higher the scores, the higher the quality of the diet. To determine the percentage of households with low diet diversity, the standard threshold of 35 scores set by (WFP, VAR, 2008) is used.

The portion of expenditure devoted to food is one of the most useful household level food security indicator(Smith and Subandoro, 2007). The indicator measures the share of household's total expenditures devoted to food and is constructed by dividing the total household food expenditures by the entire household expenditures. The value stems from Engel's law, which is that poorer people generally devote a large proportion of their resources to food (Lele et al., 2016). Economic vulnerability to food insecurity relates to people's ability to acquire food. Economically vulnerable households are those who are monetarily unable to purchase food and households whose food expenditure is a large share of their total budget. Households that spend a large percentage on food are highly vulnerable to food insecurity regardless of their current status of consumption.

3. Empirical Strategy

When non-experimental data are used for analysis, selection bias poses a challenge in impact evaluation. In our case, households may choose improved seeds due to observed and unobserved characteristics. Estimating the effect of improved seed

[4]The food groups include: cereals; root and tuber; vegetables; fruits; meat, poultry and offal; eggs; fish and seafood; pulses, legumes, and nuts; milk and milk products; oil and fat; sugar and honey; and miscellaneous.

[5]Food groups include cereals, root and tubers; vegetables; fruits; meat, poultry and fish; pulses, legumes and nuts; milk and milk products; oil and fats; sugar and honey; and miscellanies. Weights for the food groups range from 0.5 to 4 based on nutrient density. Condiments receive zero nutritional weight. Frequencies are truncated at 7 for each food group. The measure ranges from 0 to 112.

adoption on household food and nutrition security without taking self-selection into account may result in endogeneity bias. However, econometric approaches have been developed to deal with endogeneity issues. One is the two-step endogenous switching regression (ESR) framework, which controls observed and unobserved heterogeneity by estimating two isolated outcome equations alongside the selection model.

Household i adopts improved seed varieties at time t if the expected utility from adopting improved seed (U_{ita}) exceeds from not adopting (U_{itna}). Let A^*_{it} be the latent variable that represents the benefit from improved seed adoption by the i^{th} household at time t.

$$A^*_{it} = Z_{it}\alpha_{it} + \epsilon_{it}; A_{it} = \begin{cases} 1 & \text{if } A^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Where A_{it} is a binary indicator of whether the farm household adopts improved seed varieties or not, Z_{it} is vector of observed household and community level characteristics that affects adoption decisions and ϵ_{it} is the error term.

Following Jaleta et al. (2018), Kassie et al. (2014) and Shiferaw et al. (2014), ERS model is estimated in two steps. In the first step, probit correlated random effects is used to estimate the relationship between adoption of improved seed and household and village level variables. In the second step, two equations of the outcome variables of each group of households in the two treatment statuses are estimated using the correlated random effect model (CRE). The selection bias is addressed by adding generalized residuals. The outcome equations for both adopter and non-adopter after corrected for endogeneity are given by:

$$\text{Regime 1: } Y_{1it} = \beta_1 X_{1it} + \mu_{1it}; \text{ if } A_{it} = 1 \tag{2a}$$
$$\text{Regime 2: } Y_{2it} = \beta_2 X_{2it} + \mu_{2it}; \text{ if } A_{it} = 0 \tag{2b}$$

Where Y_{1it} is the outcome variable for improved seed adopting household i at time t, Y_{2it} is the outcome variable for non-adopting household i at time t. X_{1it} and X_{2it} are a vector of observed household and village level characteristics that determines the outcome variable for adopting and non-adopting household i at time, respectively. β_1 and β_2 are parameters to be estimated and μ_{1it} and μ_{2it} ares error term for regime 1 and 2.

The ESR model can also be used to compare the expected outcome variables of adopting (Eq. 3a) with respect to not-adopting households (Eq. 3b), and to examine the anticipated outcome variables in the counterfactual scenario (Eq. 3c) that the treated households happened to be untreated, and (Eq. 3d) that the untreated households happened to be treated. The conditional expectations of the outcome variables in the four possible scenarios are specified as follows:

$$E[Y_{1it}|X, A = 1] = \beta_1 X_{1it} + \delta_{1v}\lambda_{1it} \tag{3a}$$
$$E[Y_{2it}|X, A = 0] = \beta_2 X_{2it} + \delta_{2v}\lambda_{2it} \tag{3b}$$
$$E[Y_{2it}|X, A = 1] = \beta_2 X_{1it} + \delta_{2v}\lambda_{1it} \tag{3c}$$
$$E[Y_{1it}|X, A = 0] = \beta_1 X_{2it} + \delta_{1v}\lambda_{2it} \tag{3d}$$

Case (Eq. 3a) and (Eq. 3b) are observed from the data, while (Eq. 3c) and (Eq. 3d) are the counterfactual outcome. Then, we calculate the average treatment effect on the treated households (ATT) as the difference between (Eq. 3a) and (Eq. 3c).

$$\begin{aligned} ATT &= (3a) - (3c) = E[Y_{1it}|X, A = 0] - E[Y_{2it}|X, A = 0] \\ &= X_{1it}(\beta_1 - \beta_2) + \lambda_{2it}(\delta_{1v} - \delta_{2v}) \end{aligned} \tag{4}$$

Likewise, the average treatment effect on the untreated (ATU) can be calculated as the difference between (Eq. 3d) and (Eq. 3b).

$$\begin{aligned} ATT &= (3d) - (3b) = E[Y_{1it}|X, A = 1] - E[Y_{2it}|X, A = 1] \\ &= X_{2it}(\beta_1 - \beta_2) + \lambda_{1it}(\delta_{1v} - \delta_{2v}) \end{aligned} \tag{5}$$

Table 1: Conditional expectation and treatment

Households	Decision stage: Adopted	Decision stage: Non-adopted	Treatment effect
Adopted	$(3a)E[Y_{1it}\|X, A = 1]$	$(3c)E[Y_{2it}\|X, A = 1]$	ATT $((3a) - (3c))$
Non-adopted	$(3d)E[Y_{1it}\|X, A = 0]$	$(3b)E[Y_{2it}\|X, A = 0]$	ATU $((3d) - (3b))$
Heterogeneous effect (HE)	$BH_1 = ((3a) - (3d))$	$BH_2 = ((3c) - (3b))$	$TH = (ATT - ATU)$

From conditional expectation equations, heterogeneous effects can also be calculated (Carter and Milon, 2005; Di Falco et al., 2011). For instance, rural households that did adapt may have better food and nutrition security than farm households that did not adopt regardless of the fact that they decided to adopt but because of unobservable characteristics. Base heterogeneity effect for households that decided to adopt can be defined as the difference between (2a) and (2d) (Carter and Milon, 2005);

$$\begin{aligned} HB_1 &= (3a) - (3d) = E[Y_{1it}|X, A = 1] - E[Y_{1it}|X, A = 0] \\ &= (X_{1it} - X_{2it})\beta_1 + \delta_{1v}(\lambda_{1it} - \lambda_{2it}) \end{aligned} \tag{6}$$

Similarly, the base heterogeneity effect for households that decided not to adapt is defined as the difference between (2c) and (2b);

$$\begin{aligned} HB_2 &= (3c) - (3b) = E[Y_{2it}|X, A = 1] - E[Y_{2it}|X, A = 0] \\ &= (X_{1it} - X_{2it})\beta_2 + \delta_{2v}(\lambda_{1it} - \lambda_{2it}) \end{aligned} \tag{7}$$

Finally, transitional heterogeneity (TH), which measures whether the effect of improved seed adaption is greater or lesser for farm households that adapted or that did not adapt in the counterfactual case that they did adapt Di Falco et al. (2011) is computed as the difference between equations (4) and (5) (i.e., ATT and ATU).

ESR model to be identified covariates in the selection equation needs to have at least one instrumental variable additional to automatically generated by the non-linearity of the selection model (Di Falco et al., 2011; Kassie et al., 2014; Shiferaw et al., 2014). However, the instrument variables should have directly affected the selection variable but not the outcome variables. For this study, information source variables (ownership of mobile phone and participation in agricultural extension program) are proposed as the best candidates for instrument variables. But, to ascertain the suitability of instruments they are subjected to tests. The appropriateness of instrumental variables is assessed using a simple falsification test following Di Falco et al. (2011). Only participation in the agricultural extension program passed the falsification test and was included in the selection model while excluded in the outcome models of ESR (Appendix Table A).

Using panel data gives an advantage of controlling for unobserved time-invariant heterogeneity. Usually, this unobserved heterogeneity is estimated using either fixed effects (FE) or random effects (RE) models. However, RE models are based on a strong assumption that there is no correlation between unobserved heterogeneity and observed characteristics (Wooldridge, 2010). In contrast, the FE approach assumes a correlation between unobserved heterogeneity and observed characteristics. But, the biggest weakness of the FE model is that in the process of transformation, it removes important time-invariant variables from the model (Wooldridge, 2010; Cameron and Trivedi, 2005). These become problematic when the researcher's interest is to examine the effects of time-invariant explanatory variables. Therefore, a correlated random effects (CRE) model is employed following the Mundlak–Chamberlain device (Mundlak, 1978; Chamberlain, 1982) to estimate all the empirical models in this study. The CRE approach preserves the FE approach's advantages while simultaneously enabling the inclusion of time-invariant explanatory variables in the analysis and thus adopted in this study.

4. Results

4.1. Descriptive Statistics

Table 2 reports descriptive statistics of variables used in the main analysis. Approximately 22% of households used at least one type of improved seed on their cultivated land. Adopting households consumed significantly more protein, fat, and iron than non-adopting households, with total average intakes of about 82, 26, and 108.90 mg, respectively. Adopting households also consume significantly more diverse foods than non-adopting households, with an average HDDS and FCS of about 6 and 42, respectively. The average per capita calorie intake of the sample households was around 3183 kilocalories, with no significant difference between adopting and non-adopting households. Furthermore, non-adopting households spent a significantly higher proportion of their income on food than adopting households.

Table 2: Descriptive Statistics

Variables	Variable description	Total	Adopter	Non -adopter	Diff.
		Mean	Mean	Mean	
Adoption	=1 if the HH adopt improved seed , 0 otherwise	0.22	1.00	0.00	
Protein	Daily per capita protein consumption	81.80	84.42	81.06	3.36^{*}
Fat	Daily per capita fat consumption	26.35	27.24	26.11	1.13^{*}
Iron	Daily per capita iron consumption	108.37	114.90	106.52	8.37^{**}
HDDS	HH Dietary diversity	5.73	6.15	5.62	0.54^{***}
FCS	Food consumption score	42.12	44.43	41.47	2.96^{***}
FCS (dummy)	Proportion of HH who are nutrition insecure	0.34	0.27	0.36	-0.10^{***}
Calorie	Daily per capita calorie consumption	3182.7	3207.9	3175.6	325.35
Food insecurity	Proportion of HH who are food insecure	0.45	0.42	0.46	-0.04^{**}
Food share	Share of food expenditure	0.79	0.77	0.80	-0.03^{***}
Gender	=1 Male; =0 Female	0.80	0.83	0.79	0.04^{***}
Age	Heads age in years	47.58	47.66	47.56	0.10
Education	=1 Literate; =0 illiterate	0.31	0.34	0.31	0.03^{*}
HH size	No. of families in the HH	5.34	5.52	5.29	0.23^{***}
Land	Cultivated land in ha	1.35	1.43	1.33	0.10
Livestock	Livestock holding in TLU	2.76	3.10	2.66	0.43^{***}
Mobile	=1 Had mobile; 0 otherwise	0.39	0.46	0.37	0.09^{***}
Extension	=1 if the HH Participated in agri. extension; 0 otherwise	0.44	0.79	0.34	0.46^{***}
Market	Nearest market distance (km)	63.43	51.05	66.93	-15.87^{***}
Road	Nearest road distance (km)	14.49	11.48	15.34	-3.86^{***}
Market access	=1 if there is market in the village; 0 otherwise	0.51	0.51	0.52	-0.01
Credit access	=1 if there is microfinance in the village; 0 otherwise	0.23	0.25	0.22	0.03^{**}
Rainfall	Total annual rainfall (mm)	1287.31	1380.24	1261.02	119.2^{***}
Market risk	=1 if HH perceives increase in input price; 0 otherwise	0.13	0.19	0.11	0.08^{***}
Drought	=1 if HH perceives drought; 0 otherwise	0.20	0.16	0.21	-0.05^{***}
N		4090	902	3188	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The majority of sample households were male headed (80%) however compared to non-adopting households (79%), improved seed adopting households had a higher proportion of male household heads (83%). This might occur because female-headed households either face information and/or income barriers to adopting improved seeds or rely on local seeds to minimize risk. The average age of sample household heads was about 48 years. Of the total sample households, only 31% of household heads were attended formal education. Adopting households tend to be more educated (34%) than those non-adopting household heads (31%). Educated household heads possibly will take more risk and tend to have more knowledge about technologies than their illiterate counterparts and thus can easily accept and adopt improved seeds. Again, adopting households had larger family sizes (5.52) than their non-adopting counterparts (5.29) with the total average of 5.34.

On average, sample households had about 1.35 ha of cultivated land. The average livestock holding of sample households was about 2.76 TLU. Compared to non-adopting households (2.66 TLU), adopting households had more livestock (3.10 TLU). Households with more assets could invest in external productivity enhancing inputs as they have easier access to credit. The proportion of households that participated in the agricultural extension program was about 44%. Again, adopting households (79%) participated in the agricultural extension program at a higher rate than non-adopting households (34%).

Further summary statistics show that the average distance to the nearest weekly large market is about 63 km for the total sample households. On average, each household lived about 14 km far from the nearest main road. The proportion of households who have lived in the village where there is microfinance was 23%. About 13% of households in the sample have faced market shocks due to increase in input prices and 20% have experienced weather shocks due to drought.

4.2. Impact of improved seed adoption on nutritional security

This section presents estimated results from the impact of improved seed adoption on a household's nutrition security. We used both nutrition security indicators derived from household food consumption and food aggregate datasets. The outcome variables of interest are compared under actual and counterfactual scenarios for both adopting and non-adopting households.

As presented in the last column of Table 3 in most cases, both adopters and non-adopters would be benefited from adopting improved seed. The average treatment effect on the treated (impact of improved seed on adopting households) is 2.89, 1.35, and 2.85 mg for protein, fat, and iron consumption, respectively. This means that if adopting households had not been adopt, their protein, fat, and iron consumption would have decreased by 2.89, 1.35, and 2.85 mg, respectively. On the other hand, the average treatment effect on the untreated (impact of improved seed on non-adopting households) is approximately 5.45, 0.49, and 2.60 mg for protein, fat, and iron consumption, respectively. This implies that if the non-adopters had adopt, their average protein, fat, and iron consumption would have increased by 5.45, 0.49, and 2.60 mg, respectively.

Table 3: Impact of improved seed adoption on nutrition intake

Outcome variable	Treatment effect	Decision stage: To adopt	Decision stage: Not to adopt	Average treatment effect (ATE)
Protein	ATT	84.39(0.76)	81.50(0.69)	2.89(1.03)***
	ATU	86.53(0.63)	81.08(0.37)	5.45(0.74)***
	HE	−2.14(1.26)*	0.42(0.79)	−2.56(1.05)**
Fat	ATT	27.15(0.22)	25.801(0.22)	1.35(0.31)***
	ATU	26.60(0.19)	26.11(0.12)	0.49(0.22)**
	HE	0.55(0.37)	−0.317(0.25)	0.86(0.33)**
Iron	ATT	114.67(1.28)	111.82(1.15)	2.85(1.72)*
	ATU	108.97(1.43)	106.36(0.65)	2.60(1.571)*
	HE	6.70(2.77)**	5.45(1.37)***	0.24(2.38)
HDDS	ATT	6.15(0.02)	5.93(0.03)	0.22(0.03)***
	ATU	5.74(0.02)	5.62(0.01)	0.12(0.02)***
	HE	0.41(0.04)***	0.30(0.03)***	0.10(0.03)***
FCS	ATT	44.36(0.26)	42.01(0.23)	2.35(0.35)***
	ATU	42.49(0.16)	41.49(0.12)	1.00(0.20)***
	HE	1.87(0.33)***	0.52(0.26)**	1.35(0.20)***
FCS (dummy)	ATT	0.27(0.01)	0.35(0.01)	−0.08(0.01)***
	ATU	0.30(0.004)	0.36(0.003)	−0.06(0.005)***
	HE	−0.03(0.01)***	−0.01(0.01)*	−0.02(0.005)***

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Results from diet diversity indicators of nutrition security also show that adopters and non-adopters benefited from adopting improved seeds. Adopters' HDDS and FCS would have decreased by about 0.22 and 2.35 scores, respectively if they had not adopt. On the other hand, If non-adopters had adopt, their HDDS and FCS would have increased by 0.12 and 1.00 points, respectively. Results from the binary FCS indicator also show that the probability of being nutrition insecure would increase by eight percentage points for adopting households if they did not adopt. Likewise, the likelihood of nutrition insecurity would decrease by about six percentage points if non-adopting households had adopt.

Results from the heterogeneous effect in the sample show that households who actually adopt would have significantly higher iron intake and consume more diverse foods (HDDS and FCS) than households that did not adopt in counterfactual cases. This will show that some sources of potential heterogeneity make adopters consume more nutrition than non-adopters, irrespective of improved seed adoption. However, in the case of protein consumption, if non-adopting households had adopt, they would have consumed more protein than households actually did. On the other hand, if adopting households had not adopt, they would have consumed the same protein and fat as households that actually did not adopt. Similarly, if non-adopting households had adopt, they would have consumed the same fat as households that actually did adopt. However, some potential sources of heterogeneity cause households that adopting to consume more diverse foods (HDDS and FCS) and iron than households that did not adopt, regardless of adoption status.

4.3. Impact of improved seed adoption on food access and economic vulnerability

Table 3 depicts the impact of improved seed adoption on food access (as measured by calorie consumption and the percentage of people experiencing a food energy deficit) and household economic vulnerability (as measured by the share of household food spending in total expenditure). According to food access indicators' results, adopters and non-adopters would benefit from adopting improved seeds. Adopters' energy consumption would have been reduced by approximately 80 kilocalories if they had not adopt. While, if non-adopting households had adopt, their energy consumption would have increased by about 91 kilocalories. Similarly, if adopting households had not adopt, their likelihood of being food insecure would have increased by about three percentage points. In addition, if non-adopting households had adopt, the likelihood of food insecurity would have decreased by about two percentage points.

Table 4: Impact of improved seed adoption on food access and economic vulnerability

Outcome variable	Treatment effect	Decision stage		Average treatment effect (ATE)
		To adopt	Not to adopt	
Calorie	ATT	3208.47(25.17)	3128.51(25.00)	79.96(35.48)**
	ATU	3268.69(18.85)	3177.47(13.83)	91.22(23.38)***
	HE	−60.21(37.88)	−48.95(29.20)*	−11.26(31.66)
Calorie (dummy)	ATT	0.42(0.01)	0.45(0.01)	−0.03(0.01)***
	ATU	0.44(0.004)	0.46(0.003)	−0.02(0.005)***
	HE	−0.02(0.01)**	−0.01(0.01)	−0.01(0.01)*
Food exp. share	ATT	0.77(0.002)	0.79(0.001)	−0.02(0.002)***
	ATU	0.79(0.001)	0.80(0.001)	−0.01(0.001)***
	HE	−0.02(0.002)***	−0.01(0.001)***	−0.01(0.002)***

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Adopting improved seeds reduces the economic vulnerability to food insecurity of both adopting and non-adopting households. Adopters' share of food expenditures would have increased by about two percentage points if they had not adopt. Non-adopter households, on the other hand, reduce their share of food expenditure by about one percentage point if they adopt.

4.4. Mechanism

We proposed two paths for improved seed adoption to impact food and nutrition security. The first is through its own dietary content. Some improved seeds contain more nutrients than native varieties. Second, the effect will be felt in terms of income. Improved agricultural inputs have the potential to produce higher yields than local varieties (Abate et al., 2017; Alwang et al., 2019)), encouraging farmers to participate in marketing activities, which in turn improves farm household income and food and nutrition security (Von Braun, 1995; Kennedy and Cogill, 1988). We are unable to evaluate the first mechanism due to data constraints. On the other hand, the available data on ESS helps to determine the role of commercialization in mediating the impact of improved seed adoption on food and nutrition security. Therefore, commercialization is defined as a dummy variable with a value of one if the household sold any crops and zero otherwise.

Table 5 presents the impact of improved seed adoption on commercialization. According to the findings, if adopting households had not adopt, their probability of being commercialized would have been reduced by about 4 percentage points. Non-adopting households, on the other hand, would have increased their probability of being commercialized by 7.4 percentage points if they had adopt improved seed.

Table 5: Impact of Improved Seed Adoption on Commercialization

Outcome variable	Treatment effect	Households		Average Treatment Effect
		Commercialized	Not-Commercialized	
Commercialization	ATT	0.886(0.003)	0.844(0.002)	0.042(0.004)***
	ATU	0.917(0.003)	0.843(0.001)	0.074(0.005)***
	HE	$-0.030(0.010)^{***}$	0.001(0.003)	$-0.031(0.010)^{***}$

Standard errors in parentheses. The dependent variable is market participation which takes 1 if the household sale any agricultural product, 0 otherwise. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.5. Differential Effect of Extreme Weather Shock

An additional dataset from Climate Hazards Group Infrared Precipitation with Station Data (CHIRPS) is used to examine the differential effect of extreme weather shock on food and nutrition security in the presence of improved seed adoption. CHIRPS is a quasi-global rainfall data set spanning 35+ years. The data set includes rainfall data from 1981 to the present with 0.05-degree (5×5 km) spatial resolution satellite imagery (Funk et al., 2015). This study uses CHIRPS data with a spatial resolution of around 5 km (at the equator) and a temporal resolution of one month. CHIRPS have been used in previous research focuses on the effects of weather shocks (Hirvonen et al., 2020; Tambet and Stopnitzky, 2019; Aragón et al., 2018).

Rainfall data from CHIRPS and household latitude and longitude coordinates from the Ethiopian Socioeconomic Survey (ESS) are matched using an inverse distance-weighted average of the four nearest satellite observations. After matching, the extreme weather shock (drought) variable is defined following previous literature (Thiede, 2014; Andalón et al., 2016; Hirvonen et al., 2020) as a standardized deviation (z-score) of rainfall from the long-term mean (i.e., 1981-2015) in the same village. Then, drought is defined as a dummy variable for which rainfall was below negative two standard deviations. Because data collection and the drought (2015/16 En Nino) event occurred in the same year, only the last wave of ESS is considered for differential analysis. Among the total sample households, 17% received two standard deviations less rainfall than the long-term average. Approximately 37% of households affected by the El Nino drought used improved seeds in at least one of their plots. On the other hand, only 19% of drought-unaffected households adopt improved seeds in 2015.

Table 6: Differential Effect of Extreme Weather Shock

Outcome variable	Treatment effect	Households		Differential effect
		Drought affected	Drought unaffected	
Protein	ATTDA	15.14(2.27)***	1.48(1.34)	13.94(1.49)***
	ATUDU	28.90(1.82)***	4.84(0.78)***	22.76(0.93)***
Fat	ATTDA	5.18(0.48)***	2.18(0.46)***	3.01(0.45)***
	ATUDU	6.48(0.29)***	2.22(0.26)***	4.16(0.29)***
Iron	ATTDA	6.75(4.48)	11.65(2.55)***	−4.90(3.03)
	ATUDU	21.65(3.62)***	7.97(1.56)***	10.79(1.90)***
HDDS	ATTDA	0.38(0.06)***	0.01(0.05)	0.38(0.06)***
	ATUDU	0.32(0.04)***	0.02(0.06)	0.33(0.06)***
FCS	ATTDA	2.71(0.45)***	0.24(0.56)	2.47(0.49)***
	ATUDU	2.00(0.37)***	1.61(0.35)***	0.70(0.28)**
FCS	ATTDA	−0.31(0.02)***	−0.02(0.01)*	−0.28(0.02)***
(dummy)	ATUDU	−0.21(0.01)***	−0.08(0.01)***	−0.11(0.01)***
Calorie	ATTDA	570.36(74.50)***	110.49(48.60)**	459.87(49.95)***
	ATUDU	810.74(53.98)***	227.94(30.83)***	548.54(34.08)***
Calorie	ATTDA	−0.08(0.02)***	−0.08(0.01)***	0.001(0.02)
(dummy)	ATUDU	−0.33(0.03)***	−0.07(0.01)***	−0.24(0.01)***

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Results from Table 6 show that in the presence of extreme weather shocks, the adoption of improved seed benefits drought-affected households more than drought-unaffected households in most cases. Due to the use of improved seed, drought-affected households consume significantly more protein, fat, and calories, as well as more diverse foods (HDDS and FCS), than drought-unaffected households in both actual and counterfactual cases.However, there is no significant difference in iron consumption between drought-affected and drought-unaffected households in the actual case, whereas drought-affected adopter households consume more iron than drought-unaffected households in the counterfactual case.

4.6. Robustness Check

We considered alternative estimation methods to test the robustness of the main results. Thus, Nearest Neighbor One to Many (One to Five) is used as an alternative estimation model. As shown in Table 7, the results are consistent with the main result in almost all cases. As a result, adopting improved seeds improves nutrition security, lowers the likelihood of food insecurity, and lowers households' economic vulnerability to food security. However, the impact of using improved seed on calorie consumption is not statistically significant, in contrast to the main finding.

Table 7: Robustness Check-Nearest Neighbor one to many

Food Utilization		Food Access and Economic Vulnerability	
Outcome Variable	ATT	Outcome Variable	ATT
Protein	$4.08(2.00)^{**}$	Calorie	$24.44(78.88)$
Fat	$1.75(0.71)^{**}$	Food Insecurity	$-0.05(0.02)^{**}$
Iron	$-1.03(3.72)$	Food Expenditure share	$-0.03(0.005)^{***}$
HDDS	$0.44(0.067)^{***}$		
FCS	$4.14(0.63)^{***}$		
FCS (Dummy)	$-0.13(0.02)^{***}$		

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

5. Conclusion and Policy Implication

Increasing agricultural productivity through the dissemination and application of improved technologies benefits economic growth, food security, and poverty alleviation (World Bank, 2020). However, in developing countries such as Ethiopia, the adoption of improved agricultural technologies is low Given the above fact, this paper aims to investigate the impact of improved seed adoption on the food and nutrition security of rural households. We used two recent waves of Ethiopia Socioeconomic Survey (ESS) data and a panel ESR model to examine the impact. Various indicators have been used to capture the multidimensional nature of food and nutrition security.

The panel ERS model results show that adopting improved seed has a positive and statistically significant effect on food and nutrition security in actual and counterfactual cases. If adopting households had not adopt, their protein, fat, iron, and calorie consumption would have been significantly reduced, and they would have consumed less diverse foods. On the other hand, if non-adopters were adopt improved seed, they would consume more protein, fat, iron, and calorie as well as have consumed a more diverse diets. Then again, adopting improved seed reduces the likelihood of households experiencing food energy deficiency and economic vulnerability to food insecurity in both actual and counterfactual cases. When disaggregated by weather shock, the results show that benefits of adopting improved seeds are greater for drought-affected households than drought-unaffected households with the former consuming significantly higher protein, fat, and calories; and having a more diverse diet in both actual and counterfactual scenarios. Thus, we can conclude that improved seed adoption improves rural households' overall food and nutrition security.

This finding has significant policy implications. First, adopting improved seed improves not only food consumption but also nutrition intake and reduces households' economic vulnerability to food insecurity. In particular, we showed that using improved seed increased protein, iron, and fat consumption. Finally, reallocating scarce resources, such as improved seed, is a major challenge in developing countries; however, our findings show that when there is a shock, allocating improved seed to drought-affected households results in significant food and nutrition improvement compared to allocating improved seed to drought-unaffected households.

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