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Innovation complementarity, adoption patterns and food security

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Abstract

This article studies the effect of the adoption of agricultural innovation on the dietary diversity of rural smallholders in Ethiopia. For the analysis, we used a three years panel data collected by the World Bank through the Living Standards Measurement Study-Integrated Surveys on Agriculture in Ethiopia. We measured the adoption of agricultural innovation as the intensity of land use of a technology (i.e., use of fertilizers, or improved seed varieties). To control for endogeneity, we used a two stage Fixed Effect regression approach. We identified that the adoption of one technology was not significant or had a minimal effect on dietary diversity, but when households adopt the technologies as a package, we observed more substantial and highly significant improvements on nutrition. In addition, it appears that the adoption of one technology impacts dietary diversity through enhancements in subsistence production, while when adopted as a package the improvements are achieved through income and access to food from the market. We conclude that the impact of adoption of innovation depends highly on the type of technology a household is adopting and whether it is applied individually or in a package.

Key words: adoption, complementarity, innovation, impact, dietary diversity

JEL Code: O33, Q18,

1. Introduction

In rural areas of sub-Saharan Africa (SSA), agriculture plays a crucial role in confronting the challenge of improving food and nutrition security. On average, this sector contributes 15% of total GDP or even more in certain regions (OECD/FAO, 2016, p.61). For instance, in Ethiopia agriculture is approximately 45% of the GDP and it has been the main contributor to poverty reduction. However, the poverty remains relatively high in rural areas (ADBG, 2015). Agriculture represents both a source of income and of food for the SSA rural population, especially households that depend on small-scale production (Haddad, 2000 and 2013; Ehui and Pender, 2005). These small holdings constitute approximately 80% of all farms in SSA and employ about 175 million people directly (Alliance for a Green Revolution in Africa, 2014). Currently, SSA has both the highest poverty rates and percentage of undernourishment in the world

(Olinto & Uematsu, 2013; FAO, IFAD and WFP, 2015). While extreme poverty has fallen, the pace was considerably slower in lower-income countries, such as Ethiopia (Olinto et al., 2013). Therefore, it is of great importance for their food and nutrition security that the agricultural production rises radically both in terms of yield and quality (nutritious food) (Haddad, 2000).

SSA population is highly dependent on agriculture or related activities, though they have the lowest productivity in the world (Ehui & Pender, 2005). In addition, the region has been suffering from climate change manifestations, such as drought, floods, and elevated temperatures, intensifying soil erosion and soil fertility depletion (Ehui & Pender, 2005; FAO, 2016). Increasing agricultural production by expanding the area under cultivation is not an option, because, like water and other natural resources, the land is scarce and in demand (Godfray et al., 2010). Therefore, scholars have considered that the adoption of agricultural innovation is a significant and necessary element to increase agricultural productivity and improve rural households' nutrition and food security (Baiphethi & Jacobs, 2009; Kassie et al., 2011). Innovation involves both traditional and advanced crop and livestock breeding, as well as the continuing development of better chemical, agronomic, and agro-ecological control measures (Godfray et al., 2010). Unfortunately, due to restricted access to agricultural inputs, lack of financial aid, market inefficiencies and low absorptive capacity, the innovation adoption levels in SSA are low compared to other developing countries (Ehui & Pender, 2005).

Different factors determine the adoption of agricultural innovation in developing countries. The most common ones are participation in extension programs, risk aversion behavior, wealth, land characteristics (e.g., fragmentation) and production specialization (Asfaw et al., 2010; Yu & Nin-Pratt, 2014; Yu et al., 2011). Once farmers have adopted the innovation, this might impact household nutrition through several pathways (Haddad, 2000 and 2013; Herforth and Ballard, 2016; Turner et al., 2013). The pathways can be classified into two groups depending on whether the effect is direct or indirect (Kassie et al., 2011; Herforth & Ballard, 2016). Direct effects refer to improvements in dietary quality and food access. These effects can take two main pathways, improving the quantity, quality, and diversity of the subsistence production, and/or improving access to markets by increasing their income or availability to trade (Shiferaw, Kebede & You, 2008; Akinola et al., 2009; Herforth and Ballard, 2016). On the other hand, indirect effects influence nutrition and food security by changes in food prices (Haddad, 2000; Kassie et al., 2011; Kerr et al., 2011; Haddad, 2013) or in off-farm labor demand (Kerr et al., 2016). Households can achieve these improvements through innovation adoption, which is also expected to enhance their nutrition (Hoorweg et al., 2000; Kassie, Shiferaw and Muricho, 2011; Kerr et al., 2011). Study cases have shown that the adoption of either fertilizer (Akinola et al., 2009) or improved seeds varieties (Shiferaw, Kebede & You, 2008; Kassie et al., 2013) has a positive impact on household income and welfare.

Many studies have evaluated the uptake of a single technology or practice in one specific crop (Asfaw et al., 2010; Yu & Nin-Pratt, 2014) or a group of crops (Croppenstedt, Demeke & Meschi, 2003; Ricker-Gilbert, Jayne & Chirwa, 2011). However, farmers tend to use more than one technology simultaneously or sequentially as complements, rather than only one (Kassie et al., 2013; Sheahan & Barrett, 2017). Therefore, a more comprehensive approach to evaluate the impact of agricultural innovation adoption might be to consider the adoption of a package of technologies instead of one. This approach has been employed in some studies to identify the determinants of innovation adoption (Holden & Yohannes, 2002; Yu et al., 2011; Kassie et al., 2011; Tefera et al., 2016). However, the evidence is rather rare when it comes to evaluation impacts on nutrition generated by innovation adoption.

Therefore, it is in our interest to explore the role of agricultural innovation adoption on the dietary diversity of households as an indicator of household nutrition and food security. The objective of this report is two-folded, i) evaluate if innovation adoption has an impact on diets and what is the impact's magnitude when the technologies are adopted individually or in package, and ii) identify the pathway by which agricultural innovation adoption impact nutrition. The considered innovations are the following: organic and inorganic fertilizer and improved seed varieties. We used a three-year panel data sample of Ethiopian rural households from LSMS-ISA (2011), to demonstrate that agricultural innovation adoption improved farm household's dietary diversity. However, we show that the magnitude of the impact depends on the type of technology adopted and whether it is used individually or in a package. More specifically we demonstrated that the effect on dietary diversity is stronger when farmers adopt more than the package of technologies. Highlighting the fact that programs and policies that are aiming to improve household nutrition through agricultural production should focus on enhancing the adoption of groups of technologies instead of one. Besides, we identified that when fertilizer is adopted individually, the impact on dietary diversity is through subsistence production, but the effect was through income when households adopt package of technologies.

2. Data, Variables and Empirical Strategy

2.1. Data

For this report, we used the Ethiopian Rural Socioeconomic Survey (ERSS) datasets, which is the result from a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study- Integrated Surveys on Agriculture (LSMS-ISA) team. While the panel survey is implemented by the CSA, the LSMS team is responsible for the management and technical design of the project, as well as for the data analysis. The ERSS is integrated with the annual Agricultural Sample Survey (AgSS) and resulted in a two-stage probability sample. The first s of sampling is related to selection of enumeration areas (EAs) (i.e. the primary sampling units) using simple random sampling from the sample of the AgSS EAs[1]. For the rural sample, 290 EAs were selected from the AgSS EAs. The EAs for small towns and urban areas were selected by population size and comprises a total of 43 EAs and 100 EAs respectively.

The sample for the ERSS was collected in three waves 2011-12, 2013-14 and 2015-16[2]. The sample for Wave 1 comprises 4,000 households in rural and small towns areas across Ethiopia, and "provides estimates at the national level for rural and small-town households and […] provides estimates for four regions including Amhara, Oromiya, SNNP, and Tigray." (CSA & WB, 2013, p.7). For Wave 2 and 3 the sample was expanded to include 1,500 urban households, for a total sample of 5,500 households; in order to correspond with the existing Wave 1 design while ensuring that all urban areas were included, the population frame was stratified to be able to provide population inferences for the same five domains as in Wave 1 plus an additional domain for the city state of Addis Ababa. Due to the fact that non-farm households were not considered for the analysis and data cleaning processes, the initial sample was reduced; leaving the following sample sizes: Wave 1 (1,827), Wave 2 (2,403) and Wave 3 (2,564). During the data cleaning process observations were dropped when variables, such as land size, and farm income, showed extreme outliers, under the assumption that all extreme values are due to measurement error. The reduction in the sample can also be explain due to the fact that the analysis was done at the household level but many of the questions were answered at the plot level or at the community level; hence observations were lost while merging all the information. The total sample has 6,794 households.

2.2. Nutrition, innovation and other important indicators

To assess the effects of innovation adoption on household nutrition, we need appropriate indicators. The following section will present the important indicators, why they were selected and how they were measured. The analysis includes the level of dietary diversification as an indicator for nutrition, agricultural technologies used in farm and fields as an indicator for innovation and other indicators.

2.2.1. Nutrition indicators

We used Household Dietary Diversity Score (HDDS) as an indicator to measure dietary diversity at the household level. The score is a numerical variable that range between 1 and 12, where each of the categories represent one food group (see Annex Table A1). The larger the score the more diversified is the diet a household is eating, hence a better nutritional status. In addition, we classified the food groups in to three bigger categories: HDDS_crops food that comes from crop production, HDDS_livestock food that comes from livestock production, and HDDS_processed highly processed food (see Annex Table A1). These categories helped us to clarify in if all the food groups were impacted in the same magnitude

[1] The AgSS EAs were selected based on probability proportional to size of population
[2] Fieldwork for Wave 1, from September 2011 to March 2012, Fieldwork for Wave 2 began in September 2013 and finished in April 2014, and Fieldwork for Wave 3 began in September 2015 and finished in April 2016.

by the agricultural technology adoption.

We also considered measuring age-adjusted per-capita caloric intake, however this measurement does not provide sufficient information to measure food security (Maxwell et al., 2013; Vaitla et al., 2017). The indicator provides information about the food quantity, but it is not comprehensive enough to capture more complex notions (Maxwell et al., 2013). compare to indicators that measure if a food was consumed or not, the recall of food quantities eaten by a household might be less accurate and less reliable (Lele et al., 2016, p. 36), can also be very time consuming and expensive to measure (Lele et al., 2016; Maxwell et al., 2013). Lastly, per-capita caloric intake might differ between and within regions; however, the latter can be amended by standardized surveys

Because a diet depends on cultural and geographical factors, the literature does not present established or common thresholds in terms of number of food groups to indicate adequate or inadequate dietary diversity (Kennedy, Ballard & Dop, 2011). One approach to create thresholds is to stratify HDDS using a wealth/income scale (Kennedy, Ballard & Dop, 2011), using a similar approach we obtained three categories low dietary diversity (1-6 food groups), moderate dietary diversity (6.3-7 food groups) and High dietary diversity (≥ 7 food groups) (see Annex Table A2), which will be used as cut-off points.

Table 1. Descriptive statistics of nutrition variables

Variables	**Total sample**	**Non-Adopters**	**Fertilizer adopters**	**Improved seed adopters**	**Fert. & imp. seeds**
HDDS	6.457 (1.612)	6.485 (1.576)	6.358 (1.642)	6.529 (1.520)	6.864 (1.485)
HDDS_c	2.746 (1.036)	2.71 (1.082)	2.715 (1.030)	2.602 (1.080)	2.983 (.921)
HDDS_l	1.536 (.630)	1.586 (.648)	1.501 (.612)	1.705 (.624)	1.577 (.664)
HDDS_p	2.174 (.742)	2.184 (.743)	2.141 (.754)	2.220 (.750)	2.303 (.663)
	N = 3056	N = 1355	N = 2194	N = 67	N =577

Notes: Th numbers in parenthesis are standard deviations

Column 3 form Table 1. shows the summary statistics for the nutrition indicators of the total sample. According to the values of the HDDS the average households are considered to eat 6.4 food groups, meaning that these households have on average a moderate diversified diet. On average households consumed 55% of the food categories that come from crop production, 38% of the ones from livestock production, and 72% of the highly processed foods. Suggesting that on average farm-households consume less food that come from livestock, such as meat or milk compare to the remaining categories. This coincide with results from other studies that indicate that African countries tend to eat few livestock derivate (Speedy, 2003; Schönfeldt & Hall,2012).

On columns 4 to 7, we presented the descriptive statistics of the nutrition indicators according to a technology adoption stratification. The classification is as follows: households that are non-adopters (households that have not adopted either fertilizer or improved seed varieties, neither individually nor simultaneously), households that adopted either fertilizer or improved seed varieties individually, households that adopted the two technologies in the same farm. While the HDDS of the non-adopters do not highly differentiate with the fertilizer adopters, they do when compare to the adopters of improved seed varieties and the ones who adopt the two technologies. This suggest a positive relation between nutrition with the adoption of those technologies; however, no causal relation can be stablished jet. Similar results can be observed with HDDS_c and HDDS_p, insinuating that not only farmers tend to use more than one innovative technology simultaneously but that might be positively correlated to nutrition. On the other hand, HDDS_l seems only to be positively related to the adoption of improved seed varieties.

2.2.2. Innovation adoption indicators

Measuring agricultural innovation in developing countries is challenging due to the lack of and/or inaccuracy of information. In addition, adoption is a decision at the individual farmer level and due to heterogeneity across the regions conclusions cannot be generalized, making it difficult to identify patterns (Feder et al., 1985). Lastly, the majority of the developing countries have innovation systems that rely on imitation and adoption, or are supported almost exclusively by public financing, rather than private investment (Spielman & Birner, 2008, P.18). Therefore, researchers have developed indicators such as the use or not of an innovation (dummy) (fufa & Hassan, 2006), the amount of innovation used (quantity or expenditure) (Ogutu et al., 2017), and area or share of the area where an innovation is used (Anley, Bogale & Haile-Gabriel, 2007; Shiferaw, Kebede & You, 2008; Asfaw et al. 2010; Barrantes & Yagüe, 2015).

From the list of indicators, we decided to use the first and the last indicator. We decided to base our analysis on the third indicator because it gives us information about the intensity of use of each innovation. The intensity of innovation use per unit operated area imply that the greater the area in which an innovation is used, the higher is the likelihood of adoption. To compute the intensity of adoption, we calculated the number of field where each of the innovations were used and divided it into the total number of field planted by the household. Therefore, we were able to obtain the proportion of field where these innovations have been used, the covered area.

Kassie et al., (2013) and Sheahan and Barrett (2014) mentioned, farmers tend to use more than one innovation simultaneously and/or sequentially as complements, rather than only one. To confirm whether this hypothesis is true for our case study, we created a household innovation score (HIDS) that showed us if more than one innovations are being used at the same time. HIDS is an unweighted score with a scale of 0 to 5 that reflects the number of technologies that a household has adopted in at least one of its fields. The 5 possible technologies are: irrigation, fertilizer (chemical and organic), erosion protection methods, improved seed varieties and pesticides.

Table 2. Descriptive statistic of the innovation indicators at the field level.

Variable: **Innovation Indicators**	Mean (Std. Dev.)
HIDS	2.032 (1.128)
Use of only fertilizer (1: use it, 0: do not use it)	.591 (.491)
Use of only improved seed variety (1: use it, 0: do not use it)	.010 (.100)
Fertilizer land utilization proportion (0-1)	.416 (.430)
Improved seed varieties land utilization proportion (0-1)	.002 (.037)
Fertilizer and improved seed in the same field (1: use both, 0: do not use both)	.196 (.397)
Fertilizer, improved seed and pesticides (same field) land utilization prop. (0-1)	.017 (.060)

Table 2. presents the descriptive statistics of the innovation indicators. The household innovation diversity score shows that the average household uses more than one innovation (2) in the same farm. While 33% households reported the use of one innovation 66% of the sample informed that they have used more than one (see Annex Table A3). More specifically, 2,278 households adopt 2 innovations; confirming that, in our sample, farmers tend to adopt groups of innovations rather than one. From the households that reported to use more than one innovation, one of the popular combination was improved seed varieties and fertilizers (see Annex Table A4). Similar findings were reported for a case study in Kenya, where scholars fund that when inorganic fertilizers and improved maize varieties were adopted as a package, rather than as individual elements, significant improvements in yield where observed (Nyangena & Juma, 2014). Both fertilizer and improved seed increase have been found in the literature to have a positive welfare effects (Shiferaw, Kebede & You, 2008; Akinola et al., 2009; Kassie et al., 2011). Therefore, we decided fertilizers and improved seed varieties as the focus for our innovation adoption analysis.

The dummy variables "use of fertilizer" and "use of improved seed varieties", show the information about the people that have used any of the two technologies individually. The results showed us that 59% of the households have used fertilizer and only 1% of the households have used improved seed varieties. None of the two innovations has been used by all the households, a possible explanation might be the lack of access to inputs and extension services[3] (Baiphethi & Jacobs, 2009). On the other hand, the variables regarding the technology land use proportion indicate that an average household used fertilizers in 41% of the fields and improved seed varieties in only 0.2% of the fields. Lastly, in the last two rows of Table 2 it is possible to observe that 20% of the households have used fertilizers and

[3] "The lack of assets for agricultural production is predominant in sub-Saharan Africa, as evidenced by unsustainably small and falling farm sizes and poor-quality land, and the fact that investment in irrigation is negligible. In addition, poor health services and education further limit productivity of agriculture and access to other livelihood options." (Baiphethi & Jacobs, 2009, p18).

improved seed varieties in their farms and they have used them as a package on average in 1.7% of their fields. While 4,016 households have adopted fertilizer individually, and 577 have adopted the package, only 68 have adopted seed varieties individually. Because of the group of households that have adopted only improved seed varieties is small, we will only focus on the impact of the adoption of fertilizer individually and in a package with seed varieties.

2.2.3. Other Descriptive Statistics

In Table 3., we present summary of important socio-economic variables that are related both to household nutrition status and innovation adoption. Form the description of the household variables one can notice that on average household's size if of 4 according to the household equivalent and that the majority of the families (82%) have a male household head.

Table 3. Summary statistics of important household and farm variables

Variable	Total sample	Non-adopters	Fertilizer adopters	Improved seed adopters	Fert. & imp. seed same field
Sex (1: male 0: fem)	.819 (.384)	.818 (.38)	.817 (.386)	.867 (.341)	.827 (.378)
Age (years)	46.31 (14.6)	45.2 (14)	46.8(14.6)	43.976 (15.12)	46.273 (14.009)
Education (years)	3.631 (2.87)	3.57 (2.9)	3.61(2.80)	3.80 (3.03)	3.798 (3.090)
Age dep. ratio (0-1)	76.57 (33.8)	75.2(34.8)	76.9 (33.6)	77.598 (35.2)	77.504 (32.106)
Family size (adult eq.)	4.198 (2.35)	4.09 (2.4)	4.21 (2.28)	4.318 (3.187)	4.374 (2.422)
Income (ETB)	35,561.07 (148680.3)	42,788.41 (225398)	32,568.96 (111959.6)	28,034.63 (39102.12)	34,325.55 (72156.94)
Off-farm income (1: receives,0: otherwise)	.619 (.485)	.645 (.478)	.610 (.487)	.720 (.452)	.594 (.491)
Market distance (km)	7.038 (11.7)	8.4 (16.1)	6.628 (9.6)	13.397 (11.91)	5.340 (8.248)
Farm size (Ha)	1.747 (6.94)	1.41 (2.5)	1.785 (7.6)	7.170 (32.990)	1.882 (2.444)
Number of fields	12.01 (7.08)	10 (6.806)	12.49 (6.9)	8.955(5.409)	14.401 (7.286)
Number of crops	9.155 (7.49)	7.82 (7.4)	9.418 (7.2)	7.661 (7.731)	11.016 (8.088)
Crop and Livestock (1: both, 0: only crop)	.937 (.242)	.906 (.291)	.948 (.221)	.867 (.341)	.960 (.195)
Landholding (1: with rights, 0: otherwise)	.779 (.414)	.796 (.402)	.782 (.412)	.75 (.436)	.732 (.442)
Farm income (ETB)	17627.9 (105783.3	19812.68 (170838)	16453.76 (70613.53)	10622.69 (16024.6)	18938.52 (38501.39)

Market supply (1: sell crops, 0: otherwise)	.592 (.491)	.545 (.498)	.602 (.489)	.647 (.481)	.643 (.479)
Total Livestock Units	3.004 (8.16)	2.84 (3.8)	3.03 (10.1)	4.246 (5.671)	3.168 (2.882)
Access to extension (1: yes, 0: otherwise)	.411 (.492)	.247 (.431)	.4011 (.490)	.279 (.452)	.841 (.365)
Agricultural credit (1: access, 0: otherwise)	.225 (.418)	.133 (.339)	.236 (.424)	.132 (.341)	.392 (.488)
Consultation (1: have access, 0: otherwise)	.690 (.462)	.551 (.497)	.709 (.453)	.588 (.495)	.913 (.281)
Observations	N =3056	N =1355	N= 2194	N = 67	N = 577

Notes: 1) the values reported are: mean and in parenthesis the standard deviation. 2) Non- adopters refer to the households that has adopt neither improved seed varieties nor fertilizers individually or in a package.

The area under cultivation is relatively small. On average, famers cultivate 1.7 hectares. SSA rural areas are characterized by having small farms in terms of size, according to Ehui and Pender (2005) and Alliance for a Green Revolution in Africa report (2014) the holdings are on average around 1 and 2 hectares. In addition, to the fact that the area is relatively small, it is divided in several fields (on average 12-13 fields). The small sized farms and highly fragmented makes it difficult for parents to inherit land to their children, demotivating the young generation to stay in the rural areas and develop agricultural production (Peters, 2011; Quan, 2007; White, 2012). Farm-households tend to plant on average 8 or 9 different crops, and 94% of the total sample combine crop production and livestock by having on average 3 livestock units. This suggest that they tend to diversify their agricultural production. While approximately 69% of the households have access to consultation services, the access to agricultural credit and extension programs is rather low.

When comparing these variables for adopters and non-adopters, the mean values of several variables are slightly higher for the households that adopt agricultural innovations compared to non-adopters. Household characteristics, such as the size of the farm and household and the years of education are higher for the adopter families. Similarly, the farms size, the ownership of agricultural assets and access to credit, extension services and consultation services are slightly higher for adopters of innovation. As expected innovation adoption is related with more commercialization. On the other hand, an average household that have adopted a technology have slightly more diversified farms, producing approximately from 8 to 11 crops out of the 24 options, compared to the average non-adopter family. This Suggests that in our sample innovation adoption is more likely related to lower levels of farm specialization.

2.3. Empirical strategy

The aim of the article is to estimate the overall effect of agricultural innovation adoption on nutrition and food security; therefore, the analysis will start with a regression model of the following type:

$$N_i = \beta_0 + \beta_1 I_i + \beta_2 X_i + \varepsilon_i$$

where N_i is the nutrition indicator for household i, I_i represents the indicator for the adoption of agricultural innovation, X_i is a vector of control variables for household i that may affect nutrition, and ε_i is a random error term. The parameter of interest in this model is β_1. Significant estimates for this parameter will mean that adoption of agricultural innovation can generate changes in the nutrition status of the household. It is expected that, in addition of being significant, β_1 will be positive, meaning that innovation adoption has a positive impact in household nutrition. However, both the sign and the significance might change across the different models.

As stated above, we are using HDDS as our dependent variable. HDDS can be consider a categorical variable, hence one might think that the correct approach to evaluate adoption impact is by using the Poisson regression. The idea behind using Poisson regression is that this approach is often used for modelling count data, similar to our variable of interest HDDS. In addition, Poisson regression is commonly used in the literature in cases were the dependent variable is highly skewed and are not normally distributed (Hutchinson & Holtman, 2005). However, our dependent variable HDDS contain more than 10 foods groups and shows an approximately normal distribution (see Annex Table A1 and Figure A1) with a mean of 6.45 food groups and standard deviation of 1.6. Therefore, OLS regression may be the simplest approach and an appropriate choice in this case even when HDDS is a categorical variable.

Control vector X_{ij} include variables as age, gender and education of the household head, as well as other household, farm and contextual variables that may affect nutrition. Assuming that we captured all the possible factors that affect nutrition and there is no correlation between the I_i and the error term ε_i, OLS estimations will give us unbiased estimations. However, this might not be entirely true, there are some characteristics that are difficult to measure time and considered as unobservable. In our case we have time invariant characteristic (or with very small variation across time), such as the farmer's abilities, entrepreneurial skills or risk aversion (Ogutu et al., 2017). which are considered as unobservable variables. This is an important econometric concern, and not controlling for this leads to unobserved heterogeneity (endogeneity) and biased estimations (Wooldridge, 2010).

Therefore, we decided to panel data models, more specifically Fixed Effect (FE). Compared to Random Effect (RE), FE use more relaxed assumptions that can consistently estimate partial effects in the presence of time-constant omitted variables that can be arbitrarily related to the observables explanatory variables (Wooldridge, 2010). While, FE analysis is more robust than RE analysis one cannot include time-constant factors as dependent variables. although it can be a drawback in certain applications, in our case ore variables of interest are time-varying. Hence using FE, we account for heterogeneity and omitted variable bias and we can still measure the effect of the technology adoption. Using FE can help us to control local characteristics, such as growing periods, climate, or animal production or wealth, this is very important because these characteristics impact both household dietary diversity and the level of innovation in a given village. To confirm that FE was the correct fit to our sample we used the houseman test. This test's null hypothesis states that the estimations from the two methods are both Consistent, thus they should yield similar coefficients. The alternative hypotheses, on the other hand, is that the FE estimation is the correct and the RE estimation is not; if this is the case, then we would expect to see differences between the two sets of coefficients (Wooldridge, 2010). Nevertheless, FE do not account for potential endogeneity bias caused by self-selection. Because wealth might be related to food security and innovation adoption, richer households for whom one can observe higher dietary diversity self-select into technology adoption as well. Therefore, we decided also to perform an IV estimation and control for the self-selection bias.To control for endogeneity bias, we decided to use instrumental variables (IV) method two least square (2SLS). One of the key challenges of these approaches, is to find variables that can serve as valid instruments (Stock, Wright, and Yogo 2002). According to Wooldridge (2010), valid instrument Z_i should comply with two conditions relevance and exogeneity. To be relevant, Z_i, should be partially correlated to our interest variable I_i; meaning that $\theta \neq 0$ in the first stage equation $I_i = \partial X_{ij} + \theta Z_i + u_i$. In addition, the IV should be uncorrelated with the error term of equation 1 in order to be exogenous, therefore $Cov(Z_i, \varepsilon_{ij}) = 0$. Consequently, Z_i should only influence nutrition N_i indirectly through agricultural innovation adoption. As mentioned, these approaches require at least one instrument per innovation indicator for inclusion in the first-stage regression. We created a variable by counting the number of families in each EA that have use the specific innovation excluding the household that has used it. Approximately 12 households were interviewed in each EA. This number of adopters in an EA (community) is related to network effect mentioned in the literature. Evidence suggests that network effects are important for individual decisions, and that, in the particular context of agricultural innovations, farmers share information and learn from each other (Foster and Rosenzweig 1995; Conley & Udry, 2000). Therefore, the larger the group of adopters in a community, the larger the influence of adoption to the rest of the members of the network. In addition, we used a variable that measure the distance in kilometer between each EA the nearest place where an extension agent lives as instrument. Each of the variables previous mentioned represent strong and valid instrument for the adoption of innovation.

3. Results and discussion: Dietary diversity and agricultural innovation adoption

3.1. Adoption of innovation in the same farm

Table 5. presents the results of four models, that estimate the relation between HDDS and innovation adoption. Models 1 and 2 present the results of a pooled OLS, with and without socioeconomic control

variables. Similarly, Models 3 and 4 describe the results from a Poisson estimation. The Poisson and pooled OLS estimation seem to yield very similar results in terms of the coefficients' sing and significance, except for the fertilizer adoption in Model 1. While the effect of individual adoption of fertilizer and improved seed varieties do not appear to be significant for dietary diversity in either of the estimations, the package adoption does. The inclusion of socio-economic control variables reduces the magnitude of the coefficient but does not change the sign of the effect. This early stage of the estimation, provide us with evidence to think that significant impacts on nutrition might be achieve through the adoption of packages of technologies instead of using them individually. Before proceeding with the rest of the variables, the next paragraph will be dedicated to the comparison of the models pooled OLS and Poisson regression.

In general, both the Poisson and pooled OLS estimations look similar in terms of signs and individual significance of the coefficient. Nevertheless, by looking in further detail, one can say that the coefficient of both innovation adoption indicators, as well as the rest of the coefficient, estimated by the Poisson regression are lower compared to the ones from OLS estimations. In addition, both models present a significant joint effect of all the variable; however, model 2 (OLS) has better adjusted R squared. This implies that model 2 predicts better the data variability. This result, coincide with what was mentioned on the previous section (empirical strategy).

Table 5. Pooled OLS and Poisson regression (Dependent variable: HDDS)

Variable	Pooled OLS		Poisson regression	
	Model 1	Model 2	Model 3	Model 4
Only Fertilizer adoption	0.0813*	0.0514	0.0121	0.0079
Only improved seed adoption	-0.0505	-0.1027	-0.0073	-0.0150
Fertilizers and improved seed	3.2066***	2.8357***	0.4735***	0.4175***
Sex		0.0413		0.0079
Age dependency ratio		0.0008		0.0001
Age		-0.0002		-0.0001
Education		0.0898***		0.0130***
Household income		0.0000***		0.0000***
Farm size		0.0076		0.0011
Total Livestock Production		0.0065		0.0008
Number of Oxen		0.0939***		0.0145***
Distance to market		-0.0038***		-0.0006***
Regional dummies	yes	Yes	yes	yes
Number of observation	6794	6794	6794	6794

Legend: * p<.1; **p<.05; ***p<.01

3.2. Control for endogeneity bias

As mentioned in section 2.3 Pooled OLS with socio-economic factors might not account for all unobserved effects and might yield biased estimations. Therefore, we decided to use RE and FE. Table 6., presents the results from the random effect and fixed effect panel data regression. Where the Dependent variable is HDDS and main independent variables are the 3 innovation adoption indicators. In terms of significance and direction of the effect both approaches yield similar results. In Models 6 and 8, the impact of the adoption of improved seed varieties on dietary diversity is negative but insignificant. On the other hand, the adoption of fertilizer and the technology package appear to have a positive and significant effect on HDDS, coinciding with Models 1 and 2 from Table 5. The differences between the magnitudes of the coefficients in Models 6 and 8, lead us think that only one of them is inconsistent. In section 2.3, we described how the theory suggests that giving our model's specifications FE should provide a better fit, nevertheless we used the Hausman test to provide statistical evidence that support our assumption. The Hausman test for fixed versus random effects model yielded a chi-squared of 43.00 (p-value: 0.000) (see the coefficients in Table A6 in the annex). Our Hausman chi-squared statistic is big enough to reject the null hypothesis that the two methods have no systematic differences. Therefore, we can set RE as inconsistent and use FE as our preferred model. The Breusch and Pagan test Lagrangian multiplier test resulted in a p-value of 0.000 (592.36).

Table 6. Random and Fixed Effects regression (Dependent variable: HDDS)

Variable	Model 5: RE	Model 6: RE	Model 7: FE	Model 8: FE
Only Fertilizer	0.1500***	.1187*	0.2940***	0.2522***
Only improved seed	-0.1213	-.177	-0.7224	-0.6714
Fertilizers and improved seed	2.5577***	2.342***	1.3650***	1.1617***
Sex		.048		-0.1609
Age dependency ratio		.0008		0.0001
Age		.0004		0.0229***
Education		.088***		0.0457***
Household income		8.70e-07***		0.0000**
Farm size		.005***		0.0002
Total Livestock Production		.005		0.0027**
Number of Oxen		.087***		0.0561**
Distance to market		-.002		0.0016
Regional dummies	yes	Yes	Omitted	Omitted
Number of observation	6794	6794	6794	6794

legend: * p<.1; **p<.05; *** p<.01

Additional controls are needed because FE do not account for potential endogeneity bias caused by self-selection. Because wealth might be related to food security and innovation adoption, it could be the case that richer households for whom one can observe higher dietary diversity self-select into technology adoption as well. Therefore, we decided also to perform an IV estimation and control for the self-selection bias.

Table 7. present a simple (Model 9) and a multiple (Model 10) 2SLS regressions that helped us to control for endogeneity bias by using instrumental variables. The statistic presented in the model summary show that the instruments used in the two models are strong and that the model is well identified. (see also fist stage regression and other statistics in annex Box 2). The small p-value of the Kleibergen-Paap rk LM statistic shows that the model is identified and that the excluded instruments are relevant[4]. Moreover, the Cragg-Donald Wald F statistic is sufficiently high (28.101 and 25.521, see critical values in annex Table A2.3) to demonstrate that the correlation between the three IV and the adoption indicators are not weak, meaning that the model is well identified. Lastly, as the equation is exactly identifying there is no need for the overidentification Hansen J. test. As there is sufficient evidence to reject the null hypothesis for over-identification, one can say that jointly the IV are uncorrelated with the error term in equation. Once again adding evidence to support that our models are well defined.

Table 7. Simple and multiple Fixed Effects 2SLS regressions form (Dependent variable=HDDS)

Variable	Model 9: FE 2SLS	Model 10: FE 2SLS
Only Fertilizer adoption	1.4849***	1.4193***
Only improved seed adoption	0.5118	0.7110
Fertilizers and improved seed in the same field	12.0383***	10.8961***
Sex		-0.0180
Age dependency ratio		0.0003
Age		0.0100*
Education		0.0414**
Household income		0.0000**
Farm size		-0.0018
Total Livestock Unit		0.0025**
Number of Oxen		0.0342
Distance to market		-0.0003
Number of observation	6113	6113
Model summary	Eq. exactly identified C.-D. Wald F = 28.101	Eq. exactly identified C.-D. Wald F = 25.521

[4] The instruments are correlated with the endogenous regressors.

	K.-P. LM= 0.0001	K.-P. LM=0.000

Notes:* p<.1; **p<.05; ***p<.01

Similar to Model 8, the results from Model 10 show that controlling by unobserved heterogeneity the adoption of fertilizers individually and in a package have a positive and significant effect on dietary diversity. However, in Model 10 both coefficients increased in magnitude, and the effect of Improved seed varieties adoption became positive (although insignificant). Expansions in the proportion of fields where the fertilizer and improved seeds are adopted as a package increase the diversity score by approximately 10 food groups. The effect of the package adoption is bigger than when farmers adopt only fertilizers.

Increases in the years of education, income and the number of livestock owned, increase the household's dietary diversity and are significant. the coefficients were as expected, coincide with the theory and other cases in the literature. For instance, the positive and significant effect of household head education on dietary diversity, were as Uaiene, Arndt and Masters described "[…] education gives farmers the ability to perceive, interpret and respond to new information much faster than their counterparts without education." (Uaiene, Arndt, & Masters, 2009, p. 16). Therefore, as expected more years of education have a positive effect in the nutritional status of the family members and are good controls for innovation adoption.

The results reported in this table helped us to corroborate the hypothesis raised by Kassie and colleagues (2011) in our sample. Our results also coincide with the ones reported by Sheahan and Barrett (2017) in Ethiopia, who by using descriptive statistics they found out that there are sets of inputs that complement each other and improve efficiency, for example, improved seed varieties and inorganic and organic[5] fertilizers. In addition, we identified that farmers tend to adopt more than one innovative technology and using them as a package has a larger effect on dietary diversity than using them individually.

3.3. Disaggregated Effect: the pathway by which the adoption of innovation impact nutrition

To make a comprehensive evaluation of the role from innovation adoption in nutrition, we tested the impact of innovation adoption on household and farm income. This will help us identify by which pathway is the adoption of technologies impacting the dietary diversity. The models were estimated by using the FE 2SLS. Approach, which is appropriate for our analysis as mentioned above. Table 8 displays two estimations that display the relationship between the adoption of agricultural technologies and household income. The model summary demonstrates that the model is well defined, the IV are relevant (Kleibergen-Paap rk LM=0) and strong (Cragg-Donald Wald F statistic=28.101 and 25.521, see critical values in annex Table A3.3), and the equation is exactly identified (see fist stage regression

[5] Although this was true for Ethiopia this was not the case for the other five countries that were also included in the analysis (see Sheahan & Barrett, 2017 section 3.5)

in Annex Box 3). The coefficients of improved seed varieties adoption are positive and insignificant in the two models. The models also display the positive and significant effect of the package adoption on farm income. Hence, one can think that the agricultural production improvements gained through the jointly use of fertilizer and improved seed varieties in the same field are translated into higher farm and household income. Because the package adoption also has an impact on dietary diversity, the gained income is used to acquire food from the market, which appears to increase the household's dietary diversity. One must consider, that the effect on income is not translated in the same magnitude to the increase of HDDS, households might also use it in other expenses (Haddad, 2000 and 2013). The way the income is used differ between household and communities, and it depends on both its source and the person who manage (Duflo & Udry, 2004; Kerr, 2008). For instance, Duflo and Udry (2004) found that in the Ivory Coast increases in the output of crops predominately harvested by women rises the food consumption. On the other hand, when the crops are harvested by men, no effect is observed on the food consumption, rather in non-food items. Interestingly, even though the individual adoption of fertilizer has a positive and significant on dietary diversity, the significance is not the same for household income. This suggest that farm production improvements achieve through fertilizer adoption impact dietary diversity through subsistence production improvements rather than by income.

Table 8. Fixed Effect 2SLS regressions (dependent variable=household income)

Variable	Model 11: FE 2SLS	Model 12: FE 2SLS
Only Fertilizer adoption	3.3e+04*	2.3e+04
Only improved seed varieties adoption	1.5e+05	1.5e+05
Fertilizers and improved seed in the same field	8.9e+05***	7.3e+05***
Sex		-1.3e+04
Age dependency ratio		-1.9e+02***
Age		1.6e+03**
Education of household head		-6.6e+02
Farm size		-1.1e+02
Total Livestock Unit		172.6926
Number of Oxen		-2.2e+03
Distance to market		-4.7e+02
Model summary	Eq. exactly identified C.-D. Wald F = 28.101 K.-P. LM=0.000	Eq. exactly identified C.-D. Wald F = 25.56 K.-P. LM=0.000

Notes: * p<.1; **p<.05; ***p<.01

The results printed on Table 7 helped us to identify the pathway by which the adoption of agricultural innovation impact nutrition. Higher yields achieved through the adoption of a technology package –

ceteris paribus –has a positive effect on household income and increase the access to food from markets. On the other hand, the effect of individual adoption of fertilizers not only has an insignificant effect on household income, but also has a smaller effect compared to the one when the technology package is adopted. Therefore, the adoption of complementary technologies positively impacts dietary diversity through improving income, and the adoption of fertilizers through enhancing subsistence production.

3.4. Impact on the different dietary diversity categories

To have deeper understanding on how the adoption of agricultural innovation impact nutrition, we classified the household dietary diversity score in three groups, which are the following: food that comes from crop production, food that comes from livestock production and highly processed food (see Annex Table A1). Table 9 shows the estimations of the effect of technology adoption on the three HDDS, from crop production (Model 13), from livestock production (Model 14) and from processed food (Model 15). The test for relevance of the IV (Kleibergen-Paap rk LM=0) and the test for weakness in the identification (Cragg-Donald Wald F statistic=25.521) show that the three models are well defined (see fist stage regression and other statistics in Annex Box 2.).

Table 9. Fixed Effects 2SLS from HDDS categories and innovation adoption indicators

Variable	HDDS_crops	HDDS_livestock	HDDS_processed
	Model 13	Model 14	Model 15
Only Fertilizer adoption	1.1600***	-0.0677	0.3270***
Only improved seed	0.2552	0.0733	0.3825
Fertilizers and improved seed	11.1074***	-0.8837	0.6724
Sex	0.0195	-0.0045	-0.0330
Age dependency ratio	-0.0004	0.0002	0.0004
Age	0.0098**	-0.0027	0.0028
Education	0.0364***	0.0042	0.0008
Household income	0.0000***	0.0000	-0.0000
Farm size	-0.0038***	0.0021*	-0.0001
Total Livestock Production	0.0029***	-0.0006	0.0003
Number of Oxen	0.0218	0.0228**	-0.0104
Distance to market	0.0020	-0.0000	-0.0023*
Regional dummies	0.0020	-0.0000	-0.0023*
Model summary	Eq. exact. identified C.-D. Wald F=25.52 K.-P. LM=0.000	Eq. exact. identified C.-D. Wald F=25.52 K.-P. LM=0.000	Eq. exactly identified C.-D. Wald F=25.52 K.-P. LM=0.000

Legend: * p<.1; **p<.05; ***p<.01

The three models show that the individual adoption of improved seed varieties although positive is insignificant for the three HDDS groups. Model 15 resembles the outcomes from Model 10 (in Table 7), both the individual adoption of fertilizer and the technology package generate a positive and significant impact on the HDDS_crops. This suggests that the adoption of both technological options help households to diversify their diets through the following food categories: cereals, legumes, tubers, vegetables and fruits. On the other hand, in Model 16 the adoption of neither of the agricultural technologies proposed is significant to HDDS of food that is derivate from livestock, such as meat or milk. Therefore, the results indicate that rural households are less likely to diversify their diets with animal–based food products, which in general contain the highest amount of protein per unit energy (Schönfeldt & Hall,2012). Lastly, in Model 17 only the individual adoption of fertilizer has a small but significant effect on HDDS from highly processed foods, such as oils, sweets and beverage.

According to the literature African countries consume the least amount of meet in the world, and their dietary protein sources are mainly limited to cereals or other plant foods (Speedy, 2003; Schönfeldt & Hall,2012). This pattern appears to be related to wealth and access to super markets or large grocery stores. Hence one can think that rural households might not diversified their diets with animal-based food and other highly processed products due to the lack of access to stores where these products are sold. An additional possibility, is that even when these products are sold in local markets at a very high price, and the increase in income generated by the adoption of innovation is not enough to afford it. According to Schönfeldt and Hall "often smaller spaza shops in the rural areas sell a smaller selection of foods at a higher price which are often unaffordable to the majority of the population" (Schönfeldt & Hall,2012, p.74-75).

4. Conclusion

Previous studies have shown that innovation adoption can improve productivity and income for smallholder farmers. Effects of agricultural innovation adoption on rural household's nutrition are less understood. Therefore, we used a sample of rural household in Ethiopia to evaluate whether the adoption of specific agricultural technologies impacts the dietary diversity of the adopters. In the literature, the individual use of fertilizers (Akinola et al., 2009) and improved seeds varieties (Shiferaw, Kebede & You, 2008; Kassie et al., 2011) has been shown to have a positive impact on household income and welfare. However, there is evidence that demonstrates that farmers tend to adopt groups of technologies (Kassie et al., 2011; Sheahan & Barrett, 2017). Hence we decided also to evaluate if the impact on nutrition changes when households adopt one technology or more than one.

We identified that on average households consume six food categories and the number of food categories varied between the different groups of adoption. We classified Households into the following adoption groups: non-adopter, adopters of only fertilizer, adopters of only improved seed varieties and package adopters. To measure adoption, we calculated the proportion of fields where a farmer has used the technology, to account not only the use of it but the amount of the technology that has been used.

Overall, we conclude that the impact of agricultural innovation adoption depends highly on the type of technology or how it is applied (i.e., individually or in a package). By doing different estimations, we corroborate that, in our case study, the effect of adopting only improved seed varieties is not significant for nutrition. On the other hand, even when controlling for unobserved heterogeneity and unobserved fixed effects the adoption of only fertilizer and the adoption of fertilizer and improved seed varieties as a package in the same field appears to be significant and positive for the nutrition indicator. In addition, the magnitude of the effect on HDDS generated by the adoption of the technology package is higher than the adoption of fertilizer only.

> "[…] *the complementarity between particular sets of inputs makes adopting them together advantageous for farmers, as well as the fact that inputs are generally sold alongside each other at input shops or provided together via government subsidy programs. […] If there are agronomic (or other) synergies among modern inputs, it is believed, then farmers will use them together, especially if farmers behave "efficiently."" (*Sheahan & Barrett, 2017, p. 17

These results showed that even when both fertilizer and improved seed varieties function as a yield sustaining and enhancing, the two technologies are considered by households as complements rather than substitutes. Moreover, by adopting them as a package, they achieve improvements in their nutrition.

We were also interested in identifying the pathway by which agricultural innovation adoption impact nutrition. Therefore, we analyzed the impact of innovation adoption on household income, and we determined the coefficient for the individual adoption of improved seed varieties and fertilizers was positive but non-significant. This result showed that the impact of fertilizer adoption on HDDS is through improvements of the subsistence production. Lastly, the joint adoption of fertilizer and improved seed varieties appeared to have a significant and positive impact on household income. On the contrary, the adoption of the technology package impact dietary diversity by increasing income and improving access to food that comes from the market. These results suggest two things, 1) production improvements achieve through the adoption of the technology packages are bigger than the ones when adopting an individual technology, hence only the former type of adoption allow farmers to sell their produce in the market and increase their income. 2) Dietary diversity improvements are more intense when farmers have access to food from the market rather than enhancing the subsistence production; it is more difficult to produce all the different types of food in one farm. Besides, we identified that part of the excess of income generated through the adoption of innovations is used to consumed crops rather than food that comes from livestock production or other food groups.

Consequently, programs that aim to improve nutrition through agricultural innovation adoption should consider enhancing the use of technology packages rather than one. An important policy implication is that the results are context-specific and should not be generalized across regions and countries. More specific, complementary interventions may be needed to not only increase the availability of agricultural inputs but to offer consultation and extension services to improve their intensity of use. If policymakers want to achieve an effect on nutrition, it is of great importance to identify what is the exact pathway the adoption of a technology is affecting and how to ensure the improvement in nutrition. Finally, agricultural interventions that aim to improve income rather than subsistence production should also be accompanied by improvements in infrastructure and financial markets to ensure that rural populations can access markets.

While several tests confirmed the robustness of our findings, a few limitations remain. To have a broader picture of the effect, for instance on food security and nutrition rather than just in the dietary diversity, one should use additional indicators that measure experience-based scales, or consumption behaviors. It will also be interesting to compare these results with the ones from other countries. Further research is needed to provide more insights on the nutrition effects of agricultural innovation adoption in different settings.

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Annex

List of abbreviations

2SLS	Two Stages Least Squared
EAs	enumeration areas
ETB	Ethiopian Birr
HDDS	Household Dietary Diversity Score
HIDS	Household Innovation Diversity Score
LSMS-ISA	World Bank Living Standards Measurement Study- Integrated Surveys on Agriculture
OLS	Ordinary Least Square

SSA	Sub-Saharan Africa
TLUs	Tropical livestock units
FE	Fixed Effects
RE	Random Effects

Table A1. HDDS food groups

Categories	**Food Groups**	**Categories from the interview**
From crops	Cereals	1, 2, 4, 16
	Tubers and roots	3
	Vegetables	7
	Fruits	8
	Legumes, nuts and seeds	6
From livestock	Meat	9, 10
	Eggs	11
	Fish and other seafood	12
	Milk and milk products	14
From process	Oils and fats	12
	Sweets	5
	Spices, condiments and beverages	15

Note: the 12 food groups were created according to responses of the household consumption over a period of 7 days. **Source: (**Kennedy, Ballard, T & Dop, 2011).

Table A2. HDDS cut-off points using income stratification

Household income teriles	Number of observations	Income Mean	HDDS mean
Low income and HDDS	2265	2776.927 (1789.693)	5.931 (1.482)
Middle income and HDDS	2265	12014.89 (3996.733)	6.402 (1.535)
High income and HDDS	2264	91916.26 (248051.3)	7.037 (1.621)

Table A3. Household innovation diversity score (HIDS)

Household innovation diversity score	Freq.	Percent
0	606	8.92
1	1,625	32.84
2	2,211	65.38
3	1,712	90.58
4	572	99.00
5	68	100.00

Total	6,794	100.00

Table A4. Frequency of combination of two innovations, years 2011-12

Combination of two innovations	Frequency
Fertilizer &irrigation	73
Fertilizer & erosion protection	39
Fertilizer & improved seed varieties	99
Fertilizer &ppp	332
irrigation& erosion protection	17
irrigation & improved seed varieties	34
irrigation &ppp	84
Improved seed varieties & erosion protection	26
Improved seed varieties &ppp	183
ppp& erosion protection	33
Total	920

Figure A1. Histogram HDDS

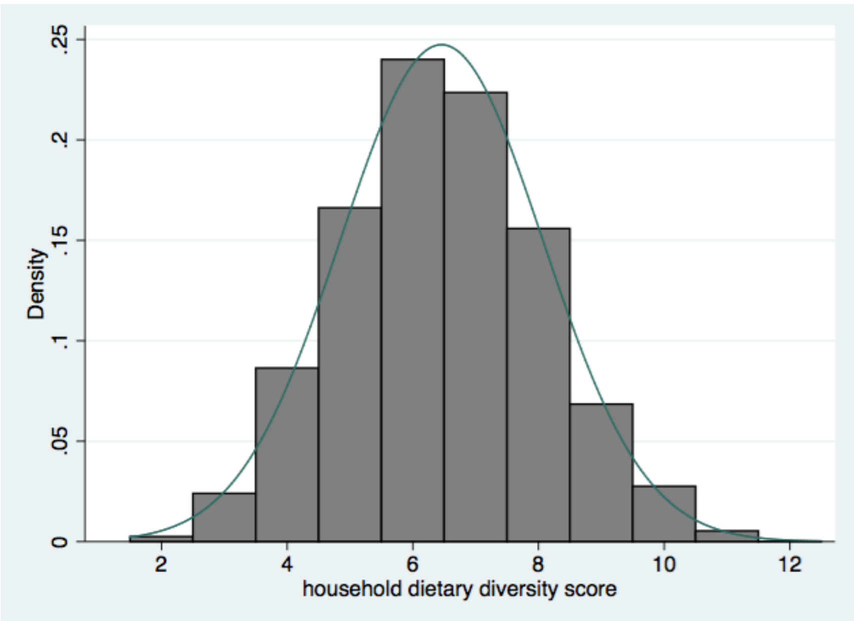

Table A5. Farm income growth

	ETB (mean)
Farm income 2011	4949.762
Farm income 2013	16623.51

Farm income 2015	27603.15

Table A6. Hausman test for fixed versus random effects model

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Only Fertilizer	.2940453	.1029909	.1910544	.0385441
Only improved seed	-.7224195	.1942662	-.9166856	.4885413
Fertilizers and improved seed	1.36498	1.96609	-.6011098	.2719558

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Table A7.1. First stage estimation (HDDS IV fixed effect estimation)

Variable	Only fertilizer adoption		Only Improved seed varieties adoption		Fertilizer and improved seed variety adoption	
Only Fertilizer	.052***(.00)	.050***(.003)	-.000 (.00)	-.000 (.00)	-.001*(.00)	-.001**(.00)
Only imp. seed	.022 (.017)	.019 (.016)	.018*(.007)	.018**(.01)	-.002 (.002)	-.002 (.002)
Fert.& imp. seed	-.062***(.02)	-.061*** (.02)	-.018*(.01)	-.02**(.01)	.009***(.00)	.009***(.00)
Sex		-.085* (.039)		-.003**(.0)		.001 (.004)
Age dep. ratio		-.0002 (.00)		-.000 (.00)		.000 (.000)
Age		.005 (.001)		-.000 (.00)		.0003**(.00)
Education		.002 (.004)		.000 (.00)		-.000 (.00)
Income		.000 (.000)		.000 (.00)		-.000 (.00)
Farm size		.001*(.000)		.000 (.00)		.000 (.00)
Total Livestock		.0004*(.000)		.000 (.00)		.000 (.00)
Number of Oxen		.009 (.006)		-.000 (.00)		.000 (.00)
Market distance		.001*** (.00)		.000 (.00)		-.000 (.00)
Region dummies	Yes	Yes	yes	yes	Yes	Yes

Notes: * p<.1; **p<.05; ***p<.01. The numbers in parenthesis are robust standard errors.

Table A7.2. Summary results for first-stage regression.

Variable	F (3, 3726)	P-val	(Underid) SW Chi-sq (1)	P-val	(Weak id) SW F (1, 3726)
Only Fertilizer adoption	98.75	0.0000	145.28	0.0000	144.81
Only improved seed adoption	2.14	0.0935	16.84	0.0000	16.78

Fertilizers and improved seed	24.02	0.0000	65.70	0.0000	65.49

NB: first-stage test statistics heteroskedasticity-robust

Table A7.3. Stock-Yogo weak ID F test critical values for single endogenous regressor:

5% maximal IV relative bias	13.91
10% maximal IV relative bias	9.08
20% maximal IV relative bias	6.46
30% maximal IV relative bias	5.39
10% maximal IV size	22.30
15% maximal IV size	12.83
20% maximal IV size	9.54
25% maximal IV size	7.80

Source: Stock-Yogo (2005). Critical values are for i.i.d. errors only.

Table A7.4. Underidentification test

Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified). Ha: matrix has rank=K1 (identified)

Kleibergen-Paap rk LM statistic	Chi-sq(1)=21.61	P-val=0.0000

Table A7.5. Weak identification test. (Ho: equation is weakly identified)

Cragg-Donald Wald F statistic	25.52
Kleibergen-Paap Wald rk F statistic	7.62

Table A8.1. First stage estimation. HH-income and farm-income IV fixed effect estimation

Variable	Fertilizer adoption		Improved Seed		Fert.& imp. seed	
Fertilizer	.052***(.00)	.051***(.00)	-.00 (.00)	-.000 (.00)	-.001*(.00)	-.001**(.00)
Improved seed	.022 (.017)	.019 (.016)	.018*(.007)	.018**(.007)	-.002 (.002)	-.002(.002)
Fert.& seed	-.062***(.01)	-.06***(.02)	-.018*(.00)	-.018*(.00)	.009*** (.00)	.009***(.002)
Sex		-.09**(.04)		-.003**(.00)		.001 (.004)
Age dep. ratio		-.000(.000)		-.000(.000)		.000(.000)
Age		.01*** (.00)		-.000(.000)		.0003*(.000)
Education		.002 (.004)		.000(.000)		-.000(.000)
Income		.001**(.00)		.000(.000)		-.000(.000)

Farm size		.001*(.000)		-.000(.000)		.000(.000)
Livestock		.009 (.006)		-.000(.000)		.001 (.001)
Oxen		.002**(.00)		.009*(.005)		-.000(.000)
Market dist.		.001***(.00)		.000 (.00)		-.000 (.00)
Region	Yes	Yes	Yes	Yes	Yes	Yes

Legend: * p<.1; **p<.05; ***p<.01. The numbers in parenthesis are robust standard errors.

Table A8.2. Summary results for first-stage regressions

		(Underid)		(Weak id)	
Variable	F (3, 3727)	P-val	SW Chi-sq(1)	P-val	SW F (1, 3727)
Only Fertilizer adoption	98.61	0.0000	145.73	0.0000	145.31
Only improved seed adoption	2.13	0.0941	16.85	0.0000	16.80
Fertilizers and improved seed	23.98	0.0000	65.63	0.0000	65.44

NB: first-stage test statistics heteroskedasticity-robust

Table A8.3Stock-Yogo weak ID F test critical values for single endogenous regressor:

5% maximal IV relative bias	13.91
10% maximal IV relative bias	9.08
20% maximal IV relative bias	6.46
30% maximal IV relative bias	5.39
10% maximal IV size	22.30
15% maximal IV size	12.83
20% maximal IV size	9.54
25% maximal IV size	7.80

Source: Stock-Yogo (2005). Critical values are for i.i.d. errors only.

Table A8.4. Underidentification test

Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified). Ha: matrix has rank=K1 (identified)

Kleibergen-Paap rk LM statistic	Chi-sq(1)=21.59	P-val=0.0000

Table A8.5. Weak identification test. (Ho: equation is weakly identified)

Cragg-Donald Wald F statistic	25.57
Kleibergen-Paap Wald rk F statistic	7.62

Conflict of interests: There is no conflict of interest.