Impact of agricultural diversification and off-farm income on household food security in rural Ethiopia: A dose-response analysis

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ABSTRACT

In developing countries like Ethiopia, food insecurity is a widespread problem that affects about 58% of the population, especially in rural areas, where diversifying agriculture and finding off-farm employment is crucial to improve household food security. Despite previous studies investigating the relationships between farm diversification, off-farm employment, and food security, the results have been mixed, and the impact may depend on the intensity of the interventions. This study aimed to examine the effects of farm diversification and off-farm employment intensities on food security using cross-sectional data from 295 randomly selected rural households in Ethiopia. To estimate dose-response functions, we used a generalized linear model adjusted for generalized propensity score as treatments are continuous and not necessarily normally distributed. The findings revealed that diversifying crops in rainy season up to a certain level (0.3) and specializing in dry season improved food consumption and dietary diversity, which highlighted the importance of income generated from diverse farming and specialization in the respective season. Additionally, livestock diversity could improve food security, mainly from diverse food groups (0.6) may suggest that livestock husbandry is more nutrition sensitive than cropping. The study recommends that households focus on cash crop production during dry season to increase income and promote diversification up to certain level (0.3) during rainy season to improve food security through subsistence and income pathways. Off-farm employment is also suggested as a means of enhancing household resilience to withstand shocks and improve agricultural productivity.

Keywords: Dietary diversity; Farm diversity; Generalized propensity score; Off-farm employment; Smallholder farmers
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INTRODUCTION

Agriculture is the main stay of Ethiopian economy, which contributes to 34% of the GDP, 82% of export earnings and employs 67% of the total population of the country in 2019 (EEA, 2021; FAO, 2021). The sector is dominated by smallholder farmers who work more than 95% of the agriculture land. Small landholding - as low as 0.8 ha (FAO, 2018a), and heavy reliance on rain-fed production highly expose the sector to risks of environmental shocks. Moreover, the recent food prices driven by the crises

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of civil war and conflict, COVID-19 pandemic and climate change have adversely impacted agriculture production, trade, income and food security (FS) globally mainly low-income countries, further heightened the proportion of people suffering from food insecurity. According to the 2021 Global Food Security Index report that assessed food security situations across 113 countries, Ethiopia ranked 108th with a score of 37.6 out of 100 and has experienced reduction in net FS score of 0.6 between 2020 and 2021 (EIU, 2020, 2021), which is much lower than Ireland the most FS by 46.4 percentage points.

Poverty and food insecurity (FI) are quite pervasive in rural Ethiopia, where the rate of poverty among smallholder farmers is nearly 67% (FAO, 2018a) and the FI remains quite large, i.e., 57.8% for the years 2014 to 2020 (FAO, 2021). Promoting diversification of household income into off-farm income may be a new way out of households from poverty and FI (Chang and Mishra, 2008; Mohammed Adem and Fentahun Tesafa, 2020) by smoothing food consumption overtime and ameliorating food shortage risks in case of yield shocks (Qureshi *et al.*, 2015). Ethiopian development paths have given prime attention to reduce poverty and FI by introducing various initiatives. The agricultural development industrialization road map (2013), the two successive five-year growth and transformation plans (2010-2020) and the recently endorsed ten-year development plan for the period 2020-2030 (PDC, 2020) have clearly set out agricultural diversification and off-farm activities alongside agricultural transformation to reduce risks of rural areas to poverty and FI. Yet, reducing FI and malnutrition in Ethiopia continues to be a key policy challenge and development problem. Around 65% of children under five were stunted, underweight or wasted in 2019 (FAO, 2018a) and anemia was pervasive among women of reproductive age (24%) and children (57%) in 2016 in Ethiopia (EDHS, 2016).

Researchers have recognized the importance of studying the link between agriculture, food and nutrition on a global scale. However, studies exploring this connection have provided mixed results. Some scholars have found that agriculture diversification (AD) can significantly improve FS in terms of dietary diversity (Jones *et al.*, 2014; Habtamu Yesigat *et al.*, 2017; Mulat Demeke *et al.*, 2017), while others have identified the synergies between crop and livestock production as a means of securing food availability and access for households (Herrero *et al.*, 2010). Frelat *et al.* (2016) pointed out the link between nutrition and agriculture that the matter goes beyond just food production and many of the world's undernourished people are smallholder farmers. Yet, others (Webb and Kennedy, 2014; Bhavani and Rampal, 2018; Ruel *et al.*, 2018) have obtained little evidence to support the assumption that increasing AD is an effective strategy to improve diets and nutrition of smallholders, emphasizing the need for proper research design and appropriate metrics to strengthen the evidence base and inform policy. Other researchers also underscored the importance of market access in improving FS in rural areas (Bellon *et al.*, 2016; Jones, 2017). All of this suggests that agriculture-food-nutrition (AFN) nexus is contextual and examining it is important particularly in developing countries with majority of rural populations, heavy reliance on subsistence production, and high prevalence of malnutrition. Ultimately, positively influencing this nexus can lead to improvements for rural populations and better pathways for the transformation of local food systems (Gómez *et al*., 2013).

The extant literature has also given due attention on growth and poverty implications of off-farm income (OFI) in developing countries, yet little is known about its impact on FS and nutrition (Duong *et al.*, 2020; Rahman and Mishra, 2020). Moreover, the key evidence disclosed little policy efforts have been made to promote the off-farm sector in a pro-poor approach that can overcome potential constraints mainly in sub-Saharan Africa, where production on smallholder farms is critical to FS of the rural poor (Herrero *et al.*, 2010). Understanding the capacity of farming systems and off-farm employment opportunities to meet food and nutrition needs of rural households is overriding. In the face of a growing evidence demonstrating HFS impacts of AD and OFI, there is a tendency to treat these two interventions as binary decision variables seems an oversimplification. The fact that farmers produce at different intensity levels of diversification may have different effects on HFS operationally measured in food consumption and dietary diversity. The current paper extended this conventional econometric setup to accommodate issues of continuous treatments (AD & OFI intensities) and evaluated their impact on HFS. This is the novelty of this paper that adds a new dimension to the discourse on AD, OFI & FS linkages by analyzing the varying levels using dose-response functions (DRFs) and generalized propensity score (GPS) approach. To help evaluate AD and OFI as critical strategies for improving HFS in case of rural Ethiopia, the following are the key questions raised to answer: (1) What is the status of AD among smallholder farmers and how far does it affect HFS? (2) How does participation in off-farm employment influence HFS?

MATERIALS AND METHODS

Study settings

The study generally aims to evaluate impacts of AD and off-farm employment intensities on HFS of smallholder farmers in northwest Ethiopia in Amhara region. With a 2019 population of 22.5 million, Amhara Region is the second most populous region next to Oromia (UNICEF, 2021). Its economy remains highly agrarian primarily managed by smallholders, and nearly 84% of the population is engaged in agriculture (UNICEF, 2018). The region is large in terms of area and it is endowed with diverse agro-ecologies that give it a huge potential for the production of a variety of agricultural products for domestic consumption and exports. Yet, poverty is pervasive in the region with 26.1% of the population living below the national poverty line compared to 23.5% in the entire country in 2016; it is more rampant in rural (28.8%) than in urban areas (11.6%) (NPC, 2017). Childhood stunting in the region (46%) is among the highest in the country (38%) (EDHS, 2016).

A cross-sectional survey data on quantitative and qualitative variables was collected between July and August 2020 from 295 households randomly selected in Bahir Dar Zuria, Dangila and Bure districts of the Amhara region. The household selection was based on a two-stage stratified sampling. The survey team comprised of 12 experienced agricultural experts. An intensive two-day training was given to them to create understanding on contents of the questionnaire and how to manage face-to-face interviews with farmers using local the language and probing the difficult questions through examples and farmers' wordings. Pilot-testing of the survey instruments and fieldwork procedures were conducted prior to the main survey. The quality of the data was checked through close supervision of enumerators and encoders during data collection and entry, respectively.

Conceptual framework and empirical model

The impact evaluation framework of this study was developed from counterfactual perspective that allows to make causal claims in case of observational data and continuous treatments adopted (Austin, 2019; Wu *et al.*, 2021). In experimental research, as study units are randomized to receive different treatment levels, the units assigned to different levels of treatment will have similar distributions of pre-treatment covariates (Wu *et al.*, 2021). When the treatment is binary, like the standard propensity score matching (PSM) presumed, by pairing treatment group with control group that has nearly identical values of covariates, the two groups are theoretically interchangeable. In observational studies, as one group received a treatment prior to the survey, the two groups would not be the same on pre-exposure covariates. In this case, we cannot observe the counterfactuals and the groups are not interchangeable. As units in observational studies are not randomized to different treatment levels, the imbalance in pre-treatment covariates may lead to confounding bias (Antonakis *et al.*, 2010). To obtain consistent estimates, this selection bias to treatment or control group has to be modeled.

In most FS studies, confounding adjustment is traditionally made by fitting a multiple regression model with FS outcome as dependent variable, AD, for example, as a key independent variable and many potential confounders are additional independent variables (Adjimoti and Kwadzo, 2018; Muthini *et al.*, 2020; Sekabira and Nalunga, 2020; Lemlem Teklegiorgis *et al.*, 2021; Sinyolo *et al.*, 2021; Kabir *et al.*, 2022). It has been well documented in the literature that traditional regression methods do not allow for clear distinction between the design and analysis stages (Wu *et al.*, 2021) are susceptible to model misspecification and often their results cannot be interpreted as causal effects (Bellon *et al.*, 2016). In reply to this, some others have used the standard PSM method (Abebaw Degnet *et al.*, 2010; Justus *et al.*, 2015), but this approach is limited to capture continuous treatments. Many researchers have advocated for the development and implementation of methods for causal inference to inform FS and nutrition policy (e.g., Mofya-Mukuka and Kuhlgatz, 2016; Ogutu *et al.*, 2019). When the treatments are continuous, like AD & OFI intensities in our case, there is no explicit way to distinguish units as exposed and unexposed, which calls for a different procedure. In such conditions, the generalized propensity score (GPS) specification is more appropriate than the standard PSM for estimating dose response functions (DRFs). We developed the impact evaluation framework at household level with a generalized linear model (GLM) for estimating the DRFs at each treatment level using GPS for adjusting confounders.

To quantify the impact of AD and OFI one can employ the typical impact evaluation framework considering AD (or OFI) as treatment and HFS is the observed outcome. This section details the econometric approaches used in this study focusing on AD as treatment, but all details also hold OFI. For simplicity of demonstrating the estimation strategy, first we use a simplified model of the conventional impact assessment scenario where D is a binary exposure representing household's decision to choose whether to diversify its farm production ($\mathrm{D} = 1$) or not to diversify ($\mathrm{D} = 0$). Later, we will see GLM, a flexible approach of interest that can address issues of continuous and the different distribution functions of the treatment. We sought to quantify the expected treatment effect on treated as specified in Equation (1):

$$\tau|_{\mathrm{D}=1} = \mathrm{E}(\tau|\mathrm{D} = 1) = \mathrm{E}(\mathrm{Y}_1|\mathrm{D} = 1) - \mathrm{E}(\mathrm{Y}_0|\mathrm{D} = 1) \qquad (1)$$

where τ is the average treatment effect on treated (ATT), D is a dummy variable for AD decision, Y_1 denotes the outcome when the household diversified its production and Y_0 shows the outcome in case the household did not diversify its production.
The estimation problem arises as it cannot be observed how a diversified household would have performed had in fact not diversified its production, i.e., $\mathrm{E}(\mathrm{Y}_0|\mathrm{D} = 1)$ cannot be observed. Although the difference $[\tau^{\mathrm{e}} = \mathrm{E}(\mathrm{Y}_1|\mathrm{D} = 1) - \mathrm{E}(\mathrm{Y}_0|\mathrm{D} = 0)]$ could be estimated, it would potentially be a biased estimator of ATT, as the groups compared are likely to be different in their characteristics. This is because of self-selection of households, which is likely to occur when farm characteristics affect the utility that a farm derives from AD or OFI. In formulating the effect of farm characteristics on treatment variable, we assume the relationship between utility (U) and farm characteristics (Z) of the i^{th} household can be expressed as Equation (2):

$$\mathrm{U} = \beta^{'}\mathrm{Z}_\mathrm{i} + \epsilon_\mathrm{i} \qquad (2)$$

where ϵ_i shows the residual. Given the farmer maximizes utility by choosing whether to or not to diversify, the probability of employing diversification strategy is shown by Equation (3):

$$\mathrm{P}(\mathrm{D}_\mathrm{i} = 1) = \mathrm{P}(\mathrm{U}_1 > \mathrm{U}_0) = \mathrm{P}\left(\epsilon_\mathrm{i} > -\beta^{'}\mathrm{Z}_\mathrm{i}\right) = 1 - \Phi\left(-\beta^{'}\mathrm{Z}_\mathrm{i}\right) \qquad (3)$$

where U_1 is the maximum utility gained from choosing the treatment; U_0 is the maximum utility derived from being in the control group; Φ shows the distribution of the residual, which is logistic in case of Logit model that can be applied for analysis as one considered AD as a binary variable. Results of outcome comparisons between groups are biased even if farm characteristics are controlled for as one uses an OLS regression. To show this, consider a reduced-form relationship between technology choice and outcome variables specified in Equation (4) as follows:

$$\mathrm{Y_i} = \beta_0 + \beta_1 \mathrm{D_i} + \beta_2 \mathrm{Z_i} + \mathrm{u_i} \qquad (4)$$

where Y_i represents a vector of outcome variables for household i such as demand for foods; $\mathrm{D_i}$ denotes a binary choice variable of diversification as defined above; Z_i represents farm level and household characteristics; and $\mathrm{u_i}$ is an error term with $\mathrm{u_i} \sim \mathrm{N}(0, \delta)$. The issue of selection bias arises if the error term of technology choice $\in_\mathrm{i}$ in Equation (2) and the error term of outcome specification $\mathrm{u_i}$ in Equation (4) are influenced by similar variables in $\mathrm{Z_i}$. This leads to a non-zero correlation between the two error terms, which would in turn imply biased regression estimates if Equation (4) were estimated using OLS approach. Specifically, β_1 would not be a valid estimator of ATT.

Several econometric approaches are available in the literature on impact evaluation to re-establish a randomized setting in case of self-selection bias. Difference-in-differences is the one that is not applicable in our study, as this requires panel data over certain periods. The instrumental variables method is the other one that relies on parametric assumptions regarding functional form of relationship between outcomes and predictors as well as on exogeneity of instruments used. As this method is also quite sensitive to violation of these restrictive assumptions, we adopt the nonparametric, matching approach in which households of the group of diversified farmers are matched to those households in the control group, who are similar in their observable characteristics.

Moreover, it is common in the impact evaluation literature to treat diversification as a binary decision variable in which most studies have employed PSM to address the selection bias as discussed above. Yet, PSM is an oversimplification in situations when farmers produce at different intensity levels of diversification may have different effects on HFS. The current paper tries to extend this econometric setup to handle household's exposure to different levels of diversification, and measure its impact on HFS. So, the GPS method will be adopted from Hirano and Imbens (2004) to balance differences among farms of different intensity levels conditional on their observable characteristics. This approach has been used in observational studies since its formulation by Bia and Mattei (2008) addresses exposure to continuous treatments. Even Bia and Mattei have used the maximum likelihood estimator that does not allow for distribution assumptions other than normal density. Instead, the present paper used a flexible GLM following Guardabascio and Ventura (2014) for estimation of DRFs adjusted for GPS captures issues of both continuous and different distribution functions of a treatment. This means that adjusting for GPS removes all biases associated with differences in covariates. The unbiased impact of different intensities among farms of diversification on HFS can then be demonstrated with DRFs. The GPS approach involves three stages. First, the GPS are generated based on observed covariates. Second, the conditional expected values of the outcome variables (FS indicators) are estimated as a function of treatment exposure (AD intensity) and the GPS. Third, the average DRF is estimated. The DRF depicts for every treatment exposure level the direction and magnitude of the relationship between AD and HFS, after correcting for observed covariate bias (Hirano and Imbens, 2004). Following Guardabascio and Ventura (2014), the GPS was specified as Equation (5):

$$\widehat{R_i} = r(T, X) = c(T, \widehat{\Phi}) \exp\left\{\frac{T\widehat{\theta} - a(\widehat{\theta})}{\widehat{\Phi}}\right\} \quad (5)$$

where $\widehat{R_i}$ is the GPS generated for household i; $\widehat{\theta}$ and $\widehat{\Phi}$ are the estimate parameters of θ and Φ of the selected conditional distribution of the treatment given the covariates. The GPS was estimated using Bernoulli quasimaximum estimator, called GLM, with covariates X_i and fractional logit specification with Bernoulli distribution and logit link function, which takes into account both treatments (AD & OFI) range between 0 and 1. Like the conditional independence assumption (CIA) in PSM setting for dichotomous treatment, we presume weak confoundedness. This assumption essentially postulates that once all observable characteristics are corrected for, there is no systematic selection into specific levels of AD intensity left that is based on unobservable characteristics (Flores and Flores-Lagunes, 2009). The GPS is a balancing score suggested to derive unbiased estimates of the DRFs (Hirano and Imbens, 2004). Given T_i & R_i, the conditional expectation for outcome Y_i is modeled as a flexible function of the two arguments expressed in Equation (6) as,

$$\varphi\{E(Y_i/T_i, R_i)\} = \lambda(R_i, T_i; \alpha) = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 T_i R_i \quad (6)$$

where T_i & R_i are the treatment level measured as diversification index and GPS for household i respectively; α's are parameters to be estimated. Finally, we estimate the DRFs by averaging the expected FS outcome of Equation (6) at each level of treatments (AD or OFI) as in Equation (7).

$$E\{\widehat{Y}(t)\} = \frac{1}{N}\sum_{i=1}^{n} \widehat{\gamma}\{t, r(t, X)\} = \frac{1}{N}\sum_{i=1}^{n} \varphi^{-1}\left[\widehat{\lambda}\{t, \widehat{r}(t, X_i); \widehat{\alpha}\}\right] \quad (7)$$

where N is number of observations, t is each treatment level, $\widehat{r}(t, X_i)$ is expected value of conditional density of treatment at varying levels of AD & $\widehat{\alpha}$ are parameters estimated at second stage.

We tested the balancing property of the estimated GPS by employing the approach proposed by Guardabascio and Ventura (2014). The conditional expectation of the outcome for each farm was estimated using a flexible polynomial function, with quadratic approximations of the treatment and GPS as in Equation (6). The specification for continuous outcomes was estimated using OLS regression. Then the DRF in Equation (7) was evaluated at 5 evenly distributed levels of treatments. The set of the potential treatment values was divided into three intervals and the values GPS evaluated at the representative point of each treatment interval were divided into five intervals. Confidence bounds at 95% level were estimated using bootstrapping procedure with 100 replications. Results of the DRFs are presented graphically. We used Stata 13.1 statistical software for data analysis.

Descriptions and measurement of variables used in econometric analysis

Measuring household food security

Household FS is the key outcome variable of interest operationally conceptualized as the sum of unique foodstuffs consumed by household in a specified period. Food consumption can be better estimated using expenditure data collected over 7 day recall, rather than 24 hour time frame, as a longer recall period might capture a variety of foods consumed by household despite adding some level of noise reduces its accuracy (Jones *et al.*, 2014; Mulat Demeke *et al.*, 2017). The study adopted not just a 7 days recall food frequency module from WFP (2008) for measuring HFS in terms of food consumption, it also applied a standardized 24 hours recall dietary diversity module of Swindale and Bilinsky (2006) to compare and enhance robustness of results obtained via food consumption score (FCS) and household dietary diversity score (HDDS).

Measuring agricultural diversification

A wide variety of approaches have been employed in empirical literature to measure agricultural diversification (AD) to examine the association between AD, FS and nutrition. Several studies have used household biodiversity index (HBI) as an indicator of AD (e.g., Herforth, 2010; Jones *et al.*, 2014; Sekabira and Nalunga, 2020) with some iteration of a count of specific crop species cultivated and livestock species raised. Biodiversity index is conceptualized as a simple count of all crops and livestock species produced on household farm usually in one production year as a measure of AD. Some others have used production diversity score (Koppmair *et al.*, 2016), aggregated production diversity index (Habtamu Yesigat *et al.*, 2017) and agriculture enterprise score (Mulat Demeke *et al.*, 2017) which only counted food groups produced by household to measure AD with the assumption that HBI (i.e., agricultural diversification index-ADI in our case) does not necessarily reflect diversity from dietary point of view. We developed aggregated production diversity metric- so called agricultural diversification score (ADS) operationally defined as the number of food groups produced by household per year. The ADS was constructed based on the food groups formulated similar to those used in FCS module customized with local contexts in northwest Ethiopia.

However, both ADI & ADS do not address differences in distribution of diversification, as all items/groups are equally weighted regardless of quantity produced. Arimond and Ruel (2004) suggested ADI/ADS can be more or less meaningful depending on the relative share of each food produced. We adopt the Simpson index (Simpson, 1949) to capture the relative intensity of each food item/group produced by the household. This relative index was estimated using area share of each crop species (group) from total crops cultivated, and number share of each livestock species (group) among total livestock raised by household as in Equation (8).

$$\mathrm{SI} = 1 - \sum_{i}^{K} \mathrm{W}_{i}^{2} \qquad (8)$$

where SI is the Simpson index, W_i is the area (number) share of crop (livestock) species/group i respectively. SI ranges between 0 and 1; a value of 0 implies only one food species/group is produced while a value closer to 1 reflects more even distribution of area (number) by crop (livestock) type.

Using Equation (8) we constructed six Simpson indices via simple and group count approaches to address seasonal variations in crop production during *Meher* (rainy) and irrigation (dry) seasons: (1) Meher season crop diversity Simpson index (mCDSI) and (2) irrigation season crop diversity Simpson index (iCDSI) that calculated based on relative share of crop species produced; (3) Meher season crop diversity Simpson score (mCDSS) and (4) irrigation season crop diversity Simpson score (iCDSS) based on relative share of crop groups produced; (5) both seasons crop diversity Simpson index (bCDSI) represents diversification of crop species produced in both seasons; (6) both seasons crop diversity Simpson score (bCDSS) reflects diversification of crop groups produced in both seasons; and (7) livestock diversity Simpson index (LDSI) and (8) livestock diversity Simpson score (LDSS) are the two indices for measuring intensity of livestock species and groups diversification reared last year, respectively. The other two, (9) agriculture diversity Simpson index (ADSI) as the average value of bCDSI and LDSI and (10) agriculture diversity Simpson score (ADSS) is the average value of bCDSS and LDSS, are composite indices of crop and livestock species and groups produced by household to measure the overall AD. Overall, we used 10 measures of AD to assess its effect on HFS not only to differentiate the role of intensity in terms of species and groups of crops and livestock produced, but also to determine the implication of seasonal variations in diversification of production on FCS and HDDS.

Off-farm income

Off-farm income is the other key explanatory variable that can influence HFS. Rural off-farm employment as an income stream may affect dietary diversity of households comprises: (a) wage employment, (b) annual private transfer income (remittances) and (c) non-farm self-business. The value of this off-farm variable could be measured as if a household received income from all the three sources scored 3; those who received income from none of these sources scored 0. While counting the number of income sources can capture income diversification, it does not automatically imply households with more off-farm income sources have higher income levels relative to families engaged in fewer off-farm activities. As such, we measured off-farm employment level (intensity) operationally defined as a proportion of off-farm income to total income of household last year prior to the survey.

Confounding factors

Other covariates were identified based on existing theory regarding determinants of HFS and potential confounding factors of the relationship between AD (OFI) and HFS from extant literature (e.g., Bellon *et al.*, 2016; Chang and Mishra, 2008; Duong *et al*. 2021; Sibhatu Kibrom *et al.*, 2015). Factors that may have confounded the association between AD and HFS were corrected for sex, age and education level of household head, household size, cultivated farm size, farm income, access to off-farm income, and location dummies. Moreover, access to extension and credit, presence of local food market, travel distance from nearest town market, road quality and access to irrigation were considered to control for effects of institutional services and market infrastructure on AD, OFI & FS linkages.

RESULTS AND DISCUSSION

Household characteristics

Table 1 presents the socioeconomic characteristics of households used as balancing variables for estimating GPS. A typical household in the study area had around six people, similar to the national average, and was mainly headed by a male with an average age of 47 years. Almost half of the household heads had completed 2.5 years of education. On average, the size of cultivated land was 1.6 ha, and agriculture was the primary occupation, contributing 85% of the household's annual gross income. The average family farm generated a gross annual income of 1793 USD (62660 ETB). On average, households had to walk 2.31 hours to reach the market in the nearest town from their homes. While 86% had access to local food markets in their villages, half of them reported better access to all-weather roads connecting their villages to the nearest town. Households with access to irrigation and credit each accounted for 62%, while those who accessed extension services registered 89%. Table 2 summarizes the outcome and treatment variables. The average FCS and HDDS were 55.6 and 7, respectively. Crop, livestock, and agriculture production diversities, measured in a simple count, were 0.68, 0.64, and 0.66 Simpson index, respectively. The corresponding figures via group count averaged to be 0.37, 0.64, and 0.49, respectively. These findings showed that households had better diversification in livestock than crop farming. Approximately 39% of households had access to off-farm employment, with a diversification intensity of 0.04 Simpson index. Off-farm income contributed only 5% of the household's annual gross income (Table 2).

Table 1. Descriptive statistics of household characteristics used as balancing variables.

Balancing variables	**Measurement**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Sex of household head	Binary (1=male, 0=female)	0.91	0.28	0	1
Age of household head	Continuous (years)	46.56	10.61	20	72
Education level of household head	Continuous (years)	2.52	3.32	0	12
Household size	Continuous (number)	6.27	2.13	1	14
Cultivated land size	Continuous (ha)	1.56	0.7	0.25	4
Annual gross farm income	Continuous ('000 ETB)[a]	53.22	61.13	0	562.25
Annual gross total income	Continuous ('000 ETB)	62.66	132.77	0.30	2072.61
Distance to nearest town market	Continuous (walking hours)	2.31	1.27	0	7
Presence of food market in village	Binary (1=yes, 0=no)	0.86	0.35	0	1
Access to all weather road	Binary (1=yes, 0=no)	0.50	0.50	0	1
Access to irrigation	Binary (1=yes, 0=no)	0.62	0.49	0	1
Access to credit	Binary (1=yes, 0=no)	0.62	0.49	0	1
Access to extension	Binary (1=yes, 0=no)	0.89	0.31	0	1

Source: Own survey data (2020).
` The official exchange rate of money during the survey period was 1 USD=35 ETB.

Table 2. Summary statistics of outcome and treatment variables.

Variables	**Descriptions**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Outcome variables:					
FCS	Food consumption score of households	55.61	17.61	22	100.5
HDDS	Household dietary diversity score	7.04	1.82	1	12
Treatment variables:					
CDSI	Crop diversity Simpson index	0.68	0.12	0.07	0.86
LDSI	Livestock diversity Simpson index	0.64	0.21	0	0.86
ADSI	Agriculture diversity Simpson index	0.66	0.13	0.16	0.84
CDSS	Crop diversity Simpson score	0.37	0.19	0	0.81
LDSS	Livestock diversity Simpson score	0.64	0.17	0	0.84
ADSS	Agriculture diversity Simpson score	0.49	0.12	0.09	0.78
SOFI	Share of off-farm income to total income	0.05	0.13	0	1
AOFI	Access to off-farm employment (1=yes, 0=no)	0.39	0.49	0	1
OFIDSI	Off-farm income diversity Simpson index	0.04	0.12	0	0.5

Source: Own survey data (2020).

The purpose of Figure 1 is to analyze the distribution of crops produced by households and determine whether crop diversification is due to specific or diverse food groups. The findings indicate that most households have crop diversification intensities ranging from 0.65 to 0.8 Simpson Index (CDSI), which is measured by counting the crop species, regardless of their food group (Figure 1a). When diversification intensities are estimated based on food groups, a larger proportion of households have crop diversification intensities between 0.25 to 0.5 Simpson score (CDSS), which is lower than the values obtained from the CDSI method (Figure 1b). A comparison of panels (a) and (b) suggests that while many households are more specialized in crop groups, they are more diversified in crop species from only a few food groups. The results imply that most crop diversification comes from the same food group, which may be starch staples, as almost all households produced at least one crop species in this food group.

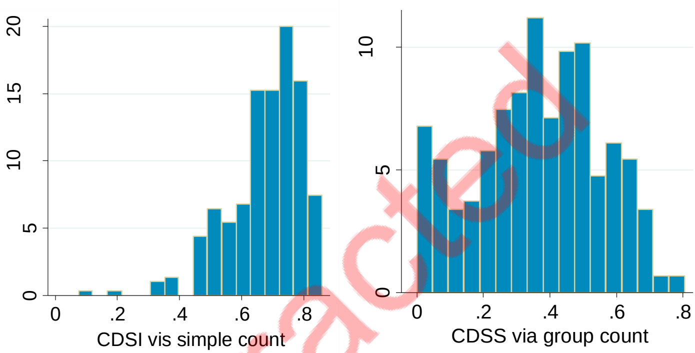

Figure 1. Distribution of crop diversification intensities by households. (a) Left, (b) Right

Regarding livestock diversification, Figure 2a and 2b show that the majority of households have diversification levels between 0.6 to 0.8, indicating better livestock diversity both in terms of individual and group of livestock species raised. This suggests that livestock diversification is more diverse in terms of food groups compared to crop diversification.

Figure 3 displays the overall AD intensity combining both crop and livestock productions by household. The majority of households have AD levels ranging from 0.6 to 0.8 Simpson index (ADSI) using the simple count method (Figure 3a) and between 0.4 and 0.65 Simpson score (ADSS) using the group count method (Figure 3b). These results imply that the majority of households have better AD intensities, indicating a balanced mix of crop and livestock diversification.

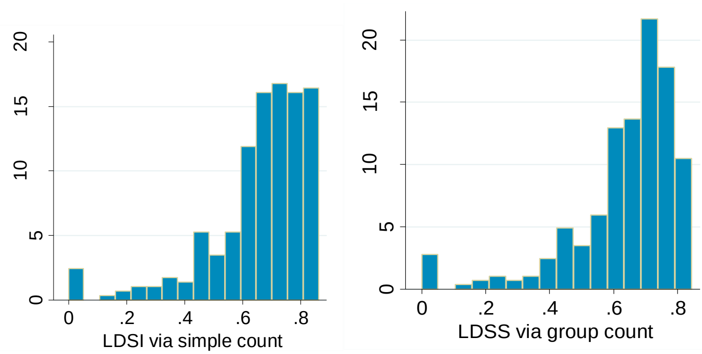

Figure 2. Distribution of livestock diversification intensities by households. (a) Left, (b) Right

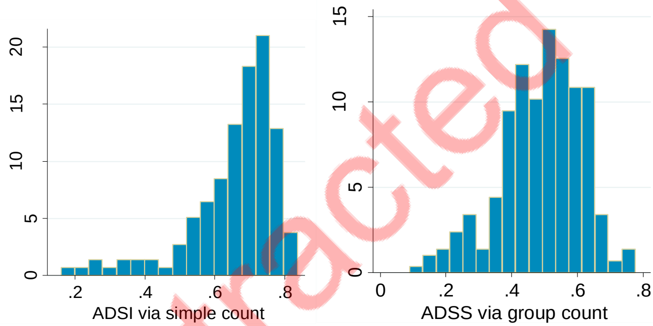

Figure 3. Distribution of agricultural diversification intensities by households. (a) Left, (b) Right

Food security impacts of crop, livestock and agriculture diversifications

This section discusses the results of continuous treatment effects of production diversification and off-farm employment intensities on HFS estimated using GPS matching. Covariate balancing tests compared three different groups varying in levels of each diversification indicators (CDSI, LDSI, ADSI, CDSS, LDSS & ADSS) as dependent variables of different models analyzed each separately. Before matching, most of the covariates for these three treatment groups differ significantly across all the six models. After matching, most of the differences turn insignificant. This implied the variables used for balancing fairly balance the differences in household and farm characteristics, which in turn verified GPS is an appropriate approach for analyzing continuous treatment effects (Albeit this result not shown in this paper). The subsequent subsections present DRFs estimated at each level of crop, livestock and agricultural diversification and off-farm employment intensities graphically.

Effects of crop diversification on food security

Figure 4 presents the role of crop diversification intensities in Meher (rainy) and irrigation (dry) seasons production on food consumption (FC) and dietary diversity (DD) of households evaluated through DRF and GPS framework. The horizontal axes in panels (a), (c) and (e) of Figure 4 represent crop diversification intensity in Meher, irrigation and both seasons production in Simpson index such as Meher season CDSI, irrigation season CDSI and both seasons CDSI respectively; and the vertical axis measures the expected effects on food consumption score (FCS) and dietary diversity score (HDDS) of households at a given level of diversification.

Rainy and dry season crop diversification intensity based on simple count

Controlling for confounding factors, the results have shown evidence in favor of crop diversification in rainy season improved HFS through better FC and DD as an increasing trend seen in panels (a) and (b) of Figure 4. This finding corroborates the works in Malawi (Jones *et al.*, 2014), Kenya (Mulat Demeke *et al.*, 2017) and in Ethiopia and Tanzania (Habtamu Yesigat *et al.*, 2017) that revealed farm diversification can improve household DD. It was crop-specialization in irrigation season favored HFS to increase by enhancing FCS & HDDS (panels c and d of Figure 4); the latter, however, implied diversification in dry season might have positive implication on DD had it also been above certain level of intensity (0.4). This slightly agrees with the finding of another study in Ethiopia (Bakhtsiyarava and Grace, 2021) suggested more diversity in farm production can adversely impact child height-for-age in the context of poor rainfall. The overall crop diversification intensity combining rainy and dry seasons' production also demonstrated the relevance of crop diversity for better HFS as an upward trend of FCS and HDDS seen in panels (e) and (f) of Figure 4.

Rainy and dry season crop diversification intensity via group count

Figure 5 depicts HFS impacts of diversification intensity in crop groups to evaluate whether diversity in production of crops from different food groups or specific group enhances HFS. Both the FC and DD indicators demonstrated that HFS effects of crop diversification from diverse food groups tend to be positive at low diversification levels (i.e., high specialization). The DRFs in panels (a) and (b) of Figure 5 have a maximum at roughly 0.3, and become lower at high levels of diversification in rainy season production. This non-linear relationship on the one hand might reflect specialization in production of crops from very few food groups results in less diverse diets with rising adverse consequences on HFS. The extremely high diversification levels on the other hand slow down HFS as less efficient production structure prevents gains from specialization (i.e., less diversified farms). Thus, crop diversification in Meher season at 0.3 implied for most farmers moderately increased diversification in crop production would be beneficial for improved FC and DD. A comparative analysis of same panels (a) and (b) of Figure 4 with those in Figure 5 implied diversification in production of crops from very few food groups in rainy season would have positive implication on HFS.

The DRFs for the effect of diversification in dry season production of crop groups on FC and DD of households are similar (see panels c and d of Figure 5), but show a very different shape relative to rainy season production. Both panels reveal a negative relationship of dry season crop diversification with FCS & HDDS. Comparing panels (c) and (d) of Figure 4 with those panels (c) and (d) in Figure 5 revealed all have similar patterns that implied it is entirely specialization in production of crop from specific food group in dry season improved HFS. Specialization in cash crops production may be beneficial for farmers not only because more efficient to use the water resource, which is so scarce, during dry season, they are also more attractive economically. It has to be kept in mind, however, that very few farms have actually reached diversification levels of crop production above 0.5 Simpson score in irrigation season as shown in the histogram. In these high intensities of dry season diversification, the estimation of the DRFs on HDDS are, therefore, based on few treatment units and should therefore be interpreted with caution. This is also seen by the spread of confidence interval at that point of intensity in all graphs of interest.

Whereas when comparing same panels (e) and (f) of Figure 4 with those in Figure 5, the DRFs for the effect of overall crop diversification intensities on FCS & HDDS disclosed diversification in production of diverse crop species would yield better HFS had it been from limited food groups than from diverse food groups. This suggested yet there is scope for improving crop production systems of smallholder farmers a bit more nutrition sensitive; may be through strengthening and supporting the extension system to promote diversification of crop production to be from diverse food groups instead of being from specific group- for example starchy staples as most households produced in the study areas. This, meanwhile, encourages smallholder farmers to adopt a sustainable production system in crop farming similar to the findings identifying crop diversification as part of sustainable production practices (FAO, 2018b; Getachew Teferi *et al.*, 2018) can improve dietary quality while protecting household food production and income from weather shocks as different crops have different sensitivity to climate variability (Bakhtsiyarava and Grace, 2021). Herrero *et al.* (2010) also confirmed the synergy between cropping and livestock husbandry can increase FS and income of the people while maintaining environmental services.

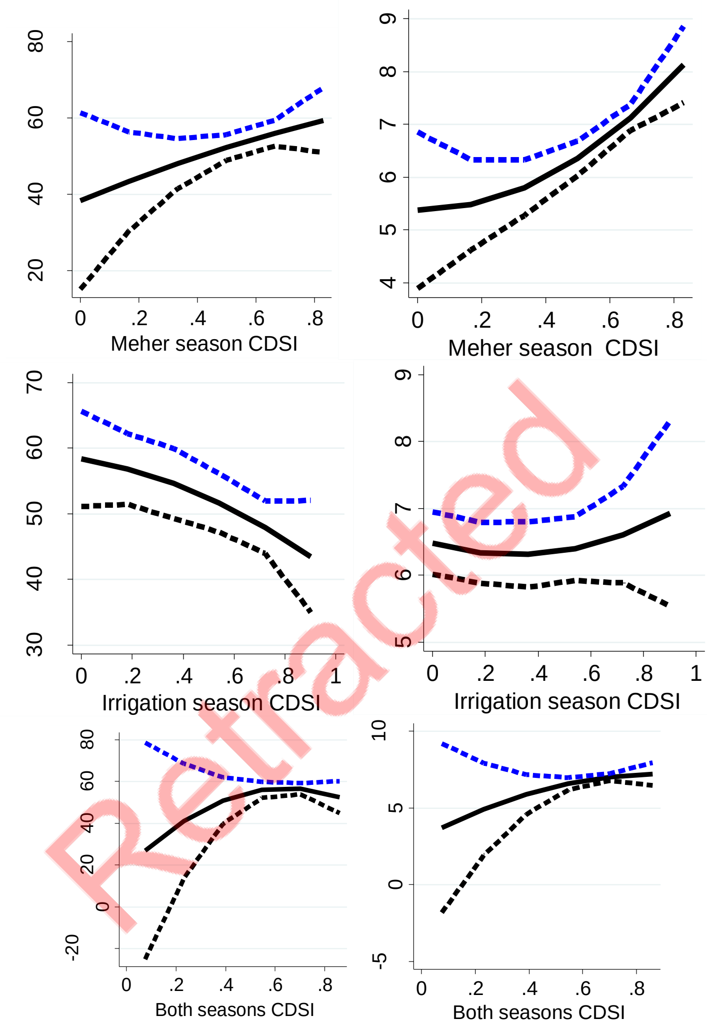

Figure 4. DRFs of seasonal crop diversification effects on FCS and HDDS (simple count).
Note: Solid lines are DRFs and dashed lines show 95% confidence intervals obtained through bootstrapping. (a) Top left, (b) Top right, (c) Middle left, (d) Middle right, (e) Bottom left, (f) Bottom right

Effects of livestock diversification on food security

Livestock husbandry is another major part of smallholder agriculture that has generally had a favorable impact on HFS. As shown in Figure 6, both the basic count (panels a and b) and group count (panels c and d) methodologies indicated that livestock variety improves HFS. This implied that a broader portfolio of animals raised was driven by different food categories rather than distinct food groups. It also found that livestock production is more nutrition sensitive than crop farming, which is comparable to the findings of Muthini et al. (2020) in Kenya, who reported that the number of animal species has the greatest magnitude of association with DD of households and women.

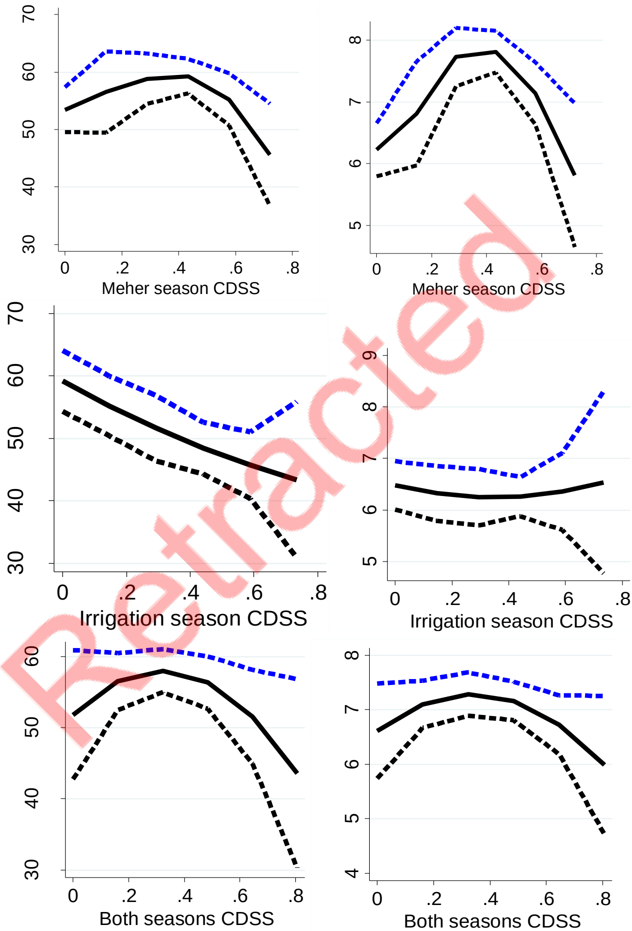

Figure 5. DRFs of seasonal crop diversification effects on FCS and HDDS (group count). *Note: S*olid lines are DRFs and dashed lines show 95% confidence intervals obtained through bootstrapping. (a) Top left, (b) Top right, (c) Middle left, (d) Middle right, (e) Bottom left, (f) Bottom right

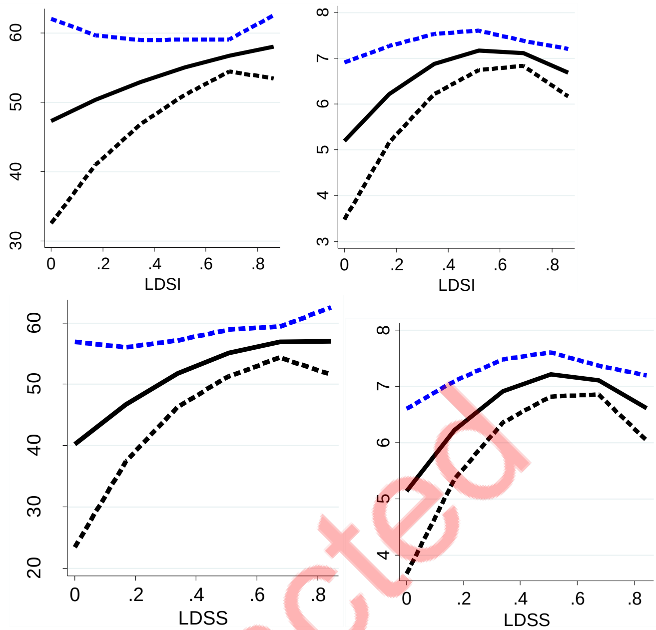

Figure 6. DRFs of livestock production diversification effects on FCS and HDDS
Note: Solid lines are DRFs and dashed lines show 95% confidence intervals obtained through bootstrapping. (a) Top left, (b) Top right, (c) Bottom left, (d) Bottom right

Effects of agricultural diversification on food security

As AD, which includes total crop and livestock production, as shown in Figure 7, the DRFs peaked around 0.5 Simpson score and thereafter decline (panels c and d in Figure 7). This implies that increasing AD up to a certain degree can improve HFS in both FC and DD, which peaked at 0.5 and subsequently declines at high levels of diversification. Furthermore, diversification in farm output would have a favorable impact on HFS if it reached this maximum level, after which diversification within the same food group may improve HFS, as evidenced by an increasing trend in panels (a) and (b) in Figure 7.

Effects of off-farm employment on food security

Figure 8 depicts the effect of off-farm employment on HFS in terms of FCS (Figure 8a) and HDDS (Figure 8b). Off-farm employment at both the lower (up to 0.2) and higher (beyond 0.6) levels seems to have a positive effect on FCS and HDDS. This suggested that when the level of employment intensity increased, not only would there be fewer treatment units, but there would also be over dispersion, and hence it is up to intensity level of 0.2 Simpson index increased HFS in both FCS and HDDS. Off-farm employment has an adverse effect on the HFS at moderate levels ranging from 0.2 to 0.6.

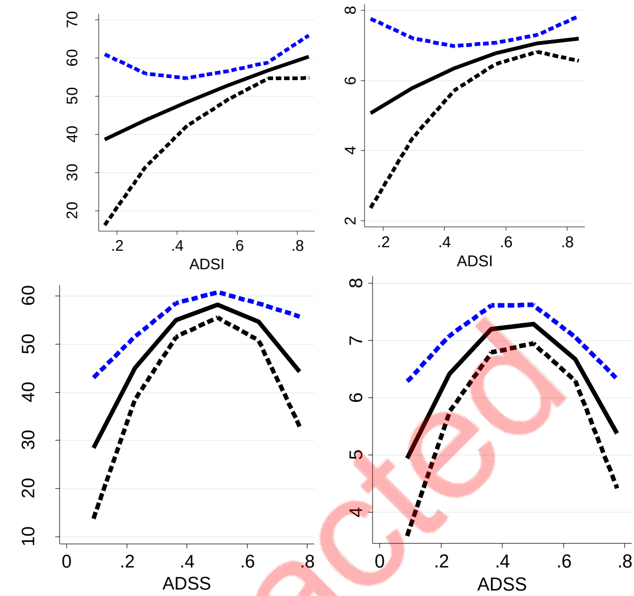

Figure 7. DRFs of overall agricultural diversification effects on FCS and HDDS
Note: Solid lines are DRFs and dashed lines show 95% confidence intervals obtained through bootstrapping. (a) Top left, (b) Top right, (c) Bottom left, (d) Bottom right

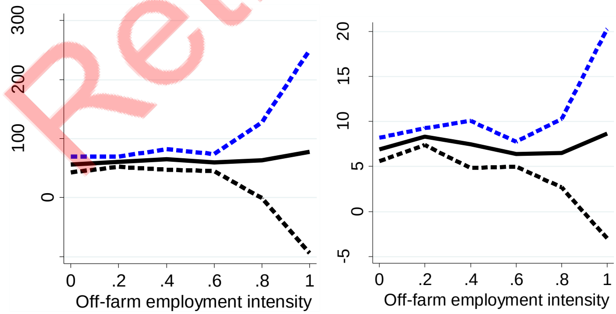

Figure 8. DRFs of off-farm employment intensity effects on FCS and HDDS
Note: Solid lines are DRFs and dashed lines show 95% confidence intervals obtained through bootstrapping. (a) Left, (b) Right

CONCLUSIONS AND POLICY IMPLICATIONS

The study investigated the relationship between AD, off-farm employment, and HFS in northwest Ethiopia. Our analysis focused on the role of crop diversification in both the rainy and dry seasons, as well as livestock diversification. We found that moderate levels of crop diversification in the rainy season could have a positive impact on HFS, while specialization in cash crops during the dry season could improve HFS in both food-crop and cash-crop dominant areas. Furthermore, diversification in livestock production could have positive implication on HFS, particularly when diversification occurred across diverse food groups. Our analysis suggests that AD across crop and livestock production can heighten the positive effects on HFS. We also found that off-farm employment can help improve agricultural productivity and diversify household income, which in turn can increase HFS resilience. This study suggests that AD and off-farm employment are crucial factors in ensuring HFS in northwest Ethiopia, and that diversification across diverse food groups up to a certain level is essential for maximizing the positive impact of AD on HFS.

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COMPETING INTERESTS

Authors declare no competing interests.

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