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Impacts of Livelihood Diversification on Food Security in Rural Households of West Gojam Zone, North West Ethiopia

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Abstract

The aim of this study was to evaluate the impact of livelihood diversification on the food security of rural households in West Gojjam Zone, located in North West Ethiopia. The research utilized primary data collected from 391 households, using structured questionnaires. To assess the effect of livelihood diversification on food security, the study employed Propensity Score Matching (PSM). The results from different algorithms also revealed that livelihood diversification significantly improves food security. Households in the study area experienced an increase in kilocalorie intake by 118-136 kilocalories, confirming that diversifying livelihoods positively affects food security. Based on these finding, the study recommends that policies which encourage rural households to participate in different livelihood diversification strategies should be implemented to enhance household resilience and improve food security in the study area.

Keywords: *Kilocalorie, food security, rural households, livelihood diversification, Ethiopia.*

1. Introduction

Smallholder households in many parts of the world, including rural areas in Ethiopia, face significant barriers to agricultural productivity due to limited access to essential agricultural inputs such as seeds, fertilizers, and irrigation systems. These limitations often result in low agricultural output, which in turn leads to food insecurity, as these households are unable to produce sufficient food to meet their needs (Bekele et al., 2017). The lack of resources for efficient farming, compounded by the continuous reduction in cultivable land due to factors such as population growth and land fragmentation, further exacerbates the vulnerability of these households (Dawit et al., 2019).

In response to these challenges, many smallholder households turn to livelihood diversification as a strategy to reduce their dependency on agriculture and to mitigate the risks associated with food insecurity. These households often engage in non- and off-farm income-generating activities such as the sale of fuel wood, charcoal, rope, handicrafts, trading, and wage labor. These supplementary income sources are crucial for bridging the gap between household income and food needs, especially when agricultural production is insufficient or when the available land is no longer able to sustain the household's food requirements

(Alemayehu et al., 2020). Diversifying their livelihoods provides households with the cash needed to purchase food and other essential goods, enhancing their food security and overall resilience.

Diversification of livelihoods is widely recognized as a critical strategy for reducing household vulnerability, as it provides additional sources of income, enhancing economic resilience and helping to reduce food insecurity in the long term (Ellis, 2000). By broadening income sources, households can better withstand economic shocks and ensure a more stable food supply, especially when their primary agricultural activities fail to meet their needs. However, the success of livelihood diversification is contingent on the creation of non-farm opportunities that can compensate for declines in agricultural productivity, which often exacerbate food insecurity. This problem becomes even more severe in areas affected by environmental degradation, land loss, and other shocks that undermine the livelihoods of rural households (Tessema & Tsegaye, 2021).

Despite the widely held belief that livelihood diversification improves food security, there is considerable empirical debate regarding its actual impact. Some studies have found positive interactions, while others have suggested that the benefits may not be as straightforward (Barrett et al., 2001). For instance, Thuo (2011) and Hanazaki et al. (2012) reported that households engaging in a variety of income-generating activities, such as off-farm work and wage employment, were better able to meet their food demand and cope with economic shocks. The diversified income sources allow households to build economic resilience, which is particularly valuable during periods of drought, poor harvests, or market instability. These households are more likely to be able to purchase food when local production is insufficient, thus improving their food security (Jayne et al., 2003).

Kuwornu et al. (2019) and other scholars argue that while livelihood diversification can provide benefits, it can also reduce food security in some cases. One possible explanation for this is that non-farm activities do not always generate sufficient income, or they may require significant time investments that divert smallholders' attention away from agricultural production. In scenarios where diversification leads to a shift of labor away from farming, households may lose valuable time and resources that would otherwise be spent on agricultural activities, ultimately worsening food insecurity due to lower agricultural productivity (Omonona et al., 2007). For example, households that spend more time engaging in non-farm activities may have less time available for food production, which could result in lower crop yields and insufficient food supplies to meet household needs (Haggblade et al., 2007). This shift in focus can create a paradox, where households diversify to increase income but inadvertently reduce their agricultural productivity, leading to a net negative impact on food security. Therefore, the net effect of livelihood diversification on food security may vary depending on the type of non-farm activities pursued, the resources available to the household, and the extent to which non-farm income can compensate for the loss of agricultural productivity.

In Ethiopia, several researchers such as Chernet (2023), Andualem and Ebrahim (2021), and Fikire and Zegeye (2022), have attempted to explore the impact of livelihood diversification on food security. However, their studies have been critiqued for failing to adequately capture the complexity of this relationship. These critiques often focus on the limited scope of their methodologies, which may overlook contextual factors such as local economic conditions, social structures, and environmental factors. Furthermore, these studies tend to simplify the diverse pathways through which livelihood diversification might influence food security, neglecting the intricate dynamics that could either enhance or undermine food security depending on specific circumstances.

Therefore, the main objective of this study was to assess the impact of livelihood diversification on the food security of rural households in the West Gojam Zone. This research seeks to address the limitations of previous studies by considering the complex and context-specific factors that influence the relationship between livelihood strategies and food security. By focusing on this region, the study aims to provide a more nuanced understanding of how different livelihood diversification strategies contribute to or hinder food security outcomes in rural settings, with attention to local economic, environmental, and social dynamic.

2. Data and Materials

2.1. *Study Area Description*

West Gojjam Zone, located in the Amhara Regional State of Ethiopia, is a region with considerable agricultural potential. The area is predominantly characterized by a mixed farming system, where both crop production and animal husbandry are practiced. Rainfall is a key factor for agricultural activities in the region; however, the reliance on rain-fed agriculture makes it vulnerable to climatic fluctuations and irregular rainfall patterns. The West Gojjam Zone Administration Office (WGZAO, 2021) reports that 921,587 hectares of land are potentially suitable for irrigation. This presents an opportunity to enhance agricultural productivity through the introduction of small-scale irrigation systems, which could help mitigate the risks posed by unpredictable rainfall and improve food security for local households. Geographically, West Gojjam is bounded by the Abay River to the south, which separates it from the Oromia and Benishangul-Gumuz regions. To the northwest, it is bordered by Alefa, to the east-by-East Gojjam, to the north by South Gondar, and to the west by the Awi Zone.

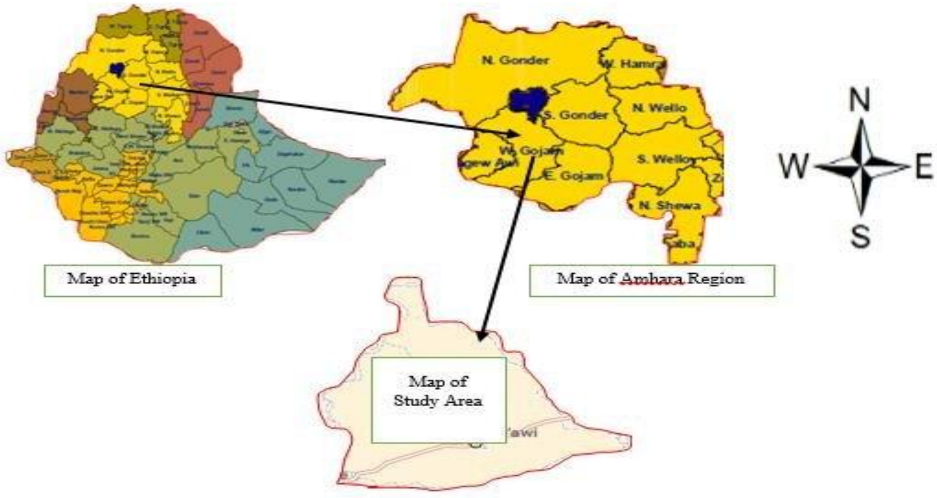

Figure 1. Location Map of the study area.
Source; Arc GIS :(2022)

2.2.Explanatory Research Design and Cross-sectional Research Approach

This study employed explanatory research design to explore the relationship between livelihood diversification and food security among rural households in West Gojjam Zone, that is, to understand the cause-and-effect relationships between variables. It goes beyond just describing a phenomenon (as in descriptive research) and focuses on explaining the reasons or mechanisms behind the occurrence of a particular event or trend. The mixed research approach which is both qualitative and quantitative research methods were employed to ensure a comprehensive understanding of the research issue. Qualitative data were gathered through interviews, and open-ended surveys which allowed the researchers to capture rich, detailed accounts of the participants' experiences and perspectives on livelihood diversification and food security. These qualitative data were analyzed using summarization and narration techniques, helping to identify key themes, patterns, and individual experiences. Quantitative data were collected through structured surveys or questionnaires, focusing on measurable variables such as household income, the number of income sources, food consumption patterns, and various food security indicators.

2.3.Type, Source, and Method of Data gathering

Primary data served as the main source of information for this study. A structured questionnaire was employed to collect primary data from the sampled respondents. This approach enabled the researchers to obtain specific and relevant information regarding livelihood diversification and food security from the target population. In addition to primary data, the study also incorporated secondary data collected from various sources. These included both published and unpublished reports from government offices, as well as articles and journals pertinent to the study.

2.4. Sampling Procedure and Techniques

The representative households for this study were selected using a multistage sampling approach, combining purposive and simple random sampling techniques. Initially, two woredas, Burie Zuria and Jabitenan were purposefully chosen for inclusion in the study. The purposive sampling technique was employed to focus on households involved in a variety of rural livelihood activities aimed at enhancing food security, making them relevant to the study's objectives. The unit of analysis for the study was at the household level, with the target population comprising the 17,500 households residing in Burie Zuria and Jabitenan woredas. To ensure the sample was representative, nine kebeles were purposefully selected from the two woredas five from Burie Zuria and four from Jabitenan based on the presence of diverse livelihood activities practiced by farm households. The selected kebeles from Burie Zuria were Wangedam, Wundigi, Alefa, Winma Abay, and Tsengaha and Jigayelmda, Woyenema, Mankusa Abdegoma, and Agomamit from Jabitenan. Within each of these kebeles, sample households were chosen using proportional sampling based on the number of households in each kebele, ensuring that the sample was representative of the population in each area. This sampling approach allowed for a balanced representation of households engaged in various livelihood strategies across the two woredas.

2.5.Sample Size Determination

By using probability sampling technique (Simple random sampling), a proportional sample of households were obtained from selected kebeles and thus 391 sample respondents were selected. The Yamene (1967) formula was used to calculate the sample size, since households in this study area engage in similar diverse livelihood activities.

$\boldsymbol{n} = \frac{\boldsymbol{N}}{1+\boldsymbol{N}(e)^2}$, where n is sample size, N is total household numbers, e is margin of error equal to 5% (0.05). $n = \frac{17,500}{1+17,500(0.05)^2} = \frac{17,500}{1+43.75} = 391$

2.6.Data Management and Analysis

The identified interaction of livelihood diversification and the food security of rural households using the Propensity Score Matching (PSM) method. This is so because there is a concern that there may be time-varying or unobserved confounders that differ between treatment and control groups, and matching individuals based on pre-treatment covariates can better isolate the treatment effect. The impacts of diversifying livelihood can be estimated by comparing the differences in outcomes between observationally similar families that did not diversify and those who did. In this study, livelihood diversification was likely measured using an index rather than just a percentage. This is because livelihood diversification often involves multiple dimensions (such as the number of income sources, types of activities, and the extent of engagement in those activities), and an index allows for a more comprehensive and nuanced assessment. A diversification index typically quantifies the level of diversification by assigning numerical values to different livelihood activities. These values may reflect the number of income sources, the diversity of sectors or activities a household engages in (e.g., farming, off-farm work, etc.), or the relative importance of each income source to the household's total income.

The Propensity Score Matching (PSM) approach is often used in cross-sectional studies to estimate treatment effects in the absence of a panel dataset. In a cross-sectional study, there is no temporal variation to observe how individuals or households change over time, making it difficult to directly compare groups based on their exposure to different interventions or treatments. PSM helps address this by matching treated and control groups based on their likelihood (propensity) of receiving the treatment, based on observed characteristics. This allows for a more balanced comparison and can help mitigate selection bias (Rosenbaum& Rubin, 1983). Secondly, the model makes the self-selection problem easier by estimating the propensity score (the likelihood that a household will engage in livelihood diversification) and matching the propensity scores of two groups of households within the same support region. Thirdly, the model allows us to calculate the average effect of livelihood diversification on untreated and treated (ATT and ATU) households' food security status.

The PSM was utilized in this study to match households that were and were not diversify their livelihood. A set of matching households that resemble the diversified households in all pertinent pre-intervention characteristics can be extracted from the sample of non-diversified households using the PSM technique. Families that diversify their livelihoods may differ from those that did not, not just in terms of the livelihood diversification level, but also in other aspects that impact food security status of the two groups. The matching techniques identify a non-diversified families who had similar living characteristics to a diversified household and hence avoiding biases. The Propensity Score Matching (PSM) approach enables the assessment of the impact of livelihood diversification by comparing households that have diversified their livelihoods with a matched set of non-diversified households. The matching process helps to create a comparable control group (non-diversified households) by pairing them with diversified households based on similar characteristics, except for their livelihood diversification status. This reduces selection bias and provides a more accurate estimate of the effect of diversification on outcomes like food security. For households that have diversified their livelihoods, PSM estimates the mean impact of diversification by averaging the outcomes (e.g., food security) across all the diversified households. This estimate reflects the difference between the actual outcomes for diversified households and the expected outcomes had those households not diversified, using the matched control group as a benchmark

What this study aimed to calculate was, the average impact of treatment on the treated (ATT), which refers to the change in food security status that is quantified in kilocalories. In this study, the term "treatment" refers to households that diversify their livelihoods, meaning they engage in multiple income-generating activities in addition to their primary source of livelihood. These households are considered as the "treated" group because they receive the "treatment" of livelihood diversification. Conversely, the "control" group refers to households that do not diversify their livelihoods, meaning they rely primarily on a single source of income (such as farming or another activity). These households serve as the comparative group in the study, representing those who have not been exposed to the "treatment" of livelihood diversification. There are steps involved in putting PSM into practice, including testing the matching quality, estimating the propensity scores, selecting a matching algorithm, and verifying the common support condition (Kopeinig, 2005).

2.6.1. Propensity Score Matching (PSM) Framework

Estimating the propensity score is the initial stage in PSM analysis. Since treatment is usually dichotomous (i.e., D=1 for the treated (diversified) and D=0 for the untreated (not diversified) units), a logit or probit function is frequently utilized for this purpose. In this study, logit model was selected over probit model due to its mathematical simplicity (Gujarati, 2004). The logit model can be written as;

$$\boldsymbol{P(Y=1|X_1, X_2, \dots, X_k)} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e^{-(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_kX_k)}}} \dots\dots\dots\dots\dots\dots \text{(1)}$$

Where $P(Y=1)$ is probability of owning a house; X_i's, list of independent variables; β_i's, parameters to be estimated

In terms of the odds ratio, the ratio of the probability of a household to diversify their livelihood (P) with respect to not diversifying (1-p), can be written as:

$$\frac{\boldsymbol{P_i}}{\mathbf{1}-\boldsymbol{P_i}} = \boldsymbol{e^{(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_kX_k)}} \dots\dots\dots\dots \text{(2)}$$

Finally, in terms of the Logs of odds ratio, equation (2) can be written as;

$$\boldsymbol{L_i = ln\left(\frac{P_i}{1-p_i}\right) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \cdots + \beta_kX_k} \dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(3)}$$

2.6.2. Area of Common Support Situation

The area of the common support region of the lowest and maximum propensity scores of households in the treatment and control groups refers to the region where the propensity score distributions for the treatment and control groups overlap. This concept is crucial in propensity score matching (PSM), where the objective is to ensure that treated and control units have comparable propensity scores, so as to make the groups as similar as possible based on observed covariates. The common support region is defined as the interval of propensity scores where both treatment and control groups have positive probabilities. To compute the common support region mathematically, we focus on the range of overlapping propensity scores between the two groups (Rosenbaum & Rubin, 1983).

Let p_T^{min} and p_T^{max} represent the minimum and maximum propensity scores in the treatment group, respectively and p_C^{min} and p_C^{max} represent the minimum and maximum propensity scores in the control group, respectively. Then the common support region can be defined by the overlap between the two groups' propensity score distributions where common Support Region=[max (p_T^{min}, p_C^{min}) ,min(p_T^{max}, p_C^{max})]. This formula provides the bounds of the common support region, where max (p_T^{min}, p_C^{min}) is the lower bound of the overlap (the highest of the minimum propensity scores) and min(p_T^{max},p_C^{max}) is the upper bound of the overlap (the lowest of the maximum propensity scores). Therefore the area of the common support region can be calculated as the difference between the upper and lower bounds as min(p_T^{max},p_C^{max}) - max (p_T^{min}, p_C^{min}) This value represents the length (or range) of the overlap in propensity scores. If the result is positive, it indicates that the treatment and control groups have overlapping propensity scores. If the result is zero or negative, it means there is no common support, and there is no overlap between the treatment and control groups' propensity scores (Stuart, 2010).

2.6.3. *Algorithmic methods and matching approach*

According to Rosenbaum & Rubin, (1983) the two common methods for matching treated units with control units based on their propensity scores are Nearest Neighbor Matching (NNM) and Kernel Matching. In Nearest Neighbor Matching, each treated unit is matched with the control unit that has the closest propensity score, according to a distance metric (often the absolute difference between the propensity scores). There are variations like 1-NN (one nearest neighbor) or k-NN (multiple nearest neighbors).

Let: $p_T(x_i)$ be the propensity score of treated units i and $p_C(x_j)$ be the propensity score of control unit j. For each treated unit i, the nearest neighbor control unit $j*$ is the one that minimizes the distance between the propensity scores, usually measured by the absolute difference: $j*$=arg min $p_T(x_i)$ - $p_C(x_j)$ This formula selects the control unit $j*$ whose propensity score is closest to that of the treated unit iii.

For 1-NN, each treated unit is matched with the single control unit with the smallest absolute difference. For k-NN, you match the treated unit with the k closest control units, and then often take the average of the outcomes for the selected controls as the matched outcome for the treated unit. In k-NN, the matching rule can be written as: Matched Outcome i=1/k$\sum_{jENi} Yj$, where Yj is the outcome for control unit j and Ni is the set of the k-nearest neighbors of treated unit i.

In Kernel Matching, the treatment effect is estimated as a weighted average of the control group outcomes, where the weights depend on the kernel function and the distance between the propensity scores of the treated and control units. The kernel function assigns higher weights to control units whose propensity scores are closer to the treated unit's propensity score.

Let: $p_T(x_i)$ be the propensity score of treated units i and $p_C(x_j)$ be the propensity score of control unit j and K (·) be a kernel function, typically a Gaussian kernel, then the kernel-weighted average of the control outcomes for treated unit i is:

Matched Outcome=$\sum_{jE\ Control} KpT(xi) - pc(xj)\ ) . Yj$, Where $pT(xi) - pc(xj)$)is the weight for control unit jjj, based on the distance between the propensity scores p_T(xi) and p_C(xj)p, and the chosen kernel function and Yj is the outcome for control unit j.

Evaluating the treatment effect and Propensity Score Matching Framework

PSM uses comparable features (propensity scores) to compare each observation of the treated group versus the control group. The treatment group consisted of households who diversified their livelihood and the control group consisted of non-diversified households. Outcome variable of the study was the households' status of food security. Given a vector of observable covariates, the conditional likelihood of receiving treatment is known as the propensity score (Rosenbaum and Rubin, 1983).

The **propensity score** P(x) is the probability that a household receives the treatment given the observed covariates x. It is mathematically expressed as: $P(x) = P(T = 1 \mid X = x) = E(T \mid X = x)$,where P(x) is the propensity score (the probability of treatment given covariates x),T is the treatment indicator (1 for treated, 0 for control) and X is a vector of observed covariates.

The **ATT** is the difference in outcomes between the treated and control groups, adjusted for their covariates. $ATT = E[Yid - Yind \mid T = 1]$. This expresses the expected difference in the outcomes Yid (for diversified households who diversified their livelihood) and $Yind$ (for households who did not diversify their livelihood) conditional on receiving the treatment $T = 1$. This can also be rewritten as: $ATT = E[E[Yid - Yind \mid T = 1, P(X)]]$ (Imbens, & Wooldridge, 2009), where Yid is the outcome for the treated and $Yind$ is the outcome for the control and $P(X)$ is the propensity score.

This expression means that the ATT is the difference in the expected outcomes for the treated and control groups, with both outcomes conditioned on the covariates (through the propensity score).

3. Results and Discussion

To assess the impact of livelihood diversification on food security in the study area using a propensity score-matching (PSM) model, here's a step-by-step outline for matching the farm households with diversified livelihoods (treated group) to those with non-diversified livelihoods (control group) based on propensity scores and socio-economic characteristics.

3.1.*Common support*

The area of common support is depicted in Figure 1 below. The common support region is identified to lie between [0.1297252, 0.9977594]. Out of 391 observations, 372 (95.14%) are within the common support region, while the remaining 19 (4.86%) are outside the common support region. As a result, the propensity score matching (PSM) estimate can be carried out using only the observations within the common support region, as shown in Figure 1 below.

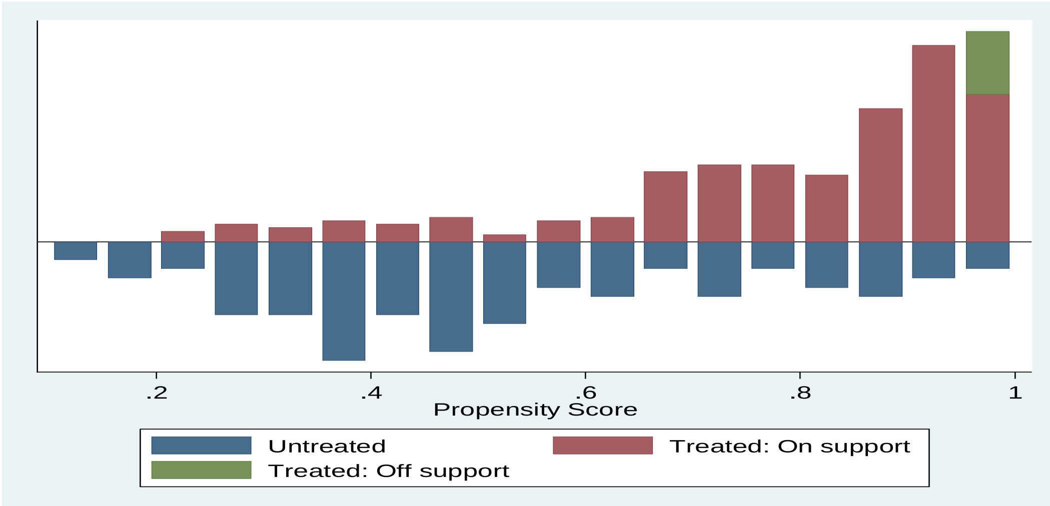

Figure 1. Common Support Graphical Expression

Source: Own Computation, 2024.

The remaining 19 out of 391 observations, or 4.86%, have propensity scores either below 0.1297252 or above 0.9977594. However, given the significant overlap in the distribution of propensity scores between households that diversify their livelihoods and those that do not, as shown in Figure 1, the common support condition is considered to be met.

3.2.*Matching Algorithm selection*

Before estimating the impact of livelihood diversification on a household's food security, the quality of different matching algorithms was assessed both before and after matching using likelihood ratio tests, mean standardized bias, and pseudo-R^2. The mean standardized bias was 24.7% prior to matching (as shown in Table I), and it decreased to between 18% and 12.2% after matching, with a notable reduction in bias ranging from 27.12% to 50.61%. The pseudo-R^2 was 0.235% before matching, and it was reduced to 0.035% afterward. Additionally, after matching, the likelihood ratio tests indicate that the covariates are jointly insignificant, whereas they were significant prior to matching. Therefore, the PSM method is considered successful when certain conditions are met: - Low pseudo-R^2 which indicates that the propensity scores are well-calibrated and not overly influenced by covariates a low bias which suggests that the treated and control groups are similar across the observed covariates, high reduction in bias which demonstrates that the matching process has substantially reduced the differences between the treated and control groups, improving comparability, insignificant p-values in the likelihood ratio test suggest that there are no significant differences in the covariates after matching, reinforcing the idea that the matching has succeeded in balancing the groups, ensuring high quality matching which means that matching process is designed to minimize the potential for confounding variables to affect the estimated effect of livelihood diversification on food security and addressing covariate imbalances: Before matching, there are typically noticeable differences between the treatment and control groups in terms of covariates. The objective of matching is to reduce or eliminate these differences, making the groups more comparable. After matching, the treated and control groups should be similar on the key covariates, which makes any estimated effects on food security more reliable and less prone to bias.

Table 1. Indicators of Covariate Balance prior to and after Matching.

Algorithm for Matching	NNM-1	NNM-5	KBB-0.03	KKB-0.06
Standard bias Mean (before)	24.7	24.7	24.7	24.7
Mean standard bias (after)	18.0	12.2	18.0	18.0
Percentage of bias reduction	27.12%	50.61%	50.61%	50.61%
Pseudo R^2 (before)	0.235	0.235	0.235	0.235
Pseudo R^2 (after)	0.074	0.035	0.074	0.074
LR X^2 with p-value (before)	108.18	108.18	108.18	108.18
$P>X^2$	0.000	0.000	0.000	0.000
LR X^2 with p-value (after)	53.94	25.26	53.94	53.94
$P>X^2$	0.000	0.003	0.000	0.000

Source: Own calculation, 2024.

NNM-1: Nearest neighbor matching with single neighbors. KBM-0.03: Kernel based matching with 0.03 bandwidth. NNM-5: Nearest neighbor matching with five neighbors.KBM-0.06: kernel-based matching with 0.06 bandwidth.

The use of Nearest Neighbor Matching (NNM) and Kernel Matching algorithms to estimate the Average Treatment Effect on the Treated (ATT) helps assess the impact of livelihood diversification on households' food security. the Nearest Neighbor Matching (NNM) and Kernel Matching (KBB) algorithms to estimate the Average Treatment Effect on the Treated (ATT), focusing on how livelihood diversification affects households' food security. The NNM-1 estimator suggests that households that diversified their livelihoods had an increase of 136 kcal in food consumption and statistically significant at the 1% level. NNM-5 estimator indicates that households without livelihood diversification could have increased their food consumption by 118 kcal, suggesting a similar but slightly lower impact than the NNM-1 estimator. According to the Kernel-Based Balancing (KBB) method, households that diversified their livelihoods saw an increase in their food intake of 136 kcal. The results across the different matching algorithms (NNM-1, NNM-5, and KBB) are consistent in showing that livelihood diversification leads to a positive increase in food security, with a food intake increase of approximately 136 kcal for diversified households. This consistency across the different methods enhances the reliability of the conclusion that livelihood diversification improves food security in these households. The statistical significance and similarity in the results across various methods indicate robustness in the estimation, providing strong evidence of the positive impact of livelihood diversification on food security.

But as shown in table II, the Kernel Matching approach creates more homogenous observation where the estimator shows that households with livelihood diversification increased their food intake by 136 kcal. The income differential between households that diversified their livelihoods and those that did not is significant at the 1% significance level, meaning that the difference in income due to livelihood diversification is large enough to significantly affect food security. These findings consistently show that livelihood diversification has a positive effect on food security, reflected by increased calorie intake. ports the importance of livelihood diversification in improving food security outcomes.

Table 2. Livelihood Diversification estimated Impacts on Food Security.

			Mean outcome		
Matching	Treated	Control	ATT	T-value	Standard error
NNM-1	2546.96591	2410.81439	136.151515	3.55***	88.0023184
NNM-5	2546.96591	2428.675	118.290909	3.32***	89.8255773
KBB-0.03	2546.96591	2410.81439	136.151515	3.55***	88.0023184
KBB-0.06	2546.96591	2410.81439	136.151515	3.55***	88.0023184

Source: own estimation calculation by Stata, 2023.

Note *** represents significance at 1% level of significance.

The results presented in Table II align with findings from previous research, such as Andualem and Ebrahim (2021), Esubalew and Danie (2019), and Titay et al. (2017), which all suggest a positive relationship between livelihood diversification and food security. Specifically, these studies highlight the positive effects of livelihood diversification on food consumption or calorie intake. All studies, including the current findings, consistently demonstrate that households engaging in livelihood diversification tend to have better food security outcomes, particularly in the form of increased food consumption or higher calorie intake. The consistency between the current findings and past research enhances the validity of the relationship between livelihood diversification and improved food security. This convergence across different studies and contexts suggests that the impact of livelihood diversification on food security is robust.

4. Conclusions and Recommendations

The primary objective of this research was to investigate how livelihood diversification affects food security among rural households. This is an important area of study, particularly in developing regions where households often rely on limited income sources and are vulnerable to food insecurity. A multi-stage sampling process was used to select a representative sample of 391 households. This approach is common in large-scale surveys and ensures that the sample accurately reflects the broader population, allowing for generalizable findings. To determine the causal relationship between livelihood diversification and food security, the study employed propensity score matching (PSM).

This method is commonly used in observational studies to estimate treatment effects, especially when randomization (as in a controlled trial) is not possible. PSM works by matching households with diversified livelihoods to similar households with non-diversified livelihoods based on observable characteristics. This allows for a more accurate comparison of food security outcomes between the two groups, reducing bias that may arise from confounding variables.

In summary, matching helps ensure that any differences in food security outcomes can be more confidently attributed to livelihood diversification rather than other factors, improving the validity and reliability of the causal estimates. PSM is a valuable technique for estimating causal relationships by ensuring that any observed differences in outcomes are not due to confounding factors, but rather the treatment being studied—in this case, livelihood diversification. These findings consistently show that livelihood diversification has a positive effect on food security, reflected by increased calorie intake. The similarity in results in Kernel matching algorithms strengthens the robustness of the conclusions. The significance of the income differential further supports the importance of livelihood diversification in improving food security outcomes. The alignment of current results with earlier studies reinforces the reliability of the conclusion that livelihood diversification positively impacts food security. This highlights the importance of encouraging diversified livelihoods in policy frameworks aimed at reducing poverty and enhancing food security.

These results support the view that households with diversified livelihoods are better positioned to achieve food security, which has significant implications for policy-making. Specifically, promoting livelihood diversification can be a key strategy in addressing poverty and improving nutrition among vulnerable populations. This could inform policies that target the reduction of food insecurity, especially in resource-constrained areas where diversified income sources can provide a buffer against shocks.

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