An Analysis of the Contribution of Small-Scale Farming to Rural Household Income. A Case of Honde Valley, Zimbabwe

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ABSTRACT

Small-scale farming plays a critical role in reducing rural poverty and contributes significantly to household income. This study aimed to assess the contribution of small-scale farming to rural household income in Honde Valley, Mutasa District, Zimbabwe. A survey was conducted, during which 60 questionnaires were distributed. Key findings revealed that small-scale farming significantly contributes to household income, with an average annual income ranging from $1201 to $2000, accounting for 78% of total rural household income. However, the heavy dependence on farming exposes households to climate shocks and income insecurity. A multivariate linear regression model was applied, and the analysis indicated that larger household size—likely due to increased labor availability—had a positive effect on income. Marital status, particularly being widowed or single, was associated with lower income levels. The model also demonstrated that crop diversification, market access, and irrigation use positively influence household income. Conversely, off-farm and non-farm income sources were found to be insignificant contributors to overall household income. The study concludes by emphasizing the importance of policies and programs that support small-scale farmers. Enhancing irrigation development, improving market access, promoting crop diversification, and adopting climate-resilient practices can significantly improve livelihoods, income generation, and food security in the region.

Keywords: poverty; income; diversification; food security; farm income

INTRODUCTION

In Zimbabwe, small-scale farmers are the main actors in the agricultural sector, producing approximately 80% of the country's agricultural output (Nyamutukwa, 2019). According to Glover et al. (2014), small-scale farmers not only sustain their households but also promote food security and rural development. Small-scale farmers constitute the foundation of Zimbabwe's agricultural industry, providing livelihoods for nearly 70% of the population and ensuring food security (Denison et al., 2016). Zimbabwe's Honde Valley district exemplifies this potential through its thriving cash crops—such as bananas, sugar beans, tea, and coffee—which attract entrepreneurs and provide income to over 5,000 farmers (Fintrac, 2017).

To promote climate change resilience and improve household incomes in the Honde Valley community, notable interventions have been initiated, which encompass the USAID Zim-AIED Program (2010–2015) provision of training and support for sustainable farming practices and market access, and the government's Pfumvudza Program, introduced in 2020, to promote climate-resilient agriculture and sustainable water management. Despite these interventions, challenges persist (Ministry of Agriculture, Zimbabwe, 2020).

Broader structural challenges, including inadequate market access, fluctuating prices, and high input costs, continue to plague households in the Honde Valley (FAO, 2018).

Addressing these challenges is key to unlocking the full potential of small-scale farming in Honde Valley and beyond, and thereby reducing rural poverty in Zimbabwe. The authors are aware of no studies on the contribution of small-scale farming to household income in the Honde Valley district. Studies have concentrated on banana value chain analysis (Mapfumo et al, 2014; Fintrac, 2017; FAO,2010), and other studies looked into the effect of climate change on small-scale farming (Terera et al, 2024). This leaves a gap in the literature which this study seeks to fill. Therefore, this study's main objective is to assess the contribution of small-scale farming to rural household income in Honde Valley, Zimbabwe. This study also endeavors to analyse the effect of off-farm and non-farm activities on household income for Honde Valley small-scale farmers.

Understanding the contribution of small-scale farming to rural household income is essential for designing targeted support programs that empower farmers to improve their livelihoods. By analysing the income generated from small-scale farming, the study will provide valuable insights for policymakers, development practitioners, and rural communities.

The article is made up of three sections: Section One is the introduction, which looks into small-scale farming in Honde Valley, Zimbabwe. Section two covers the materials and methodological framework, and findings and discussions are in section 3, whereas section four presents the conclusions and recommendations from the study.

METHODOLOGY

Description of Study Area

The research was conducted in Honde Valley, Mutasa District, which is located in the eastern parts of Zimbabwe. It is located between 18° 29' 48.40" S and 32° 51' 11.52" E. The Honde Valley study area has a subtropical to temperate climate and lies within agroecological region 1, with a total annual rainfall of 900-1000 mm (Mugandani et al., 2012). The mean annual temperature ranges from 15-18ºC with mean minimum temperatures of 10-12ºC and mean maximum temperatures of 19-23ºC (Mugandani et al., 2012).

The valley hosts approximately 5,000 small-scale farmers, with an average farm size of 2 hectares (Fintrac, 2017). Its average altitude is around 900 meters above sea level, and it is considered a low-lying area. The local economy is predominantly agro-based, with most rural dwellers engaged in subsistence and semi-commercial to commercial farming (Terera et al, 2024). Farmers in Honde Valley rear various types of livestock, including cattle, goats, and sheep (Mupenzi et al., 2022). They also cultivate a wide range of crops, among which bananas serve as a major source of income (Mapfumo et al., 2014). Additionally, households diversify their livelihoods through off-farm activities, such as employment in nearby commercial farms—particularly the Eastern Highlands Tea Estate—and through apiculture production (Mazorodze, 2015).

Sampling and Data Collection Method

The study employed purposive sampling to select small-scale farmers for interviews. The sampling method was preferred due to its cost-effectiveness and time efficiency (Stratton, 2024); however, it has limitations, including a lack of generalizability of results and susceptibility to researcher bias (Tajik et al., 2024). A sample size of sixty (60) households was selected, which comprised 25 individuals from Ward 3, 20 individuals from Ward 5, and 15 individuals from Ward 7 of Mutasa District, Honde Valley. While it is acknowledged that a large sample size improves the statistical power of cross-sectional research, the study sample of sixty households was deemed optimal due to the encountered resource constraints and geographic dispersion of the households. The wards and households were selected based on accessibility, as public transport was used to conduct the research.

Ethical clearance for the study was obtained from the Ethics Clearance Board of Manicaland State University of Applied Sciences under approval number MSUAS00035/24. Data collection took place between May and July 2024. Written informed consent was obtained from all the participants before data collection. Participants were

assured of the confidentiality of their responses and informed that their participation was voluntary. They were also informed that their identities will be anonymised and that their responses will not be disclosed to any third party.

The questionnaire and interview schedule were designed to collect information on household demographics, types of crops cultivated, crop yields, percentage of income derived from farming, off-farm and non-farm activities, other income-generating activities, the type of farming, animals they rear, and the marketplaces of their farm products.

Research Design

The study used a cross-sectional design to collect data from many individuals at a single time (Thomas, 2022). The design was preferred because of its simplicity, it is relatively inexpensive and requires little time to conduct, it can estimate the prevalence of the outcome of interest because the sample is usually taken from the whole population, and many outcomes and risk factors can be assessed (Hemed, 2015). The study used a descriptive research and quantitative research approach. This is because the descriptive research design accommodates both in-depth understanding and finding facts on the topic under study (Terera et al, 2024). The quantitative data were used on the average incomes that the small-scale farmers received from the different farming activities, off-farm activities, and other activities contributing to household income.

Data Collection Method

Primary data were gathered directly from the target population through interviews and structured questionnaires administered to small-scale farmers within the selected wards. The researcher distributed 60 questionnaires to the sampled participants in selected wards.

Data analysis

A multivariate linear regression model was used to examine the relationship between multiple independent variables and a continuous dependent variable while controlling for potential confounding effects. The research adopted and varied the model by Zou and Wang (2022) and also borrowed and modified a multivariate analytical technique from a study by Thewelli et al (2023) The model assumes a linear relationship between the independent variables and the dependent variable and estimates the regression coefficients (β) that represent the change in the dependent variable for a one-unit change in the independent variable, while holding all other independent variables constant.

$$RHI = \beta 0 + \beta_1 CD + \beta_2 ANOW + \beta_3 IRRIF + \beta_4 ACSP + \beta_5 ONIS + \beta_6 HHS + \beta_7 MSS + \beta_8 EDU + \varepsilon$$

Where:

RHI = Rural household income

β_1-β_8 = Regression coefficients

β_0 = Intercept

ε = Error term

Justification of Variables

The selection of variables for this study was guided by their relevance to the research objectives and their potential influence on the contribution of small-scale farming to household income in Honde Valley. Table 1 below shows that the variables in this study are a combination of continuous, discrete, and dummy variables.

Table 1: Model Variables

Symbol	Variable	Description
Y (THI)	Dependent variable	Continuous variable Household income
CD	Practice Crop diversification	Dummy variable 0. No 1. Yes
ANOW	Animal ownership	0.No 1. Yes
ACSP	Access to Selling points (Market linkages)	Dummy variable 1. Yes 2. No
IRRF	Use of irrigation (water access)	Dummy Variable 0. No 1. Yes
ONIS	Off-farm and non-farm income source	Dummy variable 0. No 1. Yes
HHS	Household size	Discrete variable
MS	Marital status	Categorical variable 1. Single 2. Married 3. Divorced 4. Widowed
EDU	Education level	Categorical variable 0. No education 1. Primary 2. Secondary 3. Tertiary

Diagnostic Tests

Cross-sectional data analysis using regression models hinges on the validity of underlying assumptions. Violations of these assumptions can lead to spurious results and unreliable coefficient estimates (Wooldridge, 2012). This section outlines four key assumptions, diagnostic tests for identifying potential violations, and potential solutions for addressing them.

Normality of **residuals**

The residuals were randomly distributed around zero with no obvious pattern, although formal tests (e.g., Shapiro-Wilk) indicated some deviation from perfect normality.

Autocorrelation

According to Woodridge (2012), autocorrelation refers to situations where the error terms (residuals) in a regression model are not independent. The error in one observation is related to the error in another observation

(Wooldridge, 2012). This is a concern in cross-sectional data, if there are underlying group effects or sampling design issues that are not accounted for in the model.

The Durbin-Watson test, a statistical test specifically designed for this purpose (Wooldridge, 2012), was used to test for autocorrelation. Additionally, examining residual plots, such as residuals versus order of observation, can reveal non-random patterns that might indicate autocorrelation.

Multicollinearity

Multicollinearity occurs when there is a high degree of correlation (linear relationship) between two or more independent variables in the regression model. Identifying influential data and sources of collinearity can be problematic because it becomes difficult to isolate the unique effect of each independent variable on the dependent variable.

Multicollinearity can be identified by examining the correlation matrix between the independent variables. A high correlation coefficient (> 0.8) may indicate multicollinearity. Another diagnostic tool is the Variance Inflation Factor (VIF). A VIF value greater than 5 suggests potential multicollinearity.

The model selection can also be considered. The theoretical justification for including each independent variable in the model is considered. Redundant variables that capture similar underlying effects are eliminated. This approach requires a strong understanding of the theoretical relationships among the variables in the study.

RESULTS AND DISCUSSION

Descriptive Statistics

The demographics and socioeconomic traits of the households surveyed provide a valuable context for understanding the contribution of small-scale subsistence farming to households in Honde Valley, Mutasa District. These characteristics, which include household size, marital status, gender, and educational background, can shape the impact of small-scale farming on household income.

Table 2: Respondents' Biographic Information

Respondents' biography Variable	Frequency	Percent%)
Gender:		
Male	37	61.7
Female	23	38.3
Marital status:		
Single	4	6.7
Married	46	76.6
Divorced	1	1.6
Widowed	9	15
Level of education:		
Not been at school at all	13	21.7
Primary education	15	25
Secondary education	26	43.3
Tertiary	6	10

Source: Authors' compilation based on field survey, 2024

Gender of the participants

From Table 2 above, a total of 61.7% (37) of the participants were male and 38.3% (23) were female. There was fair gender parity in the distribution of the questionnaire, although it was slightly skewed towards males. This skewness is mainly attributed to the patriarchal nature of society, in which men are generally the heads and leaders of households in most rural settings.

Marital status

From Table 2, 76.6% (46) of the interviewed household heads were married, and 6.7% (4) were single, while widowed heads comprised of 15% (9), and 1.6 % (1) were divorced.

Level of education of the participants

A total of 21.7% (n = 13) of the participants had never attended school, while 25% (n = 15) reported primary education as their highest level of attainment. Participants whose highest level of education was secondary school accounted for 43.3% (n = 26), whereas 10% (n = 6) possessed a certificate, diploma, or degree qualification. Overall, the results indicate that 68.3% of household heads had attained at least primary or secondary education, suggesting that a substantial proportion of respondents possess some level of formal schooling.

Table 3: Social-economic characteristics

Variable	Obs	Mean	Std. Dev	Min	Max
Household head age	60	40	10.919	20	62
Household size	60	4	2.025	2	12
Years of farming experience	60	12	7.5233	1	25

Source: Authors' estimation based on field survey, 2024

Table 3 shows the respondents' socioeconomic characteristics. The average age of the respondents was 40. The average number of years of experience in small-scale farming was 12. The average family size of respondents was 4.

Table 4: Rural farm household characteristics

Variables		Frequency	Percentage
Crop diversity	No	10	16.7%
	Yes	50	83.3%
Animal ownership	No	8	13.3%
	Yes	52	86.7%
Selling point	Local buyers	31	51.6%
	Urban farmers market	17	28.3%
	Processors	3	5%
	Boarding school supplies	7	11.7%
	Others	2	3.3%
Use of irrigation	No	28	46.7%
	Yes	32	53.3%
Land Ownership	Yes	55	94.5%
	No	5	4.5%
Valid		60	100%

Note: Farmers could only select a selling point if it generated over 80% of their revenue, limiting them to a single choice.

Source: Authors' estimation based on field survey, 2024

The results shown in Table 4 revealed that the majority of farmers, 83.3%, engaged in multi-cropping, with the remaining 16.7% practicing monoculture. Animal ownership is also prevalent, with 86.7% of farmers owning animals, and the remaining 13% are not engaged in animal farming. In addition, approximately 51.6% of local

produce by smallholder farmers is sold at the local marketplace. Thus, smallholder households are a market for their production. In addition to the local market, 28.3% had access to the urban markets. In terms of land ownership, 90% owned land and 4.5% leased land for farming. A small percentage of farmers sell to processors, boarding schools, or other markets. The use of irrigation (water access for irrigation) was inaccessible to nearly half, 46.7%. Therefore, the results highlight areas of strength and weakness in farmers' practices and market access.

Contribution of small-scale farming to rural household income

Table 5: Gross farm income from both crops and animals

Income Range (USD)	Frequency	Percentage	Cumulative Percent
$100- $400	2	3.3	3.3
$401 - $600	2	3.3	6.7
$601 - $800	1	1.7	8.3
$801 - $1200	11	18.3	26.7
$1201 - $2000	18	30.0	56.7
$2001 - $5000	22	36.7	93.3
>$5001	4	6.7	100.0
Total	60	100.0	

Source: Authors' compilation based on field survey, 2024

Table 5 presents the distribution of gross annual farm income among the surveyed households. The results indicate that a small proportion of farmers (8.3%, n = 5) earned below $ 800 annually from small-scale farming. The largest group (36.7%, n = 22) reported incomes ranging between $2001 and $5000. On average, the mean annual net farm income fell within the 1201–$2000 range, representing the typical income contribution of small-scale farming to household livelihoods in Honde Valley.

Crop Sales and Diversification

Crop sales constitute the primary source of income for most smallholder farmers in Honde Valley. As shown in Table 5, net income is derived from both crop and livestock production. The commonly cultivated crops include bananas, yams, ginger, tea, coffee, pineapples, beans, maize, and sugarcane. Smallholder farmers practice crop diversification to mitigate risks.

Maize Production

Although some households produce maize for sale, maize is primarily grown for household consumption. In certain cases, families engage in barter trade to obtain maize from neighbouring areas such as Nyanga. Additionally, some farmers focus solely on cash crops such as bananas and yams (madhumbe).

Tea, Coffee, and Livestock Production

Fluctuations in market prices have led many farmers to reduce tea and coffee cultivation, opting instead for the more profitable banana production. In the wards of Zindi, Muparutsa, and Samanga, small-scale farmers primarily practice subsistence agriculture while also rearing livestock, including chickens, goats, and cattle, for both household use and income generation.

Some households in Zindi and Muparutsa also earn supplementary income through the use of donkeys for local transportation, particularly to markets such as Murara. The majority of respondents raised indigenous chickens and goats, while a smaller proportion owned cattle and donkeys. These findings are consistent with the Statistical Survey (2017), which reported that indigenous chicken ownership was the most prevalent across Zimbabwe's smallholder agricultural sector (87.9%).

The table shows that the mean average income from small-scale farming fell between $1201 - $2000. The average income of Honde Valley small-scale farmers aligns with a 2020 study published in the Journal of Agriculture and Rural Development, which found that small-scale farmers in Zimbabwe had an average annual income of $1,200 - $1,500. However, this is also in line with the results from a 2019 report by the Zimbabwe National Statistics Agency (ZIMSTAT, 2019), which estimated the average annual income for small-scale farmers in Zimbabwe to be around $1,400 - $1,800.

Table 6: Small-scale average rural annual incomes in Honde Valley

Small-scale average incomes	N	Min	Max	Mean	Std. Deviation
Farm annual gross average farm income	60	80.00	7780.00	1954.1667	1704.62332
Household annual average household income	60	400.00	8580.00	2510.0833	1889.33907
Off-farm and non-farm annual average income	60	0.00	3000.00	552.5000	801.45128

Source: Authors' estimation based on field survey, 2024

Using information from Table 6, the percentage contribution of small-scale farming to rural household income was computed by dividing the gross farm income by the household income multiplied by 100%. From the above table, the percentage contribution of small-scale farming is represented by 78%, and the remaining 22% is represented by other incomes beyond farming, namely off-farm and non-farm incomes.

Statistical tests

Test for Multicollinearity

Diagnostic tests were conducted based on the results of the regression model to verify the validity of key statistical assumptions. A multicollinearity test was performed to assess the degree of interdependence among the independent variables using the Variance Inflation Factor (VIF) method. As presented in Table 7, the VIF values for all explanatory variables show that there was no evidence of multicollinearity among the independent variables.

Table 7: VIF (Variance Inflation Factors) values

Variable	Centered VIF
Marital status	1.407
Education level	1.371
Household size	1.356
Crop diversity	1.206
Animal ownership	1.625
Farm product selling point	1.249
Irrigation farming (access to water)	1.461
Off-farm and non-farm income source	1.283

Source: Authors' estimation based on field survey, 2024

In addition, there was no evidence of autocorrelation with test results showing the Durbin-Watson statistic at approximately 2, indicating no significant autocorrelation. In addition, the normality of the residuals was randomly distributed around zero, with no obvious pattern or structure. However, the residuals were not perfectly normally distributed, as indicated by the minimum and maximum values.

Table 8 - Test for Heteroscedasticity

Breusch-Pagan/Cook-Weisberg Test of heteroscedasticity Assumption: Normal error terms Variable: Fitted values of THI	
H0	Constant variance
Chi2(1)	13.57
Prob > chi2	0.0002

Source: Authors' estimation based on field survey, 2024

Table 8 above presents the results of the test for heteroscedasticity, and from the test results, the null hypothesis of constant variance of errors (homoscedasticity) is rejected. The p – value is 0.0002. To correct for heteroscedasticity, the researcher used White's Heteroscedasticity-Consistent Variances and Standard Errors method. The standard errors from this method yield corrected standard errors, which are termed robust standard errors.

The standard errors so estimated are significantly bigger than the normal Ordinary Least Squares (OLS) standard errors, resulting in estimated t- statistics being smaller than the OLS t-values. The results of the robust standard errors estimation technique are shown in Table 9 below.

Endogeneity

Endogeneity is a situation in which an independent/exogenous variable is correlated with the error term (Wooldridge, 2010). This violates the classical assumptions of OLS that Cov (μ/X_i) = 0. An estimation of OLS in the presence of endogeneity will result in inconsistent estimates. The study notes that there may be a potential problem of endogeneity between the dependent variable, household income, and independent variables like irrigation use and access to selling points. The variables, irrigation use and access to selling points, though exogenous, may be influenced by income.

Multivariate regression model

Table 9: Results of obtained from the multivariate regression model (Robust Standard Errors)

THI	**Coefficient**	**Robust standard errors**	**t**	**P > (t)**
HHS	606.3083	254.8447	2.38	0.021
MS	-710.2631	221.3393	-3.21	0.002
EDU	125.8343	211.9104	0.59	0.555
IRRF	1251.849	376.9029	3.32	0.002
CD	1543.922	523.1138	2.95	0.005
ANOW	529.0236	388.5674	1.36	0.179
ONIS	260.9389	398.0756	0.66	0.515
ACSP	615.0927	181.09	3.40	0.001
Constant	-930.9466	690.268	-1.35	0.183
			Number of Obs: = 60 F (8, 51): = 9.68 Prob > F = 0.0000 R – squared = 0.5914 Adjusted R-squared = 0.5273 Root MSE = 1298.9	

Source: Authors' estimation based on field survey, 2024

The regression model yielded an R^2 value of 0.5914, indicating that the independent variables collectively explained approximately 59% of the variation observed in household income. The remaining 41% of the

variation was unexplained by the model and may be attributed to other unobserved factors or inherent variability within the data. The adjusted R-squared value of approximately 53% in Table 9 above indicates that the model is a moderate fit, thus 53% of the variance in total household income is explained by the model, taking into account the number of independent variables included in the estimation.

The regression analysis revealed that household size is significant at 5%. A positive relationship exists between household size and annual average household income, ceteris paribus, such that a one-unit increase in household size is associated with a 606.30-unit increase in household income. This suggests that larger households tend to have higher incomes because of increased labor force participation and potential economies of scale. The results are supported by Chayanov's theory (Chayanov, 1966 as cited in Ellis, 2000), which assumes family labor on the farm; a larger family tends to have more labor to work on the farm. In addition, it is also consistent with Martinez et al. (2017) on household size and rural household income in Brazil. Meena et al (2025) found a contrary result while researching the determinants of rural household income in India. In the study, household size adversely affects rural household income.

Access to a selling point outlet for farm products is highly significant at 1%. A strong relationship exists between stable farm product selling points and higher household income, with a notable increase of 571.55 units. This finding suggests that households with market access tend to have higher incomes because of reduced market risks and price fluctuations. The results are similar to those of Chikuvire (2020) on the effects of price fluctuations on agricultural productivity and household income in Gweru, Zimbabwe.

High crop diversity is significant at 1%. There is a positive relationship between crop diversity and the annual average household income, holding another variable constant. Holding other variables constant, farmers who practice crop diversification earn, on average, $1,544 more per year than those who do not. This finding is consistent with the results of Moyo and Moyo (2018), who found that crop diversification is instrumental in the growth of household income in rural Zimbabwe. Thus, crop diversification is often considered a risk-mitigating strategy that enhances household income, thus reducing poverty and ensuring food security.

In addition, widowed and single-parent-headed households face significant challenges in propping up household income. This proves that marital status is a significant factor when it comes to smallholder farming's contribution to household income. The annual average household incomes for widowed and single-parent-headed households are lower than those of their married counterparts. This finding agrees with a study by Chant (2016), who found that widows often face significant economic vulnerabilities, including reduced access to resources, credit, and social support, leading to lower income and greater poverty.

Irrigated crop farming was also found to significantly increase average household income. The results are consistent with Hussain et al. (2019), who reported that irrigation enhances crop yields and farm profitability in Pakistan. In Honde Valley, irrigation mitigates moisture stress and reduces yield losses arising from rainfall variability—an increasingly common issue attributed to climate change. Hence, irrigation access remains a crucial determinant of household income growth.

The finding that education level does not significantly impact household income contradicts the literature on human capital theory by Schultz (1964), who posits that education increases earnings and income. However, this can be because some of the respondents, small-scale farmers, had not been to school and others ended up in primary school. In addition, education in the area is low, with few primary and secondary schools; education is not important in the area and hence insignificant.

Animal ownership is insignificant to rural household income in Honde Valley, suggesting that animal ownership does not significantly affect household income. This contradicts theory, as they are assets that can increase income. This may be because a few small-scale farmers in Wards 3, 5, and 6 own cattle and a few own goats, and most of them own traditional chickens that can raise less than $100 per annum. This is supported by data from a survey of the Mutasa District Profile, for example, Ward 5, Muparutsa with an average of 375 cattle holdings, 703 average goat holdings, and 8164 average chicken holdings; hence, the results are supported by the statistics of the Mutasa District profile.

Off-Farm and Non-Farm Income Sources

The coefficient is insignificant for rural household income, indicating that off-farm and non-farm income sources do not significantly impact household income.

Assessing how a change in off-farm and non-farming income affects household income.

Additional income includes income from casual agricultural labor (maricho) and non-farm income from government support/pensions, small businesses, renting property, artisanal work, and remittances from children living and working abroad.

Table 9: Income off-farm and non-farm income ranges of small-scale farmers

Income Ranges (USD)	Frequency	Percentage	Cumulative Percent
Less than $100	14	23.3	23.3
$101 - $200	7	11.7	35.0
$201 - $400	6	10.0	45.0
$401 - $600	11	18.3	63.3
$601 - $1000	9	15.0	78.3
$1001 - $5000	6	10.0	88.3
$5000 and above	7	11.7	100.0
Total	60	100.0	
	Min	Max	Mean
	1	7	4

Source: Authors' estimation based on field survey, 2024

The averages from off-farm and non-farm farms were 4, which falls within the range $401 - $600. Table 9 shows that a larger percentage of the small-scale farmers in Honde Valley 37.6% (24) have off-farm incomes that are less than $100. In addition, less than 10% of the small-scale farmers 9.4 % (6) have additional income other than farming, which is above $1000.

The study reveals that a few residents in Honde Valley have attained tertiary education, and some are illiterate. Education is often deprioritized due to distant schools and limited secondary facilities. According to the Ministry of Primary and Secondary Education (2019), rural Zimbabwe has lower educational attainment (average 7.4 years) compared to urban areas (9.1 years). This skills gap restricts access to better-paying off-farm jobs. International studies confirm the importance of education: Huang et al. (2020) found that off-farm income accounted for over 30% of rural household income in China, while Ogbanje et al. (2015) reported that most rural households receive income from off-farm and self-employment activities. Conversely, Mutsami et al. (2025) found that off-farm income contributed only 5% in Africa, partly due to low education levels. The UNDP (2020) found no significant correlation between off-farm income and rural household income in some contexts.

When it comes to infrastructure, Honde Valley households face a tight rural jobs market. This is common for rural Zimbabwe, where average job opportunities are only 1.1 per household (Ministry of Agriculture, 2019), and off-farm work is seasonally unstable—the unskilled labor market (*maricho*) dries up after harvest, with demand peaking only during planting, weeding, and harvesting. Infrastructure deficits further limit opportunities: UNDP (2020) found only 30% of rural households in developing countries have electricity, and the Postal and Telecommunications Regulatory Authority of Zimbabwe (2019) reported just 10% of rural Zimbabwean households have internet access, with residents in Zindi, Panana Village, and Muparutsa traveling to find connectivity. Mutsami et al. (2025) similarly noted that rural areas in developing countries have fewer job opportunities (1.3 per household) than urban areas (3.5 per household). In contrast, Osarfo et al. (2016) in Ghana found that participation in non-farm activities significantly improved household income and food security, but only where infrastructure and market access were adequate.

The study also uncovered that Honde Valley is predominantly an agro-based economy—specialising in bananas, sugarcane, yams, and ginger—which makes agriculture the dominant livelihood. Consequently, off-farm and non-farm incomes are negligible: 37.6% of small-scale farmers earn less than $100 from off-farm sources, fewer than 10% earn above $1000, and the average falls within $401–$600 (Table 9). Households with the most stable off-farm incomes include bus drivers, tea estate workers, pensioners, and small business owners, while those earning under $100 depend on unpredictable remittances due to economic instability.

CONCLUSION

The study provides clear evidence that small-scale farming plays a vital role in enhancing both food and income security for households in Honde Valley. Off-farm and non-farm income sources also play an integral role in Honde Valley households. This calls for programs geared toward fostering rural development to improve the rural economy and boost rural job supply. Access to the agricultural market is also vital for enhancing rural income. Households with access to the market have significantly higher incomes than those without. Moreover, female-headed households are economically disadvantaged and at risk of food and income poverty. Furthermore, widowed households and single-parent households face the same risk as female-headed households. These vulnerable households have little access to farming inputs or credit. Policy makers must provide input support, such as providing input purchase vouchers to vulnerable rural households, in order to improve input access.

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Author Contributions

CRediT: Ruvarashe Patricia Mutasa: Conceptualisation, Data curation; **Radios Mutumburanzou:** Conceptualisation, Methodology, Writing-original draft, Data curation, Formal analysis, Writing-reviewing and editing, **Nyasha Sakadzo:** Writing-original draft, Writing-review and editing; **Friday Nguvayasvika Mudondo Kubiku:** Data curation, Writing-review and editing, and data curation. All authors have read and approved the final version of the manuscript.

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Data Availability

The data that support the findings of this study are available from the corresponding author, R.M, upon reasonable request.

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