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Homestead coffee production in Southern Ethiopia: A promising approach to enhance household asset building

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Abstract

Ethiopia is one of the largest coffee producers, and the status of coffee production and people's resource endowment are inextricably linked. However, coffee production and its impact on family assets have yet to be fully studied. This study explores the relationship between households' livelihood asset building and their coffee production status in southern Ethiopia, Wolaita zone. Data were collected through face-to-face interviews with 250 households. Employing the data produced from surveys, a composite household livelihood asset index incorporating three components (household ownership, access to agricultural resource endowments, and the empowerment of human capital) was developed. And then, the effect of asset dimensions on coffee production status on household asset building was calculated using step-wise regression. The multivariate analysis showed a significant role of home garden coffee production on household livelihood asset building in the context of the mixed farming systems of the study area. The two (access to agricultural resource endowments and the empowerment of human capital) out of the three assets latent dimensions were found to be significantly predicted by the farm's coffee production status. It was recommended that enhancing the asset capital status of rural farm households merits special attention, including their human capital, independent ownership rights over land and other resources, and participation in social processes.

Keywords: homestead coffee; livelihood assets; principal component analysis; smallholder farmer

Introduction

Ethiopia is one of the biggest producers of coffee and is the birthplace of the well-known Arabica coffee (Tamagn and Satinder, 2020). A quarter of Ethiopia's population depends on coffee production and exports for a living, making coffee the foundation of the country's economy (Chemura et al., 2021). Coffee makes up about 25% of the GDP, 41% of all export revenue, 60% of agricultural export revenue, and 10% of all government revenue (Tesfaye et al., 2020). The country is fortunate to have a variety of intriguing coffee varieties with distinct flavors, agro-ecologies that support coffee production, and a populace knowledgeable about coffee consumption and agriculture.

Smallholder farmers with homestead farms of less than two hectares control ninety-five percent of the nation's coffee output, with the state's remaining five percent on a massive scale (Alemayehu, 2022). The farmhouse coffee production technique is widely recognized as being organic, meaning that very few or no external inputs, such as chemicals used as fungicides and inorganic fertilizers are used in the process (Habtamu, 2019).

The status of coffee production and people’s wealth endowment is closely related, although their relationship is nuanced and reciprocal (Polignano, 2023). On the one hand, using resources to manufacture products and services from accessible choices may be the catalyst for the populace's high production and economic activities, resulting in revenue flows from different sources (Delabre et al., 2021). Resource utilization potential and efficiency are frequently considered when making alternative options. However, the actual distribution of resources may be prompted, usually by economic factors, though occasionally, non-economic elements may also exist, pushing individuals to engage in other activities (Royd, 2021). The hypothesis of this study is that family asset base determines the status of household coffee production.

Strong household asset bases are frequently cited in the literature as significant determinants of coffee production decisions (Jezeer et al., 2019). Members of wealthier households, in particular, can innovate or take up highly paid wage labour (i.e., migrate overseas) to save money for future land acquisition, educational opportunities for the next generation, or health and ageing insurance. Furthermore, coffee production might also be a way to increase the environmental sustainability of a specific coffee crop, which would consolidate family natural capital (Börjeson and Ango, 2021).

A clear prerequisite for determining whether or not rural households and individuals can increase coffee production is the availability of critical assets like savings, land, labour, education, employment opportunities, access to common property, natural resources, and other public goods (Endris et al., 2022). Coffee production opportunities are not the same for every family (Tadesse et al., 2020), and the degree to which coffee is produced depends on resource endowments (land, labour, and money) as well as access to markets and institutions (Mpirwa, 2022). In addition to asset portfolios, the amount of coffee a family produces are also influenced by its ability to pursue other activities due to its location, capital, credit, and social networks (Anderzén et al., 2020). Any autonomous endeavor begins with investing in an appropriate blend of asset endowments. Additionally, labour capability and education impact one's ability to get employment, and saving money is frequently required before moving (Wahba, 2021).

Numerous researchers have examined Ethiopia's national and regional coffee cultivation and distribution systems (e.g., Olana et al., 2023; Chemura et al., 2021; Girma et al., 2021; Chelkeba et al., 2019; Pham et al., 2019; Gizachew et al., 2017). These studies focused on coffee commercialization, technology adoption, coffee quality issues, coffee diversity, coffee breeding, and the relationship between coffee and other issues like food security, environmental management, and climate change. To the best of the authors' knowledge, the topic of producing coffee in a home garden and its role in family assets has not yet been adequately covered and documented in the research environment. Therefore, this study examines the connection between the amount of coffee produced by small-scale farmers and their asset development in the Wolaita zone, South Ethiopia.

Research methodology

The study setting

This study focused on the coffee-producing smallholders in the Wolaita zone, located 317 km southwest of Addis Ababa, Ethiopia’s capital. On average, it has a total area of 4,541 km2. While the mean monthly temperature varies from 26°C to 11°C, the amount of rainfall is bimodal, averaging roughly 1000 mm. Climate variability and erratic rainfall contribute to poor agricultural productivity, leading to acute food insecurity. In addition, soils (mainly vertisols and nitosols) vary in PH from 5 to 6, with most of the ground being acidic, which is poor infertility (Vignola et al. 2015). As a result, farmers often use different agroforestry and crop diversification practices to enhance soil fertility (WSURCS, 2022). The population of Wolaita is about 2,610,760 with growth rate of more than 3% per year and average population density of 464 people per square kilometre (WZFEDD, 2020).

Sampling technique

A multi-stage sampling technique was employed to select the representative target. In the first stage, the Wolaita Zone was chosen as the study area purposively due to its location among the highest coffee-producing zones in the Southern Regional State, where a total of 19,333.36 hectares of land were covered by coffee and 198,333 farm households were engaged in production. In addition, the potential for farmers to participate in coffee marketing and the high demand for coffee produced were also considered. Four districts (Boloso Sore, Damot Sore, Damot Gale, and Sodo Zuria) in the zone were selected based on coffee production, smallholder coffee producer households, and farmer participation. These districts cover 47% of the area and have 89,335 farm households. Two kebeles were chosen from each district, and a total of eight were selected for the study. Farm households were selected using simple random sampling, and final sampling units were proportional to each sampled kebeles (smallest administrative units).

Sample size determination

This study has applied a published table by the University of Florida (UF, 2013) as the scientific strategy in order to calculate the sample size. Two things were noted in this determination strategy: First, the number of replies that were gathered is reflected in these sample sizes, not the number of survey interviews that were originally intended (this number is typically adjusted to compensate for nonresponse). Secondly, the sample sizes assume that the characteristics under study have a normal distribution or are very close to one. Green (1991) recommended several procedures to decide how many respondents are necessary for research. In order to calculate the sample size for the coefficient of determination (R2), he suggested $N \geq 50+8m$, where m is the number of predictors in the model. Although the homogeneity of the sample size is high, the expected closeness of agreement among the set of results is +/- 7%. Hence, this study keeps precision at +/-7%, confidence level at 93%, and p (variability) at 0.3. One of the many ways to use public tables that offer the sample size for a certain set of criteria is to calculate the sample size.

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The sampling population (N) of the study area was 11764. As per the recommendation of UF (2013), 201 households were likely to be representative and adequate for a population ranging from 10000 to 15000. The researcher further adds 49 households (a non-response rate) to fill any gap that may arise due to sample withdrawal, refusal, and the like**.** Thus, the total sample units used for this study were 250 farm households that were homestead coffee-producing farmers in the study area.

Data collection methods

This study used a cross-sectional design involving both qualitative and quantitative data, which were collected through household survey across sampled respondents. A questioner was prepared and pre tested and validated before the inception of actual collection of quantitative data. Participatory Rural Appraisal (PRA) technique was also employed majorly involving focus group discussions. Eight focus group discussions (two per a woreda, one involving 7 to 8 model farmers, community leaders and women representatives) were conducted to gather qualitative data. Trained enumerators administered the survey, and the researcher supervised the fieldwork daily to ensure enumerators' compliance with established survey procedures. The field survey occurred within three months. Secondary data was collected from unpublished and published documents of zonal and district agricultural and natural resource management offices.

Methods of data analysis

Measuring household coffee production status

Various methods have been applied to estimate coffee yield in smallholder farmers' contexts (Marten et al., 2019). Self-reported measures of coffee yield estimations are usually collected pre-harvest (farmer predictions) or post-harvest (farmer recall), with most statistical systems in sub-Saharan Africa relying on the latter. Inherently subjective and conditional on farmers' experience and education, this method is also susceptible to recall bias (Abay et al., 2019). Such a method may lead to overestimating or underestimating actual coffee yields per hectare or plant. This study, therefore, employed a field-based coffee yield estimation based on farmer recall using previous yield information on coffee post-harvest. However, every precaution was taken to address these possible drawbacks.

The dependent variable in this study was smallholder coffee production status, which is measured in terms of yield estimated per hectare for the one crop season. In a skewed distribution, the median is often a preferred measure of central tendency, as the mean is not usually in the middle of the distribution (ABS, 2019; 2023). Also, we can use the interquartile range since it is the middle half of the data, like the median, which is suitable for a skewed distribution. Similarly, we can divide the data into quarters as quartiles and denote them from low to high as Q1, Q2, and Q3. The lowest quartile (Q1) contains the quarter of the dataset with the smallest values. The upper quartile (Q4) includes the quarter of the dataset with the highest values (Jim, 2019). So, in our case, the response variable is skewed, and we prefer to take the median as the classification of coffee production in the study area as low, medium, and high. In this regard, below the median value is treated as 'low production' status in Q1, the median value is treated as 'medium production' status in Q2, and above the medium value as 'high production' in Q3. This ordinal scale variable represents smallholder coffee production status in the study area. It is classified into three levels: low, medium, and high yield levels, keeping the optimum level of production statistics for the coffee variety (ARABICA) in the study area. Such categorization was widely applied by several studies focusing on agricultural production and yield estimation research (Tadesse et al. 2020; Zemach, 2019; Minten et al. 2019).

Measuring household asset basis

In the current study, the household asset accumulation status is measured by a composite index. This is because 'asset' is a multidimensional concept that is not directly observable and is challenging to measure. In circumventing this problem, previous studies on similar topics have followed the same procedure of developing a composite index (Poirier et al., 2020; Abo et al., 2018) to represent this latent variable.

Against this background, this paper employed a multidimensional measurement approach that combines issues of agricultural resource endowments, housing conditions, and human capital using cross-sectional data. Specifically, in any one setting, the assets to be included in the index must be selected carefully, and the technique used to compile it must be applied with caution. The challenge lies in defining assets for a local index determining household living standards, which was addressed through participatory rural appraisal and household surveys. Adopting procedures employed by previous studies on similar areas (Filmer and Scott, 2012; McKenzie, 2005), thirteen theoretically important (contextually appropriate) and policy-relevant variables

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were chosen for the present study and computed on PCA (Table 1). A principal component analysis of this set of variables can generate p new variables, known as the main components, $PC_1, PC_2, \dots, PC_m$, which can be expressed as follows (Equation 1):

$$PC_{m=} a_{m1}X_1 + a_{m2}X_2 + \cdots a_{mn}X_n \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (1)$$

Where a_{mn} represents the weight for $the\, m^{th}$ principal component and the n^{th} variable, following equation (1), the main features were computed using 13 variables identified as possible indicators of household asset accumulation.

Table 1. List and definition of variables originally entered in PCA analysis

Variables	Description
Family education	Number of household members who graduated grade 10 and above.
Dependency ratio	The ratio of the dependent age groups (below 15 and above 65) to the working age groups (15 to 65 years) in the family
Education status	Educational status of household head (years of schooling).
Roofing typing	The type of material which the roof of the house is made from (corrugated sheets, grass, or others)
Number of houses	The number of houses that the household owns in the homestead.
Enset crop diversity share	Crop diversity index (percentage) of *Enset.*
Household income	Total annual income of the household
Land size	Total farmland size (in *time)* that a household owns.
Ox ownership	Number of oxen (traction) that a household owns.
Livestock ownership	Livestock ownership (with the exclusion of ox/oxen as it is measured separately as traction power and exotic cow/s owned by a household) is measured in tropical livestock unit (TLU).
Investments in farm inputs	The annual cost of a household for agricultural inputs (seed, fertilizer, pest sides, etc.)
Investments in durable assets	Total market price of stable assets owned by household
Institutional membership	Number of social institutions (self-help groups, cooperatives, village committees, etc.) that a household head is a member

In this study, a two-step approach was employed to estimate the asset accumulation index of households. The first procedure involved the identification and measurement of observed variables or indicators for the estimation of the latent dimensions of asset accumulation. Secondly, the asset index (AI) of each household was determined based on the estimated values of the latent variables (principal components). Principal Component Analysis (PCA) was used to transform the original set of variables into a smaller group of linear combinations that account for most of the variations in the original data set. PCA examines the percentage variance explained by each of the components as well as their commonalities. Algebraically, the asset index for a household i is expressed as follows (Equation 2):

$$AI = f(PC_i, PC_{ii}, PC_{iii} \dots) \qquad (2)$$

Where AI is the asset index of n household i, $PC_{i\dots}$ are the respective factors generated by the factor analysis representing each latent principal component of the household i.

Econometric model selection

The nexus between livelihood coffee production status and household asset accumulation status was analyzed using a multivariate regression model: stepwise regression model (SWR). This approach of multiple linear regressions is preferable to our situation because it enables us to enter our predictors (the asset dimensions) in multiple predetermined steps (levels or coffee production status of households). This is generally known as "hierarchical regression" and is appropriate when you have meaningful groups of predictors (Herral et al., 2015). Among the identified dimensions of household assets, it was analyzed to determine the household asset dimensions, which scored statistically significant correlation coefficients with household coffee production status. To recognize the considerable relationship between each asset dimension to be predicted by the household coffee production status, we entered them into stepwise regression models. The stepwise regression model, according to Green (2003), is expressed as given in equation (3).

$$Y = a + b_1 x_1 + b_2 x_2 + \cdots + b_i x_i \qquad (3)$$

Where, Y is the household coffee production score computed through household annual cherry amount per hectare, a is the intercept, b_i is the coefficients, and x_i are the predictor variables (or latent dimensions of assets).

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Results and discussion

The principal component analysis (PRA) exercise in the study area revealed that household assets are understood as multidimensional as and broader than the conventional money-metric measures of income or consumption expenditures, which have so far been relied on by economists as indicators of living standards. The identified indicators of household assets among the rural community in the study area are broad enough and include a set of proxies such as household ownership of consumer durables, household socioeconomic characteristics, household dwellings, and land ownership.

The discussants define household assets (Table 2) as material, intellectual, social, and living standard quality aspects of human welfare. The material elements of assets identified by the focus group discussants encompass flows and stocks. The flow aspects capture income and liquid assets recurring periodically, while the store comprises asset accumulation and buffers such as livestock, houses, land, savings, etc. The asset is also associated with the outcomes of intellectual ability, social position, and individual competence, such as hard-working attitudes.

Table 2. Summary of asset indicators and categories set by FGDs

Economic group	Local term	Indicators and estimates
Rich (or Better-off)	*Keehhippe duriya*	Livestock size (3 or more milking cows, pair/s of oxen) At least one crossbreed of cow Land size (up eight *timad*), one or more *timid* rented in 1–2 *timad enset* in their backyard (more mature ones) Coffee and eucalyptus tree (up to 1 *timad*) Educated family members. Having an additional house in a nearby town. Modern residence (corrugated roofed) Known for qualities like hard work by the community
Middle	*Giddo duriya*	1-2 milking cows, an ox, sheep/goat, chicken Up four *timad* land; Up 250 trees of *enset*; some coffee trees Able to send their children to school and higher education Better housing condition
Poor	*Hiyyeesa*	Up to 2 *timad* land, but half of it rented out One or more livestock raised on the shared arrangement Small *inset* coverage (up 100, only immature) 1–2 chicken; works as daily laborer; PSNP beneficiary
Destitute	*Keehhippe Hiyyeesa*	No livestock, no *enset* (except very few and immature at their backyard, one *timad* and often rented out PSNP beneficiaries, socio-economically vulnerable groups such as low caste clan members, displaced and returnee households,

*Note: *Timad* is a local unit used to measure the size of farmlands. One *timad* is approximately 0.25 ha, and 1 ha is about four *timad*; FGDs= Focus group discussions.

Before being submitted to a principal component analysis, the correlations among the identified variables were checked for multicollinearity problems. The Kaiser-Meyer-Olkin (KMO), a Measure of Sampling Adequacy (MSA), was used to detect multicollinearity in the data so that the appropriateness of carrying out a PCA could be seen. Table 3 describes the statistical test results.

Table 3. KMO measure of sampling adequacy and Bartlett's test of sphericity

KMO Measure of Sampling adequacy	Bartlett's Test of Sphericity		
	Chi-Square	Df	Sig
0.692	413.891	55	0.000

The results of the present study indicated that the value of KMO is 0.692 and is relatively high; that means the data are suitable for the Principal Components Analysis and the appropriateness of the model, which is within an acceptable range for a well-specified model and which is good to warrant interpretation of results (Tefera et al., 2016).

Another test of the strength of the relationship among variables was done using Bartlett's (1954) Test of Sphericity. Bartlett's Test of Sphericity tests the null hypothesis that the variables in the population correlation matrix are uncorrelated. The results of the analysis in the present study showed a significance level of 0.00, a value that is small enough to reject the hypothesis. It can be concluded that the strength of the relationship among variables is strong or that correlation matrix is not an identity matrix, as is required by PCA to be valid. These diagnostic procedures indicate that principal component analysis is appropriate for the data.

Among the 13 variables included in the principal component analysis, the correlation matrix was used as an input to PCA to extract the three factors. The number of factors extracted was defined and determined by following one of the most commonly used techniques: Kaiser's criterion, or the Eigenvalue rule. Under this rule, only those factors with an Eigenvalue (the variances extracted by the elements) of 1.0 or more are retained. By using criteria, our data revealed three factors (Table 4). The results showed that five factors accounted for 50.096 % of the total variance in the data. The first principal component accounts for the most significant portion of the variation in the data (26.120 %), the second principal component accounts for the second most considerable variation in the data (13.154 %), and the third accounts for 10.822 %, respectively.

Table 4. The principal components and total variance explained

Components	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	2.873	26.120	26.120	2.725	24.777	24.777
2	1.447	13.154	39.274	1.550	14.093	38.870
3	1.190	10.822	50.096	1.235	11.226	50.096
4	0.988	8.981	59.077			
5	0.882	8.018	67.095			
6	0.815	7.409	74.504			
7	0.741	6.737	81.242			
8	0.681	6.188	87.430			
9	0.606	5.508	92.938			
10	0.573	5.206	98.144			
11	0.204	1.856	100.000			

The question "What are these three latent factors (extracted principal components), and how were the separate indicator variables merged to make up the aggregate component factors so as to formulate a composite index of household assets?" needs further elaboration. To solve a challenge, the results of PCA using varimax rotation are estimated using the most significant factor loading values of the separate variables included in the principal component analysis. The varimax is a variance-maximizing strategy where the goal of the rotation is to maximize the variance (variability) of the factor (component) or, put another way, to obtain a pattern of loadings on each element that is as diverse as possible (Mwansa, 2023; Antony and Rao, 2007).

Table 5. PCA: Varimax rotation factor matrix

Variables	Components		
	1	2	3
Sex of farm household head	0.138	-0.039	0.687
Educational status of household head	-0.090	-0.212	-0.416
Dependency ratio	-0.102	-0.115	0.753
Family education	0.455	0.066	0.569
Cultivable land (in *timad*)	0.455	0.021	0.077
Local oxen/bulls	0.746	0.191	0.055
Agricultural investments/farm inputs/	0.609	0.092	0.008
Household durable assets in monitory value	-0.355	0.689	0.005
Number of houses in Homestead	0.276	0.710	0.047
Livestock ownership in TLU	0.855	0.127	0.062
Social institutions' membership	0-.255	0.689	-0.052
Roofing type	0.114	-0.546	-0.409
Enset Crop diversity share	-0.346	0.114	-0.049
Coffee monitory value	0.802	0.003	0.069

The results (Table 5) indicated that PCA transforms a large number of variables in a data set (13 variables) into a smaller and more coherent set of three uncorrelated (orthogonal) factors, the principal components. The first factor involves five variables, including farmland size, ox ownership, exotic breed cow's ownership, livestock ownership, and investments in farm equipment, which are related to Agricultural Resource Endowments (ARE). For the first factor, all the variables, except *Enset* crop diversity share, showed markedly higher positive loadings. The higher values of the variables land size, oxen, *Enset* crop diversity share, livestock ownership, coffee value, and farm equipment investment in the original data indicate better agricultural resource endowments in a household. The positive sign on these variables means a robust positive relationship between the latent factor and the indicator variables. This factor, which accounted for 26.120% of the total variation, is a reasonable representation of the asset situation or status of the household. It means that better asset accumulation is associated with

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large land size, the number of oxen as traction power, livestock size, household income, and the size of investment in farm pieces of equipment in the community.

The second factor is related to the housing conditions (or physical-social facilities) of households; household durable assets in monetary value, number of houses in homestead, and membership in social institutions showed solid and positive loadings, whereas roofing type showed negative loading with a relatively smaller magnitude of relationship as compared to the other three variables in the original data. The third factor can be interpreted as human capital (HC) at the household level, and four variables: sex of household head, family education, dependency ratio, and educational status of household head are related to it. Except for the academic level of the household head, the other three variables showed favourable loading and a high magnitude relationship with the latent factor.

Distribution of the household asset accumulation profile

The question is, “What are these three latent factors (extracted principal components) and how were the separate indicator variables merged to make up the aggregate component factors so as to formulate a composite index of household asset base (AI)?” needs further elaboration. To solve this challenge, the results of PCA using varimax rotation are estimated using the largest factor loading values of the separate variables included in the principal component analysis (Ogunniyi et al., 2021). Likewise, their distributions in terms of asset accumulation do vary. After determining each household's quantified asset accumulation status, a multidimensional measurement approach is used, which combines issues of agricultural resource endowments, housing conditions, and human capital. Each indicator was composed of several sub-indicators that can help quantify asset accumulation. Following this approach, AIs (asset indices) were constructed, and the sample observations in the study districts were classified into four quartiles, each group having approximately equal population numbers. Thus, the four groups created range from the least accumulating (first quartile) to the highest accumulating (fourth quartile) households (Table 6).

Table 6. Mean standardized asset accumulation status scores by quartile

Quartile	Mean	SD	N
1	10.776	0.51160	34
2	20.345	0.21659	22
3	26.834	0.25083	92
4	45.101	0.50378	102
Total			250

Levene statistic: 39.084***; df1=3; df2= 246

The mean values (10.776, 20.345, 26.834, and 45.101 of the successive quartiles) are good indicators for the central tendency of the distribution of household asset ownership. More than three-fourths (194 or 77.6%) of the home garden coffee-growing farmers fall under the last two quartiles (3 and 4) with average asset indices of 26.83 and 45.1, respectively. Beyond all, the coffee-producing farmers' most enormous figure (more than 40%) recorded the highest average asset accumulation score (45.1). The results indicate that the asset accumulation status of smallholder coffee-producing households in the zone is considerably strong. The sequential increase in the asset accumulation score in the descending order of the quartiles indicates the significant role of home garden coffee production for household asset buildings in the context of the mixed and diversified farming systems of southern Ethiopia.

Relationships between household asset dimensions and coffee production status

To identify the asset dimensions that predict hierarchically (from the most significant to the least) the live coffee production status of the households, we entered the factor scores (or indices) of the three dimensions in the stepwise regression analysis. Here, the household coffee production index computed through the household annual cherry amount per hectare was the dependent variable. In contrast, the three composite indices of the asset dimensions were used as independent variables. The regression results indicated that the determinant coefficients (R^2) consistently increased with adding the first and second independent variables, from 0.41 in Model 1 to 0.62 in Model 2 (Table 7). The two models (Model 1 and Model 2) are statistically significant ($p < 0.01$ and $p < 0.05$), respectively, and loaded two asset dimensions that significantly explained household coffee production status: human capital and agricultural resource endowments.

Table 7. Summary of household asset dimension models (derived by stepwise regression)

Model	R	R^2	Adjusted R^2	Std. error	Change statistics				
					R^2 Change	F Change	df1	df2	sig.
1	0.210[a]	0.44	0.41	0.15	0.44	17.573	1	246	.000
2	0.258[b]	0.67	0.67	0.16	0.23	9.204	1	231	.003

The model summary explains the overall fitness of the model. R is the correlation between the variables, and the adjusted R square value indicates the amount of variance in the dependent variable by each predictor variable, with respective values ranging from 0.41 for the lowest to 0.62 for the highest degree of variance. We use the adjusted R square value since we have more than one predictor variable (Joshi et al., 2021; Green, 2003). In this case, the maximum degree to which the amount of variance in the dependent variable is explained by the predictor variables accounts for 6.2 % of the variance in several offences.

Table 8. ANOVA for the model fit

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0.387	1	0.387	17.573	0.000[b]
	Residual	8.414	382	0.022		
	Total	8.801	383			
2	Regression	0.586	2	0.293	13.577	0.000[c]
	Residual	8.215	381	0.022		
	Total	8.801	383			
3	Regression	0.751	3	0.250	11.820	0.000[d]
	Residual	8.050	380	0.021		
	Total	8.801	383			

a. Dependent Variable: Coffee Production Indices

b. Predictors: (Constant), Human Capital

c. Predictors: (Constant), Physical Capital, Human Capital

d. Predictors: (Constant), Human Capital, Physical facilities, Agricultural resource endowments

The ANOVA results are another indicator of the model's fitness for the data. Table 8 explains the F −test to determine whether the model fits the data well. According to this, all the independent variables significantly predict the outcome variable, livelihood diversification, because P< 0.001. Table 9 shows the results for regression estimates predicting the effects of different household asset dimensions on household coffee production status. Among the independent variables put into the stepwise regression analysis, two (human capital and agricultural resource endowments) were found to explain household coffee production status positively. At the same time, the third (physical facilities) was influenced insignificantly. These are the priority dimensions of household assets that were found to impact household coffee production status significantly.

Table 9. Coefficients of predictor variables included in the regression model

Dimensions	Un-standardized Coefficients		Standardized Coefficients		Collinearity Statistics	
	β	Std. error	*β*	***t***	Tolerance	VIF
Constant	0.592***	0.008		78.116		
Human capital	0.023**	0.008	0.150	3.034	1.000	1.000
Agri. resource endowments	0.017*	0.007	0.110	2.259	1.000	1.000

The human capital

Human capital was found to be the most promising asset dimension that affects household coffee production status. Holding other dimensions constant, the increase in human capital made a 0.023-unit contribution to household coffee production status ($p < 0.01$). The leading indicators of human capital in this study are the age of the household head, education level of the household head, family education, household labour and dependency ratio of the households. Human capital is the knowledge and capacity of the people. It can be measured in terms of people's education, health, labour, skills, and expertise.

These results are in line with the existing empirical literature. Human capital, comprising labour, health, education, and skills, is an important asset that enables the household to pursue different livelihood strategies (Boli, 2005; Carney, 1998). Regarding the education level of the household head, the more educated household heads are better engaged in producing commercial crops like coffee, and they are likely more productive in-home garden farming as they utilise appropriate farm inputs and technologies. The effectiveness of labour as an asset depends on good health and education. When enhanced through training and other skills, household labour becomes a powerful tool for households to gain more production. This can also be justified by the fact that better-educated households can calculate the costs and benefits of market-orientated productions, enabling them to engage in coffee production.

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Agricultural resource endowments

The other statistically significant predictor among the aggregated latent household asset dimensions versus the coffee production model was agricultural resource endowment, which is an aggregate of variables like land, livestock ownership, ox ownership, and agricultural investment inputs. It uniquely explained that an increase in a unit of farming resources would create 0.017 unit increases in the production status of home garden coffee for a household, and it was statistically significant ($P< 0.05$). The finding is consistent with empirical evidence. Barrett et al. (2000) and Reardon et al. (2000) provide some evidence that households with more land develop more supplementary activities. Barrett et al. (2001a) illustrate the same pattern for a rice-producing area in Ivory Coast. Households with relatively much land appear to generate income either by full-time farming or by a mix of agriculture and skilled supplementary work. Households with meagre endowments generate limited additional income.

Conclusion

It seems worth returning to the initial question: "Is home-garden coffee production determined by access and ownership of household asset endowments?" The answer, according to the findings of this study, is quite positive. The level of household coffee production, survival or accumulation substantially varies between and across households depending on the conditions of the two significant household asset dimensions: human capital and agricultural resource capacities. At the same time, the findings of this study suggest that practical intervention strategies are needed to enhance household asset bases so as to promote the homestead coffee production of the farm households in the study area, in particular, and the nation, in general as a significant and contemporary policy agenda. As hypothesized in the study's basic research question, motivation and practices for coffee production lie in the access and endowment of different dimensions of household assets. Enhancing the asset capital status of rural farm households merits special attention, including their human capital, independent ownership rights over land and other resources and participation in social processes.

The policy formulation process in Ethiopia should embrace enhancing essential resources such as social capital on which rural communities can depend to manage risk and develop resilience against vulnerability. Human capital is widely substantiated as a key to successful coffee production at the household level. Therefore, the delivery, access and quality of rural education and various life skills acquisition require continuing emphasis. Agricultural inputs and endowments that enhance crop and livestock production have a powerful effect on household coffee production status; it continues to merit priority. The conventional wisdom for many years has been that rising agricultural output and incomes are the catalysts for coffee production in rural areas. Future rural poverty reduction policies need to be better informed on the nature of these interactions.

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Data availability

Data will be made available on request.

Conflict of interest

The authors declare no conflict of interest, financial or otherwise.

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