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SHAPLEY REGRESSION BASED INCOME INEQUALITY DECOMPOSITION OF HOUSEHOLDS IN FOREST AREAS OF SOUTHWESTERN NIGERIA

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ABSTRACT

The study decomposed income inequality of households in rural southwest Nigeria by Shapley Regression-based decomposition. The Shapley value decomposition approach estimates marginal impact on the level of inequality, which makes it advance over other regression-based inequality decompositions. A proportionate sampling approach was employed, along with a formal survey, to gather information from 450 household heads, of which 430 were deemed valid. Summary statistics tools (specifically percentage, frequency, and mean) and Shapley Regression Base Income Decomposition were used for the analysis. The socioeconomic characteristic showed that male-headed households constituted 92%, and the majority of the household heads were married. The mean age was 47.63 years, and the average household size was 6.92 persons. Age (0.42), farm size (0.021), distance to market (0.029), and education (0.27) had the highest attributed income share, therefore increasing income inequality. The analytical approach regression result showed that income inequality was exacerbated by being a male-headed household (β=0.6811 high household size (β=0.07) and farm size (β =0.14), while age (β=-0.23) reduced it, the Gini inequality decomposition using Shapley value gave sources that largely explained inequality such as farm size and household size with relative contributions sum up to 25.40%. The weighted marginal contribution results for all the income source variables show that there was a progressive inequality impact, which reduced from level 2 to level 10. This study emphasized that inequality cannot be attributed to a single factor, but rather to a combination of factors. Therefore, stakeholders should not focus solely on a single factor to address the challenges of inequality.

Keywords: Decomposition, income, Inequality, Marginal, Regression, Shapley

INTRODUCTION

The significance of forest resources in improving the well-being of forest-dwelling communities has become increasingly recognised in recent decades, specifically over the last 30 years. Initiatives like social forestry, community forestry, and joint forest management, as well as conservation and development projects, reflect this understanding (World Bank, 2024; Bolaji et al., 2025). Following the Sustainable Development Goals of the United Nations Development Project, there is growing attention on enhancing welfare and boosting revenue from forest resources, consequently reducing hunger by half by 2030 (FAO, 2021). Furthermore, economic progress in the forest areas has been inequitable, with significant disparities in benefits. Notably, extreme poverty rose by 36 million between 1990 and 2005. The number of undernourished people increased from 817 million in 2017 to 828 million in 2018 and further to approximately 870 million in 2022. More recent data indicated a substantial increase in hunger, with around 152 million more people affected in 2023 compared to 2019 (WHO, 2022; FAO, 2022).

Income from the forest is important in reducing inequality, as well as improving household welfare in Nigeria. It contributes to minimising the variability of rural household income. Fonta et al. (2012) found that when forest-based earnings were excluded in poverty calculations, poverty metrics in rural Nigeria showed significant increases – the headcount ratio rose by 3%, the poverty gap by 4.4% and poverty severity by 7.9%. Similar research by Wu et al. (2021) applied Shapley Decomposition to analyse inequality of opportunity in Australia from 2001 to 2017. Chantreui et al. (2020) decomposed US income inequality with Shapley-based regression decomposition with respect to race and gender. Mukaila & Egwue (2022) worked on the analysis of rural income inequality in Nigeria, comparing the trend before and during the democratic era, while Obiakor et al. (2022) examined Nigeria's economic magnitude, uncertainty, and income inequality.

Nigeria achieved an average growth rate of 6.8% from a substantial economic foundation. The country's real gross domestic product (GDP) growth increased to 6.23% in 2014, up from 5.49% in 2013. Following the National Bureau of Statistics (2019), GDP rebasing in April 2014, Nigeria's economy was revalued at $454 billion (2012) and $510 billion (2013), surpassing South Africa's largest economy. Nigeria's revised GDP revealed a more diversified economy than previously thought. However, despite the economy's growth, inequality worsened, with the number of Nigerians living below the poverty line increasing from 69 million (2004) to 112 million (2010), affecting 69% of the population, as cited by the Nigeria Bureau of Statistics (NBS) (2019). Rising inequality threatens national unity (Oxfam, 2017) and undermines poverty reduction efforts. With four in ten Nigerians currently living below the poverty line, many lack access to basic necessities like electricity, healthcare, and education (World Bank, 2022; Olaitan et al., 2025). Hence, this study, therefore, examined key factors influencing income inequality in rural southwest Nigeria using Shapley Regression Income Decomposition with marginal effects of each income source on overall income. Therefore, inequality is conceptualised as the dispersion or pattern of income distribution and welfare.

METHODOLOGY

Sample Procedure

The study was carried out in selected forest reserve areas in Ogun, Osun, and Ondo States in southwestern Nigeria, using a structured questionnaire. A proportionate sampling technique was used for various forest communities. A total of 450 household heads were interviewed, but only 430 were valid and used for the research analysis.

Methods of Data Analysis

i. Descriptive statistics tools such as percentage, frequency, and mean were employed for analysis.

ii. Shapley Regression-Based Income Decomposition.

Regression-Based Inequality Decomposition

The regression-based inequality decomposition procedure, originally developed by Blinder (1973) and Oaxaca (1973), and later extended by Morduch and Sicular (2002) and Fields (2003), provides a systematic way to quantify the contribution of individual factors to overall income inequality. Unlike standard group decomposition, this method captures the marginal effects of explanatory variables while accounting for their correlations.

The income-generating function for household is specified as:

Where is household income; are explanatory variables (age, sex of household head, education, household size, farm size, distance to forest, distance to market, access to credit, asset ownership, and marital status); represents the estimated coefficient of variable ; and is the error term.

From the estimated regression, the predicted income is computed and used to calculate the explained component of income inequality, denoted. The total observed inequality is represented as. The residual inequality term is then expressed as:

Where captures the portion of inequality not explained by the included regressors. This distinction between explained and unexplained inequality ensures that both the systematic effects of household characteristics and the unobserved heterogeneity are explicitly accounted for.

The Shapley value decomposition, introduced by Shorrocks (1999), is then applied to attribute inequality contributions fairly across explanatory variables. This approach evaluates each variable's marginal impact by sequentially removing it from the regression and calculating the resulting change in inequality. Because the Shapley procedure averages contributions across all possible sequences of variable elimination, it treats factors symmetrically and incorporates their correlations.

RESULTS AND DISCUSSION

Socioeconomic Characteristics

The respondents' sex distribution indicated male-headed households dominated, making up 92%, while female-headed households accounted for 7.9% (Table 1). This indicated a typical Western Nigerian family pattern in which men are mostly heads of the households (Leitner, 2015; Shomkegh et al., 2019). This also implies that more males were involved in forest extraction, like timber activities, which are energy demanding, and snail harvesting and hunting, which are done mostly in the dark hours. Furthermore, married household heads made up the largest proportion (89.5%), with single, widowed, and divorced making up smaller percentages (5.6%, 3.5%, and 1.4%, respectively), indicating a prevalence of married households in the forest areas.

Therefore, more helping hands in their occupations. The average age of household heads in the study area was 47.63 years (± 11.65), implying that they were economically active and capable of engaging in forest activities. This finding aligns with Obiakor et al.'s (2022) study, which reported an average household head age of 46.6 years in Nigeria.

The average household size was 6.92, exceeding the 6.2 reported by Nwera (2014) in Ngong Forest, Nairobi. Household heads averaged 2.38 ± 5.02 years of schooling, indicating primary education as the typical level, which likely contributed to their forest dependence (Mukaila & Egwue, 2022; Adedigba et al., 2025). The average residency duration was 19.89 ± 14.86 years, consistent with findings by Garekae et al. (2017) on socioeconomic factors influencing forest dependency in Botswana, which reported 40.26 ± 20.73 years. The study area's primary occupation breakdown showed farming (65.30%) as the leading activity, with forest resource extraction (17.90%), artisanal workers (5.6%), wage/salary (2.80%), and trading (8.40%).

Table 1. Socioeconomic Characteristics of the Household Heads

Variable	Category	Frequency	Percentage	Mean	Std. Deviation
Sex	Male	396	92.10		
	Female	34	7.90		
	Total	430	100		
Marital status	Married	385	89.50		
	Singled	24	5.60		
	Windowed	15	3.50		
	Divorced	06	1.40		
	Total	430	100		
Age	≥ 25	13	3.00		
	26–35	64	14.90		
	36–45	113	26.30		
	46–55	142	33.00		
	≤ 56	98	22.80		
	Total	430	100	47.63	11.65
Household size	1–5	160	37.20		
	6–10	218	50.10		
	Above 11	52	12.70		
	Total	430	100	6.92	3.639
Education level (year)	0	84	19.50		
	1–6	150	35.30		
	7–12	152	34.90		
	Tertiary	44	10.20		

	Total	430	100	2.38	5.016
Years of residency	1–10	141	32.80		
	11–20	137	31.90		
	Above 21	152	35.30		
	Total	430	100	19.89	14.86
Primary Occupation	Farming	281	65.30		
	Forest activity	77	17.90		
	Artisanal activity	24	5.60		
	Wage/salary	12	2.80		
	Trading	22	5.11		
	Transfer	14	3.25		
	Total	430	100		

Source: data analysis, 2023

Notably, forest activities were the most common secondary occupation (40.70%), supporting the idea that forests serve as economic safety nets during periods of economic hardship (Nwera, 2014; Olaitan et al., 2025). The forest activities in the study include planting of trees, fuelwood collection, leaf packing for food wrapping, and hunting of snails and animals. Secondary occupations included agriculture (28.10%), trading (21.60%), artisanal activity (8.60%), and wage/salary (0.90%) (Table 2).

According to Table 2, most household heads (76.5%) practised monogamy, while 23.5% practised polygamy, potentially contributing to larger family sizes due to more children. Land acquisition patterns included inheritance (38.1%), purchasing (21.4%), renting (19.30%), and leasing (12.3%). The land use pattern indicated small-scale subsistence farming, with crops like cocoa, palm trees, and food crops such as oranges, plantain, and bananas.

Membership in an association or village was relatively low, with 38.30% of household heads belonging to a group and 61.70% not affiliated with any. Group membership action in rural areas typically facilitates cooperation, financial support, labour sharing, and collective action. Regarding access to credit, 22.70% of the household heads utilised formal credit, while 42.30% relied on informal credit sources. Greater access to credit could help to diversify their income and reduce reliance on forest resources.

Table 2. Supplementary Socioeconomic Characteristics

Variable	Category	Frequency	Percentage	Mean	Std. Deviation
Secondary Occupation	Farming	121	28.10		
	Forest Activities	175	40.70		
	Artisanal	37	8.60		
	Wage/ Salary	04	0.90		
	Trading	85	19.76		
	Transfer	08	1.86		
	Total	430	100		
Family Type	Monogamy	101	76.50		
	Polygamy	329	23.50		
	Total	430	100.00		
Land acquisition	No land	39	9.10		
	Inheritance	164	38.10		
	Rented	82	19.10		
	Leased	53	12.30		
	Other	92	21.40		
	Total	430	100.00		
Farm size	0–10	418	97.21		
	11–20	10	2.33		
	21– above	02	0.46		
	Total	430	100	2.40	3.57
Member of village group	Yes	164	38.30		
	No	266	61.70		
	Total	430	100.00		
Formal credit	Yes	98	22.70		
	No	332	77.30		
	Total	430	100.00		
Informal Credit	Yes	182	42.30		
	No	248	57.70		
	Total	430	100.00		

Source: data analysis, 2023

Contributory Factors to Income Inequality in the Study Area

Contributions of various estimated factors were calculated using two approaches, analytical and Shapley value-based. The analytical approach measured inequality using the Gini index derived from income shares and the concentration coefficient. The Shapley approach was based on axioms outlined by Shorrock (2001), which provided marginal contributions of estimated sources offering insight into their specific impacts. Table 3 gives the estimated income share attributed to the independent or socioeconomic variables. Age (0.42), farm size (0.021), distance to market (0.029), and education (0.27) had the highest attributed income share, while forest distance, credit access, asset ownership, and marital status had low estimated income shares.

The estimated income share for age showed that different age groups in their occupations contributed to household welfare. The income estimated for farm size implied that farm income plays an important role in improving household welfare; moreover, farming was the primary occupation of most household heads, contributing to increasing inequality. Education played a key role in both enhancing welfare and widening inequality, as differences in educational attainment led to income disparity. Better education expands knowledge, makes informed choices, provides access to better job opportunities, and improves their household income.

The analytical approach regression result showed that income inequality was exacerbated by being a male-headed household (β=0.68), high household size (β=0.07), and farm size (β=0.14), while age (β=-0.23) reduced it. However, education (β= 0.002), distance to forest (β=0.02), distance to market (β=0.002), access to credit (β=0.111), asset ownership (β= -0.112), and marital status (β=0.093) contributed to income inequality but were not significant at any level. The asset ownership was negative; therefore, it had a reducing effect on the income inequality. The sources that explained the Gini index (2) inequality based on an analytical approach were distance to the market, with a relative contribution of 25.57%, and marital status, 24.68%, to income inequality. But the residual relative contribution was 60.48%, which was an inequality that could not be explained by the Gini based on the analytical approach. Table 3 further explains the *Gini* index (3) inequality decomposition based on the Shapley.

The sources that predominantly explained inequality were farm size and household size. The relative contributions of these factors add up to 25.40%. This implies that the aforementioned variables contributed 25.40% of the total inequality in the study area. The reason is that the majority of the rural people were engaged in farming, which contributed the highest income share to total household income, invariably worsening inequality. A marginal increase in household size ($p<0.1$) increased inequality by 9.44%. This was because the higher the number of household members, the greater the demand for more income. Mukaila et al. (2022) noted that in rural Nigeria, the net effect of high family size is lower real per capita income, little saving, and poor welfare. Demand for more children increases inequality because large family sizes exist among rural people. The Shapley approach *Gini* index explained all the income distribution, unlike the analytical approach.

The age of the household member had the third-highest relative contribution of 7.39%, accounting for income inequality and variation in household welfare, ranking after education (6.14%). This implies that as one grows in age, income inequality may be reducing, expenditure, strength to livelihoods, and demand for some material goods may be decreasing. The predicted residual term accounted for 60.48% income inequality; the residual value informed policymakers and entrepreneurs how regressed sources can explain the overall inequality, indicating that included variables accounted for about 40% of total inequality. Policy decisions can be made accordingly so as to deal with inequality with some confidence based on the included variable and residual value.

Table 3. Determinants of Income Inequality Using Regression Base Decomposition

Income Source	Regression Coefficient	Analytical Approach: Income Share (1)	Analytical Approach: Gini index (2)	Shapley: Gini Index (3)
Sex	0.6811***	0.0082	-0.0004 (-0.0002)	0.0025 (0.0501)
Age	-0.2285***	0.4207	0.0323 (0.1309)	0.0038 (0.0739)
Education (years)	0.0015	0.2677	0.0004 (0.0018)	0.0007 (0.0614)
Household Size	0.0677***	0.0613	0.0069 (0.0278)	0.0048 (0.0944)
Farm Size	0.1432***	0.0212	0.0109 (0.04440)	0.0081 (0.1596)
Distance to forest	0.0225	0.0119	0.0003 (0.0011)	0.0003 (0.0056)
Distance to market	0.0006	0.0298	0.0631 (0.2557)	0.0001 (0.0012)
Credit access	0.1113	0.0027	0.0003 (0.0012)	0.0004 (0.0087)
Asset ownership	-0.1162	0.0002	-0.0001 (0.0010)	0.0002 (0.0033)
Marital Status	0.0935	0.0079	0.0002 (0.2468)	0.0002 (0.0046)
Residual			0.0307 (0.6048)	
Constant	12.1291		0.0000	
Total Value		1.000	0.2468 (1.0000)	0.2468 (1.000)

Source: data analysis, 2023; *significant at 10% significant at 5%; ***significant at 1%.**

Marginal Contributions of the Various Estimated Income Sources.

The marginal contributions were calculated using the Shapley value concept (Shorrocks, 2001), which assesses the impact of each income source by determining the difference in overall income inequality with and without that factor. It gives the result of the contributory effect of different independent factors, providing insight into their specific roles in shaping income inequality. Factors were later combined to justify that, in reducing inequality in any society, at times, it cannot be effective if policy is based just on a variable. There is usually a need for a policy package for the reduction of inequality. Level one gives the contributory effect of each of the 10 variables, one after the other, to the 10th independent variable (Table 4). Therefore, in the case of sex, the involvement of more male household heads in contributing to household income, as seen in level 1, gives the contributory effect of 0.0033 to overall inequality. The contributory effect of age on total inequality is 0.012. Education, household size, farm size, forest distance, urban market distance, access to credit, asset ownership, and marital status had contributory effects of 0.0028, 0.0085, 0.0153, 0.0010, 0.0005, 0.0014, 0.0067, and 0.0007, respectively, on total inequality.

In level 2, two variables were removed at a time, given the resultant effect on the total inequality. Removing variables 1 and 2 gave a contributory effect of 0.0080. These were reduced to the 10th variable and represent the contribution of income source 1 in level 2 to total inequality, income source 2 in level 2, income source 3 in level 2, up to the 10th variable. Level 3 involves three variables being removed at a time to give the effect on total inequality, and this continues to level 10. Table 4 shows that inequality decreased with more combinations of variables from level one to ten. It also shows that age along the line, combined with other variables, had negative signs. This implies that policymaking in reducing inequality in any society cannot be effective if policy is based just on a variable. There is a need for a policy package for the reduction of inequality.

The weighted mean of the marginal contribution of farm size to measured income inequality (0.2468) is 0.0153 at level 1; that is, while other regressed-income sources were removed, farm income had the highest share in the total household income. But as the effect of other regressed income sources is steadily considered from level 2 through 10, the contributory effect decreases. The source farm size at all levels of entry registered no negative impact. The impact of this was that encouraging agriculture for all would be equity enhancement, but promoting it with other variables that reduce inequality would enhance the effectiveness of a policy. The variable age, when considered alone, had a marginal impact of 0.0102. This signifies that age differences widen inequality, but at the levels, the contributory effect was reducing, meaning that in reducing inequality, other factors had to be considered.

The marginal contribution of education in explaining inequality was 0.0028. This suggested that education played a crucial role in improving rural welfare. Differences in education levels cause income variation, and acquiring education enhances household welfare. Progressively considering other estimated sources increases the impact of the education source in explaining inequality, and the impact reduces steadily. The number of years in school has the tendency to increase inequality by increasing demand for better welfare, better livelihoods, infrastructure, and skills. It creates awareness about the environment and causes forest dwellers to move to urban areas. Promoting education alone to reduce inequality would not be enough; it has to be along with other variables to be effective.

Marital status, sex, household size, forest distance, credit access, and asset ownership had positive and negative values at certain levels of entry. The variable, sex, when considered alone, had a marginal impact of 0.0033, which amounts to one-eighth of the total impact of this source in explaining observed inequality. At the ninth level, the weighted marginal contribution of this source became constant. For household size at level one, the weighted marginal contribution was 0.0085, one-fifth of the total impact that household size had on total inequality.

The remaining was constant from level 9 to level 10, inferring that there was no change in inequality. The income distribution remained the same at this level when household size, with other income sources, was removed from the analysis.

The weighted marginal contribution of forest distance to total inequality was 0.0010, and the contribution of the impact of other levels on total inequality was 0.0126. The contribution was constant from levels 8 to 10, meaning that the weighted marginal contribution did not change. There was no impact on the total inequality as the source variables were removed with the distance to the forest. The variable contribution became constant from levels 8 to 10. The variable distance to the urban market, when considered alone (level 1), had a marginal contribution of 0.005; the total impact of urban distance on total inequality was 0.0103.

The weighted marginal impact was half that of the total impact. Access to credit had a weighted marginal effect of 0.0014 out of the total impact on inequality of 0.0043. The marginal contribution was very small and was more or less constant from levels 8 to 10. Household assets, such as a lorry, contributed the marginal impact of 0.0067 to total inequality. It was constant from level 7 to 10, but negative at level 10. However, removing the constants meant that there was equity in income distribution at level one. The weighted marginal contribution was zero because total inequality was equal to total household income. It can be deduced that farm size and age constituted key factors that influenced inequality in the study area. The marginal effect revealed that they had equalising effects on total income equality. These results for all the income source variables show that there was a progressive inequality impact, which reduced from level 2 to level 10.

The marital status had a weighted marginal effect of 0.007. The marginal contribution to inequality was reduced from level 1 (0.007) to 4 (0.001) and constant from 4 to level 11, meaning that the weighted marginal contribution did not change. There was no impact on the total inequality as the source income variables were removed with marital status. It should be understood that in all the processes of combining source income variables through levels 1 to 11, inequality would be reduced, and equal distribution of income would be reached. As we get to levels 10 and 11, there would be an equalising effect on income inequality.

Policy Interpretation of Marginal Contributions

The decomposition results indicate that not all household characteristics contribute uniformly to inequality; some act as inequality-enhancing while others exert inequality-reducing effects. For instance, farm size and household size consistently widened disparities, underscoring the unequal distribution of land resources and the strain of larger families on household welfare. By contrast, asset ownership and age displayed negative contributions at certain levels, signaling potential equalizing effects. Ownership of productive assets, such as transport equipment, can reduce reliance on extractive forest activities and diversify income sources, thereby narrowing inequality. Similarly, the diminishing effect of age at higher levels reflects a life-cycle dimension, where older household heads often reduce consumption and diversify income strategies, mitigating inequality pressures.

These findings hold important policy implications. First, interventions should not narrowly target single determinants, as isolated measures may fail to offset structural disparities. Instead, a multi-pronged approach is required. For example, land redistribution or support for smallholder farming should be complemented with credit access, asset-building initiatives, and education investments to ensure that productivity gains are broadly shared. Second, the equalizing role of asset ownership suggests that programs promoting household capital formation, such as microcredit for equipment purchase or community-based cooperative schemes that could help bridge welfare gaps. Third, demographic policies that encourage manageable family sizes, combined with social protection for older households, may stabilize inequality trends over time.

Overall, the marginal contributions analysis demonstrates that inequality in forest-dependent communities is multidimensional. Effective policy must therefore focus on bundles of complementary interventions that recognize the interplay between education, demographic dynamics, asset ownership, and land access, rather than privileging a single factor.

Table 4. Marginal Contributions of the Various Estimated Income Sources

Source	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10	Level 11
P_Sex (1or 0)	0.0033	0.0029	0.0025	0.0023	0.0021	0.0019	0.0018	0.0018	0.0017	0.0017	0.0017
P_Age (year)	0.0102	0.0080	0.0063	0.0043	0.0037	0.0027	0.0019	0.0011	0.0006	-0.0001	-0.001
P_Education (year)	0.0028	0.0114	0.0007	0.0004	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
P_ householdSize	0.0085	0.0068	0.0055	0.0045	0.0038	0.0033	0.0029	0.0027	0.0025	0.0025	0.0025
P_farmsize (Heactare)	0.0153	0.0128	0.0107	0.0090	0.0076	0.0064	0.0053	0.0043	0.0035	0.0028	0.0021
P_ Forestdistance (km)	0.0010	0.0006	0.0003	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
P_ Marketdistance (Km)	0.0005	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	-0.0001
P_Creditaccess (1 or o)	0.0014	0.0009	0.0006	0.0004	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
P_ownership of Lorry	0.0067	0.0042	0.0003	0.0003	0.0002	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
P_Maritalstatus (1or 0)	0.0007	0.0004	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
P_Constant	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: data analysis, 2023

CONCLUSION

This study applied a Shapley regression-based decomposition to identify the key drivers of income inequality among households in forest-dependent communities of southwestern Nigeria. The results indicated that household size and farm size had a higher relative contribution to income inequality under income inequality decomposition, but in order to derive further results from the estimated model, marginal effects were calculated on each income class. Education and farm size had a high relative contribution to total inequality; combining other estimated variables with them can be used to reduce inequality. By contrast, asset ownership and the age of household heads displayed inequality-reducing effects at certain levels, highlighting the potential equalizing role of productive assets and demographic dynamics over the life cycle.

Meanwhile, a critical insight from the decomposition is that inequality cannot be addressed effectively by targeting a single factor in isolation. Instead, a multi-pronged policy package is required. Programs aimed at supporting smallholder farming should be complemented with measures that expand educational opportunities, promote household asset accumulation, improve access to credit, and encourage sustainable family sizes. Furthermore, policies that recognize the changing economic role of older household heads may help stabilize inequality in rural communities over time. In sum, the study demonstrates that the drivers of inequality in forest-based households are interconnected and multidimensional. Thus, efforts to reduce inequality will be most effective when interventions are bundled, coordinated, and responsive to both economic and demographic realities of rural Nigeria.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest concerning this study.

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