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The Distributional Impacts of Forest Income on Household Welfare in Rural Nigeria

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Abstract

The study examines the distributional implications of forest income on poverty and income inequality in rural Nigeria using Gini and poverty decomposable techniques. The study finds that forest income reduces both income inequality and poverty in rural Nigeria. Analysis of the determinants of forest income using Heckman's 2-step sample selection model indicates that the decision to participate in forest extraction increases with more access to community forest areas, larger and poorer households, membership in forest management committees; and decreases with higher educational attainment and higher transfer income earnings. Likewise, forest income was found to be positively and significantly related to male-headed households, poorer heads of household and households that have more access to forest resources outside the community forestry areas. Furthermore, poverty and inequality simulations revealed that household welfare in rural Nigeria could be improved through policies and programs that; can stimulate increase earnings from minor forest resources, assist households to earn income from alternative sources such as agriculture and commerce.

Keywords: Nigeria, forest income, Gini and poverty decompositions, Heckman's method.

1. Introduction

Globally, there is a long tradition of concern about household welfare and forest dependence (Fonta et al. 2010a). The prospect of more than 300 million people the world over, especially the poor, depending substantially on forest gathering for daily subsistence and survival, cannot be a matter for policy indifference. Forest dependence can be linked to socio-economic and cultural consequences. On the economic front, there are some associated costs and benefits from using forests. The potential benefits include: (1) daily subsistence and survival from forest product gathering, and (2) income redistribution and poverty reduction. The potential costs include: (1) increase in global warming emanating from carbon emissions caused by forest use and displacement and (2) destruction of natural habitats for important ecosystem species. Socio-culturally, the benefits may include fresh water, recreational facilities, firewood, timber, medicine and the role of forestry in the local traditions and customs of the people (Fonta et al. 2010b).

However, there exists a dearth of micro level evidence in general on the distributional and poverty effects of using the forest. Very few studies have looked at the quantitative relationship between forest income, poverty and income inequality (Lopez-Feldman et al. 2007). Jodha (1986) appears to be amongst the first stream of researchers who attempted to rigorously shed more light on the distributional implications of forest income on poverty and income inequality. Jodha found out that the Gini coefficient in dry regions in India increases by as much as 34 per cent when income derived from forest gathering is ignored in Gini estimation. Still in India, Reddy and Chakravarty (1999) found out that when forest income is set to zero in poverty calculations, poverty increases by as much as 28 per cent. However, the inequality effect of ignoring forest income was very marginal. Conversely, in Zimbabwe, Cavendish (1999) observed that by calculating poverty and inequality measures with and without forest income, poverty and inequality can be overstated by as much as 98 and 44 per cent respectively, depending on the poverty line and measure used. The same could be deduced from Fisher's study in southern Malawi. Fisher arrived at a similar conclusion and in particular, Fisher observed that by excluding income from forestry when measuring inequality, income inequality in the region increases by as much as 12 per cent (Fisher, 2004). In a more recent study by Lopez-Feldman et al. (2007), in rural Mexico and the Lacandona Rainforest community area of Mexico, the authors observed that when forest income is ignored in poverty calculations, the severity of poor people increases more at the regional and community levels (i.e., 17.1% 18.4%), than at the national level (i.e., 10.8%). The headcount and poverty gap measures revealed a similar pattern of greater sensitivity of poverty at the regional and community levels than at the national level. In their inequality calculations, it was also observed that when forest income is increased by 10 per cent, the Gini coefficient reduces by as much as 0.36 and 0.11 per cent, respectively, at the national and community levels.

To the best of our knowledge, there have been no efforts in Nigeria to estimate the impacts of forest income on poverty and inequality despite the fact that Nigeria's land area is covered with over 11,089,000 hectares of forest (FAO, 2005). The aim of this study therefore, is to close this knowledge gap by providing new empirical evidence on the role of the forest in poverty mitigation and income inequality in rural Nigeria. As empirical case study, we used the Cross River community forestry area of Southeastern Nigeria. Cross River is one of the 36 States that make up the Federal Republic of Nigeria. According to 2006 National Population Census figures, the state has approximately 2.7 million inhabitants with 18 Local Government Areas (LGAs). Also, like most other States in Nigeria, population growth rate in Cross River is estimated at 2.5 per cent with a population density of about 93 persons per sq/km. Presently, Cross River has the largest forest area in Nigeria with an estimated total high forest (THF) of about 950,000 hectares (DfID, 2001). The rich and fertile soils, combined with equatorial climate, encourage the growth of a great variety of species of plant and animals on which the population is highly dependent for daily sustenance. However, the real financial and economic benefits which the rural communities and households derive from forest extraction are difficult to estimate (Udo and Udofia, 2006). In the absence of such information, it is extremely difficult for policy makers to enact locally relevant policies and programs that can help in forest-led poverty reduction and income redistribution.

The rest of the paper is sub-divided as follows. In section two, the analytical methods used for the empirical estimations are presented followed by the data in sub-section three. Section four reports the empirical findings while section five, concludes the paper with the potential policy implications of the study findings.

2. The Analytical Models

The study is driven by three specific research objectives namely: (i) to estimate the distributional and poverty effects of forest extraction income in the Cross River community forest area of Southeastern Nigeria; (ii) to estimate the impacts of forest income on rural income inequality; and, (iii) to identify the determinants of forest extraction income. To address these specific research objectives, we used; the Foster-Greer-Thorbecke (FGT) poverty decomposition index (FGT, 1984), the Gini coefficient decomposition technique (Lerman and Yitzhaki, 1985) and, Heckman's 2-step estimator (Heckman, 1979).

2.1 Measuring Poverty

To analyse the distributional and poverty implications of forest extraction income, three variants of the Foster-Greer-Thorbecke poverty index were employed (FGT 1984). The FGT index was used because it is very easy to decompose by income effects, and it also satisfies Sen's axioms of transfer and monotonicity (Sen, 1976). That is, the index increases whenever a pure transfer is made from a poor person to someone with more income, and increases when there is a reduction in a poor person's income, holding other incomes constant. The FGT poverty index is:

$$P\alpha = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_i}{z}\right]^{\alpha} \tag{1}$$

$$where\ \alpha \geq 0$$

where, $y = (y_1, y_2, ...y_n)$ represents the income vector of a population of *n* individuals with incomes sorted in increasing order of magnitude, *z* (Note 1) is the poverty line, *q* is the number of poor individuals, and α is a weighting parameter that can be viewed as a measure of poverty aversion. It usually ranges from 0 to 2 (i.e., $0 < \alpha < 2\,0$). When $\alpha = 0$, the FGT index reduces to the poverty head count ratio (i.e., the percentage of poor in the population). When $\alpha = 1$, the FGT index measures the average poverty gap ratio (i.e., the average shortfall of income from the poverty line or how far below the poverty line the average poor household's income falls). However, when $\alpha = 2$, the FGT index indicates the severity of poverty, or the spread of the poor around the level of the average poor. Generally, as α increases, the FGT index gives more weight to the lowest incomes. Foster et al. (1984) presents a decomposition of the poverty index by population subgroup, while Reardon and Taylor (1996) proposed a simulation method to decompose the FGT poverty coefficient by income source (Lopez-Feldman et al., 2007). In our study, the approach proposed by Reardon and Taylor (1996) is followed to simulate the impacts of forest income on poverty in the Cross River community forest area.

2.2 Measuring Inequality

To estimate the impacts of forest income on rural income inequality, the Gini coefficient technique presented by Lerman and Yitzhaki (1985) was used. First, Gini results are easily interpreted with the aid of a Lorenz Curve. Second, the technique allows easy decomposition of inequality by income sources. Third, the technique lends itself to easy-to-interpret decompositions of income effects (Lopez-Feldman et al., 2007). Following Lerman and Yitzhaki (1986), the Gini coefficient for any particular income source *k* is given by:

$$G_k = 2\frac{\operatorname{cov}[y_k, F(y_k)]}{\mu_k} \tag{2}$$

Where y_k denote the different components of household income (i.e., forest income and non-forest income), $F(y_k)$ represents the cumulative distribution of income source *k*, and μ_k denotes household mean income. However, suppose G_T defines the Gini coefficient of total income, then following the properties of covariance decomposition, G_T can be stated as:

$$G_T = \frac{2\sum_{k=1}^{K}\operatorname{cov}[y_k, F(y_k)]}{\mu_T} = \sum_{k=1}^{K} R_k G_K S_K \tag{3}$$

Where S_k represents household share of income source *k* on total income, and R_k stands for the Gini correlation between income from source *k* and the distribution of total income (Acosta et al. 2007). Equation (3) therefore allows the decomposion of the influence of any income component, in our case forest income, upon total income inequality, as a product of three easily interpreted terms, namely: (i) how important the income source is in total income (S_k); (ii) how equally and unequally distributed the income source is (G_k); and (iii) how the income source and the distribution of total income are correlated (R_k). In order words, what is the extent to which the income source does or does not favour the poor? Lerman and Yitzhaki (1985), showed that by using this particular method of Gini decomposition, the effects of a small change in income from any source say *k*, can be estimated, holding income from all other known sources constant. This effect is given by:

$$\frac{\partial G_T / \partial k}{G_T} = \frac{S_k G_k R_k}{G_T} - S_k \tag{4}$$

which shows that an infinitesimal change in income *k* has equalizing (un-equalizing) effects if the share of the Gini explained by that source income is smaller than its share in total income (Acosta et al. 2007).

2.3 Modelling Determinants of Forest Income

Our prime interest here is to identify the determinants of forest income. However, for forest income to be observed; a household must first engaged in forest extraction activities. The situation therefore warrants a joint decision process, first involving whether or not a household decides to participate in forest extraction (i.e., participation model), and second; having decided to participate, the actual amount derived from forest extraction (i.e., valuation model). If we estimate the determinants of forest income based only on the sub-sample of those with reported forest income, it could be incorrect if there is bias introduced by self-selection of individuals into the participation model. Thus, to check the presence of sample selection bias, we modeled the two choices simultaneously using Heckman's 2-step approach. Formally, let Y_1 denote the amount derived from forest extraction (i.e., forest income), and Y_2 for a binary variable assuming the value of 1 if a household decides to participate in forest extraction and 0 otherwise (i.e., no forest activity or income). Let x and w also represent vectors of explanatory variables for the valuation and participation models respectively such as (Note 2); the age of the respondent, educational attainment, availability of alternative income sources, household income, household size, household poverty status, gender of the respondent, household composition, availability of forest resources, market access, and participation/membership in village institutions etc. Then we can write

$$Y_{1i} = x_i'\beta + \mu_i \tag{5a}$$

For the valuation equation with Y_{1i} only observed when $Y_{2i} = 1$, and

$$Y_{2i} = \begin{cases} 1 & if \quad w'\alpha + \varepsilon_i \geq 0 \\ 0 & if \quad w_i'\alpha + \varepsilon_i < 0 \end{cases} \tag{5b}$$

for the participation equation. The joint distribution of (μ_i, ε_i) is assumed to be bivariate normal with zero means, variances equal to 1 and correlation *ρ*. When *ρ* = 0 the two decisions are independent and the parameters of the two equations can be estimated separately (Strazzera et al. 2003). The Heckman procedure is carried out in two stages. First, notice that the conditional expected value of Y_1 is:

$$E[Y_{1i}|Y_{2i} = 1] = x_i'\beta + \rho\lambda(w_i'\alpha) \tag{6}$$

Where $\lambda(w_i'\alpha) = \phi(w_i'\alpha)|\Phi(w_i'\alpha)$ is the inverse of the mills ratio, and ϕ and Φ are the standard normal density and standard normal distribution functions respectively. The first step of the Heckman's procedure entails the estimation of the participation model by probit, which gives us an estimate of λ. The second step consists of a least squares regression (for those with forest income) of Y_{1i} on x and $\hat{\lambda}$.

3. The Data (Note 3)

The data for the analysis was drawn from a recent household survey conducted in the Cross River community forest area by the state's forestry Commission (Note 4). The overall objective of the survey was to determine forest exploitation and the management initiatives of the indigenous people of the CRS of Nigeria. The survey focused on nine of the 18 LGAs in the state where community forestry is practiced under the management of the indigenous people or local authorities. These include: Akamkpa; Biase; Obubra; Yakurr; Etung; Ikom; Boki; Obudu; and Obanliku. The sample includes 1,457 heads of household from a total of about 2,906 households drawn from 18 randomly selected communities in the identified nine LGAs in the State where community forestry is practiced. The numbers of households sampled from each of the 18 communities were proportional to the household population sizes of each community. The actual sample interviewed, represented approximately 50 per cent of the entire households in the nine LGAs.

The actual survey operations lasted for over one year and was undertaken in two phases namely, adoption of a participatory rural appraisal (PRA) approach and administration of household questionnaire. The household survey spanned a period of six months and focused mainly on the collection of primary data on household-level variables, indigenous forest resources management initiatives and trees in farming systems, depletion of forest resources and effects, and constraints of forest resources management. The PRA approach was used to assess forest resources utilization and benefits (i.e., the value of harvested forest products). This lasted for over twelve (12) months because the harvesting of forest products is seasonal in nature. This therefore, enables the gathering of reliable and realistic data (Note 5) on forest resource boundaries, community territories, plants frequency and density on farm lands, total quantity of harvested forest products, quantity of forest products extracted from community and farm lands, farm types and sizes, extent of labour inputs, number of labour hours employed in forest gathering, types of equipment used, etc.

To therefore calculate the net income derived from forest extraction, harvested forest products measured in kilograms were multiplied by the local market price of the products less input costs (i.e., cash costs) such as transportation cost, cost of hiring of equipment, cost of man hours employed, direct cash payments to forest committees (FC) as yearly membership fee etc. Total household income is therefore defined (Note 6) as income derived from five major sources namely: forest extraction income; wage income (defined as income received from all wage paying activities including government salary workers); income from commercial activities; transfer income such as gifts, remittances, government transfers and others etc.; and finally, farm income (Note 7), which includes income derived from crop production, livestock and other off-farm activities such as fish and snail farming. The data therefore makes it possible to test for the influence of forest extraction on rural households' total income, income inequality, and poverty.

4. Empirical Results

Before presenting the empirical findings, we first report the descriptive statistics of the sampled households. As shown in Table 1, the average age for the sample was about 40 years. In terms of distance from a household unit to the community forest area, the average was about 3.5km. By educational attainment, the average level of schooling was about 5years (primary level). In terms of household size, the average was about 5 members with an average household per capita income of about 16,212.13 Naira or $US124.7 (Note 8). This was derived mainly from commerce (1,723 Naira), farm income (2,022 Naira), forest extraction income (4,062.2 Naira), wage income (7,006.60 Naira), and transfers (1,399.62 Naira). Furthermore, about 94 per cent of the sampled households reported frequent use of the community forest, while only about 36 per cent reported extracting forest and other minor forest products from family owned land. Likewise, about 86 per cent of the household heads interviewed were males while only about 14 per cent were females. Also, less than 29 per cent of those interviewed were above the Southeastern poverty line of 29,950 Naira or about 222.9 USD. Finally, more than 83 per cent of the sample reported that they belonged to a forest management committee in the area.

4.1 Forest income and Poverty

Table 2 presents the FGT decomposition results when forest income is ignored in the poverty calculations. The poverty line used is that of the Southeastern region of about 29,850 Naira or about $US222.9. The results indicates that when forest income is set to zero, poverty increases in all three cases, ranging from 3% (when $\alpha = 0$), to 4.4% (when $\alpha = 1$), and to finally 7.9% (when $\alpha = 2$) respectively. Suggesting that about 3% of poor households in absolute terms are further pushed into poverty, poverty depth increases by 4.4% while, the severity of poverty or poor households that are further away from the poverty line increases by 7.9%. This suggests that the poverty impacts of excluding forest income in poverty calculations in rural Nigeria is greater on the poverty depth and severity measures than on the head count ratio.

However, the poverty situation becomes entirely different when we considered the short term impact of a10 per cent (10%) increased in forest income to rural household total income. For instance, a 10% increase in forest income is associated with a decline in the number of households in poverty of about 4.9%. The same decreases are associated with the severity and depth of poverty (i.e., 7.6% and 12.4%) respectively. Implying that while forest income has a limited role in reducing the number of the poor in the state; it is more effective in alleviating the depth and severity of poverty in region. This result accords with that of Reddy and Chakravarty (1999), Lopez-Feldman et al. (2007) and Mariara and Gachoki (2008), who find that the ameliorating effect of forest extraction activities are greater in terms of lessening dire poverty than it is in lifting poverty in India, Mexico and Kenya respectively. Briefly stated, our poverty experiments suggest that ignoring forest income when estimating poverty measures in rural Nigeria would have substantial impacts on household welfare especially at the LGAs where most households depend on forest activities for their livelihood. However, the impact is greater on the poverty depth and severity measures than on the head count ratio.

4.2 Forest Income and Inequality

In Table 3, the results of the decomposition of the contributions of forest income and other income sources to total per capita household net income and income inequality are reported. The first column, labelled S_k , represents the share of each income source (i.e., commerce, farm income, forest income, transfers, and wages) in the per capita total income for the sample. As observed, the principal sources of household income for the entire sample are wages and forest income (43 per cent and 25 per cent, respectively). The second column of Table 4 labelled G_k , reports the Gini coefficients for each income source. As shown, the lowest source Gini comes from forest income with a Gini coefficient of about 0.72. Implying forest income has a very high equalizing income effect in the area after wage income. This can easily be verified from the fourth column in the same Table labeled G_T (i.e., the share of total income inequality attributed to each income source). As indicated, the share of total income inequality attributed to wage and forest incomes are 0.30 and 0.08 respectively. Implying these two income sources contribute the largest shares to total income inequality in the area. This is largely due to the fact that incomes from these two sources made up high shares of aggregate household income as shown in the column labeled S_k .

However, to assess whether a given source of income reduces or increases income inequality, all else being equal, if $R_k > G_k$ and the share of source income (S_k) is increased or decreased, then income inequality (G_k) will increase or decrease (Fisher, 2004). Results of column 3 indicate that the Gini correlation (R_k) for all the source incomes are lower than their respective source Gini. This implies that sources of income with Gini correlation or concentration ratios (R_k) with values lower than 0.52 (i.e., the aggregate income Gini), help reduce total income inequality. Results in column 4 indicate that, all else being equal, an increased share of income from farm, forest, or transfer lowers income inequality in the area; while increased income shares from commerce and wages are associated with higher income inequality. For instance, a 10 per cent increase in farm income, forest income, or either transfers income, other things being equal, are associated with declines in the Gini coefficients of total income inequality by 0.30%, 0.97%, and 0.32% respectively. Likewise, 10% increases in commerce or wage incomes, other things being equal, are associated with increases in the Gini coefficient of total income inequality by 0.17% and 1.42% respectively.

Figure 1 also illustrates the impact of forest income on income inequality. The diagonal line denotes perfect inequality. Lorenz curves are constructed with the data for household income including and excluding forest income. The figure shows that the addition of forest income to household income reduces measured income inequality by as much as 20.3%, all else equal.

4.3 Regression Results

Of the total of 1457 household heads that were actually interviewed, 1132 respondents (77.7%) reported having forest income while, only about 325 households (22.3%) had no forest income. As indicated earlier, it was also necessary to determine whether excluding households with no forest from the econometric estimation would lead to a sample selection bias. Simple comparisons of means of household co-variates between the two groups (i.e. those with forest income vs. those without) were performed using sample T-statistics (Table 4). Any significant difference between these two groups of respondents is an early warning indicator of the presence of sample selection bias and justifies the use of a sample selection model (Fonta et al. 2010b). For some of the variables (e.g. access to community forestry, farm income, distance to community forestry area, household size, household poverty status, per capita income, transfers income and years spent in school), the difference between the two groups of households (i.e., forest income and no forest income) are quite significant at 1% and 5% levels, respectively. If these variables influence a household decision to participate in forest extraction, then the final estimates obtained from the sub-sample of households with forest income may be affected by selectivity bias.

The results of the participation and valuation models estimated using Heckman's 2-step approach is reported in Table 5. However, note that the Table reports the parameter estimates for the best fitting specifications for the two models (i.e., participation and valuation), selected by means of likelihood ratio tests for nested specifications from more comprehensive models. Starting with the participation model to explain included versus excluded households in forestry participation, distance seems to have an effect on the probability to participate or not. In particular; being negatively signed, implies that households that are further away from the community forestry areas, are less likely to participate in forest extraction. This is so because, users who live closer to the forest have a more secure and accessible supply of produce regardless of whether or not there are allocation rules in place compared to users leaving further away as explained by Gunatilake (1998) and Varughese and Ostrom (2001).

Also, larger household sizes increase the probability to participate in forest extraction. Possibly because, forest gathering activities are labour intensive. A larger household therefore, has more labour to spread across various collecting and gathering activities and such households may derive more resources from using the forest. The same can be said about the educational level of household heads. The lower the educational level, the higher the probability to participate: possibly because, better education opens up alternative employment opportunities and diverts people from subsistence agriculture and gathering activities such as forest extraction. Income earned from transfers also revealed a similar effect on a household decision to participate in forest extraction. Those receiving less from transfers turn to participate more in forest extraction. This is because, the forest provides a wide range of benefits to these households such as safety nets, support of current consumption, and as a pathway out of poverty through household income sustainability as explained by Mariara and Gachoki (2008). Finally, membership in forest management committee equally had an effect on the probability to participate and in particular, being positive; increases the probability possibly because; membership increases an individual's awareness of the potential gains from utilizing the forests. In fact, Gaspert et al. (1999) and Adhikari (2005) found out that a household is 20% more likely to participate in forest gathering if it is a member of forest management committee or user groups than if it is not.

In the valuation model (columns 3 of Table 7), where the actual amount derived from forest extraction is the dependent variable, households that make frequent use of the community forest areas, were found to be earning more from forest gathering. Again, possibly because; less time and resources are spent in collecting forest products that are easily accessibility to these households. This may explain why they earned more from forest extraction activities. Another variable that is also a significant determinant of households' forest income is the variable 'Poverty_status'. Those living below the poverty line as expected, make more money from forest gathering, which is not surprising as many studies have showed that poverty is highly correlated with forest dependence. For instance, Takasaki et al. (2004), found out that in environments with alternative means of livelihood, forest dependence is almost non-existent whereas for households without alternative means, forest dependence is most common. Furthermore, the results indicate that households that make frequent use of the forest outside the community forest areas earned more from forest extraction. One possible explanation for this phenomenon is that there is a greater possibility that these same households extract forest resources from the community forestry areas hence, more forest products and more earned income. Finally, since the coefficient on λ (Note 9) is not significantly different from zero, there is no indication of a sample selection bias problem.

5. Conclusions and Policy Issues

The contribution of forest activities in mitigating poverty and income inequality has attracted very little attention in general. Very few studies have looked at the quantitative relationship between forest income, poverty and income inequality yet, more than 300 million people the world over, especially the poor, depend substantially on the forest for daily subsistence and survival. Of the few studies conducted so far, the results are mixed with respect to the forest income, poverty and inequality nexus. While some found an inconclusive relationship, others concluded that the forest has great potentials for reducing income inequality and poverty in general. However, in Sub-Saharan African (SSA) where majority of the population depend on forest gathering, there exists a dearth of micro level evidence on the distributional and poverty effects of using the forest.

The aim of this study has therefore been to contribute to the few existing empirical literature in SSA and to the developing countries in general, and in particular; to quantitatively examine the role of the forest in mitigating poverty and income inequality in rural Nigeria. We use as a case study, the Cross River community forest area of Southeastern Nigeria.

Results from our poverty simulations indicate that when forest income is ignored in poverty calculations, the head count ratio, poverty gap and severity measures in rural Nigeria, increases by as much as 3%, 4.4% and 7.9% respectively. However, the poverty situation becomes entirely different when we considered the short term impact of a 10% increased in forest income to rural household total income. For instance, a 10% increase in forest income is associated with a decline in the number of households in poverty of about 4.9%. The same decreases are further associated with the severity and depth of poverty of about 7.6% and 12.4% respectively. Similarly, in the inequality decompositions, when forest income is ignored in our calculations, the Gini coefficient for total rural per capital income increase by over 20%. However, a 10% increase in forest income, other things being equal, is associated with declines in the Gini coefficients of total income inequality by about 0.97%.

Furthermore, analysis of the determinants of forest extraction income using Heckman's 2-step estimation, indicates that the probability to participate in forest extraction increases with household size and being a member of a forest committee, and decreases with living further away from the community forest area, higher educational attainment, and higher transfers earning. Likewise, forest extraction income is positively and significantly related to poorer head of households and households that make frequent use of family land and the community forest areas.

The main policy implication of the findings is therefore that, the forest can have an important role in mitigating poverty and income inequality in the Cross River community forestry area. However, since most community forestry areas share similar characteristics, we believed that the lessons from this study will be useful for policies in other rural areas. The first policy lesson emanates from our poverty simulation analysis. The result suggests that in order to reduce poverty in the immediate short run in the community forestry area of Cross River, quick policy interventions are needed to improve household earning from forest gathering. This may include increased public spending on: underdeveloped produced markets for minor non-wood forest products (NWFPs) that are currently under marketed; recognisance surveys of the forest to identify new NWTPs that have market potentials; infrastructural development especially on transport net works and feeder roads to increase market accessibility; and storage facilities that can help conserve minor NWFPs. Alternatively, forest income could be raised also through policy initiatives that promote community-company partnership in the planting and marketing of woodlots. Partner companies provide the necessary materials, low-interest loans, and technical assistance for establishing and managing small woodlots on farm lands. In return, these companies buy and sell the mature trees ensuring the demand and supply of woodlots. This approach has proven very useful in poverty mitigation and forest conservation in many communities of the globe (Scherr et al. 2002 and Fisher, 2004).

Second, in terms of income redistribution, the results suggest that income inequality can be reduced through policies that would assist the poor who mostly depend on forest extraction so as to come out of poverty. Towards this end, increased public spending on the non-forest dependent sector of agriculture (farming) may be desirable. For instance, the marginal effect on Gini of total income suggests that if farm income increases by 10%, the Gini coefficient of total income inequality declines by 0.30%. The same can be said about transfer earning. When transfers go up by 10%, inequality declines by o.32%. Thus, inequality could be reduced through policy programs that improve alternative sources o household income in the area.

Finally, in terms of forest conservation, our regression results offer a host of policy options. The first is to increase spending on education so as to again improve the poor masses that mostly depend on forest extraction as a path way out of poverty. This is informed by the positive impact that higher education attainment has on forest dependence. The second is to enforce strict rules and guidelines governing the harvesting of forest products within the community forestry areas. This may include the granting of forest permits, categorizing of forest products to be harvested and sold, and also severe punishment for violating the rules and guidelines governing the harvesting of forest products within the community forestry areas. Third and finally, is to encourage the planting of minor forest products outside the community forest area.

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Notes

Note 1. The poverty line used for the study was that of the southeastern region of about N29, 850 or 253 USD calculated using the Cost of Basic Needs approach (Aigbokhan, 2000).

Note 2. These hypothesized variables are based on findings from forest dependence literature. These include studies by Folbre (1994); Gunatilake (1998); Gaspert et al. (1999); Varughese and Ostrom (2001); Angelsen and Wunder (2003); Cavendish (2003); Vedeld et al. (2004); Shively (2004); UNDP et al. (2005); Narain et al. (2005); Mariara and Gachoki (2008) etc.

Note 3. Only the essential are reported here however, for more details on the survey operations, the reader is referred to Ajake (2008) and Fonta el al. (2010b).

Note 4. The commission was established in 1999 by the state government to oversee sustainable utilization of her forest resources. The commission practices two types of forest ownership in the state. The first is Community Forestry (CF), which allows local communities to have control of Timber and NTFPs utilization (although such communities are required to operate within the rules and regulations of the state's forest law administered by the FC). The second is Forest Reserves, over which the FC has direct responsibility while neighbouring communities enjoy useful rights and utilization (DfID, 2001).

Note 5. Supplemented with information elicited using the questionnaire approach.

Note 6. This definition is based on the approach employed in the Nigerian First Living Standard Survey (NLSS) conducted by the National Bureau of Statistics (NBS).

Note 7. Net farm income was calculated as the quantity of farm and off-farm produce in kilograms multiplied by the local market price of the products plus the change in the value of standing herds before and after survey, less input costs associated with production.

Note 8. At the time of the survey, 1USD was equivalent to 130 Nigerian Naira.

Note 9. A major weakness of the Heckman's procedure is the failure to account for the problem of collinearity between variables of the participation and valuation models. If there is any co-linearity problem, the Heckman's estimates are less likely to be efficient when compared to other estimators such as the Full Information Maximum Likelihood (FIML) estimator. To check for the presence of collinearity between the two models, we ran an auxiliary OLS regression of λ against the co-variates of the valuation equation as suggested by Strazzera et al. (2003). The resulting R^2 from the estimation procedure indicates the absence of any collinearity problem.

Table 1: Descriptive Statistics for the Sampled Households'

Variable	Description of Variable	Mean	Std. Dev.
Age	Age of respondent (most recent birthday).	40.38	15.25
Commerce	Per capita commercial income	1,722.59	13,302.50

Community_forest	Households that utilized community forestry for forest gathering and other uses: = 1 if use and 0 otherwise	0.94*	0.23
Family_land	Households that utilized family owned land for extracting forest and other product: = 1 if family land and 0 otherwise	0.36*	0.48
Forest_distance	Distance in kilometres from household to the forest	3.46	1.64
Farm_income	Per capita farm Income	2,021.53	4,876.20
Forest_income	Per capita forest income	4,062.20	12,674.70
Gender	Male = 1, 0 = female	0.86*	0.35
Household_size	Household size	5.14	2.35
Membership	Whether a household belongs to a forest management committee or not and coded as follows: = 1 if member and 0 otherwise	0.83*	0.37
Poverty_status	Proportion of sampled population below the regional poverty line	0.71	0.45
Transfers_income	Per capita transfer income	1,399.62	10,743.04
Total_income	Total per capita household income	16,212.13	27,188.60
Wage_income	Per capita wage Income	7,006.60	1,6561.38
Years_Schooled	Number of years of schooling and coded as follows: 0 = informal, 6 = primary, 12 = secondary and 16 –21 = tertiary.	5.23	2.56
Obs.			1457

Source: Forestry Commission Database (2006); * *Proportion for dummy variables*

Table 2: FGT Index With and Without Forest Income

State Poverty Line of 29, 950 Naira or USD 222.9			
All Households (N = 1457)	FGT(α = 0)	FGT (α = 1)	FGT (α = 2)
Total Income without Forest Income	0.847	0.250	0.186
With Forest Income	0.817	0.206	0.107
% Change in FGT	**3.0%**	**4.4%**	**7.9%**
The effect of 10% Increase in Forest Income			
All Households (N = 1457)	FGT(α = 0)	FGT (α = 1)	FGT (α = 2)
Total Income	0.847	0.250	0.186
10% increase in Forest Income	0.896	0.326	0.310
% Change in FGT	**4.9%**	**7.6%**	**12.4%**

Showing the decomposition results based on the FGT poverty index

Table 3: Gini Decomposition by Income Source

Income Source	**Share in total income** (S_k)	**Income source Gini** (G_k)	**Gini correlation with total income**(R_k)	**Share in total-income inequality** (G_T)	**% Share in Gini of total income** (S_G)	**Marginal effect on Gini of total income***
Commerce	0.086	0.934	0.666	0.053	0.103	0.17
Farm_income	0.106	0.821	0.450	0.039	0.076	-0.30
Forest_income	0.251	0.718	0.444	0.080	0.154	-0.97
Transfers_others	0.125	0.841	0.457	0.048	0.093	-0.32
Wage_income	0.432	0.857	0.802	0.297	0.574	1.42
Total_income	**1.000**	**0.518**	**1.000**	**0.518**	**1.000**	

Obs.	1457

* Effects of a 10% increase in per capita income from different sources on the Gini coefficient of total income. Showing the decomposition results based on the Gini coefficient technique

Table 4: Comparison of Means and Standard Deviations by Groups of Households'

Variable	Forest Income		No Forest Income		Difference
	Mean (μ_1)	**Std. Dev.**	**Mean(μ_0)**	**Std. Dev.**	**$\mu_1 - \mu_0$[b]**
Community_forest	0.944	0.230	0.745	0.229	0.199***
Farm_income	710.43	1,267.483	1,215.338	2,347.477	-504.908***
Forest_distance	3.433	1.724	3.480	1.578	- 0.046*
Household_size	5.485	2.759	5.052	2.552	0.433***
Poverty_status	0.376	0.485	0.262	0.440	0.114***
Total_income	19,378.55	33,843.18	11,666.55	18,053.30	-7,712***
Transfers_income	1,415.69	3917.37	2,405.262	6005.476	989.572***
Wage_income	4,825.56	12,472.34	11,283.150	18,714.910	-6457.59***
Years_Schooled	0.243	0.496	0.526	0.501	-0.283***
Obs.	1132		325		

[b] Difference in means and their respective levels of significance * < 0.10, ** < 0.05, *** < 0.01

Table 5: Heckman's 2-step Estimates

(1)	Participation Model (2)			Valuation Model (3)		
Variable	**Coef.**	**Std. Err.**	**t-value**	**Coef.**	**Std. Err.**	**t-value**
Constant	0.779	0.046	16.90***	-0.741	1.198	-0. 62
Forest_distance	-0.269	0.133	-2.02**	---	---	---
Community_forest	---	---	---	4.264	0.124	34.51***
Family_land	---	---	---	0.319	0.176	1.81*
Household_size	0.01	0.004	2.59***	---	---	---
Membership	0.077	0.032	2.40***	---	---	---
Poor_status	---	---	---	299.07	34.851	8.58***
Transfer_income	-0.873	0. 475	-1.84**	---	---	---
Years_schooled	-0.25	0.12	-2.10**	---	---	---
LR chi 2 (3) = 19.03 ; Prob > chi 2 = 0.0009						
Mills lambda (λ)				-0. 417	0.634	-0.66
Pseudo R^2			0.32			0.13
Log-likelihood						-692.56
% correctly predicted			81.30%			
Observation.			**1457**			**1132**

Significance of parameters * < 0.10, ** < 0.05, *** < 001.
Results of Heckman's 2-step sample selection model

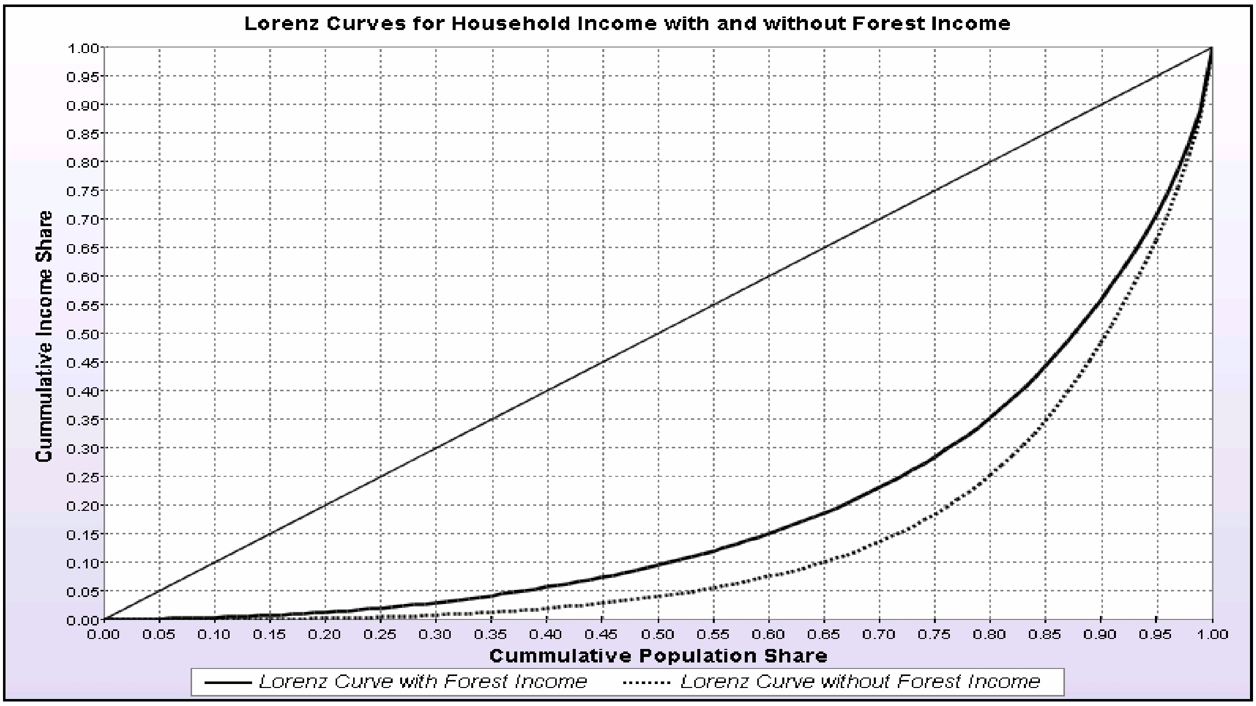

Figure 1: Lorenz Curves for Household Income with and without Forest Income