Activity Choice, Labor Allocation, and Forest Use in Malawi

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ABSTRACT

We examine the determinants of activity choice affecting forest use among low-income households in Malawi. Data from three villages are used to estimate a system of household labor share equations for maize production, forest employment, and non-forest employment. A system estimation approach is used to identify factors influencing the competing and synergistic livelihood strategies which households undertake at the forest margin. Results from constrained maximum likelihood estimation indicate heightened incentives to degrade forests when returns to forest use are high. Factors reducing forest pressure include favorable returns to non-forest employment, secondary education of the household head, and wealth.

JEL classification: J22; O13; Q12

Keywords: labor allocation, deforestation, resource extraction, Malawi

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I. INTRODUCTION

Throughout the developing world, forests contribute in important ways to the well-being of rural populations, providing land and many products and services. Nearly a quarter of the world's poor depend on forests (World Bank 2000, cited in Scherr, White, and Kaimowitz 2002). While forest use is common in the developing world, the ways in which smallholders incorporate forest activities into their livelihood strategies vary considerably (Byron and Arnold 1999). Understanding why forest use differs across households is important for both conserving forests and alleviating poverty. Conservation efforts that restrict forest access may jeopardize vulnerable households during critical periods. At the same time, policies aimed at increasing rural incomes may influence households' forest use decisions.

In this paper we examine forest use within the context of overall labor allocation, using data from smallholders in southern Malawi. We develop and estimate a labor allocation model in which households divide their labor among three sectors: farming, forest employment, and non-forest employment. The farming sector is assumed primarily to be subsistence-oriented. The two non-farm employment categories are distinguished by whether or not they are forest-based. By explicitly incorporating the forest as part of a household's diversification strategy, our study builds on previous work. Kumar and Hotchkiss (1988) was one of the first empirical studies of farm-household forest labor supply decisions. A key finding of their analysis of Nepalese households is that deforestation boosts the time allocated to fuelwood collection and thereby reduces agricultural output by shifting women's time away from agricultural work. In a more recent study with the same data, Cooke (1998) finds little support for the thesis that households, and women in particular, devote less time to agriculture as the time required to collect forest products increases. The implication may be that, as forest products become more scarce in Nepal, households have less time for non-agricultural activities or leisure. In Bluffstone's (1995) study, households are assumed to allocate labor to fuelwood collection, agriculture, and off-farm work. Based on results from simulation exercises, Bluffstone argues that the presence of off-farm labor opportunities is crucial for reducing deforestation rates among Nepalese farmers. This conclusion is also echoed by findings from the Philippines (Shively and Pagiola 2004; Shively and Fisher 2004).

The present study builds on the conceptual framework of these earlier studies while complementing them methodologically. Whereas Kumar and Hotchkiss (1988) and Cooke (1998) estimate single-equation models, we employ a system of labor share equations, using an approach similar to that in commodity and factor demand models.[1] We are thus able to provide a theoretically consistent treatment of peasant labor allocation and forest use unobscured by the likely distortions in single-equation approaches. We also include multiple sources of forest degradation. Earlier studies have tended to focus either on forest clearing (e.g. Godoy et al. 1998; Shively 2001) or fuelwood collection (e.g. Cooke 1998; Kumar and Hotchkiss 1988). By including data on a variety of forest activities, and by taking a systems approach to econometric estimation, we aim to provide an improved assessment of factors leading to forest decline.

II. A MODEL OF LABOR ALLOCATION

To investigate factors related to forest use, we develop a household model of labor allocation. We draw upon the economic theory of farm households (Singh, Squire, and Strauss 1986) and empirical studies of household resource allocation in developing countries (e.g. Abdulai and Delgado 1999; Heltberg, Arndt, and Sekhar 2000). The model explicitly accounts for the fact that many low-income farm households are both producers and consumers of agricultural, forest, and non-forest goods, and that markets for key factors and products typically are weak or absent in rural areas of developing countries. As a result, production decisions are influenced by consumption needs; that is, production and consumption decisions are made jointly in response to changes in input and output prices.

Conceptual Framework

We assume households allocate family labor across three activity categories: maize production L_M, forest use L_F, and non-forest employment L_O. The household solves:

$$\max_{L_i,\, C_i,\, X} \quad U = U(C_i, N;\ H), \qquad i = M, F, O \tag{1}$$

where utility U is derived from consumption of a representative staple crop maize (C_M), a composite forest product (C_F), (non-farm) non-forest goods (Co), and leisure (N). Household characteristics $\boldsymbol{H}$ influence preferences. We assume U is strictly convex.

Utility is maximized subject to production functions for maize, forest products, and non-forest goods, a full income constraint, a time constraint, and non-negativity constraints:

$$Q_M = Q_M[L_M, X, A_0, A_1(L_F)] \tag{2}$$

$$Q_F = A_1(L_F) + f(L_F; D) \tag{3}$$

$$Q_O = g(L_O) \tag{4}$$

$$Y = \sum_i [p_i Q_i - TC_i S_i] - \sum_i [p_i C_i + TC_i B_i] - p_X X \tag{5}$$

$$T - N = \sum_i L_i \tag{6}$$

$$C_i,\ N,\ X,\ Q_i,\ S_i,\ B_i,\ L_i \ \geq\ 0 \tag{7}$$

Equation [2] describes smallholder maize production, assumed to be a function of labor L_M, purchased inputs such as fertilizer X, the household's land endowment A_0, and additional land acquired through land clearing, represented by function $A_1(\bullet)$. Maize production can occur either through intensification (via X) or extensification [via $A_1(\bullet)$] or both (Coxhead, Shively, and Shuai 1999). Customary land ownership implies land markets generally are absent in rural Malawi, but land can be "purchased" by using labor L_F to clear uncultivated land (Barrett 1999).

Equation [3] describes production of forest goods. Production function $A_1(\bullet)$ illustrates that when forest is cleared for farming, forest products arise as a joint product. Technology $f(\bullet)$ describes forest "thinning" activities in which household labor is used to extract products from the forest, but without land clearing.[2] Distance D to forest and woodlands also enters as an argument in $f(\bullet)$, reflecting potentially lower net benefits to forest extraction as the time required to travel to collection sites increases. Equation [4] is a production function for non-forest goods, which require only labor (L_O) for production.

Equation [5] defines the household's full income. Households may be self-sufficient ($S_i = B_i$), net sellers ($S_i > B_i$), or net buyers ($B_i > S_i$) in maize, forest, and non-forest goods. Farm inputs (X) are purchased but not sold. We assume all market prices (p_i) and transactions costs (TC_i) are exogenous. Transaction costs such as marketing and transport costs and seasonal price uncertainty can be substantial in rural parts of developing countries (Omamo 1998). These costs induce gaps between the sale and purchase prices of commodities and inputs (de Janvry, Fafchamps, and Sadoulet 1991). When transaction costs are negligible, households face a single price for buying and selling. When these costs are very large, markets are effectively missing and households prefer not to trade the maize, forest, and non-forest goods they produce. Substantial evidence is present that rural maize markets are missing in Malawi. For example, many smallholders say they want to be self-sufficient in maize, partly because of concerns about food market unreliability during periods of calorie shortfall (Alwang and Siegel 1999). Forest and non-forest product and labor markets may function imperfectly in Malawi as well, largely because the variegated nature and quality of these goods leads to high transaction costs. Equation [6] describes the household's time constraint. Non-negativity constraints [7] complete the model.

The Lagrangian of the household's maximization problem is:

$$\mathcal{L} = U(C_i\,,\ T - \sum_i L_i\ ;\ H)$$

$$-\lambda \begin{bmatrix} Y - p_M Q_M\,[L_M, X, A_0, A_1(L_F)] - p_F\,[A_1(L_F) + f(L_F;D)] \\ -\ p_O g(L_O) + \sum_i p_i C_i + \sum_i TC_i(S_i + B_i) + p_X X \end{bmatrix} \qquad [8]$$

After rearranging terms, first-order conditions can be expressed as:

$$\frac{\partial U}{\partial N} = \lambda p_M \frac{\partial Q_M}{\partial L_M} \qquad [9a]$$

$$\frac{\partial U}{\partial N} = \lambda p_M \frac{\partial Q_M}{\partial A_1}\frac{\partial A_1}{\partial L_F} + \lambda p_F \frac{\partial A_1}{\partial L_F} + \lambda p_F \frac{\partial f}{\partial L_F} \qquad [9b]$$

$$\frac{\partial U}{\partial N} = \lambda p_O \qquad [9c]$$

$$\frac{\partial U}{\partial C_M} = \lambda p_M \qquad [9d]$$

$$\frac{\partial U}{\partial C_F} = \lambda p_F \qquad [9e]$$

$$\frac{\partial U}{\partial C_O} = \lambda p_O \qquad [9f]$$

$$p_M \frac{\partial Q_M}{\partial X} = p_X \qquad [9g]$$

$$Y = \sum_i \left[p_i Q_i - TC_i S_i\right] - \sum_i \left[p_i C_i + TC_i B_i\right] - p_X X \qquad [9h]$$

Equations [9a] through [9c] indicate that, at the optimum, households allocate labor across activities so as to equate the marginal value of household leisure with that of the time spent on each productive activity, that is, with the marginal product of – or net hourly returns to – labor. Equations [9d] through [9g] equate marginal values with prices. Equation [9h] recovers the full income constraint. Expressions for labor supply, input demand, and commodity demand can be derived as functions of all exogenous variables:

$$L_i = h\left(p_i, TC_i, H, A_0, D, T\right). \qquad [10]$$

Properties of Labor Supply

To better understand the implications of this model of labor supply, consider first the Slutsky equation, giving the effect on the forest labor share of a change in the price of forest products:

$$\frac{\partial L_F}{\partial p_F} = \left.\frac{\partial L_F}{\partial p_F}\right|_{U=\overline{U}} + \frac{\partial L_F}{\partial Y}(Q_F - C_F)\,. \qquad [11]$$

The first term on the right-hand side of [11] is a substitution effect; the second term is an income effect. The substitution effect is positive because a higher price of forest goods implies increased net benefits of forest exploitation.[3] The income effect is indeterminate. With rising income, the demand for leisure N should increase if leisure is a normal good; but for the same reason the demand for forest products C_F should increase as well. *Ceteris paribus*, more leisure implies a lower forest labor share. However, because forest markets in Malawi are imperfect, higher forest product consumption might require additional forest collecting rather than purchase, and thus be attended by a rise in the household's forest labor share. The sign of $\partial L_F / \partial Y$ depends on the relative demand for leisure and forest products and whether the household is a net seller of forest goods. Term (Q_F - C_F) in [11] is positive for net sellers and negative for net buyers. The income effect is non-negative for net buyers because $\partial L_F / \partial Y$ is non-positive and (Q_F - C_F) is negative. With net sellers of forest goods, the income effect is positive if the demand for forest products outweighs that for leisure, and negative if the household chooses to consume more leisure when its income rises. The net effect on the forest labor share of a change in the price of forest goods is thus ambiguous and depends on the household's utility and endowments.

The response of the forest labor share to changes in the price of maize can be found *via* the relevant Slutsky decomposition:

$$\frac{\partial L_F}{\partial p_M} = \left.\frac{\partial L_F}{\partial p_M}\right|_{U=\overline{U}} + \frac{\partial L_F}{\partial Y}(Q_M - C_M)\,, \qquad [12]$$

where, as above, the first and second terms represent substitution and income effects. The substitution effect may be positive or negative. Assume first that households do not clear forest for maize production. They should therefore respond to a rising maize price by allocating more labor to maize and less to other activities, either (for net maize sellers) in pursuit of profit or (for net maize buyers) to avoid purchasing maize at a higher price. In this case, the substitution effect is negative. Some net buyers, however, may allocate more labor to both maize *and* forest activities, if the forest is open access, forest land is available, and forests are cleared to expand maize fields. In that case, the substitution effect is positive.

Income effect $\partial L_F / \partial Y$ in [12] may be positive or negative depending on the relative demand for leisure and forest products and whether the household is a net seller of forest goods. Term (Q_M - C_M) also is indeterminate. In sum, the net effect on the forest labor share of an increase in the maize price in equation [12] is ambiguous. Van Soest et al. (2002) similarly show that the effect on forest clearing of an increase in the price of agricultural output is indeterminate. In their case, the result reflects a negative substitution effect and positive income effect. In ours, the substitution and income effect are both indeterminate and can be pursued only through empirical investigation.

Finally, the Slutsky equation describing the impact on the forest labor share of a change in the price of non-forest goods is:

$$\frac{\partial L_F}{\partial p_O} = \left.\frac{\partial L_F}{\partial p_O}\right|_{U=\overline{U}} + \frac{\partial L_F}{\partial Y}(Q_O - C_O)\,. \qquad [13]$$

This substitution effect is unambiguously non-positive, but the income effect is indeterminate. Term $\partial L_F / \partial Y$ may be either positive or negative and depends on the relative demand for leisure and forest products and whether the household is a net seller of forest goods. Term (Q_O - C_O) in [13] is positive for net sellers and negative for net buyers of non-forest goods. In sum, the net effect on the forest labor share of a change in the returns to non-forest employment is ambiguous. A negative relationship could arise under several alternative scenarios: if the household is a net seller of non-forest goods and forest products are inferior goods; if the household is a net seller of non-forest goods and forest products are normal goods but either the income-induced demand for leisure outweighs that for forest products or the household buys rather than collects forest goods; if the household is a net buyer of non-forest goods, forest goods are normal, and the household collects rather than buys forest products; or if a negative substitution effect dominates a positive income effect.

The foregoing analysis reveals ambiguous relationships between forest labor share and returns to villager activities. Some analytical models instead have posited a positive relationship between agricultural output prices and deforestation, and a negative relationship between off-farm wages and deforestation (see Kaimowitz and Angelsen 1998 for a review). Our own model yields indeterminate results for three reasons: One, it is non-separable, permitting both income and substitution effects. These effects often have opposite signs, either effect potentially dominating the other (van Soest et al. 2002). Two, net buyers of maize, forest, and non-forest products respond differently to changing prices than do net sellers of these goods (Barrett 1999). Three, because households purchase additional land with labor alone, even substitution effects can be indeterminate. As a result the forest labor share can either rise or fall in response to a change in the maize price.

Empirical Model

Our empirical model is a system of three jointly estimated labor share equations, similar to that presented by Shively and Fisher (2004) for the Philippines. Explanatory variables include labor returns, household characteristics, farm size, and labor availability. Variable selection is based on the theoretical model presented earlier (see equation 10).[4] Key household characteristics impacting labor allocation decisions are age and education of the householder. Studies show household forest use changes over the life cycle. Godoy et al. (1998), for example, find that forest clearing increases with the age of the household head but at a decreasing rate. Forest use may be a less important livelihood strategy for households with a more educated head, because such households are better able to secure remunerative (non-forest sector) jobs. Empirical work generally supports this hypothesis (e.g. Godoy and Contreras 2001; Pichon 1997).

The labor returns relevant to labor supply functions are the households' shadow or opportunity prices, namely the returns they forego by substituting out of other lines of work. When households engage in a particular forest or non-forest activity, their shadow price/wage for that activity can be assumed to equal the observed return or wage. When they do not participate, it likely is because their shadow price exceeds the observed return. Thus, either omitting the nonparticipants or imputing their returns at predicted market return rates would bias our estimate of the aggregate supply response.

To eliminate such bias, we specify a system of equations predicting each household's shadow price/wage in each activity. Because any departure of shadow from market returns would largely be indicative of market nonparticipation, shadow values and market participation are jointly determined. A system of participation equations is estimated simultaneously with the shadow value equations, using maximum likelihood methods (Nawata 1994).[5] The participation equations serve essentially as endogenous dummy variables accounting for any gap between market price and household shadow price in a given activity, as influenced by household-specific transaction costs associated with participating in the market for that activity. Such a gap, in turn, depends on the conditioning variables in the shadow value equations since the latter serve to predict the household's shadow prices, which depend on the conditioning variables. Using predicted shadow prices for every observation in the labor share equations, rather than a combination of imputed and observed prices, helps purge the variables of possible measurement error or endogeneity. Additional details on the methods for predicting shadow prices/wages are included in the Appendix.

Every household in our sample purchased some maize, while 27 households sold some as well, suggesting the maize market is incomplete. An important gauge of market incompleteness is the spread which a household typically encounters between buying price and selling price. Maize price spreads are high in rural Malawi because producer risk and consumer risk aversion are high. Large price spreads in turn lead to high rates of self-provisioning, thin markets, and volatility. Nevertheless, because of small landholdings and limited use of improved inputs, few rural Malawian households are able to achieve their maize self-sufficiency goal (Alwang and Siegel 1999). We use consumer prices to represent the per-unit maize values of net-buying households, and producer prices to represent the per-unit values of net-selling households. In this way, an accurate measure is obtained of the value of labor that every household expends on home production. The Appendix provides details on the methods used to identify net buyers and net sellers in our sample.

Final labor share equations take the form:

$$L_i = \alpha_i + \sum_j \beta_{ij} LOG(p_j) + \sum_k \delta_{ik} H_k + \gamma_{i1} A_0 + + \gamma_{i2} T + \varepsilon_i \qquad [14]$$

where subscripts i, j represent maize production, forest employment, and non-forest employment, H_k represents household characteristics (age and education of household head), A_0 is size of landholding, and T is the ratio of dependents to laborers. The model is nonseparable and theory provides little guidance on exclusion restrictions for explanatory variables. As a result, we use identical sets of exogenous variables in each labor share regression.

Our labor share model is similar to standard models of commodity or factor demand such as the Almost Ideal Demand System (AIDS). As in an AIDS model, we constrain parameters across equations. By construction, observed labor shares sum to one. In order to ensure that predicted labor shares also sum to one, we impose:

$$\sum_j \beta_{ij} = 0 \qquad [15a]$$

$$\sum_i \beta_{ij} = 0, \quad \sum_i \delta_{ik} = 0, \text{ and } \sum_i \gamma_{il} = 0 \qquad [15b]$$

$$\sum_i \varepsilon_i = 0 \qquad [15c]$$

$$\sum_i \alpha_i = 1. \qquad [15d]$$

Homogeneity restriction [15a] requires that a given labor share be invariant to proportional changes in all prices. Constraint [15b] requires that the individual effects on labor allocation of changes in a given explanatory variable be offsetting, such that the net effect of a given change be zero. Constraint [15c] indicates that, for each observation, error terms across equations are linearly dependent. Constraint [15d], along with the adding-up restrictions, ensures that the estimated labor shares sum to one. The constraints collectively imply that labor allocation decisions are related across activities. To impose the restrictions, we divide the returns to maize and forest activities by the returns to non-forest employment. The non-forest equation is dropped to avoid singularity of the disturbance covariance matrix.

We estimate the system of labor share equations with constrained maximum likelihood (ML), ensuring that outcomes are invariant to choice of equation dropped (Greene 2000). Estimating equations follow the form:

$$L_i = \alpha_i + \sum_j \beta_{ij} LOG(p_j / p_O) + \sum_k \delta_{ik} H_k + \gamma_{i1} A_0 + \gamma_{i2} T + \varepsilon_i \qquad [16]$$

where i , j = maize, forest, respectively. In quantity-dependent demand models, the two restrictions

$$\beta_{ij} = \beta_{ji} \qquad \forall\ i, j, \qquad [17]$$

ensuring symmetry of cross-price effects, follow from economic theory. In labor share models, which predict percentage allocations rather than quantities of household time, symmetry is not required. We therefore test for rather than impose this symmetry.

III. STUDY AREA AND DATA

Data come from a survey of three southern Malawian villages, enumerated monthly from June 1999 through August 2000.[6] The research villages were selected to represent three forest management types and a spectrum of market access. Village 1 is 10 kilometers from a tarmac road and adjacent to a state forest reserve managed by the Forestry Department. Village 2 has a Village Forest Area (VFA) managed by a village headman and committee of village leaders. Village 2 is 20 kilometers from a tarmac road but close to Mozambique, where farm and forest commodities can be bought at prices below those in Malawi. Village 3 is next to a tarmac road linking it to Blantyre (Malawi's largest city), 40 kilometers away. Forest access in Village 3 is *de facto* open access. The entire sample consists of data from 99 households, representing 12 percent of the total population in the three villages.

Table 1 presents data on household labor allocation. Farming occupied the majority of household time during the survey period, but forest use was also substantial. Village differences in forest use are illustrated in table 2. While all households used some fuelwood for cooking, the main energy source in Village 2 was harvest residue, likely because of relative access to cassava, which produces considerable biomass. Wood purchases were most common in Village 2, either from Mozambique or from others in the village.

Wood marketing in Malawi and in the study site is an important source of household income. Although wood marketing is a violation of forest rules in Village 1 and 2, the Forestry Department (Village 1) and village head (Village 2) appeared largely ineffective in enforcing the rules during the survey period. Villages did exhibit differences in forest clearing and charcoal marketing, perhaps reflective of differences in forest management and market access. As elsewhere in Malawi, farm sizes were small, averaging 1.2, 1.0, and 1.9 hectares in Villages 1, 2, and 3, respectively. The forest is a key potential source of farm land, but forest clearing was common only in Village 3. Enforcement of rules prohibiting forest clearing in Villages 1 and 2 appears to have been effective, perhaps because it is easy to identify forest land cleared for farming. Charcoal marketing is profitable but occurred only in Village 3, likely because Villages 1 and 2 are far from charcoal markets.

Table 3 highlights the importance of forests for household livelihood. Sample households obtained 37, 20, and 41 percent of total earnings from forests in the three villages. Individuals engaged in a wide range of forest activities during the survey year (see note b. in table 1). The relatively high forest-earning shares in Villages 1 and 3 reflect intensive employment as sawyers and plank carriers in Village 1 and as charcoal sellers in Village 3. Table 4 provides descriptive statistics of variables in the econometric estimation.

IV. RESULTS AND DISCUSSION

Regression results for the system of three share equations are shown in table 5. The calculated *F*-statistic of 136.22 is significant at the 95% confidence level, providing support for the hypothesis of joint significance of the explanatory variables. Mean observed and predicted labor shares are reported for comparative purposes at the bottom of table 5.[7] Parameter estimates of the forest and maize equations are obtained directly from constrained ML estimation. Parameters of the non-forest employment equation are calculated from the adding-up restrictions. We use a likelihood ratio (LR) statistic to test the symmetry restrictions. The 95% chi-square test statistic for two restrictions is 5.99, exceeding the calculated LR statistic of 1.45. Thus, we fail to reject the null hypothesis of symmetry. A Wald test is used to test the homogeneity and adding-up restrictions. The associated 95% chi-square test statistic in the presence of 8 restrictions is 15.51, compared to the calculated Wald statistic of 212.21. The joint null hypothesis of homogeneity and adding-up is therefore rejected. Although this suggests our data are inconsistent with the restrictions, the rejection also may reflect the Wald test's tendency to over-reject true null hypotheses in small samples (Laitinen 1978). The use of predicted shadow prices/wages in the labor share equations is akin to instrumental variable estimation. We test for exogeneity of the predicted shadow prices, using an omitted-variable regression version of the Hausman test (Spencer and Berk 1981). In each equation, the calculated F-statistic (table 5) is less than the critical value of 3.09, implying the predicted shadow prices can be treated as exogenous.

Table 5 includes results for each labor share equation. Given our interest in forest pressure, we focus the discussion on results of the forest labor share. Robust standard errors in the table are calculated by adjusting White's (1980) heteroskedasticity-consistent covariance matrix estimator for the instrumental variables case.[8] Four of the point estimates in the forest labor share equation are individually different from zero at the 90% confidence level. The positive sign on forestry shadow prices in the forest equation indicates households that obtain higher returns to forest use allocate a greater share of household labor to the forest. This finding provides insight into the Slutsky decomposition of $\partial L_F / \partial p_F$. The positive sign indicates either that a positive substitution effect dominates a negative income effect or that both effects are positive. Under what circumstances would the income effect be positive? One reasonable assumption is that most sample households are either self-sufficient or net sellers of forest products.[9] In such case, households with extra cash on hand would likely use the cash to buy food rather than forest goods. Under this net seller assumption, a positive income effect implies the demand for forest products outweighs that for leisure. This seems plausible for poor households such as those in our sample. And since a large proportion of Malawi's population is chronically food insecure (Ellis, Kutengule, and Nyasulu 2003), households enjoying a small income rise likely would choose to buy more food – and collect fuelwood to cook it – rather than buy more leisure.

We find little statistical support for the hypothesis that the price of maize influences forest labor allocation. Our maize price variable may be insufficiently variable (see table 4) to estimate such a relationship precisely. Shadow prices for non-forest employment are negatively correlated with the forest labor share at the 0.15 probability level, consistent with patterns reported in Nepal (Bluffstone 1995) and the Philippines (Shively 2001). Recall that a negative sign for $\partial L_F / \partial p_O$ implies one of four possibilities: (i) the household is a net seller of non-forest goods and forest products are inferior goods, (ii) the household is a net seller of non-forest goods and forest products are normal goods, but either the income-induced demand for leisure outweighs that for forest products or the household buys rather than collects forest goods, (iii) the household is a net buyer of non-forest goods, forest goods are normal, and the household collects rather than buys forest products, or (iv) a negative substitution effect dominates a positive income effect. Scenarios (iii) and (iv) are most plausible in our sample. Forest products are unlikely to be inferior goods in rural Malawi, where fuelwood is the main fuel in households of a range of income levels (GOM 1998). For reasons outlined above, it also is unlikely that an income-induced demand for leisure outweighs that for forest products or that households enjoying a higher income choose to buy rather than collect forest goods.

To assess whether labor allocations change over the life cycle, we include binary variables for age of household head. We find that households headed by an individual over 45 years spend more time on forest activities than do those with a head aged 35 to 44 years. Our findings also show a negative correlation between forest labor share and secondary school attendance of the household head. A plausible explanation is that education signals employers about workers' potential productivity, increasing the likelihood of their being hired into attractive non-farm, non-forest jobs and thus reducing labor allocation to the less remunerative forest sector. This contention is further supported by results in the non-forest equation, which show a positive correlation between labor share and secondary education.

A priori, one might expect farm size per household resident to provide a good indication of a household's agricultural capacity and degree of food security (Ellis, Kutengule, and Nyasulu 2003). Households with relatively small landholdings per capita should have both the need and the capacity to engage in forest product commercialization and/or forest clearing. As expected, results reveal a negative correlation between landholding and forest labor allocation. Pichon (1997) similarly finds that households operating larger farms in Ecuador clear less forest. The "dependency ratio" variable has the expected negative sign in the forest labor share equation, suggesting households with a greater ratio of dependents to laborers may have less capacity to diversify into non-farm work. The correlation is statistically weak, however.

V. CONCLUSIONS AND POLICY RECOMMENDATIONS

We have examined the factors related to forest use by jointly estimating a system of labor share equations for maize production, forest employment, and non-forest employment. We might alternatively have estimated a single-equation Tobit model of forest labor allocation. However, a systems approach more closely corresponds to theory, as forest use is one of several livelihood strategies simultaneously undertaken by households located at forest margins. Systems approaches reveal relationships among these often-competing activities. For example, we find that forest and non-forest employment are substitutes for one another. A higher return to forest use increases the forest labor share and reduces the non-forest employment labor share. Likewise, as returns in the non-forest sector rise, households devote a greater share of their labor to non-forest employment and a lower share to forests. We also find that households headed by more educated individuals have lower forest labor shares and higher non-forest labor shares.

The positive relationship between forest returns and forest labor share provides a cautionary message for those concerned with forests in low-income settings. It is probable in the near term that returns to Malawian forest use will increase as the aggregate demand for forest products rises and the supply declines. Because of the recent elimination of subsidies, rising tariffs on paraffin and electricity, and rapid population growth in Malawi's urban areas, sales of woodfuels to urban consumers seems assured (GOM 1998). Urban population growth should also stimulate the demand for wood in construction and furniture making.

More optimistically, the positive own-price effects in each labor share equation suggest sample households respond to production and work incentives, an essential element in economic development. Likewise, negative cross-price terms in the share equations indicate labor can be drawn away from one sector through price incentives in another. For example, findings here and elsewhere indicate that public investment in the (non-forest) wage-work sector can be effective for reducing forest pressure (Bluffstone 1995; Shively 2001). Human capital investments and job creation will be essential to support such a strategy. Our findings highlight the potentially complementary role of educational investments: households with a head who had attended secondary school allocated a lower share of their time to forests than did others. Unfortunately, high-wage jobs are few in rural Malawi, where education beyond the primary level pays off mainly in urban areas (Mukherjee and Benson 2003). Expanding remunerative employment opportunities in rural areas may be useful for ensuring adequate economic and environmental returns to education. Non-forest employment in our study includes entrepreneurial activities. This may suggest that the self-employment sector, similar to the wage-work sector, can absorb labor that might otherwise be engaged in forest exploitation. Food-for-work interventions and credit schemes which are self-selecting for the poor may encourage participation in self-enterprise activities.

Finally, our findings suggest that low-income households become less dependent on forests as economic well-being (proxied by farm size per household resident) improves. If reduced forest reliance is positively correlated with reduced demand for forest products, a complementarity is in turn indicated between strategies aimed at poverty alleviation and those geared toward forest conservation.

APPENDIX

Predicted Shadow Price/Wage Method

Non-farm (forest and non-forest employment) wages are defined as the quotient of annual earnings or profits and hours worked. Annual hours worked are calculated by summing, over household members, the product of labor share and total hours worked in all activities.[10] Seventy-five percent of sample households reported earnings from forest employment; their average real wage (in September 2000 MK) was MK2.22 per hour (standard deviation = MK2.99). The participation rate for non-forest employment was 73 percent of households, with an average real wage of MK3.37 per hour (standard deviation = MK4.18). Wide variability in net hourly returns is unsurprising given the variety of activities in each sector (see table 1). We use maximum likelihood (ML) to predict shadow prices/wages for forest use and non-forest employment. For each sector, we estimate jointly a participation and shadow price equation in order to account for possible sample-selection bias. Estimated parameters from the shadow price equation are then used to predict a shadow price for each observation. ML results for the participation and shadow price equations are presented in table A.1. Exogenous variables in these equations are of two main types. One group includes identifying exogenous variables; a second consists of variables included in both the participation equation and shadow price equation.

Identifying the shadow price/wage and labor share equations requires (a) including at least one variable in the participation equation that does not enter the shadow price equation and (b) including one or more variables in the shadow price equation that is not included in the labor share equations. To identify the shadow price equations, we use two variables which we hypothesize affect participation in non-farm employment by altering the household's shadow price, but which do not directly affect the observed market wage. Size of the household's landholding affects its farm work productivity and, consequently, decisions to participate in non-farm employment *via* a substitution effect. However, landholding should not directly affect offered wages. We follow other labor market studies by using a "dependency ratio" variable to identify the shadow price equation (e.g. Abdulai and Delgado 1999). Wald test statistics for joint significance of the instruments are reported at the bottom of table A.1. At the 0.05 probability level, the instruments are jointly significant.

Identification of the labor share equations is achieved with use of location variables (village of residence binary variables), an approach employed in other labor market research (e.g. Abdulai and Delgado 1999). We expect that village-of-residence's effect on a given labor share operates through its effect on participation and shadow price rather than directly. Wald test statistics for the joint significance of the instruments used in each equation are shown at the bottom of table A.1. At 0.05 probability, the instruments are jointly significant. A Hausman omitted-variable test provides additional support for the validity of the instruments. (See note c. in table 5 and the accompanying text discussion.)

The remaining exogenous variables enter both participation and shadow price equations: the household head's age and attendance at secondary school, and share of men among household laborers. Age, a proxy for general experience, and education indicate potential productivity. Experience and education should increase an individual's probability of being hired for non-farm work and should be positively correlated with shadow price. We include share of men in the household labor force because men in our sample were more likely than women or children to engage in the more lucrative activities in the non-forest sector (e.g. forestry officer, grocery sales) and forest sector (e.g. charcoal sales), due either to hiring policy, credit access, or gender division of labor.

Identification of Maize Net Buyer and Net Seller Households

Among the sample households, most (N=72) are net buyers which had observed maize purchases but no reported maize sales. Among the other households, namely those that bought and sold some maize, we distinguish between net buyers and net sellers by comparing the household's total annual maize requirements with its expected maize output. If expected maize output is below the household's maize needs, the household is assumed to be a net maize buyer; otherwise it is classified as a net seller. Expected maize output is calculated as the household's reported planted maize area multiplied by 620, the median hybrid maize yield in a random sample of 3,046 households in southern Malawi in 1998 (Poverty Monitoring System 2000). We arrive at household-specific annual maize requirements as follows. We first observe the maize basic-needs threshold recently computed for rural Malawi (the Lamp 1999). The threshold amount of 75 kilograms per month represents the quantity of maize that a reference family of two adults and five children requires to meet basic food needs. The household survey data are then used to adjust the threshold for alternative family structures. We treat young children and children as half and three-quarters of an adult consumption unit, respectively. With these methods, we identify 13 net sellers and 14 net buyers among the households in which maize sales were reported.

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[1] Kumar and Hotchkiss (1988) emphasize gender factors in household labor allocations; Cooke (1998) incorporates the role of gender and seasonality.

[2] Over time, forest "thinning" may increase the probability of forest clearing, as thinning in the presence of population growth reduces the value of standing forest.

[3] If households had secure forest rights, which they do not, higher p_F would mean higher current and future land values and the effect on current L_F would be indeterminate.

[4] The theory suggests transaction costs and distance to trees also determine household labor allocation. Transaction costs are often proxied by transportation costs (e.g. distance to markets and the quality of roads and transport systems) (Omamo 1998). Data limitations preclude the inclusion of transaction-cost measures in the empirical model. Distance to trees should affect forest labor allocation decisions, because forest activities have a potentially large opportunity cost in terms of collection time (Heltberg, Arndt, and Sekhar 2000). We exclude a distance variable in the analysis, however, because people have some degree of choice regarding place of residence and forest collect site.

[5] ML is preferred over the Heckman two-step approach because ML is consistent and efficient, whereas the two-step method is not fully efficient (Nawata 1994) and sometimes performs poorly in small samples such as ours (Zuehlke and Zeman 1991).

[6] Some of the household survey data were obtained from a single interview (householder characteristics, demographics, physical assets, and tree planting). Other data were collected twice during the year (forest use, labor allocation, agricultural production, and landholding). Data on income and expenditures were collected on a quarterly basis.

[7] Constraints (15a) through (15d) ensure that the predicted labor shares sum to one but do not ensure that predicted values of individual labor shares fall within the (0, 1) range. In all observations, predicted labor shares for maize, forest, and non-forest fall within bounds.

[8] White's (1980) heteroskedasticity-consistent covariance matrix estimator is $(X'X/n)^{-1}\hat{V}_n(X'X/n)^{-1}$, where X is a matrix of observations on explanatory variables and

n is the sample size. The estimator $\hat{V}_n = n^{-1}\sum_{i=1}^{n}\hat{\varepsilon}_{in}^2 X_i^{'} X_i$, where $\hat{\varepsilon}_{in}$ are the residuals. As White (page 821) points out, an expression analogous to $\hat{V}_n$ can be obtained for instrumental variables estimators by replacing X_i with $\hat{X}_i$ and computing $\hat{\varepsilon}_{in}$ using X_i. Our situation is somewhat different from the usual instrumental variables case in that we have complete wage data for only a sub-sample (N=57 households). For this reason, we obtain residuals ($\hat{\varepsilon}_{in}$) for 57 observations only. We calculate White's standard errors in two different ways: first using the sub-sample to calculate $\hat{V}_n$ and the covariance matrix estimator, and second using the sub-sample to calculate $\hat{V}_n$ but the full sample to compute the covariance matrix estimator. Standard errors in table 5 are calculated with the second method. Standard errors calculated *via* the first method are slightly larger than in the second but the set of statistically significant parameter estimates is similar.

[9] Number of households selling wood (table 2) is likely underestimated, because sales of wood from the commons or state forest reserve are prohibited in Villages 1 and 2.

[10] Data are not available for total hours worked in all activities for the year. We assume girls, boys, and men worked 8 hours per day, 312 days per year. We assume women worked 10 hours per day, 312 days per year. An hour of girl or boy labor is valued at half an adult labor hour.

Table 1

Means and Standard Deviations of Labor Shares, by Activity and Village, 1999/2000

Activity	Village 1	Village 2	Village 3	All Villages
Agriculture	0.55	0.59	0.55	0.56
(L_M) [a]	(0.17)	(0.15)	(0.15)	(0.16)
Forest employment	0.32	0.23	0.28	0.27
(L_F) [b]	(0.16)	(0.07)	(0.13)	(0.13)
Non-forest employment	0.14	0.18	0.17	0.16
(L_O) [c]	(0.15)	(0.17)	(0.16)	(0.16)
Number of observations	39	38	22	99

a. L_M represents the share of labor allocated to agricultural activities. Agricultural activities include crop cultivation, livestock production, and agricultural marketing.

b. L_F denotes the forest labor share. Forest employment includes forest clearing, fuelwood collection for home use, and participation in forest-based wage-work and self-employment. Forest-based wage-work at the study sites are jobs as sawyers or plank carriers. Forest-based self-employment consists of raw wood and charcoal marketing, sales of food and drink prepared with large amounts of wood (e.g. traditional beer), carpentry, construction, sales of fired bricks, sales of certain crafts (e.g. wood-fired clay pots), and traditional medicine.

c. L_O represents the non-forest labor share. Non-forest employment includes non-forest wage-work and self-employment. Non-forest wage-work includes contract agricultural labor (clearing fields, building ridges, etc.), forestry officer, teacher, mechanic, and village head. Non-forest self-employment consists of resale of agricultural commodities, tailor, money lending, fish sales, grocery sales, public transport operation, bicycle repair, tinsmith, and stone breaking.

Table 2

Selected Forest Use Indicators, 1999/2000

Activity	Village 1	Village 2	Village 3	All Villages
Main cooking fuel is wood (%)	100	18	100	69
Quantity of wood collected (kg)	2128	1141	3354	2267
Cleared forest that year (%)	3	0	50	12
Area cleared (ha)	0.30	----	0.26	0.26
Purchased wood that year (%)	18	63	36	39
Sold wood that year (%)	18	26	45	27
Sold charcoal that year (%)	0	0	36	8
Planted trees in past 5 yrs (%)	31	71	64	54
Number of trees planted	10	9	19	12

Table 3

Earning Shares, by Activity and Village, 1999/2000

Activity	Village 1	Village 2	Village 3	All Villages
Agriculture	0.11	0.23	0.08	0.15
Forest employment	0.37	0.20	0.41	0.31
Non-forest employment	0.26	0.31	0.34	0.29
Asset sales [a]	0.05	0.07	0.07	0.06
Transfers [b]	0.20	0.19	0.09	0.17

a. Asset sales include sales of livestock (cattle, goats, pigs), poultry, personal and household items (radio, bicycle parts, clothing, etc.), and property rental.

b. Transfers include pensions, remittances from household residents (mainly husbands working elsewhere), gifts from relatives and friends, and loans.

Table 4

Descriptive Statistics of Explanatory Variables, 1999/2000

Variable	Mean or Frequency (Standard Deviation)
Observed maize price (Sept. 2000 MK/kg) [a]	8.65 (1.91)
Predicted shadow price/wage, forest activities (Sept. 2000 MK/hour) [b]	2.46 (2.00)
Predicted shadow price/wage, non-forest employment (Sept. 2000 MK/hour) [b]	2.96 (1.99)
Household head aged less than 35 years (0=No, 1=Yes) [c]	0.24
Household head aged 35 – 44 years (0=No, 1=Yes) [c]	0.13
Household head attended secondary school (0=No, 1=Yes)	0.10
Farm size per household resident (ha/person)	0.33 (0.32)
Dependency ratio (dependents divided by laborers) [d]	0.23 (0.30)

a. The observed maize price is the producer price for net maize sellers and the consumer price for net maize buyers. The producer maize price is the price received by sample households reporting maize sales. The consumer maize price is average price paid during the year based on household survey data for the quarters in which households purchased maize, and on Ministry of Agriculture and Irrigation data on monthly retail maize prices in southern Malawi.

b. See Appendix for a detailed description of the predicted shadow price/wage method.

c. Age is categorical because respondents generally were not aware of their age. Our approach was to estimate age with reference to a list of historical events. The first category (15 to 24 years) and second category (25 to 34 years), are combined because only four household heads fall into the first category.

d. Dependents are young children and the elderly. Laborers are women, men, girls, and boys.

Table 5

Constrained Maximum Likelihood Results for Labor Share Equations

	Forest Labor Share [a]	Maize Labor Share [a]	Non-forest Labor Share [a]
Constant	* 0.384 (0.097)	* 0.526 (0.099)	0.090 (0.094)
Predicted shadow price/wage, forest activities (Sept. 2000 MK/hour)	* 0.110 (0.038)	-0.018 (0.045)	* -0.092 (0.044)
Observed maize price (Sept. 2000 MK/kg)	-0.018 (0.030)	0.050 (0.031)	-0.033 (0.034)
Predicted shadow price/wage, non-forest employment (Sept. 2000 MK/hour)	-0.092 (0.065)	-0.033 (0.078)	* 0.125 (0.064)
Household head aged less than 35 years (0=No, 1=Yes)	-0.032 (0.027)	* -0.103 (0.028)	* 0.135 (0.026)
Household head aged 35 – 44 years (0=No, 1=Yes)	* -0.086 (0.036)	-0.044 (0.036)	* 0.130 (0.039)
Head attended secondary school (0=No, 1=Yes)	* -0.140 (0.052)	-0.065 (0.055)	* 0.205 (0.045)
Farm size per household resident (ha/person)	* -0.058 (0.030)	0.039 (0.035)	0.018 (0.022)
Dependency ratio (dependents divided by laborers)	-0.022 (0.044)	-0.007 (0.044)	0.029 (0.027)
Number of observations	99	99	99
Predicted	0.564	0.274	0.162
Observed	0.564	0.274	0.162
Hausman statistic [b]	2.166	1.677	0.309

a. * implies significance at the 0.10 probability level or better. Parenthetical terms are robust standard errors (White 1980).

b. Omitted-variable regression version of the Hausman test for exogeneity of the predicted shadow price/wage variables, distributed as an *F*-statistic with a critical value of 3.09 for two (numerator) and 88 (denominator) degrees of freedom at the 0.05 probability.

Table A.1
Maximum Likelihood Results for Participation and Shadow Wage [a]

	Forest employment		Non-forest employment	
	Participation	Log shadow price/wage	Participation	Log shadow price/wage
Constant	* 0.669 (0.021)	* 0.749 (0.160)	* 0.752 (0.308)	* 0.932 (0.199)
Identifying exogenous variables				
Dependency ratio (dependents/laborers)	* -0.682 (0.066)		0.347 (0.531)	
Farm size per household resident (ha/person)	* -0.398 (0.092)		* -1.467 (0.378)	
Village 1 residence (0=No, 1=Yes)	* 0.308 (0.125)	-0.332 (0.180)	* -0.631 (0.193)	* -0.246 (0.126)
Village 2 residence (0=No, 1=Yes)	0.198 (0.151)	* -1.012 (0.040)	-0.353 (0.333)	* -0.461 (0.053)
Remaining exogenous variables				
Household head aged less than 35 years (0=No, 1=Yes)	* 0.296 (0.119)	0.096 (0.596)	1.112 (0.804)	-0.131 (0.199)
Household head aged 35 - 44 years (0=No, 1=Yes)	-0.402 (0.237)	* 0.887 (0.126)	0.556 (0.301)	0.073 (0.520)
Head attended secondary school (0=No, 1=Yes)	-0.671 (0.389)	* 1.110 (0.290)	0.758 (0.782)	* 1.060 (0.420)
Share of men among household laborers	* 1.089 (0.180)	0.820 (0.870)	2.291 (1.343)	* 0.993 (0.488)
Number of observations	99	75	99	73
Wald statistic [b]	6615.78	112.24	19.88	166.78

a. * implies significance at the 0.10 probability level or better. Parenthetical terms are robust standard errors, adjusted for clustering on village of residence to account for possible non-independence of observations within villages. We expect households living in the same village to be similar to each other on account of shared social and economic opportunities or residential selection processes.

b. Wald test for joint significance of the instruments, distributed as a χ^2 with a critical value of 5.99 for two degrees of freedom at 0.05 probability.