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Does Participatory Forest Management Increase Forest Resource Use to Cope with Shocks?

Empirical Evidence from Ethiopia

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Abstract

The government of Ethiopia has extensively adopted participatory forest management (PFM) programs. However, there is very little empirical evidence on whether PFM practices in Ethiopia enhance the capacity of rural households to cope with shocks. This study looks into whether forest income and share of forest income are higher for PFM members than non-members when faced with shocks. The study also examines the role of shocks on the decision to participate in PFM and the effect of PFM membership on forest income and share of forest income. We use household level data collected in 2018 from a large, representative sample of PFM sites and, unlike most other studies, we apply both propensity score matching and switching regression models in the analysis. Unlike most other studies, our findings show that forest income and share of forest income are not responsive to either idiosyncratic or covariate shocks for either PFM participants or non-participants. However, we find that households are more likely to become PFM members if they have experienced economic shocks. Considering the role of forest income in general (not specifically during a time of shocks), we find that PFM participants obtain more forest income than non-participants, but that the share of forest income in total income is higher for non-participants.

Keywords: PFM, shocks, forests, rural Ethiopia, switching regression

JEL Codes: O12, O13, Q23

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Abstract

The government of Ethiopia has extensively adopted participatory forest management (PFM) programs. However, there is very little empirical evidence on whether PFM practices in Ethiopia enhance the capacity of rural households to cope with shocks. This study looks into whether forest income and share of forest income are higher for PFM members than non-members when faced with shocks. The study also examines the role of shocks on the decision to participate in PFM and the effect of PFM membership on forest income and share of forest income. We use household level data collected in 2018 from a large, representative sample of PFM sites and, unlike most other studies, we apply both propensity score matching and switching regression models in the analysis. Unlike most other studies, our findings show that forest income and share of forest income are not responsive to either idiosyncratic or covariate shocks for either PFM participants or non-participants. However, we find that households are more likely to become PFM members if they have experienced economic shocks. Considering the role of forest income in general (not specifically during a time of shocks), we find that PFM participants obtain more forest income than non-participants, but that the share of forest income in total income is higher for non-participants.

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1. Introduction

Empirical evidence from developing countries indicates that forest products play a significant role in rural livelihoods, particularly for the rural poor. Almost a quarter of a billion people live in or around the dry forests of sub-Saharan Africa (CIFOR, 2008), and most of them depend on forests for food, fuelwood, building materials, and non-wood products, such as medicinal plants, fodder and spices. Tesfaye et al. (2020), Beyene et al. (2019) and Heubach et al. (2011) find that households derive 10-60 percent of their income from forests and forest resources. Moreover, forests provide important ecological services, including soil erosion control, biodiversity conservation, climate change adaptation and mitigation, fertility enhancement and watershed protection. In addition to timber and firewood, Ethiopia's forests are sources of non-timber products such as wild coffee, honey, spices, beeswax, bamboo, herbal medicines, gums and resins. Forests may also serve as safety nets during crises (Takasaki et al. 2004).

In the 1990s, as part of efforts to enhance the contributions of forests, Ethiopia started implementation of Participatory Forest Management (PFM), which devolves forest control from national or regional state authorities to forest user groups.[1] Several studies in Ethiopia have shown PFM contributing to improvement in forest conditions and livelihoods of the people surrounding the forest (Tesfaye et al. 2011; Tesfaye et al. 2020; Aklilu 2014). Recognizing this potentially positive role of PFM, the Federal Government of Ethiopia plans to increase forest cover (MEFCC 2018).

In sub-Saharan Africa, where credit and insurance markets are often incomplete, the option to extract forest products from communally owned forests can be an important insurance mechanism, especially for poor households (Delacote 2009). Rural households often face shocks, such as illness, death, drought, floods, and variability in prices of farming inputs and outputs. Faced by such shocks, households can use forest resources for either consumption smoothing or income smoothing. However, Wunder et al. (2014a) argue that forests have limited capacity to buffer against household shocks. Our paper explores this question.

When rural households in Ethiopia face covariate (community-wide) and idiosyncratic (individual) shocks, they adopt different types of coping mechanisms (Yilma et al. 2014).

[1]In other parts of the world, formal forest collective action such as PFM may be called community forestry or social forestry.

Shock-related studies in Ethiopia include Dercon (2004), Ali (2015) and Porter (2012), who assess the impact of shocks on consumption. Coromaldi (2020) and Yamano et al. (2005) examine household mechanisms to cope with shocks. However, there is limited literature on the effect of shocks and other household and village level covariates on forest resource extraction in Ethiopia. Unlike previous studies, this study uses a relatively large sample size and rigorous methodologies to examine the causal effect of PFM in facilitating the use of forests as safety nets during shocks.

The limited evidence on the impact of PFM is all positive with respect to improving forest conditions (Tadesse et al. 2016), providing livelihoods for local people (Kassa et al. 2009; Takahashi and Todo 2012; Gobeze et al. 2009), reducing income and gender inequality and protecting minority groups (Tesfaye et al. 2010; Gatiso and Wossen 2015; Gobeze et al. 2009), and supporting the provision of non-timber forest products (NTFPs), particularly for poorer households (Beyene et al. 2019). However, these references were all drawn from site-specific case studies. In contrast, our paper provides broad-based evidence using rigorous quasi-experimental methods to identify causal effects. We analyze a sample of households in Oromia, Ethiopia's most populous regional state, as well as the Southern Nations Nationalities and Peoples (SNNP) and Beneshangul Regional States. In total, these regional states include over 40% of the country's population.

Numerous studies have highlighted the important role of forests in providing safety nets and resources for seasonal gap-filling (e.g., Angelsen and Wunder 2003; Shively 1997; Volker and Waibel 2010). Using survey data from the Brazilian Amazon, Pattanayak and Sills (2001) find that households rely on forests to mitigate agricultural risk. Takasaki et al. (2004) find that increased collection of NTFPs is a common response to flood shocks in Peru. Lopez-Feldman (2014) shows that natural resources provide some sort of insurance for households that are subjected to negative agricultural shocks in rural Mexico. Debela et al. (2012) find that asset-poor households in Uganda depend on forests when faced with shocks related to non-labor assets. Similarly, McSweeney (2004) finds that households in Honduras sell forest products to pay for crop shortfalls and illness. The use of forests in response to shocks may also depend on the wealth status of rural households. For example, Fisher and Shively (2005) find that asset-poor households in Malawi are more dependent on forests for coping with shocks. Similarly, Kalaba et al. (2013) find that forests are important to cope with idiosyncratic shocks and seasonal food stresses and are relatively more important for the poor who do not have alternative options. Fisher et al. (2010) find that forests act as a safety net for the poor in rural Malawi by providing food during shortages, and as a source of cash for coping with weather-related crop failure. Using data from multiple continents, Wunder et al. (2014a) argue that forest resources play a relatively small role as buffer against shocks and seasonal income gap fillers and that households prefer to engage in other types of activities than exploiting forests.

Though non-timber forest products play a role as a seasonal safety net resource, empirical evidence on the role they play in times of shocks is limited (Paumgarten 2005). As argued by Volker and Waibel (2010), most available evidence on the role of forests as safety nets for both shocks and seasonality is based on qualitative studies (see, for example, Wunder et al. 2014a; Kalaba et al. 2013; and Paumgarten 2005). Furthermore, rigorous empirical studies on the role of forest management in mitigating the effect of shocks are lacking in sub-Saharan Africa in general and Ethiopia in particular. More specifically, there is a lack of empirical evidence on whether PFM institutions enhance the capacity of rural households to cope with covariate and idiosyncratic shocks. Unlike most previous studies on the topic, which use qualitative or descriptive quantitative studies, we use endogenous switching regression and propensity score matching models, which have the potential to estimate causal impacts.

The main objective of this research is to look into the role of forest resources as a safety net during shocks for members of PFM compared with non-members. In addition, we examine correlates of the decision to participate in PFM, including experiencing shocks as one of the variables, and the impact of PFM membership on forest income and share of forest income.

The rest of the paper is organized as follows: The next section discusses the empirical approach we used in the paper, including the impact evaluation framework. Section three describes the study sites, the nature of the data and the sampling techniques. It also describes the main variables used in the empirical analysis including the various types of shocks. The results of the empirical analyses are presented and discussed in section four. The last section presents the conclusions and policy implications of the study.

2. Empirical Approaches

We apply propensity score matching and endogenous switching regression models in the analysis.

2.1. Propensity score matching (PSM)

Our main objective is to understand whether forest resource use in response to shocks is related to membership status.[2] The differences in forest resource use between the participating and nonparticipating households could be calculated by just taking simple mean differences between the two categories. However, this would not allow us to attribute any difference in forest resource use in the presence of shocks to PFM membership. Since our data is cross-sectional, collected at one point in time, we do not have information on the counterfactual.

This analysis uses two outcome variables; 'forest income', and 'share of forest income'. Let us consider the following equation

$$y_i = \alpha + \beta x_i + \gamma c_i + \delta s_i + \varepsilon_i \qquad (1)$$

where the outcome variable (y_i) is forest income (or share of forest income, i.e., forest dependency). Forest income is defined as the value of forest products collected by the household in a year. Share of forest income is used as a measure of forest dependency and is defined as forest income as a share of the household's total income. The explanatory variables are participation in the program (c_i), household level variables (x_i), and various types of shocks (s_i). ε_i is the error term. y_i measures the impact of PFM membership on the outcome variable.

The main problem with estimating equation (1)is selection bias. The estimator is unbiased only if the mean counterfactual observed outcome from the nonparticipant group is truly equal to the counterfactual (i.e., the outcome for the participant group had they not participated). Self-selection bias arises if unobservable factors influence the error terms of both the selection equation and the outcome equation, resulting in a correlation between the two error terms. Moreover, estimation using ordinary least squares (OLS) would yield biased estimates. To address this selection problem, we apply a statistical matching method (Dehejia and Wahba 2002). This method involves comparing participants and non-participants who are similar in their observable attributes.

Let us define T as a binary variable equal to 1 if the household is a member or participant in the program, and zero otherwise; (y_1) and $(y_0)$are the outcomes achieved by the participants and

[2]We use membership and participation interchangeably.

non-participants, respectively. The individual treatment effect could be measured as the difference between the two, but this is not possible because we observe only one of the two potential outcomes. Therefore, we follow the propensity score matching (PSM) method introduced by Rosenbaum and Rubin (1983). The average effect of the treatment on the treated (ATT) for an individual who has access to membership is the difference between the expected outcome variable with and without participation in PFM.

$$ATT = E[Y(1) - Y(0)|T = 1]$$

$$ATT = E[Y(1)|T = 1] - E[Y(0)|T = 1] \tag{2}$$

The problem with the above equation is that we cannot control for unobserved heterogeneity, which may influence both participation and the two outcome variables (Smith and Todd 2005). Therefore, we first estimate the participation equation, i.e., the probability of participation in the program, which is the propensity score. We then calculate the ATT as follows:

$$T_{ATT}^{psm}(X) = E[Y(1)|T = 1], P(X)] - E[Y(0)|T = 1, P(X)] \tag{3}$$

Finally, a balancing test is required for the matching estimation method to check whether differences in the covariates in the two groups have been eliminated. The balancing test is satisfied if the average propensity scores of the treated and control units do not differ in each block. The test we use follows Rosenbaum and Rubin (1985).

2.2 Endogenous switching regression

An endogenous switching regression takes into account the possible endogeneity of the participation decision. It does so by estimating a simultaneous equation model of PFM membership and the outcome variables (total forest income and share of forest income) by full information maximum likelihood (FIML) which is an efficient method following Carter and Milon (2005), Maddala and Nelson (1975), Lokshin and Sajaia (2004) and Di Falco et al. (2011).[3] The regression models are specified as a two-stage framework to model both the role of shocks and other control variables in the participation decision and the impact of participation on forest income or share of forest income in the presence of a shock.

Let P_i^* be the latent variable that captures the expected benefits from the decision to participate.

[3]PFM arrangements are different in different parts of the country.

$$P_i^* = \overline{V_i} + \eta_i = Z_i\alpha + \eta_i \tag{4}$$

where $P_i = \begin{cases} 1 & if \quad P_i^* > 0 \\ 0 & otherwise, \end{cases}$

that is, household *i* will choose to participate in a PFM group if the net utility from participation (membership) is greater than the net utility from non-participation.

Equation (1) includes a deterministic component $(\overline{V_i} = Z_i\alpha)$ and an idiosyncratic unobserved stochastic component η_i which captures all the variables that are relevant to the household's decision maker but are unknown to the researcher. Since households themselves decide whether or not to participate (self-selection), the participation decision is likely to be influenced by unobservable characteristics (e.g., motivation or awareness of PFM) which may be correlated with the outcome of interest. Households were not randomly assigned to participant and non-participant groups. As a result, simple OLS estimates of the forest income and share of forest income functions, by including a dummy right-hand side variable with value of 1 for participants and 0 otherwise, might yield biased estimates because the model assumes that the decision to participate is exogenously determined. For example, those households with better understanding may be those opting to participate, and not controlling for these factors could lead to an upward bias in the estimate. Hence the observed net benefits from a household's decision to participate is defined in terms of two regimes as follows:

Regime 1: $y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \quad if \quad P_i = 1$ (5a)

Regime 0: $y_{0i} = \beta_0 X_{0i} + \varepsilon_{0i} \quad if \quad P_i = 0$ (5b)

Here, y_{1i} and y_{0i} are the outcome variables for the participants and non-participants respectively. X_{1i} and X_{0i} represent a set of household- and community-level variables including age and sex of household head, family size, asset ownership (e.g., livestock ownership), access to infrastructure (e.g., distance to nearest market), various types of shocks and other relevant control variables. β_1, β_0 are vectors of parameters, and μ is the error term.

We assume that the error terms in both equations, i.e., $(\eta, \ \varepsilon_0, \varepsilon_1)'$, have a trivariate normal distribution, with mean vector zero and covariance matrix Σ.

$$\Sigma = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix}$$

where σ_η^2 is the variance of the error term in the selection equation (4), σ_1^2 and σ_0^2 are the variances of the error terms in the outcome equations (5*a*) and (5*b*), and $\sigma_{1\eta}$ and $\sigma_{0\eta}$ represent the covariance of η_i and ε_{1i} and ε_{0i}.

The expected values of the error terms in equations 5a and 5b, ε_{1i} and ε_{0i} ,conditional on the sample selection, have non-zero expected values. Hence, the expected values are:

$$E[\varepsilon_{1i} | P_i = 1] = \sigma_{1\eta} \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} = \sigma_{1\eta}\lambda_{1i}$$

and $E[\varepsilon_{0i} | P_i = 0] = -\sigma_{0\eta} \dfrac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} = \sigma_{0\eta}\lambda_{0i}$

where $\phi(.)$ and $\Phi(.)$ are the standard normal probability density and the standard normal cumulative density function, respectively, and $\lambda_{1i} = \dfrac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)}$ and $\lambda_{0i} = \dfrac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$.

If the estimated covariances $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{0\eta}$ are statistically significant, then the decision to participate and the outcome variables, i.e., forest income and share of forest income, will be correlated indicating the presence of unobservables not known to the researcher. In other words, there will be evidence of endogenous switching and the null hypothesis that there is no sample selectivity bias will have to be rejected. .

The average forest resource use by participants and non-participants can be computed by comparing the expected values of the outcomes (for both participants and non-participants) in actual and counterfactual scenarios (see, for example, Carter and Milon 2005; Di Falco et al. 2011). Appropriate tests for endogeneity of participation are also conducted.

One of the issues in the estimation of endogenous switching regression model is identification — that is, we need a variable that can be used as an exclusion restriction which has a direct impact on participation but does not directly affect the outcome variable (forest income or share of forest income). For this purpose, we use variables representing whether any member of the household is a member of an agricultural producer group, tree nursery group or watershed management group. The selection of variables related to social capital follows the suggestion by Jumbe and Angelsen (2006), who argue that whether a respondent had previously been a member of an organization involved in collective action (e.g., farmers' associations, tree planting groups, credit associations) affects the probability of participation. However, past experience in participation in such local institutions by itself may not directly affect household forest earnings (Jumbe and Angelsen, 2006). In addition, the number of years the household has resided in the village (Mazunda and Shively, 2015) is considered to affect the decision to participate in the PFM, but we believe that this variable does not have a direct impact on the outcome variable.

Though the selected instruments are intuitively sensible, we need to support our choices with statistical tests. Following Di Falco et al. (2011), we establish the admissibility of these instruments by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the participation decision, but it will not affect the total annual value of forest resources collected by non-participating farm households.

The endogenous switching regression model can be used: (1) to compare the expected forest incomes of households that engaged in PFM with farm households that did not participate, and (2) to investigate the expected forest income in the counterfactual hypothetical cases (2a) that the participants did not participate, and (2b) that the non-participants participated.

The conditional expectations for forest income in the four cases are defined as follows:

$$E(y_{1i}|P_i = 1) = X_{1i}\beta_1 + \sigma_{1\eta}\lambda_{1i} \qquad (6a)$$

$$E(y_{0i}|P_i = 0) = X_{0i}\beta_0 + \sigma_{0\eta}\lambda_{0i} \qquad (6b)$$

$$E(y_{0i}|P_i = 1) = X_{1i}\beta_0 + \sigma_{0\eta}\lambda_{1i} \qquad (6c)$$

$$E(y_{1i}|P_i = 0) = X_{0i}\beta_1 + \sigma_{1\eta}\lambda_{0i} \qquad (6d)$$

As shown in Table 1, (a) and (b) along the diagonal represent the actual expectations observed in the sample, while (c) and (d) represent the counterfactual expected outcomes.

Table 1. Conditional expectations, treatment and heterogeneity effects

Subsamples	Decision stage		Treatment Effects
	To participate	Not to participate	

Households that participated	(a) $E(y_{1i}\|P_i = 1)$	(c) $E(y_{0i}\|P_i = 1)$	TT
Households that did not participate	(d) $E(y_{1i}\|P_i = 0)$	(b) $E(y_{0i}\|P_i = 0)$	TU
Heterogeneity effects	BH1	BH0	TH

Note: (a) and (b) represent observed expected forest income; (c) and (d) represent counterfactual expected forest income. As defined before, *Pi* =1 if household participated in PFM and *Pi*=0 if household did not participate. Share of forest income replaces 'forest income' when the former is the outcome variable analyzed.

TT, which is the average treatment effect, is the change in the outcome due to participation.[4] It can be specified as the difference between participation (a) and non-participation (c). Thus, the expected outcomes from equations [6a] and [6c] are used to obtain unbiased estimates of participation effects:

$$TT = E(y_{1i}|P_i = 1) - E(y_{0i}|P_i = 1)$$
$$= \mathrm{X}_{1i}(\beta_1 - \beta_0) + (\sigma_{1\eta} - \sigma_{0\eta})\lambda_{1i} \tag{7}$$

where $\sigma_{i\eta}$ is the covariance of the error terms and λ_{1i} the inverse Mills ratios. It is important to note that if self-selection is based on comparative advantage, $(\sigma_{1\eta} - \sigma_{0\eta})$ would be positive, indicating that participation in PFM would result in higher forest income than under random assignment (Maddala 1986).

Hence, TT represents the effect of participation in PFM on the forest income or share of forest income of the participating households. Similarly, for households that actually did not participate, the effect of the treatment on the untreated (TU) can be calculated as the difference between (d) and (b) (in Table 1),

$$TU = E(y_{1i}|P_i = 0) - E(y_{0i}|P_i = 0)$$
$$= \mathrm{X}_{0i}(\beta_1 - \beta_0) + (\sigma_{1\eta} - \sigma_{0\eta})\lambda_{0i} \tag{8}$$

[4]Propensity score matching (PSM) has been widely employed to estimate the average treatment effect. A limitation of PSM is that it assumes selection is based on observable variables only. However, in cross-sectional data, the presence of unobserved characteristics in the propensity score estimation can create mismatching and biased estimators (Heckman and Navarro-Lozano 2004).

The last row of Table 1 presents the heterogeneity effects, which can be calculated from equations (6a) to (6d). For example, households that decided to participate may have higher or lower forest income or share of forest income due to other endogenous determinants of household forest extraction (Carter and Milon 2005). This is the effect of base heterogeneity. The difference between (a) and (d) gives us the effect of such "base heterogeneity" for the group of households that decided to participate (BH_1). That is,

$$BH_1 = E\left(y_{1i} \middle| P_i = 1\right) - E\left(y_{1i} \middle| P_i = 0\right) = \left(\mathrm{X}_{1i} - \mathrm{X}_{0i}\right)\beta_{1i} + \sigma_{1\eta}\left(\lambda_{1i} - \lambda_{0i}\right) \qquad (9)$$

Similarly "the effect of base heterogeneity" for the group of households that decided not to participate (BH_0), will be the difference between (c) and (b),

$$\begin{aligned} BH_0 &= E\left(y_{0i} \middle| P_i = 1\right) - E\left(y_{0i} \middle| P_i = 0\right) \\ &= \left(\mathrm{X}_{1i} - \mathrm{X}_{0i}\right)\beta_{0i} + \sigma_{0\eta}\left(\lambda_{1i} - \lambda_{0i}\right) \end{aligned} \qquad (10)$$

Finally, the "transitional heterogeneity" (TH) effect in the last row and last column of Table 1 is the difference between equations (7) (TT) and (8) (TU). It shows whether forest income or share of forest income is larger or smaller for households that actually participated than for households that did not actually participate in the counterfactual case that they did participate.

3. Study Sites and Descriptive Statistics

3.1 Study site and sampling

We use data collected in 2018. The sample sites were from regions where PFM is widely adopted: Oromia, SNNP and Beneshangul. In attempting to make the sample representative, we used biomes for forest reference level (FRL) assessment as general strata. These were moist evergreen Afro-montane forest, *Combretum-Terminalia* woodland and wooded grassland (CTW), and dry evergreen afro-montane forest and grassland. Sample sites were then selected purposely from these regions. After considering the nature of forests under PFM, 50% of the total sample were taken from Oromia, and the remaining 50% from the SNNP (33.3%) and Beneshangul (16.7%) regions. Thirty sample households per PFM community (20 members and 10 nonmembers) were selected using a systematic random sampling technique, yielding a total of 900 households from 30 communities.[5] Information from the sample farm households was gathered in face-to-face interviews using a structured questionnaire. Experienced field workers, who could speak both the local language and English, were hired to conduct the fieldwork. The information collected includes details of each household's socioeconomic characteristics, including health and social capital, their forest products collection and consumption, production and labor allocation in agricultural and non-agricultural activities, experience of various types of shocks, credit markets, and their perceptions of forest values, rules and regulations, and forestry programs.

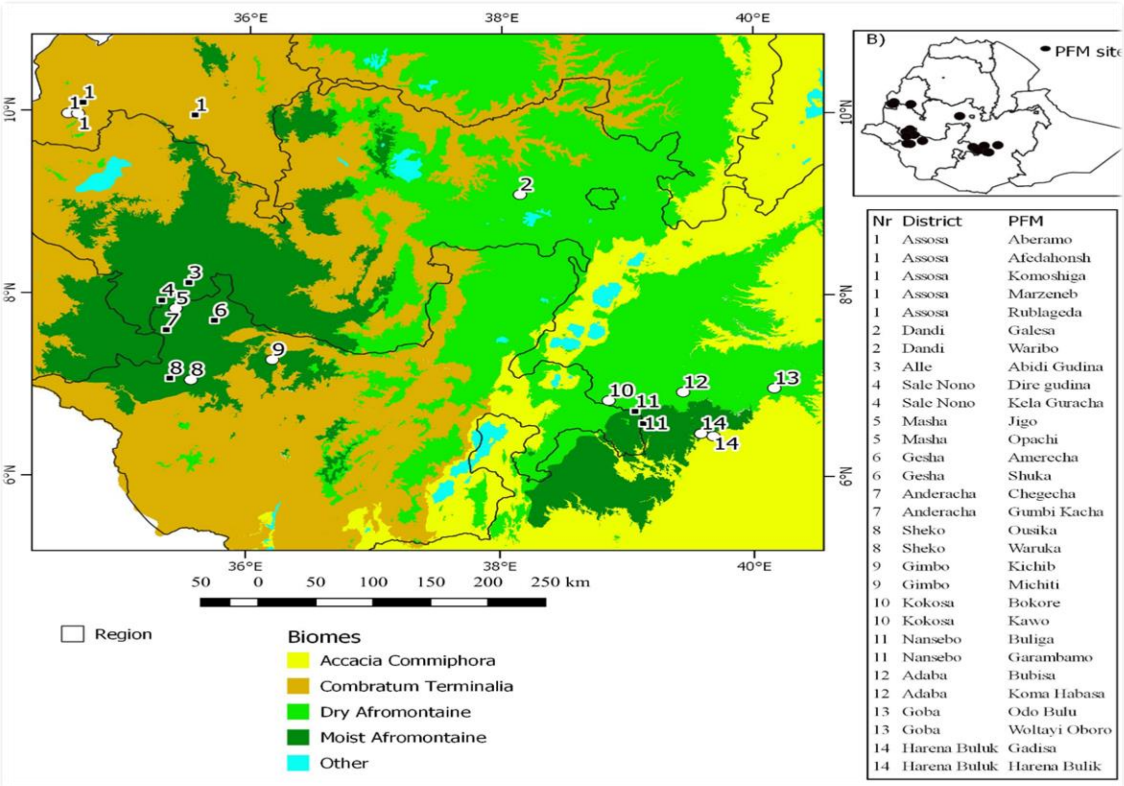


Figure 1. Map of the PFM study sites across the biomes of Ethiopia

Information on PFM programs: PFM is a forest management policy which involves local communities living in and around forest areas to achieve better and sustainable forest development through balancing conservation and utilization (MoA 2012). PFM aims to mobilize and organize local communities and to transfer management responsibilities to them. The PFM approach was initiated in Ethiopia in the 1990's by international NGOs, mainly by

[5]The total number of households was determined based on the budget allocated for the study. Unlike other empirical studies in Ethiopia and most sub-Saharan African countries conducted on PFM areas, the current study employed a household survey with a large sample size, which is an advantage for the statistical analysis.

SOS Sahel, FARM-Africa, GTZ and JICA (Gobeze et al. 2009). The program tries to promote sustainable forest management and help solve problems in the forest sector by involving local communities (Gobeze et al. 2009). The major PFM intervention sites in Ethiopia have been Oromia and SNNP, and it is currently being expanded to other regions of the country. The scaling up of PFM in Ethiopia has been emphasized in government forest policy. For example, the national REDD+ strategy plans to expand forests under PFM to 4 million hectares by 2030.

3.2. Descriptive statistics

In this section we present descriptive statistics summarizing the variables used in the empirical analysis. We further test whether there is any statistical difference between those collected from participants and non-participants. We also present the type and frequency of various types of shocks faced by sampled households in the two years before the survey.

Table 2 summarizes the descriptive statistics of variables used in the empirical analysis. We included variables based on related literature on forests. On average, sample household heads are 40 years old, 97% are male and 93% are married. More than 90% of the sample household heads can read and write. We expect that those who can read and write are more likely to participate because they are more aware of the advantages of being a member of the PFM.

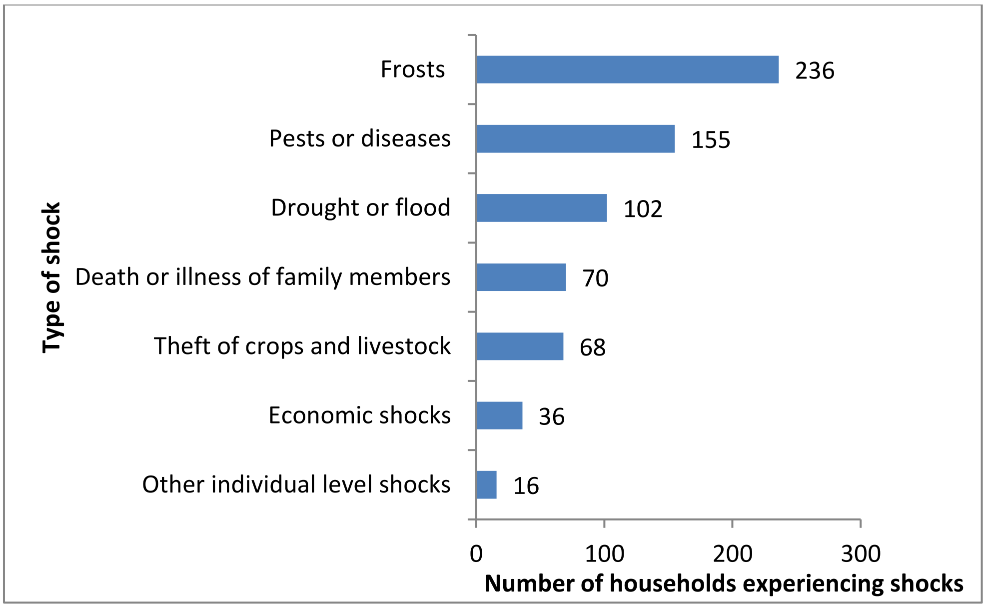
Asset ownership and related economic factors are included in the analysis. The average interviewed household had a land size of 0.6 ha and 3.8 tropical livestock units (TLU) of livestock. The role of these variables in forest resource use has been examined in several studies. However, the empirical evidence is mixed.

This study focuses on the role of PFM membership on households' forest income or share of forest income when the households are subject to shocks. To understand whether the shock type affects the coping mechanisms of households, we consider different types of shocks self-reported by respondents.

Rural households face various types of shocks, which we divide into idiosyncratic and covariate shocks. We classify idiosyncratic (individual level) shocks into the following three categories: theft of crops and livestock, death or illness of family members, and other individual-level shocks. We classify covariate shocks (which are shocks at community level or higher) into the following four categories: drought or flood, frosts, pests or diseases, and economic (lack of access to inputs and price shocks). Figure 2 presents the number of households that experienced each of these covariate and idiosyncratic shocks.

In the study areas, the most frequently reported covariate shocks are frosts, followed by pests or diseases, and then drought or flood. The most frequently reported idiosyncratic shocks are death or illness of family members, followed by theft of crops and livestock (Figure 2).

Figure 2. Number of households that experienced shocks



As shown in Table 2, more than 42% of sample households reported facing covariate shocks, while about 15% reported idiosyncratic, individual-level shocks in the two years before the survey.

Social capital indicators were included in the survey to help in assessing their contribution to the participation decision. A priori, membership in collective action was expected to encourage the decision to participate in PFM. For example, Jumbe and Angelsen (2006) and Abdulai and Huffman (2014) argue that membership in farmers' organizations, such as agricultural producer groups, constitutes a social network that will facilitate information about new technologies. We therefore expect a positive relationship between PFM membership and social capital indicators.

As discussed later, we do not expect these social capital indicators to have any significant and direct impact on forest income or share of forest income.

The number of years the household had lived in the village was included to assess whether this affected their participation decision. On average, a household has been in the village for more than 35 years (Table 2). We expect a positive relationship between this variable and participation. However, we do not expect the number of years lived in the village to have any direct effect on the amount of forest resource extraction. In order to consider the effect of location-related factors on forest resource use, we included distance from the nearest market. On average, it takes around two hours (two-way walking) to reach the nearest market and return home. The evidence in the literature on this is mixed but most argue that those far from markets are more likely to extract more forest resources. Similarly, the distance of the household from the forest is included in order to understand its effect on the decision to participate as well as amount of forest resource use. On average, the two-way walking distance from the household's residence to their PFM site is 65 minutes (Table 2). This is expected to be negatively correlated with the decision to participate as well as the amount of forest resources to be extracted.

Table 2 also shows households' PFM membership status (participants and non-participants) and whether there are statistically significant differences in the average values of the variables between the two groups. The last column shows the t-statistics, which indicate that there are statistically significant differences between participants and non-participants.

The occurrence of covariate and individual shocks is higher amongst participants. Around 45% of PFM participants had faced covariate shocks, compared to about 38% of non-participants. In addition, the experience of individual shocks is greater amongst participants (17%) than amongst non-participants (11%). For both covariate and individual shocks, the differences are statistically significant at a 5% level.

Table 2. Descriptive statistics for PFM participant and non-participant sample households

Variables	Total (1)		Participants (2)		Non-participants (3)		Difference (t-test)
HH Characteristics	**Mean**	**S. D.**	**Mean**	**S. D.**	**Mean**	**S.D.**	**(3-2)**

Age of HH head in years	40.550	13.183	43.218	12.561	35.231	12.795	-7.987***
Gender of head is male	0.970	0.171	0.980	0.141	0.950	0.219	-0.030***
HH head is married	0.934	0.248	0.956	0.204	0.890	0.314	-0.067***
HH head can read and write	0.806	0.396	0.810	0.392	0.796	0.404	-0.014
Family size in ade	4.382	1.993	4.863	1.957	3.424	1.699	-1.440***
Asset ownership							
Land size in ha	0.584	0.665	0.649	0.731	0.455	0.487	-0.194***
Livestock in TLU	3.757	4.006	4.365	4.128	2.546	3.451	-1.818***
Off-farm employment and occupation							
Off-farm employment (=1 if yes)	0.078	0.269	0.065	0.248	0.104	0.305	0.038**
HH's main occupation is agri.	0.961	0.194	0.968	0.176	0.946	0.225	-0.022*
Shocks							
1 if the HH faced drought or flood	0.074	0.262	0.079	0.2697	0.064	0.244	-0.015
1 if the HH faced human shock	0.067	0.250	0.074	0.262	0.054	0.225	-0.020
1 if the HH faced economic shock	0.104	0.305	0.121	0.326	0.070	0.256	-0.051**
1 if the HH faced pest/diseases	0.170	0.376	0.190	0.392	0.130	0.337	-0.059**
1 if the HH faced frost	0.263	0.440	0.272	0.445	0.244	0.430	-0.028
HH faced covariate shock	0.427	0.495	0.451	0.498	0.378	0.486	-0.073**
HH faced individual shock	0.149	0.356	0.168	0.374	0.110	0.314	-0.057**
Social capital indicators							
Member of Agri. Producer (=1)	0.078	0.269	0.099	0.299	0.037	0.189	-0.062***
Member of tree nursery group(=1)	0.051	0.221	0.072	0.259	0.010	0.100	-0.062***
Member of watershed group (=1)	0.079	0.270	0.086	0.280	0.067	0.250	-0.019
Years of staying in the village	35.664	13.985	38.372	13.637	30.264	13.097	-8.108***
Location related factors							
Distance from the nearest market	120.594	82.821	123.131	83.538	115.539	81.275	-7.592*
Distance from PFM in minutes	64.981	46.348	64.592	48.600	65.756	41.565	1.164
HH is in SNNP region	0.335	0.472	0.336	0.473	0.334	0.473	-0.001
HH is in Beneshangul region	0.166	0.373	0.166	0.372	0.167	0.374	0.001
HH is in Oromia region	0.498	0.500	0.498	0.500	0.498	0.501	0.000
N (Obs)		895		596			299

* Significant at the 10% level,** significant at the 5% level, *** significant at the 1% level.

Table 2 shows that the two groups are statistically different in terms of household characteristics such as age of the head, gender of the head, marital status of the head, and family size. Participating households tend to have older heads, a larger proportion of male and married heads, and larger family sizes.

In terms of asset ownership, PFM participants have more land and more livestock than non-participants, the differences being statistically significant at the 1% level. PFM participants are more likely to be primarily farmers and less likely than non-participants to engage in off-farm activities. In terms of social capital indicators, PFM participants are more likely to be members of agricultural producer groups and tree nursery groups. However, there is no statistically significant difference between the two groups in terms of membership in watershed management groups. PFM participants have, on average, lived longer in villages than non-participants. Participants lived a bit farther away from nearest markets, but the difference was only significant at a 10% level, while there was no statistically significant difference in terms of distance from the nearest PFM site between the two groups.

Descriptive statistics for the dependent variables, which are forest income or share of forest income, as well as the result of tests on whether there are statistical differences between member and non-member households, are presented in Table 3. Whether these observed differences in the dependent variables are the result of PFM membership is examined through a more in-depth econometric analysis in the next section.

Table 3. Summary statistics of share of forest income, annual forest income (ETB) and number of trips

Variable	Participants (P_1)	Non - participants (P_0)	Difference (*t* -test) (P_1-P_0)
Share of forest income	0.178	0.198	-0.020*
Forest income[6]	3077.376	2302.944	774.43***
Number of trips	13.62164	11.06656	2.56***
N	596	299	

* Significant at the 10% level; *** significant at the 1% level.

Table 3 shows that participants enjoy higher forest-based incomes than non-participants, the difference being statistically significant at a 1% level. On the other hand, the share of income that is forest based is higher for non-participants, though the difference is only weakly significant. The number of trips made to the forest, which is taken as an indicator of pressure on the forest, is also higher for participants, with a statistical significance of 1%. However, knowledge of average differences is not enough to explain the participation decisions and

[6]Forest products are valued based on market price for products which are tradable. For non-tradable products the products were valued based on respondent's response to hypothetical questions. That is, we asked households how much they are willing to pay if they were to buy that particular product from the market.

effects on forest income across sample farm households, since they do not account for the effects of other variables, such as the characteristics of farmers.

4. Results of Empirical Analysis

This section presents and discusses the effects of shocks and other variables as determinants of the decision to participate in PFM. It also addresses the impact of PFM on forest income and share of forest income, and PFM membership's influence on the use of forests as safety nets during shocks.

4.1 Determinants of participation

Table 4 presents the results of the analysis of determinants of participation in PFM.

Table 4. Determinants of participation in PFM

Variables	Coef.	Std. Err.	P-value
HH_Age	0.0871	0.0224	0.000
HH_Agesq	-0.0008	0.0002	0.001
HH_Sex	0.3360	0.3466	0.332
Married	0.1644	0.2401	0.493
Read_Write	0.2751	0.1388	0.047
Adult_equvalent	0.1145	0.0327	0.000
Land_size_in_Ha	0.1038	0.0651	0.111
Tropical_livestock_unit	0.0428	0.0147	0.004
Distpfm	-0.0840	0.0617	0.173
Nearest_market	0.0512	0.0528	0.332
Off_farm_employment	-0.0318	0.1871	0.865
Economic_shock_n	0.4261	0.1703	0.012
Shock_human	0.0660	0.2111	0.755
Shock_drought_flood	-0.0659	0.1933	0.733
shock_frost_n	-0.0400	0.1147	0.727
shock_pest_n	0.0306	0.1373	0.824
SNNP_R	0.2150	0.1326	0.105
Beneshangul_R	0.1522	0.1595	0.340
Mainocupation	-0.1745	0.2565	0.496
Agrprodgroup	0.5041	0.2274	0.027
Trenurserygroup	1.8123	0.4095	0.000
watershred_groupmem	-0.9216	0.2692	0.001
Villageyrs	0.0126	0.0053	0.017
_cons	-3.2372	0.6749	0.000
N		895	

The primary focus of this study is the effect of shocks, both individual and covariate, when a household decides whether or not to engage in PFM, and the implications of this decision for forest resource extraction. The results show that the probability of participation in PFM is higher amongst households that have faced economic shocks. However, other types of shocks considered in this study do not have a statistically significant effect on the participation decision of households.

The results show that a number of household characteristics have a significant effect on the decision to participate. Initially, as the age of the household head increases, so does the probability of participation; however, beyond some point it declines with the age of the household head, possibly because older people have shorter time horizons and become less interested in PFM. As expected, more educated farmers were more likely to engage in PFM. Household size measured in adult equivalent increases the likelihood of subscribing to PFM. This may be because households with large family size are better positioned to provide the labor required for PFM activities such as maintenance and meetings (Mazunda and Shively 2015).

As expected, the wealth indicators, livestock and land size, were positively correlated with the probability of participation in PFM, though the latter is not statistically significant. This shows that households with larger livestock holdings tend to participate in PFM. This is consistent with the findings of Mazunda and Shively (2015), who argue that households with more cattle are more likely to participate due to their high demand for fodder, because forests contain grass and fodder. Adhikari et al. (2004) and Gelo and Koch (2014) also find that households with more cattle are more likely to engage in community forest management.

Most of the social capital indicators have the expected sign. For example, establishment of tree nursery groups, and inviting households to be part of this association, could be important when encouraging households to engage in PFM. Similarly, households that are members of agricultural producer groups are more likely to subscribe to PFM.[7] Since the Ethiopian government plans to expand PFM in different parts of the country, it is logical to use such local organizations that enhance the likelihood that households will participate. The negative

[7]This result is highly significant in the estimation result presented in Appendix II, where the dependent variable is the number of trips. This result also shows that the number of years the household has stayed in the village is positively and significantly correlated with the decision to participate in the PFM.

association between PFM participation and membership of watershed management groups was unexpected. The number of years the household stayed in the village also increases the likelihood of PFM membership.

4.2 Estimation of treatment effect

4.2.1 Propensity score matching

We employ different matching algorithms, including nearest neighbor matching (NNM), radius matching, and kernel matching, to estimate the effects of participation in the program on share of forest income and total forest income. Table 5 presents the estimates of the participation effect (ATT) from the three matching algorithms: nearest neighbor, radius and kernel matching.

Table 5. Estimates of treatment effect of participation in PFM using different matching algorithms

	Share of forest income			Annual forest income ('000)		
Matching algorithms	ATT	S.E.	T-stat	ATT	S.E.	T-stat
Nearest Neighbor (0.01)	0.029	0.028	1.05	0.530	0.437	1.21
Radius (0.01)	0.030	0.028	1.07	0.550	0.433	1.27
Kernel (0.01)	0.026	0.029	0.90	0.567	0.443	1.28

The results show that consistently, across all three matching algorithms, PFM has no effect on forest income. In a test for covariate balancing, only one of the t-tests for equality of means between the treated and non-treated groups was significant after matching, indicating that the covariates were well balanced (Rosenbaum and Rubin 1985).[8] However, being based on the assumption that the impact of treatment is mainly due to observable factors, propensity score matching does not take into account unobservable factors that may influence the results. For this reason, we also estimated an endogenous switching regression model (as described in section 2.2) that accounted for unobservables.

[8]The variables included in the logit model were not the same as those in the selection equation of the endogenous regression model.

4.2.2 Endogenous switching regression

Table 6 presents the results of the endogenous switching regression model.[9] The determinants of share of forest income for participants and non-participants are estimated separately. In addition to our intuitive argument for the instruments used for identification, we also tested the validity of the instruments statistically. In Appendix I, we report the results of a chi-square test for the validity of the exclusion restrictions. The test shows that social capital variables, such as membership of a tree nursery group, membership of an agricultural producer group, membership of a watershed management group, and the number of years the household has remained in the village, were all jointly statistically significant at the 1% level (with x^2=224.21). On the other hand, these variables had no significant effect on the share of forest income accruing to households that were non-participants.

Table 6. Estimates of endogenous switching regression model (share of forest income)

	Participants			Non-Participants		
Variables	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
HH_Age	0.0021	0.005	0.649	0.0018	0.006	0.777
HH_Agesq	0.0000	0.000	0.527	0.0000	0.000	0.635
HH_Sex	-0.1488	0.073	0.040	-0.0375	0.077	0.628
Married	-0.1014	0.051	0.047	-0.0085	0.052	0.870
Read_Write	-0.0138	0.024	0.559	-0.0309	0.039	0.428
Adult_equvalent	-0.0035	0.005	0.497	0.0049	0.010	0.637
Land_size_in_Ha	-0.0168	0.011	0.118	0.0124	0.018	0.497
Tropical_livestock_unit	-0.0061	0.002	0.008	-0.0050	0.004	0.243
Distpfm	-0.0084	0.010	0.375	-0.0078	0.017	0.655
Nearest_market	-0.0064	0.009	0.468	-0.0263	0.014	0.065
Off_farm_employment	0.0602	0.035	0.090	0.1354	0.045	0.003
Economic_shock_n	0.0006	0.026	0.981	0.0203	0.056	0.716
Shock_human	0.0161	0.032	0.615	-0.0268	0.058	0.646
Shock_drought_flood	-0.0351	0.031	0.264	-0.0177	0.055	0.746
shock_frost_n	-0.0117	0.019	0.540	-0.0251	0.032	0.434
shock_pest_n	-0.0145	0.022	0.500	-0.0410	0.040	0.305
SNNP_R	-0.1274	0.021	0.000	-0.0145	0.035	0.674
Beneshangul_R	-0.0456	0.027	0.094	0.0418	0.042	0.320
Main occupation	0.0613	0.050	0.224	-0.2267	0.065	0.000
_cons	0.4920	0.153	0.001	0.6455	0.176	0.000
Numb Obs (N)		596		299		
rho (ρ_i)	-0.0601	0.148	0.684	0.1840	0.263	0.484

[9]We use the *movestay* command in STATA (Lokshin and Sajaia 2004) to estimate the parameters of the endogenous switching regression model.

Likelihood ratio test of independent equations $x^2(1)^2$	14.82***

rho (ρ_i) denotes the correlation coefficient

Table 6 presents the estimates showing the impact of shocks and of household, economic, locational, and social capital indicators, on the shares of forest income, for participants and for non-participants. The likelihood ratio tests for joint independence of the three equations, reported at the bottom of the table, show that the equations are not independent. Neither of the correlation coefficients, *rho_1* and *rho_2,* is significant, which suggests that sample selectivity bias may not be present. We first discuss treatment effects of PFM membership on forest income and share of forest income (Tables 7a and 7b). Then we discuss the effects of shocks, household characteristics and other variables on share of forest income (Table 6).

Treatment effects of PFM membership on forest income and share of forest income

The estimation results for the average treatment effect (ATT) are presented in Tables 7a and 7b. The average treatment effect (ATT) shows the impact of participation in PFM on forest income and share of forest income under the actual and counterfactual scenarios. Unlike the mean differences presented in Table 3, in which the impact of PFM participation on forest income and share of forest income might be obscured by other variables, these ATT estimates account for selection bias caused by systematic differences between participants and non-participants.

Table 7a: Impact of participation in PFM on forest income ('000 ETB)

	To Participate	Not to Participate	Treatment Effect	
Participants	3.077 (0.0699)	2.303 (0.069)	0.774*** (0.110)	(ATT)
Non-participants	3.718 (0.097)	3.481 (0.049)	0.2365*** (0.097)	(ATU)
Heterogeneity Effect	-0.641*** (0.1203)	-1.179*** (0.0849)	0.5375	(TH)
	(BH1)	(BH0)		

Note: ATT is average treatment effect on the treated; ATU is average treatment effect on the untreated.
*** Significant at 1% level. The numbers in parenthesis are standard errors.

Table 7b: Impact of participation in PFM on share of forest income (forest dependency)

	To Participate	Not to Participate	Treatment Effect	
Participants	0.178 (0.003)	0.199 (0.0057)	-0.021*** (0.006)	(ATT)

Non-participants	0.229 (0.0045)	0.2315 (0.0034)	-0.0026 (0.006)	(ATU)
Heterogeneity Effect	0.0323 (0.0062)	0.051 (0.0055)	-0.0183	(TH)
	(BH1)	(BH0)		

These results indicate that participation significantly increases forest income. Households that engage in PFM extract 774 birr (USD 29)[10] more forest income than non-participants, which is about 2 percent of the total income of participants. Non-participants would have increased forest income by about 237 birr had they decided to participate. The results also show that the share of forest income would have been higher had PFM participants decided not to participate. This suggests that share of forest income (forest dependency) is lower for participants (Table 7b). We also note that these results on the effects of PFM membership on forest income and share of forest income are consistent with the descriptive results reported in Table 3.

Effects of shocks and other variables on forest income and share of forest income

The results show that the determinants of the share of forest income (Table 6) and forest income (presented in appendix II) differ between participants and non-participants, suggesting the presence of heterogeneity in the sample. Our discussion of results is based on Table 6 (where the dependent variable is share of forest income). We find that, in general, neither participants nor non-participants depend on forests as safety nets to sustain them in the face of either idiosyncratic or covariate shocks.[11]

This is unlike the findings of Fisher et al. (2010), Wunder et al. (2014b) and Takasaki et al. (2004), who find that forest resources can be used as coping mechanisms during periods of covariate shocks. Unlike our findings, Debela et al. (2012) find that idiosyncratic shocks are the main drivers of shock-related forest pressure in Uganda while Yemiru et al. (2010) found that about 41% of sample households resort to forest extraction during crises.

Thus, we conclude that there is no significant difference between participants and non-participants on the effect of shocks on share of forest income. The type of shock has a significant

[10] The exchange rate at the time of the survey was 1 USD ≈ 27 birr.

[11] Pattanayak and Sills (2001) use the number of forest collection trips as an indicator of forest pressure and they find that such trips are positively associated with the incidence of shocks in the Brazilian Amazon. In our study, the results do not change when we use 'number of trips per month' as the dependent variable to examine the role of shocks.

effect on the participation decision, but not on (share of) forest income for both groups of households. An implication of this finding is that PFM membership does not help households to cope with crises when there are covariate or individual level shocks. Our data also show that only a small number of households reported forest products as their main coping mechanism when confronted by covariate or individual shocks, most using other strategies. More common strategies included depletion of cash savings, sale of assets such as livestock, assistance from friends and relatives; reduction in household spending; increased production of permanent crops such as fruits; and taking loans from money lenders, credit associations or banks. The type of coping mechanisms varies depending on the type and severity of shocks. Based on global data on forests and poverty, Borner et al. (2015) and Wunder et al. (2014a) find that forests are generally less important as coping mechanisms to shocks.

Several studies indicated other ways through which households could mitigate shocks. These included labor allocation to off-farm activities (Debela et al. 2012), access to extension services and credit services (Coromaldi 2020), dissaving and reduction in food consumption (Yilma et al. 2014), fishing and gathering (Takasaki et al.2004), and cash savings and selling of assets (Volker and Waibel 2010). However, it may be necessary to examine in future studies how the poor and vulnerable households interact with forests in PFM sites during periods of crisis before drawing strong conclusions regarding these.

Some of the household characteristics are important drivers of share of forest income for both groups of households. Amongst PFM participants, male-headed households and married households tend to depend less on forest products. PFM participant households with heads that read and write extract less forest products, while literacy has no significant impact on use of forest products by non-participants.

Both livestock and land ownership are negatively correlated with forest dependency, though the latter correlation is not statistically significant. Participation in off-farm activities increases share of forest income both for PFM participants and non-participants, but is only weakly significant for participants. Amongst non-participants, households whose main occupation is agriculture have lower shares of forest income; however, this relationship is not significant amongst participants.

There are also regional differences in household forest dependency. PFM participants in both SNNP and Beneshangul regions have lower shares of forest income, and hence are less dependent on forest resources than those from Oromia region, which is the base category. However, there is no difference between the three regions amongst non-participants.

5. Conclusion and Policy Implications

Rural households in developing countries use forests for their livelihoods. However, there is mixed evidence on the importance of forests for farm households when they face shocks. Specifically, there is limited literature on the impact of sustainable forest management programs such as PFM on coping capacity in times of crisis. Studies using rigorous impact evaluation techniques are especially rare. Unlike most previous studies, to capture the differential impact of PFM on participants and non-participants, we use both propensity score matching and endogenous switching regression models that take selectivity bias into account.

Our literature survey mentions several studies in developing countries that report rural households in developing countries turning to forest resources as important safety nets, and increasing the extraction of forest products. However, our study finds that forest extraction is not affected when households face either covariate or idiosyncratic shocks. Neither PFM nor non-PFM households appear to use forest resources as safety nets in times of crisis. We find that households use other options to cope with shocks, such as running down their cash savings, selling assets such as livestock, looking for assistance from friends and relatives, reducing household spending, etc. Others react by producing more agricultural products, borrowing money, and working more off their farms as coping mechanisms during periods of serious shocks.

We find that different variables have different effects on forest income and share of forest income of participants and non-participants, suggesting that there is heterogeneity, and that separate estimation for participants and non-participants was the right approach. The significance of education suggests that some kind of literacy program may need to be jointly run with the scaling up of PFM to other sites. This will help to enhance the participation decision as well as the conservation of forests as better-educated households are less dependent on forests.

Individual-level shocks, such an economic shock, may induce farmers to be a member of PFM. On the other hand, covariate shocks such as drought or floods do not have any impact on the participation decision of households in our study area. Similarly, intervention strategies that aim to enhance PFM participation amongst local residents should focus on the relatively poor, as the better-off households are already likely to participate. Local governments and other relevant stakeholders may also encourage and use local institutions such as tree nursery groups and agricultural producer groups, as such associations positively influence people's decision to participate in PFM.

Despite the limited role of forests to cope with shocks in PFM sites, forests do provide additional income to households. Our findings show that participants obtain higher forest incomes than non-participants, suggesting that participation in PFM improves access to forest resources.

This study provides important information which can be used as input for policy making. However, the analysis in this study is based on cross-sectional data. Future studies using panel data may better explain the dynamics of PFM, forest resource use and shocks, and provide more robust results.

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Appendices

Appendix I: Test of validity of variables used as exclusion restriction

	Probit			OLS		
Variables	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
HH_Age	0.0881	0.0223	0.000	-0.0003	0.0056	0.963
HH_Agesq	-0.0008	0.0002	0.001	0.0000	0.0001	0.840
HH_Sex	0.4836	0.3375	0.152	-0.0464	0.0793	0.559
Married	0.0668	0.2312	0.773	-0.0120	0.0538	0.824
Read_Write	0.2418	0.1371	0.078	-0.0406	0.0390	0.299
Adult_equvalent	0.1165	0.0325	0.000	0.0012	0.0101	0.906
LnLand_size_in_Ha	0.1100	0.0646	0.088	0.0095	0.0191	0.620
Tropical_livestock_unit	0.0435	0.0146	0.003	-0.0060	0.0042	0.155
Lndistpfm	-0.0807	0.0606	0.183	-0.0057	0.0179	0.752
LnNearest_market	0.0514	0.0522	0.325	-0.0272	0.0148	0.067
Off_farm_employment	-0.0192	0.1847	0.917	0.1361	0.0471	0.004
Economic_shock_n	0.4185	0.1696	0.014	0.0095	0.0560	0.865
Shock_human	0.0531	0.2106	0.801	-0.0354	0.0627	0.573
Shock_drought_flood	-0.0510	0.1916	0.790	-0.0171	0.0573	0.765
shock_frost_n	-0.0132	0.1134	0.907	-0.0237	0.0335	0.481
shock_pest_n	0.0204	0.1366	0.881	-0.0391	0.0421	0.354
SNNP_R	0.2033	0.1313	0.122	-0.0243	0.0379	0.521
Beneshangul_R	0.1429	0.1584	0.367	0.0374	0.0451	0.408
mainocupation	-0.1646	0.2493	0.509	-0.2243	0.0668	0.001
agrprodgroup	0.5227	0.2264	0.021	0.0265	0.0756	0.726
trenurserygroup	1.8099	0.4113	0.000	-0.0098	0.1463	0.946
watershred_groupmem	-0.9177	0.2702	0.001	0.0239	0.0625	0.702
Villageyrs	0.0111	0.0052	0.033	-0.0003	0.0015	0.837
_cons	-3.2535	0.6674	0.000	0.6944	0.1714	0.000
Number of Obs(N)		895			296	

Appendix II. Switching regression estimates (Dependent variable=forest income)

	Participants			Non participants		
Variables	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
HH_Age	0.0445481	0.0974868	0.648	0.0331726	0.0857907	0.699
HH_Agesq	-0.0007145	0.0010015	0.476	-0.000245	0.0008654	0.777
HH_Sex	-1.931763	1.522638	0.205	-0.1583814	1.126257	0.888
Married	0.6594379	1.037603	0.525	0.7669671	0.7748686	0.322
Read_Write	-0.4660499	0.5005888	0.352	0.3405618	0.5611939	0.544
Adult_equvalent	0.0938832	0.1084122	0.386	0.2590858	0.1481932	0.08
Land_size_in_Ha	0.1938992	0.2282999	0.396	0.2018151	0.2714064	0.457
Tropical_livestock_unit	-0.014896	0.0480964	0.757	0.0185386	0.0618259	0.764

distpfm	-0.1684027	0.2010011	0.402	0.0865428	0.2575033	0.737
Nearest_market	-0.0078872	0.189277	0.967	0.108993	0.211938	0.607
Off_farm_employment	-0.2037334	0.7484818	0.785	1.151219	0.6776254	0.089
Economic_shock_n	1.261981	0.5607515	0.024	1.632976	0.8205989	0.047
Shock_human	-0.6961734	0.6856212	0.310	-0.1082523	0.8765837	0.902
Shock_drought_flood	1.168609	0.6662015	0.079	-0.8267924	0.8181556	0.312
shock_frost_n	-0.7536819	0.4047656	0.063	-0.2140279	0.4793726	0.655
shock_pest_n	-0.6039135	0.4606423	0.190	-0.9441906	0.598573	0.115
SNNP_R	-3.008557	0.4512348	0.000	-1.562683	0.5152348	0.002
Beneshangul_R	-2.298354	0.5786691	0.000	-1.360232	0.6253779	0.03
Mainocupation	0.7555934	1.045762	0.470	-1.258306	0.9471995	0.184
_cons	5.726883	3.091625	0.064	1.484722	2.500819	0.553
rho	-0.1359	0.1180	0.249	0.146330	0.171009	0.392
Likelihood ratio test	chi2(1) = 1.51 Prob > chi2 = 0.2191					
Number of obs. (N)		596			299	