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Welfare and Environmental Impact of Incentive Based Conservation: Evidence from Kenyan Community Forest Associations*

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Abstract

This paper focuses on whether the provision of landless forest-adjacent communities with options to grow appropriate food crops inside forest reserves during early stages of reforestation programmes enable vertical transition of low income households and conserves forests. We consider the welfare and environmental impact of a unique incentive scheme known as the Plantation Establishment and Livelihood Improvement Scheme (PELIS) in Kenya. PELIS was aimed at deepening community participation in forestry, and improving the economic livelihoods of adjacent communities. Using data collected from 22 Community Forest Associations and 406 households, we evaluated the mean impact of the scheme on forest cover and household welfare using matching methods and further assessed the heterogeneous impact of the scheme on household welfare using the endogenous quantile treatment effects model. The study revealed that on average, PELIS had a significant and positive impact on overall household welfare (estimated between 15.09% and 28.14%) and on the environment (between 5.53% and 7.94%). However, in terms of welfare, the scheme cannot be defended on equity grounds as it has inequitable distributional impacts on household welfare. The scheme raises welfare of the least poor than the poorest and marginalizes sections of the community through elite capture and lack of market linkages.

Key words: Household welfare, Heterogeneity, Selection, Matching, QTE

JEL Classification: D02, Q23, Q28

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1 Introduction

Conservation manifests itself today in various forms in different parts of the world. From state controlled such as reserve forests and exclusionary parks to community forests managed by local communities. Initial conservation efforts involved indigenous resource management based on subsistence necessity, spiritual beliefs, experience, and traditions (Gbadegesin and Ayileka, 2000). Until the early 80s conservation efforts by governments in developing countries were mainly based on the protectionist approach also referred to as the classic approach to conservation (Blaikie and Jeanrenaud, 1997).

In developing countries, these forms of conservation have not yielded the best results in terms of conservation outcomes and welfare of local forest-adjacent communities. This is because in developing countries, natural forests are most often surrounded by high population of the poor basically reliant on extraction of natural resources for their daily subsistence. Forest-adjacent communities are also often the poor without access to other sources of income such as land, human and physical capital hence depend on income derived from the forests either directly or indirectly. Such dependence coupled with their high rate of time preference often leads to degradation of the resource thus contributing to further impoverishment of the dependent forest users. Hence, the poor are considered to be agents and victims of environmental degradation as well (Wunder, 2001; Fisher, 2004).

The failure of the classic approach in many countries led policymakers and donors to conclude that the only solution is devolution of natural forest management to forest-adjacent communities through arrangements such as Participatory Forest Management (PFM) and provision of incentives in order to enhance community support, conserve forest and offer positive welfare benefits among the forest poor. Incentive based conservation has therefore been considered as a remedy to failures associated with state control of natural resources such as, information asymmetry, incentive incompatibility or imperfect incentives, high monitoring and enforcement costs among others (Sterner, 2003; Adhikari, 2005). However, incentive based conservation has been marred with uncertainties since PFM places significant restrictions on extraction of forest resources. For example, in certain instances communities are required to pay user fees to access certain resources e.g., grazing, firewood collection etc. (Jumbe and Angelsen, 2006). Certain benefits are also restricted to membership to CFAs. These practices have previously contributed to forest degradation in a way. Distributional problems have also been experienced with structured attempts at management of CPRs (Kumar, 2002).

Attempts have therefore been made in support of incentive based conservation in a number of developing countries in recent years. In Kenya this attempt has focused on deepening community participation in forest management to aid in conservation of forest and improvement of welfare of forest-adjacent communities through CFAs and incentive schemes. This is based on the premise that other than devolution of forest management to local communities, provision of alternative incentive to landless forest-adjacent communities may help them to avoid activities that may offer short term gains in favor of activities with long term payoffs. We consider one unique incentive in Kenya known as Plantation Establishment and Livelihood Improvement Scheme (PELIS) under the realm of PFM.

1.1 Incentive based Conservation in Kenya

Kenya's forest cover of the land area stands at 7% far below the constitutional requirement of 10%. Approximately 80% of the Kenyan population reside in rural areas of which about 3 million live next to forest hence relies either directly or indirectly on benefits derived from these forests. They also directly rely on rain-fed subsistence agriculture for their livelihoods (FSK, 2006; WorldBank, 2000). The five major Water Towers[1] remains of significant importance to the economy since they supply a range of ecosystem services such as water purification, biodiversity conservation, micro climate regulation, flood mitigation and hydrological services among others.

Improving forest governance has thus been an implicit objective in forest sector reforms in the last decade in Kenya (MENR, 2005, 2016). The Forest Act (2016) and Forest Act (2005) introduced PFM that seeks to engage local communities and promote private sector investment in gazetted forests. Some features of these Acts are: devolution of forest conservation and management through PFM to local communities; introduction of benefit sharing arrangements such as PELIS; and adoption of ecosystem approach to management of forests among others. Communities have in turn been able to form community-based organizations (CBOs) known as Community Forest Associations (CFAs) in collaboration with the Kenya Forest Service (KFS). This is a departure from prior practice where the government fully managed gazetted forest reserves. In the Forest Act (2016), CFAs are recognized as partners in forest management and commercial plantations are also open to lease arrangements by interest groups to supplement conservation efforts. Apart from PELIS, there are various incentives[2] aimed at encouraging forest-adjacent communities through CFAs to sustainably manage forests. To benefit from either incentives households are required to pay a specific amount where a proportion goes to associated CBO or Forest User Group (FUG), CFA, and the highest proportion to KFS.

1.2 Motivation of the study

PELIS was first introduced in Kenya in 1910 by the colonial government as non-residential cultivation to promote livelihood of locals economically while ensuring sustainable management and conservation of forests through provision of raw materials for expanding timber industry and reduce pressure on natural forests (Kagombe and Gitonga, 2005). Since forests in Kenya are surrounded by mostly poor households dependent on agriculture but constrained by inadequate agricultural

[1] Mau forest complex, Mt Elgon, Cherenganyi hills, Mt Kenya, and Abardare Ranges

[2] These incentives include, bee-keeping, tree nursery, grazing, harvesting medicines and herbs, thinning (Silviculture) mainly for fuel-wood, cutting grass for thatching, recreational activities, scientific studies, fish farming, eco-tourism and educational activities.

land and alternative sources of income, these scheme presents an opportunity for locals to derive livelihood by planting appropriate food crops (Income from the sales of agricultural produce could be used to meet their daily household demands. There is also the nutritional value from consumption of these produce hence higher productivity due to improved health.) inside the forest reserve and also an incentive to conserve these forests as well[3]. Under the system farmers are allowed to grow both plantation trees[4] and food crops on small plots (half an acre) tending the trees and harvesting crops for 3-4 years until tree canopy closes an arrangement where both parties benefit. It was later banned after several attempts in 1986, 1994, and 2003 due to failure and mismanagement. The scheme was however reintroduced in 2007 with enactment of Forest Act (2005) through CFAs. Members are required to pay between Ksh. 400(4USD) and Ksh.750(7.5USD) per half an acre. The rules of allocation of plots also varies, with almost all CFAs purporting to use balloting. But this is just on paper as the process is marred with a lot of irregularities[5].

However, even though PELIS may enhance efficiency in forest resource use, there may be inequitable distribution of the benefits across the income groups hence a recipe for tragedy. It is therefore inherent to gauge PELIS impact not just with reference to its efficiency and effectiveness but also by sustainability of the benefits in promoting equity and improvement of environment. There is also limited understanding of the drivers of adoption of the scheme by households within CFAs which could shed light on reasons for past failures in the scheme and identify possible factors to consider in rolling out the scheme. In addition, since the opportunity cost of restriction of forest access and use is higher among the poor, there is uncertainty whether participation in PELIS can enable poor households move up the income ladder. There is also high likelihood of those high up the ladder capturing the scheme hence having a disproportionate impact on the distribution of program benefits. Empirical evidence on the impact of PELIS on environmental conservation and welfare implication is also not clear despite its significance for sustainability of PFM.

Moreover, studies that have analyzed various forms of forest management activities are more biased towards Asia mostly Nepal and India. There are relatively few studies in Africa (see Jumbe and Angelsen 2006; Kabubo-Mariara 2013; Gelo and Koch 2014; Mazunda and Shively 2015; Gelo et al. 2016). Empirical studies that have tried to evaluate the welfare effects of various incentives have mainly been focused on mean impacts assuming constant treatment effects across the income distribution (see Gelo and Koch, 2014; Ali et al., 2015; Mazunda and Shively, 2015), with very few on the heterogeneous impacts of such schemes (see Adhikari, 2005; Jumbe and Angelsen, 2006; Cooper, 2007, 2008; Moktan et al., 2016; Gelo et al., 2016). A general overview of these studies reveals significant differences in applied definition, contextual factors and methodological

[3]Once one becomes a participant in PELIS, the benefits will depend on, one's hard work and the kind of crops grown as well as, how well they market their produce to fetch better prices.

[4]Farmers are usually provided with tree seedlings by the KFS and each is tasked with nurturing the trees planted in their plots. In case any tree gets destroyed one is answerable to the CFA officials and the forester. In certain instances, a penalty is applied. In addition, CFAs may also construct their own nurseries in the forest and sell tree seedlings to members for setting up their private woodlots.

[5]During the survey, we noted that some CFA officials and members had more than one plot in the forest while some deserving members had none. Some rich established non-members also acquired plots in the forest by bribing the foresters or CFA officials. Some members therefore felt short changed because only the well-connected members or elites tend to get the plots. Hence an incentive for them to just sit back and watch as the forest gets destroyed.

approaches (ranging from, treatment effects models, PSM to instrumental variable) hence making comparison difficult. The results have also been mixed and inconclusive. On the other hand, the measurement of outcomes employed in these studies are also significantly different hence prone to measurement errors. For instance, some studies use household income which is prone to under reporting especially among poor rural communities. As a departure from past studies that have always classified households in terms of low, middle and high income households, and given the fact that measures of mean impact may not provide a clear picture of the impact of the scheme, we estimate the heterogeneous impact across the entire income distribution. The overall impact on forest cover and household welfare, and the heterogeneous impact of the scheme on household welfare therefore, motivates this study. The study therefore, seeks to fill these gaps by addressing the following research questions: What determines households' decision to participate in PELIS? What is the joint overall impact of PELIS on forest cover and household welfare? What is the distributional impact of PELIS on welfare of locals?

This study contributes to the growing body of literature on impact evaluation of environmental policies by providing a comprehensive empirical evidence from a micro perspective of the heterogeneous impact of PELIS on household welfare and its simultaneous overall effect on the environment and household welfare. From a policy perspective, an understanding of the overall and distributional impact of the scheme across the income distribution has the potential to inform design, implementation and roll out of PELIS to other CFAs. Lessons from this scheme can also be used to inform formulation of other market based incentives that can help in optimizing welfare gains and improving environmental conditions. The rest of the paper is organized as follows: Section 2 presents a description of the study area; section 3 outlines the methodological framework; section 4 presents the survey design and data collection; section 5 presents the results and discussions; conclusion and policy recommendations are presented in section 6.

2 Description of the study area

The study was conducted in the Mau forest conservancy. The choice of Mau forest was based on a set of criteria namely, high susceptibility to degradation, long history of community forestry and high level of biodiversity. It is also the largest closed canopy forest among the five major Water Towers in Kenya that has lost over a quarter of its forest resources in the last decade (Force, 2009). It is located at 0°30' South, 35°20' East within the Rift Valley Province. It originally covered 452,007 ha but after the 2001 forest excisions the current estimated size is about 416, 542 ha. The Mau forest conservancy also has the highest number of CFAs with long history of community participation in PELIS. The Mau comprises 22 forest blocks, of which 21 are gazetted and managed by KFS. The remainder is Mau Trust Land Forest (46, 278 ha) which is managed by the Narok County Council (NEMA, 2013). The Mau ecosystem is the upper catchment of many major rivers. These rivers feed into various lakes e.g., Nakuru, Baringo, Natron, Naivasha, Turkana, and Victoria. The lakes and rivers also provide water for pastoral communities and agricultural activity and supply essential ecosystem services. In addition, the estimated potential hydro-power generation in the Mau forest catchment is approximately 535 MW, which account for 47 percent of the total installed electricity generation capacity in Kenya UNEP (2008). The upper catchment of the forest also hosts the last group of hunter gatherer communities such as the Ogiek (Force, 2009).

3 Methodological Framework

The framework is grounded in Roy (1951) occupational choice model. We assume that households decide whether to participate in PELIS or not based on option that maximizes their utility. If households expect to benefit from participating in the scheme, then we assume they will join the scheme. Treatment assignment is therefore non-random. In particular, we define V_{ij} the utility of household i =1...N in treatment regime j={0,1}, with 1 representing participation in PELIS and 0 otherwise. Therefore, D_i=1 if $V_{i1} > V_{i0}$. Similarly define $\mathbf{Y_{ij}}$ as a vector of potential outcome variable. Where $\mathbf{Y_{i1}}$is per capita expenditure and forest cover for PELIS beneficiary households and CFAs respectively and $\mathbf{Y_{i0}}$ is per capita expenditure and percentage forest cover for non PELIS beneficiaries. The difference between $\mathbf{Y_{i1}}$and $\mathbf{Y_{i0}}$ can therefore be used to measure the differential impact on forest cover and household welfare.

In this study, we measure success in terms of household outcome and community level outcome that is per capita expenditure and forest cover respectively and measurement depends on counterfactual. According to Rubin (1973), we define program impact as the difference between the observed and the counterfactual outcome. The challenge is that the counterfactual is not observable and an individual or CFA cannot be in both states at the same time. To identify the counterfactual, we apply a quasi-experimental approach given that participation in PELIS is non-random. It is therefore essential to control for participation decision to identify the impact of the scheme. To examine the impact of this incentive, the study takes account of the fact that differences in per capita expenditure or forest cover for participant households or CFAs and non-participants could be due to unobserved heterogeneity. Failure to distinguish between the causal effects of participation in PELIS and effect of unobserved heterogeneity may therefore lead to misleading conclusion and policy implication.

PELIS has two possible levels of selection. In one level, households are deemed to be eligible only if they are members of CFAs and actively involved in CFA activities[6]. In another level eligible households are left to decide whether they want to participate in PELIS[7] by participating in a balloting exercise or first come first serve basis in some instances. Households are likely to participate if they expect the potential gains to exceed the costs. In addition, Poor households

[6]In some CFAs there are also non-members who have PELIS plots we consider these as contamination and avoid them in the study.
[7]However, based on their interest, they can decide to join other forest user groups for example bee keeping, tree nursery, grazing or firewood collection groups.

may be eligible but unable to raise the fee whereas richer households may capture the scheme and obtain more plots at the expense of active eligible but poor households. On the other hand, richer households may find the opportunity costs of participating in the scheme to be higher hence may consider other alternatives. Participation in PELIS is also potentially endogenous to per capita monthly expenditure. Some unobservable characteristics that influence the participation in PELIS could also influence per capita monthly expenditure e.g. household income or access to information. Therefore, neglecting these selectivity effects is likely to give a false picture of the relative per capita monthly expenditure for beneficiaries and non-beneficiaries of PELIS. Hence the estimated causal effect may reflect not only the treatment effect but also differences generated by the selection process.

On the other hand, the decision as to which CFAs get to benefit from PELIS is solely at the discretion of KFS. The study therefore adopts a combination of econometric methods namely; the PSM and ordinary least square regression to determine the average treatment effect of participation in PELIS on per capita monthly expenditure and forest cover. However, OLS and PSM would yield biased estimates if there are unobservable determinants of participation. Control function methods or Instrumental Variable methods becomes essential in such instances (see Wooldridge, 2010). In addition, since PSM and OLS models focuses more on the mean outcomes, we employed the QTE model under endogenous assumption following Abadie et al. (2002) to implicitly explore the distributional impact of the scheme on household welfare while addressing the potential endogeneity to assess the sustainability of the scheme.

3.1 Propensity Score Matching

3.1.1 Theoretical and analytical framework.

The theoretical foundations follow Roy (1951) and Rubin (1974). Accordingly, households' or CFAs' decision to participate in PELIS is assumed to depend on expected benefits, as measured by per capita expenditure and forest cover (The better the forest cover the more the benefits) in adjacent forest resource, associated with either participating in the scheme or maintaining the status quo. The main interest is the average treatment effect on the treated (ATT). That is how benefiting from PELIS affect conservation and welfare of forest-adjacent communities. Since it is not possible to observe what the results would have been in the absence of the incentive. To handle the missing data on counterfactual, we identified households, which are non-beneficiaries of the incentives and used them as counterfactual. Similarly, for forest cover we identified CFAs that were non beneficiaries of PELIS and used them as counterfactual. Since assignment to PELIS is non-random there is high possibility of selection bias. To address these issues, we first employed the PSM technique to measure the mean impact on both forest cover and household welfare.

Identification strategy

Assuming a set of observable covariates X, which are unaffected by the treatment (Participation in PELIS), potential outcomes are independent of treatment assignment i.e., Conditional Independence Assumption (CIA)[8]. A further requirement is a sizable common support or overlap condition. This rule out the phenomenon of perfect predictability of T given X:

$$(Overlap) : 0 < P(T = 1|X) < 1 \tag{1}$$

This condition ensures that households with the same X values have positive probability of being both participants and non-participants (Heckman et al., 1999). The effectiveness of PSM also depends on having a substantial region of common support or overlap (Khandker et al., 2009). For estimation of the ATT, the assumption can be relaxed to P (T=1$\big|$X) <1.

If the CIA holds and there is sizable overlap (Heckman et al., 1999), then the next step is to find the PSM estimator. PSM was undertaken in two steps. The first step was generation of propensity scores from probit model using the household socio-economic and demographic characteristics, community level characteristics and other controls. The score indicates the probabilities of respective households/CFAs participating in the scheme. From the scores, we constructed a control group by matching the beneficiaries to non-beneficiaries according to their propensity scores by comparing various methods of matching. The second stage involved computation of the ATT of households and CFAs benefiting from incentives on household welfare and forest cover respectively using the matched observations.

3.1.2 Model specification

The PSM estimator for the ATT is specified as the mean difference in Y (per capita household expenditure and forest cover as a percentage of total forest area under each CFA) over common support, weighting the comparison units by the propensity score distribution of participants. The cross section estimator is specified as:

$$\tau_{ATT}^{PSM} = E(P(X)|T = 1)\{E[Y(1)|T = 1, P(X)] - E[Y(0)|T = 0, P(X)]\} \tag{2}$$

Where Y (1) and Y (0) represents per capita household expenditure and forest cover for beneficiary and non-beneficiary households/CFAs respectively. T=1 indicates treated/beneficiary households or CFAs while T=0 indicates control/non-beneficiary households or CFAs. The PSM estimator is thus given by the mean difference in outcomes over the common support weighted by the propensity

[8]This assumption is rather strong and needs to be justified by the data quality at hand.

score distribution of participants[9] (Caliendo and Kopeinig, 2008). To determine the heterogeneous effect of the scheme on household welfare, and due to the restrictive identification condition, selection issues and potential endogeneity, the study also employed the use of the conditional QTE model under endogenous assumption described in the next section.

3.2 Quantile Treatment Effects Model

Measures of mean impact may not provide the true picture of the effect of the scheme, it is therefore essential to determine the heterogenous impact of the scheme to assess the sustainability of the scheme in providing the double dividend[10]. To determine the distributional impact of the scheme on household welfare, the study employed the parametric conditional QTE model under endogenous assumption following Abadie et al. (2002) and Chernozhukov and Hansen (2008).

3.2.1 Conceptual Framework

Given a continuous outcome variable Y, we consider the effect of a binary treatment variable D (participation in PELIS or not). Let Y_i^1 and Y_i^0 be the potential outcomes of household i that is per capita monthly expenditure. Hence, Y_i^1 would be realized if household i participated in PELIS and Y_i^0 would be realized otherwise. Define Y_i as the observed outcome, which is $Y_i = Y_i^1 D_i + Y_i^0(1-D_i)$. We estimate the entire distribution functions of Y^1 and Y^0 (Frölich and Melly, 2010).

We then define QTE conditionally on covariates as we deal with the endogenous treatment choice since in our case, selection is unobservable meaning that treatment assignment is non ignorable. Participation in PELIS is also potentially endogenous to per capita expenditure[11]. The traditional quantile regression may therefore be biased hence the need for an instrumental variable (IV) to recover the true effects. Key concerns with respect to instrumental variables are, weak instruments and over identification[12]. In addition, if the instruments affect participants in different ways interpreting the resulting treatment effects may be complicated that is treatment effects heterogeneity (Frölich and Melly, 2010). The exclusion restriction is however difficult to test as in all IV applications.

Assuming we observe a binary instrument Z, we define two potential treatments denoted D_Z. We then make use of several assumptions[13] underlying the potential outcome framework for IV with probability one as in Abadie et al. (2002). In addition to these assumptions, "individuals

[9] According to Caliendo and Kopeinig (2008), inclusion of non-significant variables cannot lead to inconsistent or biased results. We thus used all the variables in the PSM probit in the outcome analysis.

[10] That is, improving household welfare and forest conservation and management.

[11] Participation in PELIS is mostly influenced by household income which also directly influences per capita expenditure for both participants and non-participants. This implies that, systematic differences in the distribution of per capita expenditure between participants and non-participants may reflect both differences generated by the selection process and the effect of treatment.

[12] A 2SLS that contains weak instruments is not identified hence instruments treatment effect not valid (Stock and Yogo, 2005).

[13] Namely, (i) Independence: Y^0, Y^1, D_0, D_1 is jointly independent of Z given X: implies that conditioned on a set of covariates, the instrumental variable should not affect the outcome of individual except through the treatment channel, (ii) Exclusion: $Pr(Y^1 = Y^0|X) = 1$, (iii) Non Trivial Assignment: $0 < Pr(Z = 1|X) < 1$: Requires existence of propensity score of the instrument, (iv) First Stage: and $E[D_1|X] \neq E[D_0|X]$, and (v) Monotonicity: $Pr(D_1 \geq D_0|X) = 1$: Requires that the treatment variable D either weakly increases or decreases with the instrument Z for all i(Abadie et al., 2002).

with $D_1 > D_0$ are referred to as compliers. Treatment can be identified only for this group, since the always and never participants cannot be induced to change treatment status by hypothetical movement of the instrument" (Frölich and Melly, 2010). Following Abadie et al. (2002), the conditional QTE δ^τ for the compliers is estimated by the weighted quantile regression:

$$\begin{aligned} (\hat{\beta^\tau}_{IV}, \hat{\delta^\tau}_{IV}) &= \underset{\beta,\delta}{argmin} \sum W_i^{AAI}.\rho_\tau(Y_i - X_i\beta - D_i\delta) \\ W_i^{AAI} &= 1 - \tfrac{D_i(1-Z_i)}{1-Pr(Z=1|X_i)} - \tfrac{(1-D_i)Z_i}{Pr(Z=1|X_i)} \end{aligned} \tag{3}$$

To implement the estimator, we first need to estimate $\Pr(Z=1|X_i)$. $\rho_\tau(u)$ is the check function, where $\rho_\tau(u) = u \times \{\tau - 1(u < 0)\}$. This is estimated using the ivqte command in stata since it produces analytical standard errors that are consistent even in case of heteroscedasticity (Frölich and Melly, 2010). Given that some weights may be negative or positive, the ivqte stata command uses the local logit estimator and implements the AAI estimator with positive weights. An alternative provided by Abadie et al. (2002) shows that the following weights can be used as an alternative to W_i^{AAI}. Where $W_i^{AAI+} = E[W^{AAI}|Y_i, D_i, X_i]$. Which are always positive. ivqte uses the local linear regression to estimate W_i^{AAI}.

Identification Strategy

To determine QTE in equation 3, we used one binary variable as an instrument that is, being born in the village or not. This is used to show the households intention to participate in PELIS or not. Being born in a given village is assumed to determine participation in PELIS but cannot affect household per capita expenditure directly except through participation in PELIS. The motivation for the choice of instruments is based on Maslow's "self actualization" theory in (see Maslow, 1943). According to Maslow (1943), once an individual's psychological needs[14] are satisfied, their safety needs takes precedence and dominates behavior. Therefore in the absence of economic security, due to say, economic crisis, and lack of job opportunities, these safety needs manifests themselves in the form of preference for job security. Therefore, we posit that when one is born in a given village, with the urge for a sense of belonging and acceptance by their peers, desire for respect (i.e., need for self esteem and self-respect) and to be valued by others, people tend to venture into different professions or hobbies to gain recognition. Such activities give people a sense of contribution and value in a society. Individuals therefore, tend to achieve the "self-actualization" in attaining some higher goals outside one-self in altruism and spiritually (see Maslow, 1991). In that endeavor, they are less likely to participate in schemes such as PELIS. Moreover, at community level when one is born in a given place, the routine often becomes monotonous (you have been born and bred around the forest you therefore see nothing new in it. Rarely will you appreciate the resource compared

[14]These needs are the physical requirements for human survival e.g., air, water, food etc.

to someone who was not born in that community), you have always grazed in the forest, fetch firewood etc. The urge to do better in society pushes people to venture into new fields outside the normal activities within the community hence will often rarely participate in forest conservation activities like PELIS[15]. Farming may also be considered low life by peers and hence a drive to seek their own identity and stand out in society. Incentives such as PELIS may therefore be unattractive hence indirectly affects household welfare.

The Mau forest area is very agriculturally productive and surrounded by different ethnic communities consisting of natives and immigrants hence often a hot spot of post election violence as the real natives clash with the non natives whom they feel have encroached into their ancestral lands incase the election results are not in favor of the natives. There are also squatters from other areas who live in the market centers around the forest with the aim of joining the CFAs so that they can get access to agricultural land in the forest, most of them normally have no alternative homes elsewhere. However, it is important to note that, within the African setting, one may have been born in a given village but is actually an immigrant from another province based on where their parents or great grand parents came from[16]. Therefore, one born within the Mau forest area who has always enjoyed the benefit from the forest will not see any difference compared to a person born in a different area where they had no productive agricultural land but the presence of the forest provides a better source of livelihood. A Potential criticism of the instrument could also be due to unobservables. To minimize the bias, we considered conditioning this instrumental variable on distance to the nearest edge of the forest[17] and other set of covariates[18] to authenticate the validity of the instrument.

4 The Survey Design and Data Collection

A pilot study involving 44 households was first conducted in October 2015 in Londiani CFA of Kericho County. Information gathered was used to refine the instrument that was eventually used in the final survey. The survey was conducted in the months of November and December 2015. In the final survey, we used a two stage sampling procedure in data collection. In the first stage a sample of 22 out of 35 CFAs were purposively identified to reflect the entire Mau forest and also

[15] A similar argument can be based on the fact that unless constrained by say inadequate income, one would rarely want to attend a high school next to his home if he has been born and has attended say primary education in the same village. People would tend to go to areas far away from where they were born for a change because they may not appreciate the school neighboring them or would just prefer a change to attract some admiration from the society as a show of achievement.

[16] Within the African context, natives are considered those whose ancestors were the original occupants and were buried in that area. Therefore, they cannot marry from the same clan since they are considered one family because they are from the same ancestral descendant. They can however marry immigrants from other areas who have settled in their villages but not the natives of that area. There are also natives who have intermarried with immigrants. For female headed households, if never married we noted the residential status and whether was born in the area or not. However, if a widow we noted the residential status as well as place of birth of the spouse.

[17] It is important to note that, one may be born or not in a given village but the cost of extraction of the resource may be higher for households far away from nearest edge of the forest than closer households hence this may influence their participation in PELIS as well as per capita expenditure and household income.

[18] Distance to main road, distance to nearest market, years of education household land size, household size, household wealth, number of children, household income, age and sex of household head, employment status of household head, residential status, membership to other environmental organizations and institutional variables like level of participation in CFA activities.

to identify CFAs that do not participate in PELIS. This was conducted with the help of head of Mau forest conservancy[19]. The CFAs covered five counties of Bomet, Narok, Kericho, Nakuru and Uasin Gishu. The CFAs were a representation of the entire Mau forest. They also provide the variation by regions especially in terms of geographical and climatic variables.

All the CFAs sampled were well established, and the duration of existence varied hence giving a better understanding of the impact of this incentive. The 22 CFAs covers about 164,645 hectares of the Mau forest. The CFAs are constituted of CBOs or FUGs with membership drawn from residents of forest-adjacent communities (own survey from pilot). Table 10 in the appendix shows the distribution of PELIS adopters and non-adopters. From Table 10 it is clear that some CFAs had as low as four or five households sampled this was attributed to lack of cooperation from CFA officials and inaccessibility of some areas due to the terrain and bad weather conditions. However, some CFAs do not totally participate in PELIS e.g., Likia, Sururu, Nyangores, Baraget, Nairotia Olenguruone and Manengai this was basically due to their reluctance to adopt the scheme and dominance of pastoral activities in areas such as Likia and Nairotia that were mainly inhabited by the Maasai community. Some do not benefit from the scheme because they are not part of the KFS plan for PELIS roll out. The CFA level data were collected through focus group discussion with CFA officials and other members at their offices in the forest station.

Second step, was to select a sample of households within the selected CFAs. Since we were only interested in CFA members, this exercise was conducted using simple random sampling where every third household was interviewed and in cases where the membership was small snow balling approach was adopted especially where the third household was a non-member. Trained enumerators were guided by village elders or representatives selected by the CFA officials during the focus group discussion. Each group was prepared in advance.

4.1 Data

At the household level, a total of 406 households were sampled (178 non-PELIS beneficiary households and 228 PELIS beneficiary households). Household heads provided information on household socio-economic characteristics, such as income, age, gender, consumption expenditure, education, size of households, household land size, distance to nearest, market, road and edge of forest etc. At the CFA level, additional information relating to forest cover under each CFA, geographic and climate variables, participation and attendance of CFA meetings and other CFA level variables were also gathered through focus group discussion with CFA officials at the CFA offices based at each forest station. In this study forest cover was calculated by dividing the number of hectares of forest cover (including plantation and indigenous forest) by the total forest area under each CFA. This is secondary data available in each forest station and regularly updated by the foresters. It

[19] Although it is possible that the head of conservancy may have referred us to CFAs that were doing well, we can confirm that this was not the case since we also got to visit some CFAs that were in total mess. The choice of CFA was based on total representation of the entire forest and ease of accessibility since some areas are very difficult to access due to terrain and lack of motorable roads.

is important to note however, that this is measured at CFA level and not household level[20]. To assess the impact of PELIS on forest cover, we identified CFAs that did not totally participate in PELIS as controls of which seven were identified namely, Likia, Sururu, Nyangores, Nairotia, Baraget Olenguruone and Manengai constituting a sample of 130 households. We also identified CFAs that were beneficiaries of PELIS as our treatment. We considered CFAs in our sample that had fifteen households and above as beneficiaries. Six CFAs were further identified namely, Bahati, Koibatek, Esageri, Malagat, Kericho and Makutano constituting a sample of 137 households (where 128 households benefited from PELIS and 9 did not). We posit that the more PELIS beneficiaries a CFA has the higher the likelihood of improved forest cover hence the motivation for selecting CFAs with more beneficiaries of the scheme in our sample[21].

Households that participate in PELIS grow crops such as peas, potatoes, vegetables, beans and maize among other crops. Depending on the amount of harvest, these produce can be sold to other members of the communities at the market centres hence a source of income to the household. With a rise in income the household expenditure is expected to rise due to increased purchasing power. We therefore expect an improvement in welfare with an increase in per capita expenditure. We therefore measured household welfare using per capita monthly expenditure to proxy for household monthly income. We acknowledge the fact that PELIS only influence revenues from harvested agricultural produce apart from other indirect effects like increase in livestock values. Some studies have used income from non-timber forest products (e.g. Adhikari 2005; Jumbe and Angelsen 2006; Kabubo-Mariara 2013) as opposed to per capita expenditure as a measure of household welfare. Since forest-adjacent communities are often poor (some without alternative agricultural land) and almost fully reliant on forest for their livelihood either directly or indirectly, use of per capita expenditure would still provide a good proxy for their welfare[22]. Hence using per capita expenditure would still provide a better picture on the impact of the scheme than just considering income from forest harvests alone[23].

The choice of consumption expenditure is also based on the fact that households are prone to under reporting their monthly income. Secondly, per capita expenditure is also easily interpreted and widely used (see Skoufias and Katayama 2011; Gelo and Koch 2014; Gelo et al. 2016). Consumption expenditure also provides information over the consumption bundle that fits within the

[20]We acknowledge the fact that the percentage change in forest cover would be an ideal measure as opposed to the aggregate percentage forest cover as employed in this study. However, due to lack of baseline information on forest cover at the start of devolution of forest management for most CFAs, we opted to use the aggregate measure of forest cover. It is also important to note that, before devolution of forest management to CFAs, the Mau forest had been highly degraded. Therefore, the aggregate percentage forest cover can still be attributed to the actions of forest-adjacent communities through CFAs. This implies that the aggregate forest cover can still provide meaningful insights in terms of assessing the impact of PELIS on the environment.

[21]Some CFAs did not have higher numbers in PELIS due to low uptake or differences in preferences. Most households joined user groups that they felt they would benefit most e.g., firewood, bee keeping, grazing etc. Hence in swampy areas, even if the CFA has PELIS, few households would hope for the scheme since it involves a lot of work reclaiming the land.

[22]Moreover, in some instances even if a household does or does not benefit from PELIS, they could still be employed as casual laborers by the wealthier households that own plots in the forest to tend to their farms for some wages which they can expend on other requirements.

[23]During the survey, we noted that some very rich households, owning big shops at the shopping centres also had plots in the forest yet they were not registered members, but just used their influence to buy their way into the forest. We did not consider such cases as beneficiaries. The study only focused on registered CFA members. There are also CFA members who lease out their plots to non-members who are willing to pay higher amounts to farm in the forest. We avoided such beneficiaries in the study.

household's budget although this may be affected by different micro finance institutions that are enabling easy access to credit facilities among village households or even smaller women groups "chamas". We aggregated household expenditure on food supplies, education, farming and livestock, clothing and apparels, medical and other miscellaneous expenses incurred by the household. This was reported on annual basis since some expenses like education[24] were paid on annual basis. A total of the expenses was used to calculate the per capita monthly expenditure (Monthly expenditure was preferred due to ease of recall of most monthly expenses by respondents). Annual average rainfall and temperature values for the various forests were collected from the website (http://en.climate-data.org/country/124/). This data was available for most forest stations and for the ones that had no data we used the nearest weather station recorded climate data. We considered the climate variables due to the fact that the CFAs are large in sizes hence the climate variables vary significantly. A description of the variables is presented in Table 6 in the appendix.

5 Results and Discussion

This section present results from the different empirical approaches employed in the study. The first section presents the descriptive statistics of the household and CFA level variables employed in the study. The next sections present the results of the ordinary least squares, PSM technique and the QTE model respectively.

5.1 Descriptive Statistics

The summary statistics are presented in Table 7. From Table 7, as expected, the mean monthly per capita expenditure for PELIS beneficiaries was higher than non-beneficiaries. The percentage forest cover under CFAs with PELIS beneficiary household was also found to be higher than the non-PELIS beneficiaries. The summary statistics of other variables used in the study are also presented. However, when we look at the differences between beneficiaries and non-beneficiaries, as shown in Table 8, we find significant differences between beneficiaries of PELIS and non-beneficiaries. The signs are as expected. Overall, the significant mean differences for some covariates suggests that observed outcomes for non-PELIS beneficiaries may not provide good counterfactual for beneficiaries. Estimation assuming random treatment assignment would therefore produce biased results hence the need for an alternative program evaluation. As such we used the PSM and the endogenous QTE model.

[24] We included expenses on items like education because during the survey most households attributed the benefit of PELIS as for them having been able to educate their children with ease using the income from sale of agricultural produce from PELIS plots.

5.2 OLS Estimation Results

Before we proceeded to estimate the PSM and QTE models, we considered a simple approach to tease out the impact of adoption of PELIS on household welfare and forest cover using the OLS model of per capita monthly household expenditure and forest cover that includes PELIS as a dummy variable equal to 1 if household or CFA participated in PELIS and 0 otherwise. The OLS regression results are presented in Table 1 Columns (1) and (2) for per capita monthly expenditure and forest cover respectively. We can conclude from the results that participation in PELIS increases per capita monthly household expenditure by approximately ksh. 555.30 (USD5.553) and forest cover by approximately 9.4% for beneficiary CFAs all factors constant (the coefficient of PELIS dummy is significant at 1%).

Table 1: **OLS Estimation Results of Impact of PELIS on Forest Cover and Per Capita Expenditure**

	(1)		(2)	
VARIABLES	PCMonthlyEXP	s.e	Forestcover	s.e
PELIS	555.3***	(151.8)	9.380***	(1.937)
HHsex	165.0	(205.4)	2.448	(2.494)
MedAge	35.22	(31.46)	-0.245	(0.368)
MedAgesq	-0.348	(0.281)	0.00195	(0.00323)
hhsize	-270.1***	(33.55)	0.549	(0.404)
MaritSta	-573.2**	(257.9)	-4.193	(3.044)
Education	711.6***	(151.0)	-1.230	(2.126)
ResidStatus	-263.0*	(146.8)	-5.119***	(1.770)
EmploymentStat	-295.9	(180.1)	5.532***	(2.027)
Numbchild	30.80	(37.30)	0.420	(0.452)
Woodlots	-128.1	(207.4)	1.932	(2.632)
Hownership	-85.75	(254.9)	2.395	(3.125)
Membership	349.8	(278.1)	0.126	(2.935)
DistMarket	-16.12	(24.64)	-0.126	(0.300)
DistForest	-137.1***	(48.57)	-1.718***	(0.616)
DistMroad	84.53**	(33.87)	-0.195	(0.429)
Hsepartic	-213.9	(239.9)	-2.315	(3.468)
Multilingual			2.331	(2.109)
Temperature			-3.033***	(0.627)
Precipitation			0.00500	(0.00537)
Constant	3,255***	(803.4)	119.4***	(12.24)
Observations	405		267	
R-squared	0.292		0.236	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

However, participation in PELIS is voluntary and may be based on self-selection. CFAs or households that participate in PELIS may also have systematically different characteristics from non-participants since their participation may be based on anticipated benefits. Unobservable characteristics of households or CFAs may also affect both participation decision and household per capita monthly expenditure and forest cover under CFA. Ignoring all these factors may result in biased and inconsistent estimates of the impact of the incentive[25]. Since participation in PELIS was not purely random, we considered the PSM technique to estimate the mean impact on forest cover and household welfare and the endogenous QTE model to assess the distributional impact of the scheme on household welfare as we address the selectivity and endogeneity issues.

5.3 Propensity Score Matching Estimation Results

For PSM the key assumption of unconfoundedness and overlap must be met hence the need for an initial balance test. Our descriptive statistics in Table 8 suggests wide differences between participants and non-participants of PELIS. To match and balance the data we estimated a probit regression of participation or non-participation in PELIS. There is no consensus in published literature whether to include the significant variables or all prior variables as predictors of propensity scores[26] (Rubin, 1979; Austin et al., 2007). The propensity score estimates at the household level and CFA levels are presented in Table 2[27].

Table 2: **Propensity Score Estimates of PELIS adoption**

	Household Level				CFA Level			
VARIABLES	Coefficients	s.e	Marginal Effects	s.e	Coefficients	s.e	Marginal Effects	s.e
MaritSta	0.152	(0.219)	0.0469	(0.0673)	0.207	(0.306)	0.0526	(0.0776)
Numbchild	-0.00508	(0.0292)	-0.00156	(0.00899)	-0.0260	(0.0417)	-0.00660	(0.0106)
BornVil	-0.610***	(0.152)	-0.188***	(0.0442)	-0.701***	(0.205)	-0.178***	(0.0491)
hhsize	0.0178	(0.0313)	0.00550	(0.00964)	-0.00366	(0.0439)	-0.000929	(0.0111)
EmploymentStat	-0.622***	(0.182)	-0.192***	(0.0534)	-0.880***	(0.256)	-0.223***	(0.0604)
MedIncome	1.85e-05***	(6.29e-06)	5.68e-06***	(1.88e-06)	3.46e-05***	(1.11e-05)	8.77e-06***	(2.67e-06)
Woodlots	0.450**	(0.206)	0.138**	(0.0625)	0.364	(0.337)	0.0923	(0.0850)
CFAParticipation	0.209	(0.151)	0.0643	(0.0462)	0.207	(0.207)	0.0524	(0.0524)
DistMroad	0.109***	(0.0367)	0.0337***	(0.0110)	0.257***	(0.0591)	0.0653***	(0.0136)
DistMarket	0.0126	(0.0271)	0.00388	(0.00833)	-0.00228	(0.0382)	-0.000578	(0.00970)
DistForest	-0.0722	(0.0478)	-0.0222	(0.0146)	-0.0671	(0.0696)	-0.0170	(0.0176)
Temperature	0.151***	(0.0578)	0.0464***	(0.0174)	0.210**	(0.105)	0.0533**	(0.0260)
Elevation1	-0.000720*	(0.000422)	-0.000222*	(0.000128)	-0.00232***	(0.000864)	-0.000588***	(0.000210)
Precipitation	0.00106**	(0.000460)	0.000326**	(0.000140)				
Constant	-2.164	(1.729)			1.698	(3.437)		
Observations	405		405		266		266	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The probit estimation results at household and CFA levels show that holding other factors constant, those born in a given village are less likely to participate in PELIS and that household heads

[25]Another major drawback of OLS is that, it does not account for potential structural differences between the per capita monthly expenditure and forest cover for households and CFAs that participated in PELIS and those that did not.

[26]However, we identified appropriate covariates from the collected socioeconomic and institutional variables taking into account economic theory and the condition that covariates should influence the household decision to adopt PELIS and the outcome variables simultaneously but at the same time unaffected by the treatment (see Heckman et al. 1998).

[27]At the household level, we consider all the 406 households but one household was dropped due to incomplete observation on Bornvil variable hence the sample of 405 households. At the CFA level we considered 7 CFAs that did not benefit from PELIS (the controls) that is Menengai, Likia, Sururu, Nyangores, Nairotia, Baraget and Olenguruone constituting 130 households and 6 CFAs that benefited from PELIS (the treated) and had fifteen or more households benefiting they are namely; Bahati, Koibatek, Esageri, Malagat, Kericho and Makutano constituting 137 households. The household that had missing information on BornVil variable from Likia was also dropped from the analysis hence leading to a total sample of 266 households (138 controls and 128 treated).

employed in off farm jobs are also less likely to participate in PELIS given that with alternative sources of income protecting them from fluctuations in agricultural productivity, households may be less dependent on forests hence, less likely to participate in PELIS. However, the higher the income the more likely a household is to participate in PELIS supporting findings by Agrawal and Gupta (2005). In addition, the farther the distance from the main road the household is the higher the likelihood of participation in PELIS. This suggests that opportunity cost associated with distance matters. Thus, contradicting findings by Agrawal and Gupta (2005) that household likelihood of participation increases if households can easily access government offices concerned with the CPR. In terms of climate and geographical variables, a rise in average temperature increases the likelihood of participation in PELIS whereas the higher the elevation the lower the likelihood of participation in the scheme. The negative influence of elevation could be due to inaccessibility of most forest areas. However, at household level, the higher the precipitation the higher the likelihood of participation in the scheme. This is due to the fact that with higher precipitation, the anticipated benefits from farming are also higher. The results also suggest that at the household level, those who own private woodlots are more likely to participate in the scheme supporting findings by Jumbe and Angelsen (2007) that participation of most households owning woodlots is motivated by personal interests. Precipitation was however not included at the CFA level due to lack of convergence[28]. These results also correlate to the mean differences reported in Table 8. We therefore need to correct for these characteristics. These factors therefore significantly influence household decision to participate in the scheme. From the p scores, the estimated probability of participating in the scheme was estimated to be 55.9%.

5.3.1 Performance of Matching Estimators

We considered a range of matches namely the nearest neighbor matching, radius matching, and kernel matching[29]. However, we selected the matches that resulted in highest number of balanced covariates and large sample size within the common support as presented in Table 3. The kernel density showing the common support before and after matching is shown in Figure 1 in the annex. The figure shows a considerable magnitude of overlap after matching. Table 3 presents the quality and performance of the matches selected out of the different matches used. The Columns of interest are labelled (1) & (2) and (6) & (7). Fourteen and thirteen explanatory variables were used at the household level and CFA level analysis respectively[30].

[28] We tried to tease out the determinants of households participation in PELIS at both CFA and household levels to assess the robustness of our household level determinants which was the main interest.

[29] It is important to note that, the choice of matching algorithm often involves a trade-off in terms of bias and efficiency.

[30] A balance test of fourteen and thirteen variables in Column (1) and (6) suggests complete balance in matching. Whereas, the pseudo R squared in Column (2) and (7) shows the explanatory power for the re-estimated propensity score model after matching. From literature, a number of criteria have been suggested to gauge the performance of matching estimators. The criteria include: checking if after matching the significant mean difference across covariates remains. An alternative involves re-estimating the probit regression using the matched sample (see Sianesi, 2004). There should be no systematic differences between the covariates after matching hence the pseudo R squared should be low (Caliendo and Kopeinig, 2008). A likelihood ratio test of joint significance should also be rejected before matching but not after.

Table 3: **Performance of Matching estimator**

	Household Level					CFA level				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Matching estimator	Bal test*	Ps R2	LR chi^2	P>ch^2	Matched n	Bal test*	Ps R2	LR chi^2	P>ch^2	Matched n
NN (4)	11	0.048	24.44	0.041	362	11	0.055	10.50	0.653	207
NN (5)	11	0.047	24.08	0.045	362	12	0.047	9.07	0.768	207
Radius (=0.0025)	14	0.033	9.89	0.770	284	13	0.073	6.26	0.936	169
Radius (=0.005)	11	0.046	19.46	0.148	331	13	0.036	5.07	0.974	189

* covariates with insignificant mean difference between beneficiaries and non-beneficiaries after matching

5.3.2 Matching Based treatment effects on PELIS beneficiaries

We present the estimated ATT in Table 4. The ATT were estimated for household welfare and CFA forest cover using psmatch2 command in stata (Leuven et al., 2015). The Columns of interest are labelled ATT and t-stat.

Table 4: **Matching based Treatment Effects on PELIS beneficiaries**

	Per Capita Monthly Expenditure			Forest cover		
Estimator	ATT	S.Dev	t-stat	ATT	S.Dev	t-stat
NN (4)	597.02	192.32	3.10***	5.71	3.33	1.71*
NN (5)	589.65	197.55	2.98***	5.53	3.31	1.67*
Radius (0.0025)	363.48	204.68	1.78*	7.73	4.10	1.88*
Radius (0.005)	678.36	211.28	3.21***	7.94	3.30	2.40**

***<0.01, **<0.05, *<0.1

The results show that PELIS has significant (both economically and statistically) positive impact on household welfare and forest cover. The average impact of the scheme on PELIS beneficiaries' per capita monthly expenditure was estimated at between ksh. 363 (USD 3.63) and ksh. 678 (USD 6.78). Based on the average per capita monthly expenditure for households benefiting from PELIS which is Ksh. 2,409 (USD 24.09), this accounts for between 15.09% and 28.14%. The impact of the scheme on forest cover was estimated at between 5.53% and 7.94%. However, since we included even the covariates that remained significantly different even after matching (i.e., distance to market, precipitation and temperature) in the outcome analysis, to assess the robustness of the PSM estimates, we also run a matched regression with controls (We find impact on per capita expenditure to be between Ksh. 436 (USD 4.36) and Ksh. 525 (USD 5.25 whereas, on forest cover it was estimated between 4.67% and 7.27%)[31]. It is also important to note that, matching is based

[31] We find that the results for the matched regression and the PSM are not any different. These results are however not presented in this paper since they were used to assess the robustness of our PSM estimates.

on the unconfoundedness assumption which is not testable. We therefore conducted a sensitivity analysis of the matching estimates.

5.3.3 Sensitivity Analysis of the Matching Estimates

PSM is based on the assumption that the researcher should be able to observe all variables simultaneously influencing decision to participate in PELIS and the outcome variable (unconfoundedness or the conditional independence assumption) otherwise, the matching estimators may not be robust due to the hidden bias (Rosenbaum, 2002). Estimating the extent of selection bias is quite complex especially due to the fact that we used non experimental data. We therefore employed Rosenbaum (2005) bounding approach to test for robustness of the matching estimates to unobserved variables. Following Rosenbaum (2005) bounding method we examined the sensitivity of the match based treatment effects estimates with respect to potential deviations from conditional independence. The sensitivity analysis results are presented in Table 10[32].

Looking at our sensitivity analysis results in Table 10, for per capita expenditure, at Γ=1.2 and 1.3 the results will not be significant at 1% and at Γ=1.4 the result is also not significant at 10% with p-value of 0.150. Whereas for forest cover, at Γ=1.1 the result will not be significant at 10% with a p-value of 0.158. This suggests that unobserved covariates would cause the odds ratio of treatment assignment to differ between the participants and non-participants once we reach a specific Γ level. From this results, we can infer that the results to some extent reveals some levels of selectivity bias[33].

Due to possibility of selection bias, to ascertain the robustness of our PSM estimates, we also employed instrumental variables estimation technique following Lewbel's heteroscedasticity-based instrumental variable technique (see Lewbel (2012)) to test and address the potential endogeneity of participation in PELIS on per capita household expenditure and forest cover[34]. Based on this approach, our results in Table 11 revealed that, PELIS has significant positive impact on household percapita monthly expenditure estimated at Ksh. 1270 (USD 12.70) hence raising welfare for the average household by about 58%. On the other hand, the estimated impact of PELIS on forest cover was approximately 4.23% holding other factors constant[35]. These findings therefore resonates

[32] The first column contains the log odds of differential assignment due to unobserved heterogeneity, the second to fifth columns, contains the upper and lower bound significance levels respectively for the key outcome variables namely per capita monthly expenditure and percentage forest cover. The second to fifth columns examines the match based treatment effect for each measure of unobservable potential selection bias. The lower bounds are of no interests since they hold under the assumption that the true ATT is underestimated but our ATT estimates are positive (Becker and Caliendo, 2007).

[33] According to Becker and Caliendo (2007), the critical of say Γ= 1.4 for per capita expenditure and 1.1 for forest cover is not an indication that unobserved heterogeneity exists and that there is no effect of the treatment on the outcome variable. The unconfoundedness assumption therefore cannot be justified using this test hence we cannot state whether the CIA assumption holds or not. The result just indicates that if any unobserved variable caused the odds ratio of treatment assignment to differ between treatment and comparison groups by sayΓ=1.4 for per capita expenditure, then the confidence interval for the treatment effect would include zero (see Becker and Caliendo 2007).

[34] The main advantage of this approach is that, it provides options for generating instruments and allows the identification of structural parameters in models with endogeneity or mis-measured regressors when we do not have external instruments. The approach is also capable of supplementing weak instruments. Identification is consequently achieved by having explanatory variables that are uncorrelated with the product of heteroscedastic errors (see Lewbel (2012)).

[35] In the two models, we first tested for endogeneity using the Durbin-Wu-Hausman tests for endogeneity and control function approach under the null hypothesis that the variables are exogenous. The tests rejects the null hypothesis of exogeneity at 1% significance level for

well with the results from our PSM estimates although the impact on household welfare was found to be slightly higher compared to the PSM estimates[36].

5.4 Quantile Treatment Effects Model

To examine the impact of the scheme across the income distribution, the study adopted the endogenous QTE model. Since participation in PELIS is potentially endogenous to per capita expenditure, we first tested for endogeneity of participation in PELIS (our treatment variable). The control function approach was used to test for endogeneity. The approach is conducted in two stages. In the first stage, the endogenous variable which in our case is PELIS was regressed on the instrumental variable BornVil (i.e a dummy variable whether the household head is born in a given village or not) and other explanatory variables and the predicted residuals saved[37]. In the second step, the outcome variable (per capita expenditure) was regressed on the endogenous variable, other explanatory variables and the residuals[38] (Wooldridge, 2010). Using this test, the null hypothesis of exogeneity is rejected with a p-value of 0.055[39]. In light of evidence of endogeneity of participation in PELIS, we proceeded to estimate an endogenous QTE model to handle selection bias and solve the endogeneity problems. The results of the endogenous QTE model following Abadie et al. (2002) are presented in Table 12 in the appendix.

Conditioned on a set of covariates[40], the endogenous QTE model revealed that the scheme had significant positive impact on household welfare from the fourth to the ninth quantiles only showing the distributional inequity of the scheme[41]. A major observation during the survey was the fact that, most forest-adjacent households participating in PELIS were mainly involved in growing the same kind of crops i.e., peas, cabbages or potatoes which they complained that since they all harvested at almost the same time, this resulted in excess supply hence lower prices coupled with lack of market for the agricultural produce. Moreover, most forest-adjacent communities are poor hence have very limited alternatives in terms of exploring market opportunities for their produce, and even if the harvest is good, very few can afford to transport their produce to other areas

the two models. We also carried out performance statistics for the IV models. We tested for, under-identifcation based on Kleibergen-Paap rk Lm statistics, weak identification using the Donald Wald F statistics, and the Hansen J statistics under the null hypothesis that the instruments are valid. The models passed all the tests hence proving that the heteroskedasticity-based IV estimates would yield reliable estimates.

[36] It is also important to note that we also arrive at similar conclusion when we used the endogenous switching regression model.

[37] We computed the proportion of the predicted probabilities outside the unit interval. Finding only 6.4% fell outside the unit interval we chose the LPM over the probit or logit model since the LPM would still produce unbiased and consistent estimates (Horrace and Oaxaca, 2006). The F value for the LPM model was also found to be 11.15 with a p value of 0.000 showing the significance of the LPM model.

[38] The approach is same as the 2SLS approach but the only difference is that it allows for testing for endogeneity of PELIS participation. It however hinges on assumption of exogeneity of the instrument.

[39] The null hypothesis of exogeneity is also rejected when we use the Durbin-Wu-Hausman test of endogeneity at 1% significance level.

[40] Namely, level of households participation in CFA activities, ownership of land titles, employment status, sex of household head and whether the household head is a native or not, climate and geographical variables and distance to the nearest; market, main road, and the nearest edge of the forest, among other factors.

[41] One anonymous reviewer suggested that we limit the quantiles to about five instead of the nine employed in the study. A reduction of the quantiles to five does not change the results because it simply estimates the impact at that quantiles but the results remain the same. Since we were more interested in the entire income distribution leaving the quantiles at nine provided more information on the true impact of the scheme at each and every segment. It is also important to note that, even if we employed the exogenous QTE model, we arrive at similar conclusion. The same was also the case when we used household percapita income as opposed to percapita expenditure.

to fetch better prices for their produce. Another possible reason could be due to elite capture issues where richer elite households take over the scheme and other CFA activities in general and therefore set to benefit more than the poor households. This could therefore explain the inequitable distributional nature of the scheme.

We therefore reject the null hypothesis of constant impact of the scheme on household welfare because the benefits are more skewed towards the middle and upper quantile households. However, according to the Kenya Integrated Household Budget Survey (2005), the per capita monthly expenditure for rural households in the Rift valley province in which the Mau forest is located is approximately Ksh 2251(USD 22.51). Comparing this with our average per capita monthly expenditure for the sampled households which is about Ksh. 2185(USD 21.85), we find that the study population is on average slightly below the poverty line. This shows that most households living around the Mau forest are relatively poor as has been shown by most studies that, the rural poor are the most forest dependent. However, the poverty datum line lies between the sixth (average of Ksh 2082.26(USD20.82)) and 7th (average of ksh 2375.71(USD23.76)) quantiles see Table 9. Those below the poverty datum line are thus considered poor i.e. first to sixth quantile. It is therefore, evident that the scheme raised welfare of the poor but the least poor (fourth to sixth quantile households) and the richer quantile households benefit more from the scheme than the poorest.

6 Conclusion and Policy Recommendations

The study aimed at identifying the determinants of household decision to participate in/adopt PELIS, and to determine the overall and distributional impact of PELIS on welfare of forest-adjacent households as well as the mean impact on forest cover. The PSM method estimated the impact of PELIS on household per capita monthly expenditure at between ksh. 363 (USD 3.63) and ksh. 678 (USD 6.78) hence raising welfare by between 15.09% and 28.14% whereas the overall impact of the scheme on forest cover was estimated at between 5.53% and 7.94% slightly lower than the OLS estimate of 9.45%. We can thus conclude that on average PELIS meets the dual objective of raising household welfare and improving forest cover. This shows that devolution of forest management and provision of incentives to well organized communities can lead to better welfare and environmental outcomes on average. On the other hand, in terms of welfare, the QTE model under endogenous assumption, revealed that the scheme had positive impact on household welfare from the fourth quantile households and above only. We can therefore, infer that there is some distributional inequity on the impact of the scheme that needs to be addressed for the sustainability and success of the scheme and for it to be able to make low income household rise up the income ladder and also lead to improvement in forest cover at the same time.

However, we cannot conclude that the scheme is less pro poor since the scheme raises welfare of the least poor as well even though the poorest and marginalized sections of the community are left out. These results support findings by Angelsen and Wunder (2003), Sunderlin et al. (2005), Mazunda and Shively (2015), and Ali et al. (2015). Our findings also lend support to findings by Malla et al. (2000), Jumbe and Angelsen (2006) and Cooper (2008) (Gelo and Koch, 2014; Gelo et al., 2016) and Moktan et al. (2016) who found joint forest programs to improve welfare of the high income households more than poor households. On the determinants of households' adoption of or participation in PELIS, we found that, being born in a village or not, employment status of household head (i.e. employed in off farm jobs or not), household income, owning woodlots or not, distance to nearest motorable road in kilometres, precipitation, temperature and elevation levels of nearest forest are the major factors influencing household decision to participate in the scheme. These results support some findings by (Lise, 2000; Adhikari et al., 2004; Adhikari, 2005; Agrawal and Gupta, 2005; Jumbe and Angelsen, 2007; Kabubo-Mariara, 2013). These factors therefore, needs adequate consideration in allocation of PELIS plots to forest-adjacent communities.

A number of policy implications may be drawn from the study. First, the findings call for a balanced approach to forest management to ensure equitable distribution of PELIS plots and benefits across the income groups. To avoid further marginalization of any income group, policy makers need to give much consideration to equity in access and management of the resource especially with respect to forest resources and existing incentives. The design and implementation of the scheme should also be given due consideration if it is not to discriminate the very group that it is meant to benefit and to ensure sustainability of the scheme. Failure to address the equity concerns could lead to increased degradation and worsened welfare outcome for lowest income groups with the rising population in the long run.

Secondly, a mix of market based incentives and regulated command and control mechanisms based on policy makers understanding of preferences within each CFA may also create more positive impact on forest cover and household welfare. For the scheme to have significant impact on forest conservation, there is also need for increased awareness and roll out of the incentive to other CFAs that have been reluctant to adopt the scheme taking cognizant of the views and expectations of local communities especially low income households. Lastly, there is need to explore ways of training forest-adjacent communities on modern farming techniques, product diversification and improving market opportunities and linkages for various non-timber harvests from the PELIS farms by households in order to address the ensuing market failures. This objective can only be achieved through collaboration with relevant government bodies and non-governmental organizations or through formation of forest user cooperatives to provide market linkages.

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Appendix

Table 5: **Description of Variables**

Variable	Definition
Dependent variables	
PCMonthlyExp	Per capita Monthly Expenditure
Forestcover	Forest Cover expressed as a percentage of total forest size under each CFA
Explanatory	
HHWealth	Total value of household asserts (land, farm animals, agricultural implements, farm produce etc)
PELIS	Dummy=1 if household owns a PELIS plot and 0 otherwise
HHsex	Dummy=1 if Male and 0 if female
Numbchild	Number of children
BornVil	Dummy=1 if born in the village, 0 otherwise
MedAge	Age of the household head (Median age calculated from the categorical variables)
hhsize	Number of people in the household including household head
MaritSta	Dummy=1 if married, 0 not married
Education	Dummy=1 if household head has post primary education and 0 if household head has up to primary education
ResidStatus	Dummy=1 if household head is a native, 0 if household head is an immigrant/settler
HHEducyrs	Years of education
Multilingual	Dummy=1 if speaks more than two languages, 0 if speak two or less languages
Employment Status	Dummy=1 if employed in off farm, 0 if self employed i.e farming
LandTitle	Dummy=1 if Own title for household land, 0 otherwise
MedIncome	Median monthly income for the household
Woodlots	Dummy=1 If the household owns a woodlot, 0 otherwise
CFAMeeting	Dummy=1 If father represents the household in CFA meetings, 0 if Mother represents the Household
CFAParticipation	Dummy=1 If the household is active in participation in CFA activities, 0 if passive
Hsepartic	Dummy=1 if household participates in CFA activities, 0 otherwise
Hlandsize	Size of household land
Hownership	Dummy=1 if the household head owns the house, 0 otherwise
DistMroad	Distance from household to the nearest motorable road in km
DistMarket	Distance from household to the nearest market using in km
DistForest	Distance from household to the nearest edge of the forest in km
Membership	Dummy=1 if a member of other environmental organizations(e.g. CBOs), 0 otherwise
Temperature	Annual average temperature in degrees Celsius
Precipitation	Average Annual precipitation (mm)
Elevation	Level of Elevation in each forest (meters)

Table 6: **Summary Statistics**

	Total Sample			PELIS Beneficiaries			Non PELIS Beneficiaries		
variable	**N**	**Mean**	**sd**	**N**	**Mean**	**sd**	**N**	**Mean**	**sd**
Dependent									
PCMonthlyExp	406	2186	1615	228	2405	1939	178	1905	1003
Forestcover	267	77.64	14.23	137	79.54	10.47	130	75.64	17.15
Explanatory									
HHWealth	406	1.269e+06	1.759e+06	228	1.257e+06	2.043e+06	178	1.284e+06	1.311e+06
HHsex	405	0.780	0.415	227	0.767	0.424	178	0.798	0.403
Numbchild	406	4.865	2.701	228	5.171	2.729	178	4.472	2.619
BornVil	405	0.585	0.493	228	0.531	0.500	177	0.655	0.477
MedAge	406	48.14	13.73	228	49.29	12.70	178	46.67	14.85
hhsize	406	5.798	2.631	228	6.110	2.729	178	5.399	2.450
MaritSta	406	0.869	0.337	228	0.895	0.308	178	0.837	0.370
Education	406	0.360	0.480	228	0.351	0.478	178	0.371	0.484
ResidStatus	406	0.574	0.495	228	0.570	0.496	178	0.579	0.495
Hsepartic	406	0.904	0.295	228	0.908	0.290	178	0.899	0.302
Employment	406	0.241	0.428	228	0.167	0.373	178	0.337	0.474
LandTitle	406	0.522	0.500	228	0.513	0.501	178	0.534	0.500
MedIncome	406	15788	20503	228	17862	25993	178	13132	9097
HHEducyrs	406	8.404	3.639	228	8.329	3.556	178	8.500	3.751
Woodlots	406	0.850	0.358	228	0.912	0.284	178	0.770	0.422
CFAParticipation	406	0.623	0.485	228	0.697	0.460	178	0.528	0.501
Hownership	406	0.904	0.295	228	0.917	0.277	178	0.888	0.317
DistMroad	406	1.926	2.696	228	2.485	2.983	178	1.211	2.073
DistMarket	406	3.368	3.537	228	3.885	3.504	178	2.707	3.478
DistForest	406	1.481	1.478	228	1.406	1.408	178	1.578	1.561
Hlandsize	406	2.519	5.682	228	2.473	7.020	178	2.578	3.263
Membership	406	0.0690	0.254	228	0.0702	0.256	178	0.0674	0.251
Temperature	406	15.05	1.776	228	15.51	1.726	178	14.46	1.667
Precipitation	406	1164	181.4	228	1197	183.2	178	1122	170.7
Elevation1	406	2444	233.4	228	2402	254.8	178	2499	189.9

Table 7: **Descriptive Statistics**

variable	PELIS Beneficiaries		Non PELIS Beneficiaries		Mean Difference	
	mean	s.e	mean	s.e	Mean	s.e
PCMonthlyExp	2404.52***	(128.42)	1905.33***	(75.14)	499.19**	(159.82)
Forestcover	79.72***	(0.95)	75.73***	(1.41)	3.99***	(1.72)
HHWealth	1.256e+06	(135333)	1.283e+06	(98298)	27294.18	(176098)
HHsex	0.767***	(0.028)	0.798***	(0.030)	-0.031	(0.042)
Numbchild	5.171***	(0.181)	4.472***	(0.196)	0.699**	(0.268)
BornVil	0.531***	(0.033)	0.655***	(0.036)	-0.125**	(0.049)
MedAge	49.285***	(0.841)	46.67***	(1.112)	2.611*	(1.369)
hhsize	6.109***	(0.181)	5.399***	(0.184)	0.711***	(0.261)
MaritSta	0.895***	(0.020)	0.837***	(0.028)	0.058*	(0.034)
Education	0.351***	(0.032)	0.371***	(0.036)	-0.019	(0.048)
ResidStatus	0.570***	(0.033)	0.578***	(0.037)	0.008	(0.050)
Hsepartic	0.907***	(0.019)	0.899***	(0.023)	0.009	(0.030)
Multilingual	0.491***	(0.033)	0.438***	(0.037)	0.053	(0.050)
Employment Status	0.167***	(0.025)	0.337***	(0.035)	-0.170***	(0.042)
LandTitle	0.513***	(0.033)	0.533***	(0.037)	-0.021	(0.050)
MedIncome	17862***	(1721.409)	13132***	(681.868)	4729.798**	(2039.709)
HHEducyrs	8.328***	(0.235)	8.500***	(0.281)	-0.171	(0.364)
Woodlots	0.912***	(0.019)	0.770***	(0.032)	0.143***	(0.035)
CFAParticipation	0.697***	(0.030)	0.528***	(0.038)	0.169***	(0.048)
Hownership	0.917***	(0.018)	0.888***	(0.024)	0.029	(0.030)
DistMroad	2.485***	(0.198)	1.211***	(0.155)	1.274***	(0.262)
DistMarket	3.885***	(0.232)	2.707***	(0.261)	1.177***	(0.349)
DistForest	1.406***	(0.093)	1.578***	(0.117)	-0.173	(0.148)
Hlandsize	2.473***	(0.465)	2.578***	(0.245)	-0.104	(0.569)
Membership	0.0702***	(0.017)	0.0674***	(0.019)	0.003	(0.025)
Temperature	15.51***	(0.114)	14.46***	(0.125)	1.044***	(0.170)
Precipitation	1197***	(12.134)	1122***	(12.792)	74.437***	(17.787)
Elevation	2401***	(16.875)	2498***	(14.233)	-97.059***	(22.869)

Table of mean differences and test of significance. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: **Per Capita Monthly Expenditure across the quantiles**

Quantile	Mean PCMonthly Exp	No of Households
1st Quantile	695.19	46
2nd Quantile	1111.58	47
3rd Quantile	1370.93	43
4th Quantile	1596.29	45
5th Quantile	1847.10	45
6th Quantile	2082.26	45
7th Quantile	2375.71	45
8th Quantile	3019.14	46
9th Quantile	5673.27	44
All households	2185	406

Figure 1: **Kernel density before and after matching**

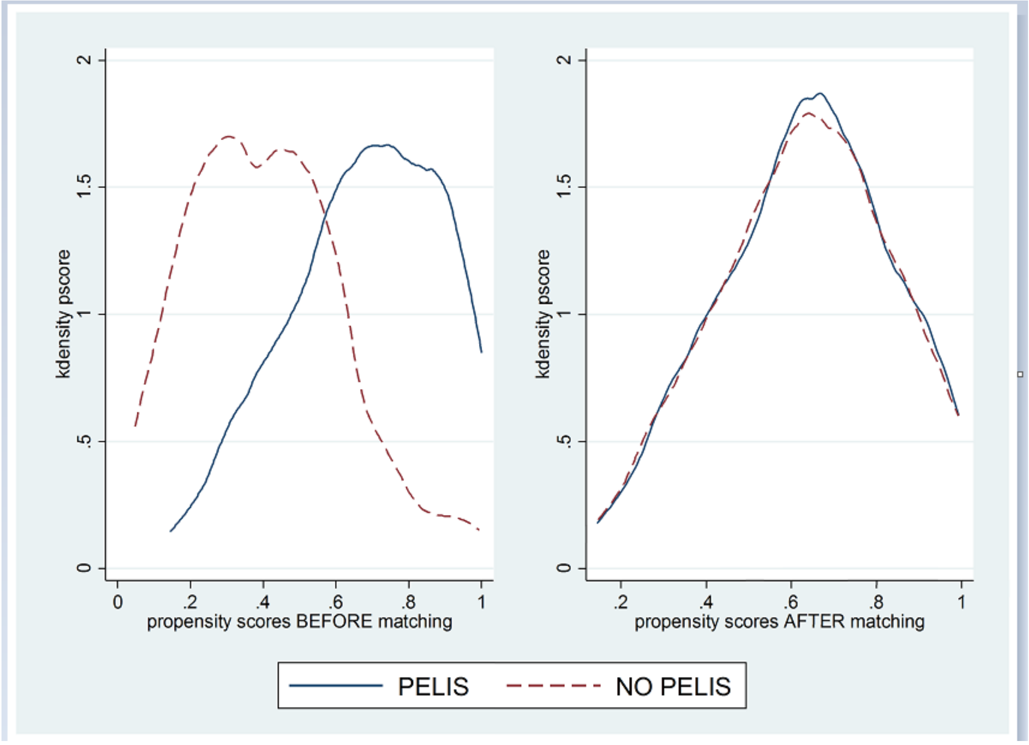

Table 9: **Distribution of adopters and non adopters of PELIS by CFAs**

No	CFA	No PELIS	PELIS	Total
1	Bahati	1	26	27
2	Dondori	9	12	21
3	Menengai	4	0	4
4	Koibatek	0	24	24
5	Molo	3	9	12
6	Sorget	10	9	19
7	Longman	3	9	12
8	Likia	56	0	56
9	Tendeno	1	13	14
10	Kerisoi	3	13	16
11	Baraget	5	0	5
12	Saino	1	12	13
13	Sururu	25	0	25
14	Esageri	0	24	24
15	Malagat	0	16	16
16	Kericho	6	15	21
17	Makutano	1	24	25
18	Kiptunga	7	11	18
19	Nyangores	10	0	10
20	Nairotia	20	0	20
21	Olenguruone	10	0	10
22	Chepalungu	3	11	14
	Total	178	228	406

Table 10: **Sensitivity Analysis of Matching Estimates**

	PCMonthlyExp		Forest Cover	
Gamma	sig+	sig-	sig+	sig-
1	0.00141	0.00141	0.0956	0.0956
1.100	0.00759	0.000191	0.167	0.0493
1.200	0.0273	2.30e-05	0.256	0.0244
1.300	0.0720	2.50e-06	0.356	0.0117
1.400	0.150	2.50e-07	0.457	0.00549
1.500	0.261	2.40e-08	0.554	0.00252
1.600	0.393	2.20e-09	0.643	0.00114
1.700	0.529	1.90e-10	0.719	0.000506
1.800	0.655	0	0.784	0.000223
1.900	0.761	0	0.836	9.70e-05
2	0.842	0	0.877	4.20e-05

*gamma: Log odds of differential assignment due to unobserved factors
sig+ : Upper bound significance level, sig-: Lower bound significance level

Table 11: **Heteroscedasticity Based Instrumental Variable Estimation Results**

VARIABLES	(1) PCMonthlyExp	(2) Forestcover
PELIS	1,270**	4.229**
	(635.6)	(2.051)
HHsex	-184.0	0.439
	(191.7)	(1.366)
EmploymentStat	-236.4	-0.261
	(185.9)	(1.427)
LandTitle	285.3**	0.767
	(139.8)	(1.135)
Woodlots	-162.4	0.225
	(247.1)	(1.644)
ResidStatus	-260.1	-0.0392
	(233.8)	(2.297)
CFAParticipation	151.9	2.244*
	(155.6)	(1.253)
Hsepartic	-522.2*	4.153***
	(302.2)	(1.504)
DistForest	-98.40**	-0.981***
	(44.75)	(0.349)
DistMroad	43.32	-0.126
	(42.18)	(0.305)
DistMarket	13.10	0.699***
	(25.45)	(0.238)
HHEducyrs	85.65***	-0.0167
	(23.36)	(0.165)
Hlandsize	4.909	-0.208**
	(19.86)	(0.0953)
hhsize	-292.4***	0.0641
	(36.34)	(0.269)
HHWealth	0.000127	6.00e-07
	(9.53e-05)	(4.43e-07)
Numbchild	41.08	0.246
	(38.94)	(0.295)
MedAge	4.254	-0.481**
	(41.05)	(0.239)
MedAgesq	-0.0577	0.00374*
	(0.351)	(0.00207)
MedIncome	0.0126*	1.64e-05
	(0.00745)	(1.95e-05)
Temperature	-191.3***	-3.827***
	(58.40)	(0.463)
BornVil	58.28	-5.203**
	(263.5)	(2.286)
Precipitation	0.0920	-0.0748***
	(0.427)	(0.00665)
Membership	175.3	0.637
	(315.4)	(1.683)
Other Controls		
Institutional variables	No	Yes
Constant	5,279***	212.7***
	(1,322)	(13.60)
Observations	404	404
R-squared	0.351	0.721

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 12: **Endogenous Quantile Treatment Effects Model Estimation Results**

VARIABLES	QT_1	QT_2	QT_3	QT_4	QT_5	QT_6	QT_7	QT_8	QT_9
PELIS	-75.21	167.2	410.6	497.6*	532.8**	565.7**	842.7***	1,227***	2,155***
	(194.2)	(382.0)	(328.1)	(288.5)	(246.8)	(258.9)	(269.8)	(411.2)	(787.1)
DistForest	-105.3**	0.379	-68.29	-78.10*	-44.18	-48.76	-176.6***	-278.4***	-256.2***
	(44.52)	(53.86)	(51.67)	(43.28)	(36.85)	(52.45)	(41.57)	(54.36)	(81.45)
DistMroad	44.76	-37.09	-46.65	39.06	71.89**	60.14	-30.60	-74.81	-109.9
	(40.70)	(33.26)	(43.54)	(41.68)	(31.16)	(49.19)	(41.81)	(55.22)	(201.7)
DistMarket	-96.78***	-32.88	-24.18	-60.19***	-44.54***	-44.82***	-24.29	-28.87	-13.12
	(17.33)	(20.12)	(19.77)	(12.21)	(12.27)	(15.03)	(20.85)	(24.27)	(34.17)
HHEducyrs	-18.78	-7.228	-24.11**	-17.48*	-11.81	-7.174	-3.824	1.239	-11.10
	(12.23)	(12.31)	(10.18)	(9.067)	(7.749)	(10.88)	(9.992)	(12.23)	(24.31)
Hlandsize	40.53	54.70***	44.86*	-2.354	-22.62*	-38.10***	-50.85***	-59.33***	-65.26
	(32.85)	(19.62)	(24.00)	(17.38)	(12.21)	(13.01)	(14.53)	(15.60)	(43.60)
hhsize	-234.7***	-182.9***	-146.0***	-177.7***	-190.8***	-188.7***	-205.6***	-238.5***	-176.3***
	(22.71)	(41.35)	(40.11)	(26.38)	(25.00)	(34.31)	(29.02)	(42.79)	(67.18)
HHWealth	0.000139	0.000206	0.000296*	0.000523***	0.000549***	0.000566***	0.000562***	0.000698***	0.000560***
	(0.000247)	(0.000142)	(0.000169)	(8.65e-05)	(6.84e-05)	(6.59e-05)	(7.17e-05)	(7.39e-05)	(0.000160)
Numbchild	-20.56	-8.951	-56.16***	-37.01***	-21.85	-7.822	39.44	-31.97	-7.319
	(24.37)	(16.36)	(13.27)	(14.22)	(15.07)	(30.68)	(37.93)	(41.56)	(110.5)
MedAge	45.19***	29.17	1.164	-27.36	-64.09***	-55.01*	-58.92*	7.636	-58.54
	(17.36)	(27.95)	(35.95)	(28.08)	(20.01)	(28.24)	(32.84)	(52.46)	(77.39)
MedAgesq	-0.305*	-0.186	0.0919	0.466	0.742***	0.650**	0.469	-0.0834	0.517
	(0.181)	(0.305)	(0.364)	(0.288)	(0.201)	(0.292)	(0.335)	(0.556)	(0.813)
MedIncome	0.0156***	0.0151***	0.0134***	0.0111***	0.0110***	0.0200	0.0225***	0.0257**	0.0416
	(0.00462)	(0.00358)	(0.00447)	(0.00350)	(0.00425)	(0.0198)	(0.00606)	(0.0112)	(0.0465)
Temperature	72.20***	58.22***	-2.278	-8.517	-24.80	25.56	34.19	35.31	43.11
	(24.37)	(13.73)	(17.73)	(15.73)	(16.62)	(55.72)	(38.63)	(35.60)	(115.6)
Precipitation	-1.084***	-1.142***	-1.217***	-1.270***	-1.248***	-1.773***	-1.780***	-2.663***	-2.560***
	(0.241)	(0.167)	(0.133)	(0.139)	(0.139)	(0.289)	(0.240)	(0.381)	(0.714)
HHsex	578.2**	443.8***	331.5*	494.8***	325.2	-81.67	-327.6	-694.6*	-1,029*
	(274.7)	(170.5)	(191.5)	(160.9)	(201.7)	(265.1)	(310.8)	(388.3)	(530.3)
EmploymentStat	-178.5***	203.6**	58.19	171.7*	86.88	-147.0	-395.8***	-364.4**	-385.8**
	(64.71)	(85.42)	(92.32)	(88.03)	(88.08)	(188.7)	(117.0)	(171.6)	(156.5)
LandTitle	-291.0	-378.4***	-285.1**	-315.1***	-279.8***	-187.5*	159.5	608.8***	893.4***
	(190.1)	(137.0)	(115.3)	(68.39)	(58.40)	(103.6)	(111.2)	(172.6)	(270.0)
Woodlots	132.2	8.014	65.88	164.9***	136.1**	16.68	114.8	138.3	372.9
	(199.8)	(110.4)	(102.2)	(54.66)	(63.22)	(124.2)	(108.0)	(144.3)	(544.7)
Membership	94.31	10.91	-100.3	-273.2	-156.5	-59.05	-356.1*	-325.6	-233.0
	(132.4)	(150.5)	(183.4)	(177.6)	(156.1)	(189.1)	(204.3)	(220.6)	(280.5)
ResidStatus	-195.7**	-223.7**	35.68	154.4*	140.0*	-4.487	-34.03	-358.2***	-396.1
	(97.44)	(103.8)	(112.4)	(84.54)	(81.65)	(143.8)	(140.9)	(104.5)	(320.6)
CFAParticipation	224.0**	312.6***	375.5***	606.7***	453.3***	593.6***	364.5***	392.9***	507.4***
	(92.38)	(68.11)	(81.77)	(79.54)	(90.47)	(190.3)	(137.6)	(147.4)	(145.5)
Hsepartic	435.2***	345.6***	433.1***	409.6***	477.1***	398.9*	257.1*	411.1**	278.4
	(86.66)	(55.30)	(76.57)	(69.12)	(66.35)	(239.9)	(135.3)	(185.7)	(554.3)
Constant	325.3	678.1	2,553***	2,783***	4,269***	4,456***	5,686***	5,777***	7,085***
	(457.2)	(604.1)	(790.3)	(497.4)	(410.5)	(640.2)	(809.7)	(1,308)	(1,609)
Observations	404	404	404	404	404	404	404	404	404

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1