Do the Poor Benefit from Devolution Policies? Evidence from Quantile Treatment Effect Evaluation of Joint Forest Management

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Abstract

Existing literature have rarely evaluated distributive effect of Joint Forest Management (JFM) augmented with improved market linkages for non-timber forest products nor have they accounted for heterogeneity in the welfare effects We assess the distributional impact of a unique JFM in Ethiopia in which additional support for improved market linkages for non-timber forest products was provided The analysis is based on matching and instrumental variable (IV) methods of quantile treatment effects (QTE) evaluation using household data from selected rural villages of Gimbo district, in southwest Ethiopia. The results confirm that the intervention affect outcomes heterogeneously across the welfare distribution. Specifically, the program was found to raise welfare for only those along upper half (median and above) of welfare distribution Thus, we infer that the program is not pro-poor, and, therefore, is not equity enhancing. Our analysis also revealed that such distributional bias of the program benefit arises from elite capture.

Keywords: Market Linkage, Joint Forest Management, Quantile Treatment Effects, Welfare Distribution

1 Introduction

In many poor regions, the poor heavily depend on the income derived from the natural resource base such as village forests, grazing land and fisheries. These resources are typically managed under *de facto* open access regime ,

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making its entry cost lower relative to that of alternative income earning sources, i.e., the poor often lack access to other income generating resources, such as land, human capital and physical capital. Furthermore, compared to alternative income sources, natural resource earnings, such as those from non-timber forest products (NTFP), are lower but less variable (Wunder, 2001). Thus, given that the poor are epitomized by high rates of risk-aversion, sales of these products offer income insurance in an environment characterized by imperfect insurance and credit markets, providing another explanation as to why the poor would be more dependent on environmental resources than the non-poor (Delacote, 2007; Debela et al, 2012).

Unfortunately, such dependence on environmental resources leads to overuse (degradation) of the resource, which feeds back through further impoverishment of the poor resource users, an outcome often described as poverty-environment downward spiral (Angelsen, 1998). This realization is best elucidated in a proposition that the poor are agents and victims of environmental degradation, a claim that represented a key hypothesis of environment-poverty nexus (Wunder, 2001 and Fisher, 2004). The implication of that proposition is that poverty alleviation ameliorates environmental outcomes, and vice versa. A corollary to this claim is a conjecture that the poverty-environment trap can be broken through interventions that restrict excessive forest resource extraction, but improves its income (resources rent)[1]. One such condition is defining and enforcing common property institutions of forestry management. Theoretically, common property institutions improve resource conditions and generate resource rents, thereby reducing poverty (Sunderlin et al., 2004 and Angelsen and Wunder, 2003).

Optimism has been proliferating within policy and donor's circles that devolution of natural forest management has the potential both to save the forests and offers positive welfare benefit especially among the poor. However, uncertainty abounds concerning whether such expectation is supported for the following major reasons. First, more often than not, forestry management decentralization has taken the form of Joint Forest Management (JFM), which basically aims at forest conservation by placing significant restrictions on forest harvest, charcoaling and agricultural encroachment, which are practices previously shown to lead to deforestation under the alternative property right regime of open access. Instead, villagers are entitled to extract minor forest products, such as fuelwood, traditional medicines and non-timber products for domestic use only, and are allowed to access to ritual sites(Kajembe et al. 2003). In some cases, they are required to pay user fee (Jumbe and Angelsen 2006, Limenih and Bekele, 2008, Robinson and Lokina, 2012). In either case, it is not certain whether program benefit outweigh the opportunity cost born by the members of communities.

Second, in light of differential level of dependency on forests to make living, the distribution of the opportunity cost arising from these exclusionary rules across different segments of participants is likely to vary. Particularly, marginal

[1] We are here referring to natural forest which is often managed under *de facto* open access regime.

households, as for example landless, are more likely to bear higher opportunity cost of JFM participation and hence to suffer negative welfare effects.

In fact, existing empirical evidences on these outcomes are limited, at best, and leans towards worsened welfare outcomes for the poor. Jumbe and Angelsen (2006) conclude that common property forestry programs have contrasting welfare impacts across study villages in Malawi; importantly, though, welfare amongst the poor was worsened. Cooper's (2007) computable general equilibrium analysis uncovers welfare losses for all income groups, although those outcomes are worse for the poor. Similarly, panel data evidence from Nepal shows increases in per-capita consumption, but greater inequality (Cooper, 2008).

From policy perspective, the success of these programs would thus, depend on providing alternative incentives basis to farmers to eschew short-term gains in favour of medium- to long-term payoffs. One innovative design option is to confer common property right usufruct of non-timber forest products (NTFP) and augment it with improved marketing opportunities of these products. The choice of this design option is defended on the following grounds; (i) the harvest of NTFP is environmentally less detrimental than timber harvesting or other forest uses (Arnold and Perez, 2001 and Wunder, 2001) (ii) given that NTFP markets are characterized by marketing impediments associated with high transaction cost (Shillington, 2002 and Neumann and Hirsch, 2002), the said design option provides alternative avenue to use the public purse, as well as donor transfer in the form of payment environmental services to correct these impediments. Particularly, shortening the marketing chain or lowering the local differences between purchase and sale prices through such leverages would leave more of the NTFP value in the hands of the extractors thereby improving their welfare outcomes.

The Ethiopian programs we consider represents this design option as it includes both access rights for own consumption and the possibility for increased returns from NTFPs marketing[2] Unfortunately, the existing literature has not uncovered poverty and income redistributive effect of this design option Furthermore, uncertainties abound concerning whether participation in this scheme can be translated into moving up the income ladder among rural poor program participants for the following major reasons. First, because the opportunity cost of restricting forest use is higher among the poor, as elucidated earlier, it is uncertain whether the purported gain from JFM augmented with NTFP marketing compensates these costs (Ainembabazi et al 2012). Second elite capture usually features in such programs (Nagendra, 2011 Iversen et al 2006) and is likely to disproportionately impact on the distribution of benefits from the program[3]

[2] This scheme is commonly described as conservation by commercialization in related literature (for example, see Evans, 1993 and Arnold , 2001)

[3] Elite capture occurs when tenure system – whether customary or state-supported – fails to treat the elite (more powerful) and non-elite (less powerful) community members alike, with regard to applying rules and sanctions for resource use, or in ensuring that rights to the commons (particularly access rights) can be claimed (Fuys, et al. 2008). For the most part, elite capture is pervasive in JFM and participatory rural development programs, because institutions governing the programs are dominated by the wealthy, at the collective choice level, which results in the devising of operational rules that selectively benefit the wealthy.

It is this potential sensitivity over trade-offs that could yield heterogeneity within any particular rural population that motivates this investigation into the distributional implications of participation in a JFM that is augmented by marketing intervention Moreover, a study of this nature has further import in sub-Saharan Africa (SSA), where poverty rates and income disparities are among the highest in the world (William and Elias, 2013). From a policy perspective, understanding the potential income redistributive effects, if any, of JFM programs of this nature has the potential to help African policymakers restructure these programs to optimize their welfare benefits.

Furthermore, unlike extant literature, we draw on an alternative methodological basis for the analysis. To this point, the literature considers either mean treatment effects of the program or the ratio of costs to benefits for different income groups[4] The focus on mean effects is common in much of the program evaluation literature, as mean outcomes have traditionally received more attention than the distribution of outcomes (Abadie et al., 2002; Firpo, 2007). Given the preceding proposition with respect to the environment-poverty nexus, it is clear that the interest lies beyond mean impacts, such that the distributional consequences of program interventions are of importance. In this analysis, we draw on recent advances in the estimation of the distribution of treatment effects, namely quantile treatment effects (QTE), to provide a wider indication of the welfare effects of interventions. QTE's ability to characterize the heterogeneous impacts of treatments across the outcome distribution makes it appealing in many economic applications (Frölich and Melly, 2010), including this one.

Overall, our study moves the related literature forward in three major ways in a bid to improve our understanding of the impacts of such programs. First, we provide comprehensive empirical evidence of heterogeneous program effects across the welfare distribution. Second, the variation across the welfare distribution is used to describe the pro-poor or anti-poor bias of the common property forestry program under consideration. Third, we test for the presence of elite capture in the program.

In effect we examine whether treatment effects are constant across the welfare distribution, and, if not, whether they are concentrated in any particular segment of the welfare distribution[5] From the analysis, we found that common property forestry interventions provide no welfare benefit for poor households that chose to participate in the program and that result was robust to various specifications. However, welfare at and above the median welfare point was found to increase as a result of program participation We also found that institutional quality, as measured by index of monitoring and penalty of JFM rules has varying impacts across welfare distributions. Particularly, the analy-

[4] Although, the cost-benefit analysis literature have improved our understanding of distributional consequences JFM interventions, their conclusions are based on strong assumption that a program accrues to each program participant the same benefits or costs or both within a given income group(poor and non-poor).

[5] In the interest of testing robustness, conditional and unconditional quantile methods, under the assumption of random and non-random treatment assignment, were considered. We employ IV estimators to identify QTE in the presence of endogeneity, with and without local smoothing.

sis shows that weaker enforcement institution offers greater program benefit to household corresponding to higher quantiles of welfare distribution suggesting that elite capture is at work in shaping the observed distributional bias of the program.

Coming to the structure of the paper, the next section describes the process and nature of decentralizing forest resources management in Ethiopia and our case study area. Sources of the data for the study are documented in section three. Section four presents framework of methodological basis employed for analysis framework. Section five discusses results of the empirical analyses and section six concludes with key findings and policy implications.

2 Common property forest management in south western Ethiopia

Much like citizens of a number of developing and emerging economies, Ethiopians depend heavily on forest resources, and the reasons for that dependence are many. Ethiopia's modern energy sector is not well developed, such that biomass fuel consumption incorporates 96% of total energy consumption (Mekonnen, 1999, Mekonnen and Bluffstone, 2008), 82% of which comes from fuel wood (World Bank, 1994). Given the lack of modern energy development, Mekonnen and Bluffstone (2008) expect this dependency to continue, and, most likely, to grow. In addition to providing fuel for energy, the forest offers agricultural risk mitigation services, providing alternative sources of income (Delacote, 2007).

In recognition of the importance of forest resources and the realization that deforestation rates, currently at 8% (World Bank, 2005), are not likely to decrease soon, Ethiopia has begun to implement a new set of forest policies (Mekonnen and Bluffstone, 2008). One of those policies is the decentralization of forest management to the communities located near those resources. Due to that policy, a number of programs have been implemented in Chilimo, Bonga, Borena and Adaba Dodola (Neumann, 2008 and Jirane et al. 2008), with the general objectives of arresting deforestation, while improving the welfare of those largely dependent on the forest for their livelihoods. Although the 2007 Ethiopian forestry policy supports decentralization (Mekonnen and Bluffstone, 2008 and Nune, 2008), bilateral donors, such as the GTZ and JICA, as well as NGOs, including Farm Africa/SOS-Sahel, are also supporting these programs. These external actors have provided financial support and helped mediate between the local communities and the local and regional governments. In Bonga, which is the site of this analysis, Farm Africa/SOS-Sahel supported the implementation of JFM; more than six JFM programs have been established to improve the management of about 80,066 ha of natural forest (Jirane et al., 2008).

As might be expected, donor involvement hinges, in part, on whether or not the donor believes the program will be successful. Therefore, Farm Africa/SOS-Sahel set intervention preconditions focusing on the possibility of success. Ef-

fectively, the level of local community and government concern over the current forest situation and the donor's perception of the degree of forest exploitation are important components of these preconditions. We now describe the process through which JFM programs were established. Farm Africa/SOS-Sahel and local government targeted specific forests as candidate sites for the JFM programs. Once a forest unit had been targeted, the location of the forest was topographically identified and then demarcated in the field. Information related to available forest resources as well as past and present management practices was gathered. Finally, an understanding of prevailing forest management problems, forest uses and forest user needs was developed (Lemenih and Bekele, 2008).

A number of observations emerged from this multi-step process. Importantly, agricultural encroachment into forests, illegal logging, and the harvest of fuel wood, for either direct sale or charcoal production, stood out as major deforestation threats, and these activities were most often associated with unemployed urbanites and a heavy concentration of individuals from the Menja tribe. The Menja tribe in Bonga province is a minority ethnic group that is entirely dependent on forests for their livelihood. They are generally ostracized, and commonly referred to as fuelwood sellers (Lemenih and Bekele, 2008; Gobeze al., 2009 and Bekele and Bekele, 2005). These observations led Farm Africa/SOS-Sahel and local government to select forests surrounded by significant Menja populations (Lemenih and Bekele, 2008; Bekele and Bekele, 2005). Although the Menja population was the overriding eligibility criterion, other criteria, including the degree of agricultural encroachment, population pressure, the forest's status, and the forest's potential to produce non-timber forest products, were considered to varying degrees

Once sites for intervention had been selected, Farm Africa/SOS-Sahel began negotiations and discussions with all stakeholders. However, since skepticism regarding JFM was rife within both the local government and the local communities, Farm Africa/SOS-Sahel provided JFM training for all stakeholders (Bekele and Bekele, 2005). In addition to problems related to skepticism, negotiations with regard to JFM participation and JFM forest boundaries were fraught with difficulties. Whereas JFM membership is meant to include those who actually use a particular area of the forest – regardless of their settlement configuration, clan and/or ethnicity – membership negotiations involved both collective and individual decisions. The result was that the entire community was allowed to determine eligibility based on customary rights, as well as the existing forest-people relationship, which includes the settlement of forest-users, the area of forest-use, and whether or not forest-use was primary or secondary (Lemenih and Bekele, 2005; Farm Africa's FMP Manual, 2006). Program participation amongst eligible households, however, remained voluntary, as long as the households satisfied the eligibility criterion and undertook to abide by the JFM's operational rules. Eligible households that chose to participate in the JFM program formed Forest User Groups (FUG) for selected sites. Those choosing not to participate would revert to using the nearest non-JFM forest, which, in effect, is a forest that operates under the status quo; that forest is unregulated, and access is open to all. It is assumed that household participation

is determined by the perceived costs and benefits of the JFM, a perception that is likely affected by training and other household-specific circumstances, which is driven, in large part, by program eligibility.

Experts from Farm Africa/SOS-Sahel and local governments, in collaboration with FUG members, then developed Forest Management Plans (FMP) stipulating the rights and duties of program members involving forest protection, forest development, forest product harvest rules and benefit share rules (Jirane et al., 2008). The FMP is implemented by a management committee in the community which comprises of a chairperson, a deputy chairperson, a secretary, a cashier and an additional member. Commonly, each member would be required to participate in forest development (planting new trees for the enrichment of the existing forest), guard against fire, vandalism (including unauthorized tree cutting) and agricultural encroachment (clearing forest for agricultural land acquisition). In return, each individual member would enjoy two kinds of rights over forest products: (1) a private right and (2) a collective right. The private right relates to the use of the forest for livestock grazing, collecting wood for energy and farm implement construction, harvesting medicinal plants for own consumption, and beekeeping, all subject to management committee approval. The collective right relates to the harvest of honey, timber, forest coffee, and spices, which members deliver to their Forest User Cooperative (FUCo),[6] which sells the products on both national and international markets The FUCo retains 30% of total income for investment and distributes the remainder across the membership as dividend (Bekele and Bekele, 2005; Lemenih and Bekele, 2008).

Possibly the most important aspect of the program is that NGOs, along with the regional government, provide FUCos with assistance in marketing, processing, grading, certification (e.g. green labeling of forest coffee), packaging of non-coffee NTFPs, storing, provision of price information and market access. Although there is no doubt that the additional assistance confounds the program's effects, the assistance is best viewed as a subsidy to engender participation in the program. Previous research has shown that forest cover and forest productivity have improved under the JFM (Bekele and Bekele, 2005 and Limineh and Bekele, 2008). However, that improvement, on its own, is not likely to offset either the participation cost – the immediate sacrifice of free forest accessing the newly established program forest – or the costs of harvest restrictions imposed by the program that are generally necessary for the long-term revitalization of forest resources. To offset both the upfront participation costs and the long-term harvest restriction costs, a subsidy of this nature may be necessary. NTFP marketing and market linkage assistance for FUCs offers a potential subsidy. Although forest coffee, for example, sells for as much as ETB 60/kg in non-JFM regions, Shumeta et al. (2012) find that revenues from the sale of forest coffee are not equally split; approximately 13% goes to farmers, while 87% goes to intermediaries in the supply chain. Moreover, the same study

[6] FUCos develop from FUGs, once the program becomes completely operational (Jirane, 2008).

argues that intermediary average profits are as much as 40 times higher than that of farmers. If the JFM program can capture a further proportion of the sales price, and pass that on to the farmer, farmers can benefit from participation, as can the environment. If those gains cannot be realized, farmers will either not subscribe to the program or the program will suffer from attrition; regardless, the environment would be expected to continue to suffer.

3 The Data

Data for the analysis was obtained from a household survey, designed for this study, undertaken in 10 Ethiopian villages in October of 2009. The villages are located in the Gimbo District, which is in southwestern Ethiopia. Sample frames for the survey were derived from the selected villages, via the lower level of local government, the kebele. The analysis was based on randomly selected households: 200 from JFM villages and 177 from non-JFM villages. Table 1 outlines the kebeles and the villages within the kebeles, including JFM participants and non-participants, and the number of survey respondents in each.

Respondents provided information on household characteristics, such as: age, education, gender, family size, household expenditure on various goods and services, household assets, household earnings from the sale of various goods and services, labor allocated to off-farm activities, distance to nearest town and distance to the nearest road. Additional information related to potential determinants of JFM participation was also collected, including: the presence of members of the Menja tribe, total number of Menja households in the village, the Menja population density, distance from the JFM forest, availability of alternative forests and experience with other collective action arrangements. Finally, data related to the community, especially forest cover and population, was gathered.

Descriptive statistics of that data are presented in Table 2, and these statistics are separated by participation status; thus the differences give some indication with respect to the vector of propensity score control variables. Therefore, the final column of Table 2 is the relevant column. As expected, total expenditure and per capita expenditure are larger for the participating households, although the mean difference is not significant. Also, given the way the program was handled, it is not surprising that participating households are located in areas that are nearly 40% more likely to incorporate individuals from the Menja tribe. Therefore, it is expected that this instrument will perform adequately. In terms of potential observable controls for participation, there are a number of significant differences between participant and non-participant households. Participating households are located nearly 43 minutes away from program forests, based on walking times. They are also nearly 10 minutes away from the nearest road, again measured by walking times. However, these households are located 26 minutes (walking time) away from the nearest non-program forest. On the other hand, participating households were 5.7% more likely to have a house-

hold member working off the farm, and they were 10.5% more likely to have previously participated in other collective programs. Finally, they own more livestock, as measured in tropical livestock units.

With regard to institutional variables, respondents' perceptions concerning enforcement of forest management rules were gathered Specifically, respondents were asked to rate their perceptions regarding the enforcement rules to four different statements on a five-point scale. This included a response to a question whether or not a respondent himself, other villagers in general and the villages' authorities monitor who takes what product from forests. Moreover, it included responses to a set of questions concerning the penalty instrument used to punish non-compliance with rules. The responses to these questions were coded as — strongly disagree, disagree, neutral, agree and strongly agree It was from these responses that we constructed an index following (Bluffstone et al., 2008; Beyene and Koch, 2013) as a measure of the quality of forest management enforcement institutions used to deter non-compliance. Bluffstone et al (2008) argues that perception based-indices are useful for two reasons as measures of the institutional quality in surrounding common property resource (CPR) management. First, in face of a pervasive mismatch between stated policies and on-the-ground management practices in developing countries, perceptions have a potential to reflect the reality. Second, compared to objective measures of CPR institutional quality through interviews with village leaders or forest managers perceptions has a better appeal, because in the former village leaders or forest manager have difficulties characterizing the details of CPR rules facing individual households in their villages

For the purpose of this study, per capita consumption expenditure, including goods produced at home, which were valued at village prices, rather than income, was used as a welfare measure for the following reasons. First, by virtue of consumption smoothing, consumption expenditure fluctuates less in the short run compared to income. Second, consumption expenditure provides information over the consumption bundle that fits within the household's budget, although credit market access and household savings affect that budget (Skoufias and Katatyama, 2011); similarly, it is easily interpreted and widely used. As such, consumption is generally believed to provide better evidence of the standard of living than income. Third, an income survey may not capture informal, in-kind or seasonal income, and, thus, may be more susceptible to under-reporting. Unfortunately, the choice of per capita expenditure is not without problems. It might be preferred to measure it in adult equivalence, which takes into account differences between children and adults, in terms of their nutritional and other requirements. However, inaccuracies in adult equivalence would result in sizable measurement errors, limiting its usefulness

4 Theoretical and Econometric Framework

The framework is grounded in Roy's (1951) occupational choice model. We assume that farmers choose to participate in the JFM program based on util-

ity maximization. Farmers, who perceive comparative advantage from participation, are assumed to join the program; thus, treatment assignment is non-random. In particular, define V_{ij} as the utility received by household $i = \{1, ..., N\}$ in treatment regime $j = \{0, 1\}$, where 1 represents participation. Therefore, $D_i = 1(V_{i1} > V_{i0})$, where 1 is an indicator function yielding 1, when the condition in brackets is true, and 0, otherwise. Similarly, define Y_{ij} as potential welfare, household per capita expenditure, where Y_{i1} is JFM welfare and Y_{i0} is non-JFM welfare. The difference between Y_{i1} and Y_{i0} can be used to measure the differential welfare associated with participation.

In this paper, we applied QTE models to evaluate the distributional consequences of common property forestry management in selected Ethiopian villages. The analysis was based on Firpo (2007) QTE estimator under exogeniety assumptions, Frölich and Melly (2010) unconditional and conditionally endogenous QTE estimator, and Chernozhukov and Hansen (2008) endogenous QTE for over-identified IVs.

Exogenous Treatment Choice

Define $p(x) = prob(D = 1|X = x)$ as the propensity for treatment, conditional on the observed covariates, which is assumed to be strongly ignorable (Rosenbaum and Rubin, 1983). Strong ignorability requires (i) (Y_{i0}, Y_{i1}) and (ii) $c < p(x) < 1 - c$ for some $c > 0$. The first of these assumptions is referred to as unconfoundedness, while the second is the common support assumption requiring that at least some individuals sharing the same values of X have a positive probability of being both participant and non-participant (Heckman et al., 1999). Strong ignorability results in conditional independence of the outcomes and the treatment, given the propensity score: $(Y_{i0}, Y_{i1}) \perp D_i|p(x_i)$.

Under the preceding set of assumptions, propensity score matching can be used to estimate average treatment effects. However, in this analysis, the focus extends beyond the first moment of the distribution. Specifically, the goal of the analysis is to use the τ^{th} quantiles of the distributions of potential outcomes to uncover the treatment effects at that quantile, where $\tau\epsilon(0, 1)$ represents the quantile index and $q_{ij}(\tau) \equiv \inf\{prob(Y_{ij} \leq q) \geq \tau|D_i = j, x_i\}$ represents the observed $\tau-$quantile value for distribution Y_{ij}; inf refers to the inverse function. Given Assumptions 1 and 2 in Firpo (2007), discussed above, the quantile treatment effect in equation (1) is identified.

$$QTE(\tau) = q_{i1}(\tau) - q_{i0}(\tau) \tag{1}$$

Estimation of the treatment effects involves two steps: first, the propensity score is estimated nonparametrically; second, equation (1) is estimated via weighted quantile regressions. The weights, $\omega_{i1} = D_i/Np(x_i)$ and $\omega_{i0} = (1 - D_i)/[(N(1 - p(x_i))]$ correct for differences in the distribution of covariates between participants and non-participants, where estimated weights, denoted with hats, are constructed from estimated propensity scores;

$$\hat{q}_{ij}(\tau) = \arg\min_{(\alpha,\delta_t)} \sum_{i=1}^{N} \hat{\omega}_{ij} p_\tau(Y_i - \alpha - D_i\delta_\tau) \tag{2}$$

In equation (2), $p_\tau(\theta) = (\tau - 1\{\theta < 0\})$ is a check function. It is only the

weights that differentiate equation (2) from the standard Koenker and Bassett (1978) specification. The estimate of δ_τ describes the difference defined by equation (1), since $D_i = \{0, 1\}$.

Non-ignorable Treatment Assignment

In the previous section, our underlying assumption of QTE identification is that the study units self-select themselves into the treatment regime on the basis of observed covariates[7]. However, such assumption is simplistic if there are unobservable determinants of participation, meaning that treatment assignment is non-ignorable, the preceding estimators will be biased. In that case, like in standard average treatment effect identification, an IV approach is, instead, needed to identify QTE (Chernozhukov and Hansen, 2006 and Abadie et al., 2002).

$$q_{ij}^{IV}(\tau) = \arg\min(\alpha^{IV}, \delta_\tau^{IV}) \sum\nolimits_{i=1}^{N} \hat{\omega}_{ij}^{IV} p_\tau(Y_i - \alpha^{IV} - D_i\delta_\tau^{IV}) \qquad (3)$$

Where the weight is given as $\omega_{ij}^{IV} = \frac{Z_i - P(Z_i=1|X_i)}{1-P(Z_i=1|X)\cdot P(Z_i=1|X)}(2D_i - 1)$

To identify QTT in (3), we used a combination of instrumental variables models by choosing different sets of variables for instrumentation. First, we chose a binary variable, namely the presence of Menja people in one's village as an instrument. This variable is used as an indicator of the household's intention to treat, i.e., the presence of Menja people in the village is assumed to partly determine participation in the PFM, but not affect welfare directly. As noted earlier, the Menja tribe was an important attribute of the forestry selection process, which further resulted in the provision of training with regard to the PFM. The exclusion restriction, although untestable, as in all IV applications, warrants further discussion. As the presence of the Menja tribe is associated with program eligibility, and the goal of the program was to improve the forest and household welfare outcomes, it is likely that eligible households were generally worse off than ineligible households. In that sense, any bias due to a violation in the exclusion restriction would tend to yield understated welfare impacts. For an upward bias to obtain in the analysis, the presence of the Menja tribe would need to be associated with better welfare outcomes for eligible households than ineligible households, which is likely if the intention to treat – forestry selection and training is confounded. In particular, Menja settlement (targeting of the forests for intervention) is associated with deforestation, the latter of which has potential to impact on household's income, and hence this IV is likely to be related with the outcome. In light of this potential endogeneity eligibility IV, we applied Frölich (2007) and Abadie et al. (2002) estimator. With this estimator, exogeneity (randomness) of IV is assumed to obtain upon conditioning it on covariates such as village's access to roads and markets and the underlying condition of the forest, each of which can be related with outcome variables-per capita expenditure through their effect on household's income as well as Menjas settlement choice.

[7] Although we have been using quantile treatment effect (QTE) and quantile treatment effect on treated (QTT) interchangeably, our analysis concerns the latter.

In the interest of greater precision of identification of QTT, we applied Chernozhukov and Hansen (2008), hereafter denoted as CH-IV estimator, for identification of QTE under over-identified instrumental variable. In effect, we combined eligibility IV with other variables as instruments; distance to alternative forest, distance to the program forest and density of Menja people to test exclusion restriction. By assumption, each of these household level instruments is expected to influence participation, but not welfare. Moreover, note that these variables provide important information in village selection (village eligibility) and hence impact on program participation. First, Menja household's density increase propensity of village selection (eligibility), as the intensity of deforestation is expected largely to depend on the size of this population, than their mere presence *perse*, although the latter was important as far as intention to treat (training) is concerned. Moreover, in village selection process, the presence of alternative forest and or the distance to it is bound to consideration given that those who opt out the participation need to lean back to alternative forest. Moreover, households that have to travel farther to use a program forest should be less inclined to participate, which is also true for households that have access to an alternative forest.

Importantly, in a simple regression of per capita consumption against forest cover, access to alternative forests and previous participation in other collective action programs, not reported here, no correlation was uncovered, providing evidence in favour of these exclusion restrictions at the household level[8].

5 Results and discussion

In this section, we present the results of estimates from different empirical strategies. In order to draw conclusions about distributional consequence of the program, the analyses are aimed at investigating whether the welfare distribution of program participants is everywhere above that of the control group, whether the program impact on welfare distribution are positive at some point and negative at other and whether the impact on the welfare distribution are concentrated over some range (bottom or top) of the distribution.

As a benchmark, we first present the results of the unconditional quantile model of non-parametric matching methods under the exogeneity assumption followed by an IV method in Table 2 We then present the results of a binary IV conditional quantile. The unconditional quantile model estimated under exogeneity (see the first column of Table 2), shows that QTTs are only positive and statistically significant at the seventh decile. We observe that the results from this model weakly reject the null hypothesis of constant treatment effect.

However, different results emerge when we control for endogeneity bias. Col-

[8] Note also that the validity of CH-IV estimator does not depend on D being statistically dependent on Z, it will be valid in cases of weak-instruments as formalized by, for example, Stock and Wright (2000) as well as in more general cases of partial- or non-identification (Chernozhukov and Hansen, 2008). We also found that this set IVs were valid instrument, when tested against Stock-Yogo 10% critical value.

umn 2 of Tables 2 reports the estimates of the unconditional quantile IV model. We see an interesting result here that the program effects are statistically insignificant at lower quantiles. This is consistent with anecdotal evidences that the poor do not benefit from participation in such programs.

Moreover, for higher quantiles the QTTs are positive and statistically significant. Specifically, we observe that that the program welfare impact at median is ETB 653.40 (USD 51.79), which compares well with parametric and non-parametric local average treatment effect (LATE) estimates of ETB645.16 and ETB567.33 respectively. Thereafter, QTE rises to ETB863.40 (USD62.56), ETB896.5 (USD 68.44), ETB806.0 (USD63.89) and ETB 1,268 (USD100.51) at 0.6, 0.7, 0.8 and 0.9 deciles respectively. Two observations can be made here; first the program is largely heterogeneous within this group of welfare distribution as QTE widely ranged between ETB 653.4 - ETB1,268. Second, QTE increases progressively as we move up the welfare distribution beyond median welfare level.

We infer the following from these analyses. First, the results reject the null hypothesis of constant treatment effect along welfare distribution in favour of heterogeneous program effects. Second, statistically insignificant QTT for the bottom half of the distribution supports the hypothesis that the program is not pro-poor. Moreover, statistically significant QTT for the top half of the welfare distribution prove that the program welfare accrual is biased towards non-poor or conceivably rich program participants.

Results from the conditional quantile QTT with intention to treat IV estimation are presented in Table 3. Here again, QTTs estimates of the program at lower quantiles are not statistically significant suggesting that the program has not offered welfare gain to participants corresponding to these welfare points. However, QTT estimate at median welfare and above are all positive and statistically significant confirming that participants at these points of welfare distribution are the main beneficiaries of the program intervention. The results show that the program has raised median welfare by ETB407.9 (USD 32.33) which is lower by 37.57% compared to QTT estimate of IV-unconditional distribution. Moreover, it is lower than local treatment effect (LATE) estimate of ETB563.33[9]. The results also show that the program has raised the 75^{th} and 95^{th} quantiles of welfare by ETB550.5 (USD 43.63) and ETB979.8 (USD77.66) respectively.

We now turn to the result of CH-IV estimator. The results are presented in table 4. Here again we see that QTT tells the same story as estimates of unconditional and conditional quantile QTT with intention to treat IV estimation; that QTTs increases progressively as we move up the welfare distribution and that the QTT estimates are statistically significant at median welfare level and above suggesting that the program has raised welfare level corresponding to these points

However, QTTs estimates here are substantially higher than their corresponding QTTs in the unconditional and conditional quantile QTT with in-

[9] LATE was estimated non-parametrically following Frolich (2007).

tention to treat IV estimators. Median estimates here, however, appears to be higher than LATEs estimates reported earlier.

In nutshell, the results from both conditional and unconditional quantile distribution models reject the hypotheses of constant treatment effects and propoorness of the common property forestry management intervention. However, the results from either empirical strategy suggest that the benefit offered by the program intervention is skewed toward the rich subgroup of the population. These results led us to the conclusion that common property forestry management intervention in our study villages could not be defended on equity grounds, although it has raised the welfare (albeit heterogeneous) of some of the participant households.

We now return to the relation of our program impact evidences to prevailing evidences so far. Our results of heterogeneous program impacts, as opposed to constant program impacts across the welfare distribution, lend support to Adhikari (2004; 2005) and Cooper (2008), who concluded that common property forestry program is heterogeneous and hence has worsened inequality in Nepal. Moreover, the finding that the program impacts are concentrated in the top half of the welfare distribution without any bearing in the lower half of the distribution, support the empirical conclusion that the program is not pro-poor (Jumbe and Angelsen, 2005; Basundhara and Ojhi, 2000; Malla, 2000 and Neupane, 2003). However, our findings stand in sharp contrast with Ainembabazi et al (2013) who finds that participation in charcoal production under open access forest management regime in Uganda has increased income of the poor relative to non-poor charcoal producers. The observation that the poor are better off under open access forest management regime implies that instituting common property right management of the forest attenuate income of the poor, but bolsters that of the non-poor, an outcome to which our finding lends support.

But, the evidence that the program benefits are unequally distributed in favour of rich program participants begs the question of why we observe such an outcome.

Observers in the field contend that unequal program benefits distribution largely has to do with local power relations as mediated by wealth distribution and differential opportunity cost of program participation across income groups (Cooper, 2008 and Malla 2000). Restriction of extraction of forest products and mandatory labour contribution demanded by the program management disproportionately disfavour the landless and those with limited opportunity of livelihood diversification or alternatives (Cooper, 2008).

Second, wealthier households are often the ones who dominate decision making and management activities of common property forestry programs (Maskey, et.al, 2003 and Agrawal, 2001), opening up the opportunity for elite capture. This result is also obtained by Adhikari (2006) who observed that, although rich households bear higher transaction cost (management cost) of common property management, taking this cost as percentage of resources appropriation cost revealed that the poor incurs relatively higher transaction cost of management as compared to middle-wealth and rich households. Given that management decision being dominated by the wealthy, as for example in terms of fixing rate

of resource harvest, pricing of the product in case of cooperative marketing, elite capture is inevitable such that such decisions selectively benefit the wealthy. In light of these backdrops, we now return to uncovering whether this outcome is underpinned by elite capture (see Table 5). In effect, we test whether the forest management enforcement institution is associated with welfare outcome across welfare distribution while controlling for level of dependency on forest. We controlled for other variables such as land holding size, livestock holding and off-farm employment, which can be used as proxy for level of forest dependency. We found that the strength of enforcement institution doesn't offer welfare benefit to all but two of the quantiles considered. When we interact institutional variable with treatment variables (program participation), the results show that, across quantiles above median – the welfare points that supposedly corresponds to elite group members, the strengths of enforcement institution attenuates welfare benefit obtained from participating in JFM program. Conversely, the result shows that the weaker is the enforcement institution, the higher will be program benefit accruing to this group of program participants suggesting that institutional dodge has enabled elite group to siphon greater share of resource rent (benefit) generated by JFM program.

Overall, our analysis establish that the program benefits are skewed to the rich households, through the mechanism of capture elite capture as the result of weak institution of JFM enforcement rules.

6 Conclusion

This study is aimed at examining the distributional consequences of JFM program augmented by the provision of NTFP marketing-based incentives. The analysis drew on data from 200 randomly selected program participant households and 177 non-participants households in selected villages of Gimbo district, southwest Ethiopia.

In terms of methodological basis, unlike existing literature which often employs cost-benefit analysis (CBA) to evaluate distributional impacts of JFM interventions(Adhikari, 2005 and 2004; Basundhara and Ojhi, 2000), we implemented the potential outcome model (POM) framework model to establish a causal link between the program intervention and household's welfare and its distributions outcomes. Particularly, we employed quantile treatment effect (QTE) evaluation of the program intervention to warrant stronger conclusion compared to extant cost-benefit analysis literature. Moreover, this analysis allowed us to measure heterogeneous welfare effects of the program and examines its distributional implication, an outcome, which would have been concealed in average treatment effect evaluation approaches. We implemented QTE methods under different empirical identification strategies; under exogeneity assumption and IV-method to account for endogeneity bias.

The results of the QTT analyses, irrespective of the identification strategies, rejected the hypothesis of constant treatment effect in favour of heterogeneous treatment effect across welfare distribution. Tellingly the program welfare effect

has been concentrated on the top half of welfare distribution without bearing effect on the bottom half of the same. In other words, the results reinforce the contentions that the current common property forestry institution couldn't benefit the poor but operated in favour of the non-poor. In effect, the apparent optimism, maintained by some observers, that common property forestry institutions offers equitable benefit is not supported. Our analysis also unfolded that the said distributional bias of welfare benefit has resulted from elite capture in lieu of weak enforcement mechanism of JFM rules.

There is the need to consider redesign of the program to ensure that its impact would reach out to the poor before implementing it as a dual policy of forestry management and rural development. Both command and control (CC) and incentive based (IB) approaches may be envisaged to redesign the program institutional structure. With regard to the former, regulations must be instituted and enforced to ensure greater participation of poor households in management decisions in cases where local elites manipulate management decision in their favour. An alternative option is to include leasehold and private property right within common property right structure which may bring about efficient and equitable transferability of property right (Adhikari, 2004). This voluntary exchange of rights within the bound of common property right structure may benefit poor people as was conjectured by Baland and Platteau (1996). In fact, these are interesting areas of empirical future researches

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Table 1: Descriptive statistics of covariates

Variable	Description	PFM participant		Non-participant		
		Mean	SE	Mean	SE	Mean difference
Totexp	Total household annual consumption expenditure (in ETH Birr)	9531.32	389.593	9000.756	337.464	530.564
cpc	per capita annual consumption expenditure (in ETH Birr)	1732.093	66.5836	1686.69	59.263	45.397
Sex	Household head sex (male=1)	0.932	0.018	.943	0.016	-0.010
agea	Age of household head in years	43.916	1.019	43.244	1.023	-0.671
Hhsize	Household size (number of members)	5.899	0.165	5.7346	0.154	0.164
Tlua	Household livestock ownership converted in to TLU(in total livestock unit)	4.256	0.193	4.501	0.215	-0.244
Lndsza	Household landholding size in hectare	2.300	0.110	2.412	0.114	-0.111
Edumax	Number of households in the village	6.257	0.220	6.707	0.220	-0.450
Offrma	Whether a household participated in off-farm activities (yes=1, no=0))	0.145	0.026	0.082	0.019	0.063**
Wealth	Whether a household has a corrugated house(yes=1, no=0)	0.251	0.032	0.239	0.030	0.011
Hhedua	Education (grade attained) of household head	4.5	0.208	5.108	0.307	-0.608*
Dsttown	Household distance to the nearest town (in minute)	69.379	3.509	72.454	2.693	-3.074
Dstroad	Household distance to the nearest road(in minute)	23.639	1.935	32.295	2.614	-8.656***
Malefa	Household labor-force (men)	1.449	0.055	1.478	0.059	0.028
Femalefa	Household labor force women	1.378	0.051	1.338	0.046	0.04
crdta	Whether a household has participated in credit market (yes=1, no=0)	0.307	0.034	0.219	0.029	0.087**
Institution	Index of enforcement strength of forest management rules	0.780	0.268	0.254	0.019	0.525*

Table 2: Unconditional QTT

VARIABLES	QTT-exogenous	QTT-IV method
Quantile_1	91.71	-159.0
	(217.8)	(340.7)
Quantile_2	253.8	-95.40
	(219.3)	(261.5)
Quantile_3	285.4	207.2
	(277.7)	(309.8)
Quantile_4	179.9	229.7
	(298.4)	(357.4)
Quantile_5	350.8	653.4*
	(483.7)	(414.4)
Quantile_6	558.9	863.4**
	(674.7)	(388.4)
Quantile_7	844.7**	896.5*
	(422.6)	(489.4)
Quantile_8	576.7	806.0*
	(476.9)	(426.7)
Quantile_9	480.9	1,268**
	(530.7)	(539.0)
%Compliers		38.7
Observations	359	337

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

Table 3: Conditional quantile binary IV- QTT estimates

VARIABLES	Quantile_5	Quantile_25	Quantile_50	Quantile_75	Quantile_95
partcp	107.8	268.8	407.9**	550.5**	979.8*
	(226.5)	(1.450)	(171.2)	(230.2)	(521.3)
sex	-161.1	-3.051	11.69	-368.6	-522.0
	(613.3)	(-0.392)	(1,397)	(655.6)	(1,334)
wealth	67.08	19.76	176.6	51.93	-119.3
	(205.9)	(0.857)	(206.8)	(264.4)	(606.6)
offrma	189.6	72.24	232.3	382.5	91.00
	(275.0)	(0.920)	(175.0)	(258.9)	(776.7)
agea	2.561	-163.5***	-8.402	-7.346	-30.87*
	(7.741)	(-3.282)	(6.423)	(8.954)	(18.57)
tlua	29.78	-4.282	38.66	66.00	1.025
	(35.03)	(-1.246)	(41.50)	(43.38)	(98.22)
lndsza	43.52	-2.322	76.67	107.2	175.9
	(70.50)	(-1.580)	(74.81)	(138.5)	(127.1)
hhsize	-114.8	13.73	-172.1***	-204.2***	-239.1**
	(79.48)	(0.457)	(40.70)	(44.79)	(110.6)
hhdstroadmin	-1.092	56.88	-5.387	-5.800	-11.63
	(3.895)	(0.123)	(4.502)	(6.873)	(9.558)
hhdstwnmin	-1.339	113.3	-3.818***	-5.686***	-7.161
	(1.593)	(0.653)	(1.338)	(2.153)	(6.115)
edumax	12.78	254.4	39.21	28.70	83.90
	(27.97)	(1.060)	(41.97)	(43.86)	(112.5)
Constant	1,264	2,039***	2,502*	3,419***	5,737***
	(780.4)	(3.245)	(1,494)	(807.9)	(2,050)
% compliers	44.5	44.5	44.5	44.5	44.5
Observations	337	337	337	337	337

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

Table 4: CH-IV- QTT estimates without institutional variable

Variables	*Quantile_1*	*Quanti-2*	*Quant-3*	*Quanti-4*	*Quanti-5*	*Quanti-6*	*Quanti-7*	*Quanti-8*	Quanti-9
partcp	-292.5	345.8	182.6	26.83	767.3**	1,358**	1,277**	1,558**	3,266**
	(363.3)	(404.3)	(345.1)	(298.4)	(343.3)	(548.3)	(393.9)	(459.6)	(614.6)
offrma	317.0	349.6	269.7	35.50	14.35	50.83	-11.56	-67.59	-82.48
	(221.0)	(223.0)	(215.8)	(191.3)	(252.5)	(247.1)	(254.7)	(341.7)	(358.6)
lndsza	-23.50	12.29	9.990	-22.84	8.847	23.80	80.12	9.938	-5.459
	(81.40)	(96.36)	(102.3)	(71.12)	(85.82)	(124.7)	(82.24)	(119.8)	(113.6)
agea	-5.929	-1.220	-2.313	-2.063	-1.541	-2.866	-4.759	-1.137	-16.59
	(4.914)	(5.494)	(4.857)	(5.557)	(5.712)	(7.810)	(6.071)	(13.49)	(12.89)
sex	152.6	191.7	173.2	202.0	30.68	211.2	236.1	-1,959*	-1,953
	(414.3)	(297.7)	(287.1)	(216.2)	(346.6)	(506.8)	(753.3)	(1,126)	(1,434)
hhsize	-92.50	-126.3**	-129.6**	-140.6**	-192.5*	-136.7*	-140.7**	-153.0*	-157.9*
	(76.14)	(58.90)	(54.17)	(46.76)	(49.50)	(72.84)	(65.64)	(91.99)	(84.10)
wealth	118.7	190.1	221.8	77.86	190.4	269.9	310.8	299.2	287.9
	(234.3)	(230.5)	(234.4)	(271.4)	(245.5)	(346.2)	(254.8)	(310.9)	(357.9)
hhdstwnm	-3.424**	-4.008**	-3.564*	-3.549**	-2.827	-3.709	-2.993	-4.935	-9.341**
	(1.491)	(1.962)	(1.992)	(1.696)	(2.263)	(3.642)	(2.283)	(3.235)	(3.831)
hhdstroad	-0.0935	-0.0817	-1.249	-3.455	-7.018**	-5.554	-7.828	-6.469	-10.04
	(2.766)	(2.388)	(3.731)	(3.964)	(3.524)	(4.892)	(5.026)	(6.239)	(7.928)
tlua	33.44	17.35	23.14	48.80	46.70	60.27	45.18	70.78	99.39
	(34.53)	(39.40)	(41.10)	(29.96)	(40.93)	(42.56)	(37.29)	(47.50)	(76.35)
edumax	18.58	7.898	0.0281	25.92	42.04	24.25	8.720	-7.844	-100.2
	(33.12)	(38.11)	(34.30)	(32.38)	(35.82)	(42.99)	(35.73)	(45.98)	(64.56)
Constant	1,735**	2,230**	2,131**	2,024**	2,833**	2,903**	2,721**	5,499**	8,953**
	(812.4)	(563.3)	(592.7)	(546.1)	(851.9)	(1,298)	(782.6)	(1,454)	(1,863)
Observation	270	270	270	270	270	270	270	270	270

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

Table 5: CH-IV- QTT estimates with institutional variable

VARIABLES	Quantile_1	Quanti-2	Quant-3	Quanti-4	Quanti-5	Quanti-6	Quanti-7	Quanti-8	Quanti-9
partcp	309.9	279.3	259.4	590.0	1,940***	1,824***	2,281***	2,153***	2,696***
	(406.8)	(449.5)	(527.1)	(443.4)	(641.2)	(633.0)	(595.2)	(604.0)	(995.6)
offrma	371.2	324.5	236.8	3.889	-126.2	-221.5	-449.6*	-355.3	-106.3
	(232.2)	(230.4)	(208.7)	(177.2)	(261.5)	(203.1)	(268.4)	(335.3)	(491.8)
invindex	-102.5	-287.8	-156.1	1,313	1,717	2,252	3,510**	3,651**	3,835
	(724.9)	(833.2)	(1,289)	(1,156)	(1,482)	(6,647)	(1,385)	(1,483)	(2,804)
interaction	-34.00	113.6	-41.88	-1,505	-2,146*	-2,692	-3,777**	-3,142**	-3,508
	(716.0)	(815.2)	(1,301)	(1,154)	(1,385)	(6,530)	(1,829)	(1,550)	(2,829)
lndsza	-6.492	20.99	-2.410	-19.69	-8.259	-15.59	-17.67	-75.73	-116.4
	(80.02)	(86.36)	(82.00)	(61.57)	(90.69)	(79.45)	(90.39)	(121.0)	(127.1)
agea	-5.006	-3.720	-3.697	-2.051	-5.404	-3.328	-4.056	-3.592	-11.55
	(5.179)	(4.905)	(4.690)	(5.738)	(5.230)	(5.302)	(7.633)	(13.63)	(14.01)
sex	327.5	274.0	256.2	347.2	-32.03	45.56	311.0	590.1	1,077
	(364.1)	(347.3)	(321.9)	(272.1)	(688.1)	(554.9)	(928.5)	(762.7)	(1,843)
hhsize	-84.89	-129.1**	-151.9***	-146.6***	-139.7**	-115.5***	-74.08	-53.43	-94.28
	(61.41)	(54.19)	(55.45)	(43.45)	(61.34)	(40.60)	(79.39)	(77.79)	(111.7)
wealth	70.85	127.4	165.5	-17.15	133.4	141.5	457.1	633.7*	577.0
	(241.0)	(238.7)	(229.8)	(288.0)	(230.2)	(233.8)	(362.3)	(379.3)	(421.6)
hhdstwnmin	-4.059**	-3.572*	-3.836*	-4.515**	-6.512*	-7.808***	-6.320	-5.927**	-9.080**
	(1.975)	(2.137)	(2.254)	(2.111)	(3.837)	(2.220)	(3.999)	(2.520)	(3.621)
hhdstroadmin	0.0702	-1.308	-1.722	-3.484	-2.550	-0.443	-1.012	-1.368	-0.385
	(3.559)	(3.750)	(3.985)	(3.277)	(4.414)	(5.998)	(9.874)	(9.284)	(12.03)
tlua	25.96	18.33	27.99	39.58	39.56	43.46	61.94	46.19	122.6*
	(33.43)	(38.03)	(35.18)	(28.05)	(36.82)	(31.98)	(58.95)	(53.18)	(72.64)
edumax	14.09	1.419	3.316	50.72**	52.37	52.14	18.76	15.70	-83.81
	(38.46)	(32.59)	(34.57)	(23.72)	(36.27)	(44.62)	(63.99)	(61.09)	(80.74)
fc	-116.6	-33.78	5.273	222.2	-77.24	3.956	-266.0	-413.6	-1,285**
	(153.4)	(161.2)	(201.3)	(202.9)	(279.3)	(380.1)	(431.7)	(377.3)	(571.4)
totvlpop	-0.0894	-0.0304	-0.0153	0.0446	-0.0562	-0.0505	-0.000725	0.0611	0.110
	(0.108)	(0.124)	(0.130)	(0.126)	(0.181)	(0.328)	(0.184)	(0.129)	(0.169)
Constant	1,935***	2,250***	2,457***	1,502**	2,855***	2,524	1,993	1,640*	3,894*
	(677.3)	(618.6)	(674.4)	(606.1)	(956.1)	(2,179)	(1,285)	(896.4)	(2,097)
Observations	200	200	200	200	200	200	200	200	200

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