Biofuels and Food Security: Micro-evidence from Ethiopia

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Abstract

This paper provides microeconomic evidence on food security impacts of privately organized biofuel outgrower schemes in Ethiopia. We conducted a household and community level survey and evaluated the impact of castor bean farming. We use endogenous switching regressions to analyze the impact on food security. Food security (as measured by a "food gap") and food caloric intake is significantly better in households producing castor beans. "Fuel" and "food" are complements rather than substitutes at the micro-level in castor production in Ethiopia.

1. Introduction

Biofuel development is a controversial issue, in particular in developing countries. Biofuels are said to cause environmental problems and to worsen food security – reflected in the 'food' versus 'fuel' debate (Cotula et al., 2010; Pimentel et al., 2009; Bindraban et al., 2009; Fargione et al., 2007). Some studies show that biofuel investments provide alternative income through employment, boost economic growth and reduce the incidence of poverty (Arndt et al., 2011; Huang et al., 2012; IIED, 2009). Others suggest that biofuel expansion jeopardizes food security goals (IFPRI, 2008; Mitchell, 2008; FAO, 2008).

So far analyses of the impacts of biofuel development have been based on qualitative case studies or on aggregate economy-wide simulation models or computable general equilibrium (CGE) analyses. The later have focused on impacts on prices (Ajanovic, 2011; Ciaian and Kancs, 2011), on income and GDP (Arndt, 2011; Ewing and Msang, 2009) or the world economy (Taheripour et al, 2009). There is no quantitative empirical evidence on the actual impact of biofuels on the rural poor and smallholder farmers.

To fill the gap in our understanding, we estimate the effects of production contracts between smallholder farmers and a biofuel company on farmers' food security. We use detailed company and survey data from Ethiopia. Ethiopia is an excellent case to study these effects. On the one hand, Ethiopia is a major energy importer. In fact it is viewed as the number one "energy poor country" in the world (Nussbaumer, et al, 2011)[1]. Developing renewable alternative resources therefore sounds appealing. On the other hand, Ethiopia's agriculture sector is heavily dominated by subsistence smallholder farmers whose food security is vulnerable and who are often food aid recipients (Devereux and Guenther, 2009). It is therefore argued expansion of biofuels may compete with the existing weak food supply

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[1] The authors constructed a Multidimensional Energy Poverty Index (MEPI) – that focuses on the deprivation of access to modern energy services and ranked countries using the scores from the index.

system. While there has been a widespread debate about the benefits and risks, Ethiopia has taken steps to support the emergence of biofuel value chains. Besides a long established state ethanol project, there are now several private biofuel initiatives, both large scale plantations and outgrower schemes (table 1).

There are several ways in which rural households can potentially engage in the biofuel supply chains: (a) through direct employment in large scale plantations, (b) indirectly through leasing land to biofuel producing companies, (c) through contract farming schemes with processors (or feedstock exporter) companies, or (d) through small scale oil extraction schemes. The way biofuel value chains are organized is key to understand both the impact of biofuels on smallholder famers and the commercial viability of biofuel production (Altenburg, 2011).

Outgrower schemes are often argued to be more pro-poor than large scale capital intensive plantations, especially when they result in technology spillovers to other crops such as observed in Mozambique (Arndt, 2010; Ewing and Msangi, 2009).[2] However, some recent studies on large scale investements on agriculture question this. For example, Maertens and Swinnen (2009) and Maertens et al (2011) find that the poorest households are more likely to benefit from employment on large scale farms than as contract farmers, based on their studies of horticultural value chains in Senegal. Moreover, achieving commercial viability in outgrower schemes may be challenging because of large transaction costs associated with managing production from widely dispersed small farms and problems of securing a sufficient supply of biofuel feedstock[3].

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[2]

[3] From our interviews with biofuel companies operating in Ethiopia, we learned that some projects were abandoned because of these reasons.

The paper is structured as follows. Section 2 reviews biofuel projects in Ethiopia and the outgrower scheme. Section 3 describes the sampling design and the data. Section 4 explains the estimation technique. Section 5 gives the results and interpretation of the results. Section 6 concludes and discusses policy implications.

2. Castor production and food security in Ethiopia

The emerging biofuel feedstock production from private firms in Ethiopia thus far is dominated by two major non-edible crops i.e. castor been and jatropha (see table 1). Castor is a short season (4-5 months average maturity period) crop that gives oil bearing seeds. Castor oil contains a toxic element and thus cannot be used as food or animal feed source. The oil (i.e. biodiesel blended or not) can replace diesel without any engine modification. Besides, it can be used as lubricant in the automotive field, raw material for cosmetics industries and in pharmaceuticals. Castor is believed to be indigenous to Ethiopia and grows both wild and cultivated in the tropical and subtropical countries of the world (Kumar and Sharma, 2011). It has been promoted in Ethiopia as a commercial crop by foreign companies during the recent wave of biofuel investments and is said to provide a good base for acquiring or expanding a profitable position on the world market (Wijnands et al, 2007).

<<Insert table 1>>

There is an important potential relationship in castor production and food security. The fact that non-edible sources of feedstock such as castor can potentially be cultivated on marginal lands makes it less threatening to local food production. However, at the same time, these marginal areas are often characterized by strong food insecurity.

In Ethiopia policy makers have allocated areas with low agricultural potentials or degraded areas for the production of biofuel crops. These areas are often recognized as food insecure areas. For example, one company planted perennial crop trees for biofuel feedstock on 15,000 ha areas of degraded hills in the Northern region of the country called Kola Temben, an area known with a large population living under extreme poverty and food insecurity. .

There are also other potential relationships between castor production and food security, such as the impact of castor production on the productivity of other (food) crops, through rotation or spillovers effects. These effects are likely to depend on the nature of the production systems (Maertens et al, 2012).

Our study focuses on the contract farming system established by a company in the Southern region of Ethiopia, more specifically in the Wolayta and Gomo Gofa districts which are known to be heavily food insecure.Castor production in the Southern region started in 2008 with castor seed distribution to more than 10,000 farm households in Wolayeta and Gamo Gofa. Farmers traditionally recognize that crop rotation with castor enhances soil fertility, but no one was interested to cultivate it because of its low value as cash crop. The company had to undertake extensive promotion activities to introduce the crop as cash crop. It resulted in widespread adoption (close to 33%) in the third year of the operation.

The company offers a contract to its suppliers. The contract resembles most outgrower contract schemes where a group of farmers signs a contract to receive all the necessary inputs such as fertilizer, herbicide, technical assistance. In return they allocate part of their land for castor production and pay in seeds during harvest. The price of castor seeds is set in advance. The firm's extension workers at village level are responsible for training farmers, facilitating group formation, input distribution and the follow up of cultivation and output collection. The

promoters of the crop are mainly extension agents hired by the company (83%), but government extension workers have also been involved in disseminating the information.

Land is an important and a key factor for participation. The company considered land as an important criterion when recruiting farmers; also to make sure that farmers have enough land to grow the crop and keep adequate land for other crops. During the initial phase of the project in 2008, a land size of 1ha was a requirement to allow farmers to engage in a castor contract. But meeting break-even quantity for export was extremely challenging for the company despite its wide coverage of areas. In the following years (2009 and 2010) the land size for eligibility was reduced to 0.75ha.

Farmers have been advised both by the government extension workers and the company supervisors not to allocate more than a quarter of their land to castor. This was also confirmed by the data. The average allocation of land to castor is 15% of total land covered by annual crops. The maximum land that farmers allocated does not exceed 25% of the total land holding (table 2).

3. Data

Four districts (woredas) were chosen as representatives of the Wolayeta and Gamo Gofa administrative zones in the SNNPR region (figure 1). Following a stratified two stage sampling technique, 24 kebeles (equivalent to villages or a few clusters of villages) were randomly drawn from those selected districts. The number of sample villages is proportional to the size of the total number of villages in each district.

<<Insert figure 1>>

All kebeles in each zone that were eligible to grow castor have received castor seeds with varying degrees of intensity. Castor growing areas of all villages within the altitude

range of 1040 to 2010 meters above sea level were included in our sampling frame. Our sampling frame has not covered the villages (commonly known as highlands) that are not agroecologically suitable to grow castor. Thus, the study best represents smallholder farmers in castor growing areas of the region. We used three sampling frames: (a), a list of all kebeles and demographic information was obtained from zone statistics office; (b), a list obtained from the company containing information about households who received castor seed and their participation history; (c), a 2010 list of all households who reside in each kebele was collected from each kebele.

18 to 22 households were interviewed in each village and households were stratified as participants and non-participants in the project. Systematic sampling was applied to select households from a list, using a random start and with selection interval equals to the total number of residents divided by the number of samples to be selected from the entire list. For the actual analysis of this paper, participants (adopters) are defined as those who participated through receiving castor seeds and inputs in the 2009 - 2010 agricultural year; and non-participants (non-adopters) as those who did not participate in the project regardless of their past participation history. Participants of 2010 count for 30% of our sample. Since participant samples are close to the actual proportion in the population (33%), we only applied weights to correct for differences in the sample proportions.

We conducted the survey in February and March 2011, soon after the main harvest season. A detailed questionnaire was prepared with main emphasis on crop production, revenue, input use, income by type, and food security. Except for general household characteristics and for quantities that is limited by seasonal change, we disaggregated our entire data enquiry over the two main crop seasons. In most of the cases, we interviewed

the household head but whenever it was possible we asked both the head's and the spouse's opinion. There were no refusals of interview.

4. Descriptive Statistics

The dataset contains 476 households. About 30% of them are "adopters", i.e. households which allocated land to grow castor and received the necessary inputs in the 2010 cropping season. The incidence of adoption over the sample villages is reported in table 3. The 24 villages in our sample vary in terms of proximity to towns, infrastructure and other economic activities besides farming. In some villages (such as Fango Sore) that are far-off from towns and constrained by a limited availability of markets for alternative commodities, the adoption intensity is above the average rate (54%). However, figure 1A shows that the correlation between distance from towns and participation is weak.

<<Insert table 3>>

Participants and non-participants differ in certain household characteristics. Female headed households and widow-headed households are less likely to participate. The proportion of working age group as well as the number of dependents does not differ between the two groups. There is no strong correlation between education and adoption. Overall, schooling is low: 42% of the total sample never attended school. Adopter households have a lower proportion of households with primary education but a higher proportion of households in junior level education. There is no difference in terms of high school education.

Land holding is a key eligibility criteria for participation, and is significantly higher for participants. The eligibility criteria has not been enforced strictly. There are non-participant households who qualify for participation (about 50%) but did not participate.

There are also households that participated but did not formally satisfy the eligibility criteria

Participants use much more fertilizer (almost double) than non-participants. The percentage of non-participants who borrowed money for input purchase purposes is higher than in the participant group. This is also expected as participants have better fertilizer access through the biofuel contract scheme.

Participants and non participants do not differ significantly in terms of proximity to extension centers, or contact with government extension agents. On average 27% of participants access information about markets, prices and agricultural practices primarily through formal media sources such as radio. Only 18% non-participants make use of the formal media sources.

4.1. Food security indicators

To assess food security, we use two type of measures. The first is the the number of "food gap" months. "Food gap" is defined as the number of months that the household runs out of own stock of food (mainly grains and other own livestock food sources) and lacks money to purchase food'. The study area is known for its severe seasonal food availability fluctuation problem. Smoothing intra-year food availability at the household level is a prime concern. The benefits from growing castor in areas that have seasonal food gap fluctuation could be associated, first, with the fact that the cash income during the harvest seasons from pre-signed castor contract may prevent farmers from selling food crops at harvest time when prices of food crops decline. Stocking food would prevent them from paying higher prices during the lean seasons. Second, castor beans, once planted can be collected twice a year. They preserve well on the field without easily

spoiling like other annual food crops that need to be harvested immediately. This allows piecemeal collection of beans and sales to village level collection centers whenever farmers are in need of cash. For rural farmers where liquidity constrains are vital to food security, flexible access to cash source: harvest and sell whenever necessary protects them from taking suboptimal strategies on investments and crop use. Better access to credit for inputs, combined with limited risk of castor beans (since they require lower land quality than food crops, improve the land quality in rotation with other crops) is another potential channel that participants households benefit from the scheme.

<<INSERT Table 5>>

Table 5 shows that the length of food gaps months on average are 1.02 months for adopter households, while they are 1.58 months for non-participants. This means non-participant households had to cope with 0.56 months or 17 more food gap days relative to participants. Table 5 shows non-participants have significantly larger proportion of households (21%) that experience longer lean seasons (more than three months of food gap) during the year while less than 10% of participants experience longer food shortage seasons.

<<Insert table 6>>

As a second indicator of food security, we used per capita food consumption. Food bundles constitutes the value of consumption from own production and purchased food. We adopt FAO/WFP (2009) guideline to convert food consumption (both self produces and purchased) into energy kilo calorie (kcal) equivalent level. The average food consumption in the data shows 2515 kcal per capita per day indicating pervasive food poverty in the area. Table 6 shows that close to 60 percent of nonparticipant households consume less than the minimum daily calorie requirements.

5. Econometric Approach

A basic approach to measure the impact of biofuel crop adoption on household food security would be to assign a dummy indicator variable for adoption and include it as a right hand side variable on food gap and food consumption equations. However, this will yield a biased estimator as adoption of the new crop is potentially endogenous. Endogeneity of such nature can be addressed by explicitly modeling the simultaneity nature of the equations (Heckman, 1977). However, pooled data estimation of both participants and non-participants assumes that the list of explanatory variables have the same impact on both groups of farmers and implies that participation has an average effect on the whole sample which may not be necessarily true due to selection problems (Heckman, 1979)[4].

To account for the differential impact of covariates on the welfare outcome of the different groups, a separate welfare outcome function can be specified and estimated simultaneously through an endogenous switching regression (ESR) model (Maddala and Nelson, 1983). Recent empirical applications of the model in studying the impact of choice decisions allowing for endogeneity, sample selection and interaction between adoption and other covariates that affect the outcome equation include Asfaw et al. (2012); Rao and Qaim (2011); Di Falco et al. (2011); and Alene and Manyong (2006). The model allows to construct the counterfactual expected outcome of the treatment effect under different regimes (i.e. adopt or not adopt) which also motivates its application in this paper.

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[4] Refer Wooldridge (2010) for recent reviews of econometric models for program evaluation; and see Cameron and Trivedi (2010) for their micro empirical applications.

Our model follows the specification given by Madalla (1983) and Lee and Trost (1982). The estimation is implemented using the full information maximum likelihood (FIML) technique to generate efficient and consistent estimators (Lokshin and Sajaia, 2004). Let d_i denote a dichotomous variable that equals 1 for households observed in regime 1 (participation in the castor program) and 0 for households in regime 2 (non-participation).

The model is consistent with the view that sorting of households into positions is an outcome of simultaneous actions of participation decision and expected output of participation. However, the model does not depend on the assumption of rational decision making behavior instead it is a testable hypotheses inherent in the model (Maddala, 1999). We observe d_i which is determined by a set of observable and unobservable variables such that;

$$d_i = \begin{cases} 1 \ if \ \gamma Z_i > u_i \\ 0 \ if \ \gamma Z_i \leq u_i \end{cases} \tag{1}$$

the latent equation for d_i given by $d_i^* = \gamma Z_i + u_i$. The outcome equation is defined for each position as follows:

Regime 1: $\quad y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \qquad if \ d_i = 1 \qquad (2)$

Regime 2: $\quad y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \qquad if \ d_i = 0 \qquad (3)$

where y_{ji} are the dependent variables in the continuous equation, X_{1i} and X_{2i} are vectors of exogenous variables, β_1, β_2 and γ are parameters to be estimated. ε_{1i} , ε_{2i} and u_i are assumed to have a trivariate normal distribution, with a mean vector zero and a covariance matrix say δ.

Following the FIML estimation results, the associated conditional expected values and the extent of heterogeneity effects are determined using formulas presented in the

appendix[5]. The model is identified by construction through non-linearities (Lokshin and Sajaia, 2004), however, it is strongly suggested to estimate it with exclusion restriction (i.e. Z_i in equation (1) contains at least one variable not in X_i) to improve identification (Verbeek, 2012; Wooldridge, 2010 and Maddala, 1999). The variable excluded from X_i needs to be strongly correlated with the regime choice equation (equation 1) but should not have a direct link with the outcome equations, or it should be a redundant variable in the outcome equation (Wooldridge, 2010).

Our instrument is a constructed variable that determines the choice of farmers for participation. Farm household's choice to participate depend on two key variables 1) the intensity of past program uptake at the village level, and 2) the fuzzy eligibility criteria of participation used by the company to contract farmers i.e. having a land size of 0.75 ha or more. The first term in this choice variable, intensity of program uptake (a -qualitative indicator in the pre-evaluation period) is measured as the ratio of the total number of households who received castor seed in the first phase of the program to the population[6]. We assume participation can be induced through village level peer/social network effects in places where adoption intensity has been over the median before the evaluation period.

The second term in the choice variable is the selection criteria (having a land size of at least 0.75ha) - the company's main screening criteria used to engage farmers. From this two terms explained above, we constructed a dummy variable termed as 'farmer choice'. To be a valid instrument, we need to assume it can be omitted from the outcome equation (Wooldridge, 2010). Since the direct role of land is adequately captured by the regressor (land per capita) in the outcome equation and there exists no active land market in the area, we can safely assume the exclusion of this variable from the outcome equation can

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[5] See the appendix about the details of the estimation procedures
[6] This ratio is displayed in the second column of table 1.

be satisfied. A combination of this choice variable indicator with pre evaluation period household asset indicators (such as livestock holding) substantiates the strength of our excluded variable.

6. Results

6.1. Determinants of adoption decision

We first run a Probit regression jointly with the food consumption equation to analyze what factors determine incidence of participation. We controlled for a range of variables including household characteristics, land size, squared land, livestock asset and price of maize at the beginning of the year before planting decision is made , access to information and district dummies. For consistency checks and easy of calculating marginal effects, we also estimated an independent Probit and Tobit model. The estimated coefficients have the expected signs and magnitude.. The model fits well predicting 70% of the observations correctly. In the Tobit estimation, the total area each farmers allocated to castor is used as dependent variable.

<<Insert table 7>>

Land is the most important factor that determines the incidence and intensity of adoption. From table 7, we see the marginal effect of per capita land is the highest; indicating that holding all other factors constant, a per capita increase of land would lead to an allocation of 1.8 points increase in castor cultivation area. Squared land has a negative sign indicating that as land increases beyond certain level, allocation to castor also goes down and this is also in line with most economic predictions as well as what we

observed during our field visits. Rich farmers tend to cultivate castor less compared to small and medium farmers since castor considered to be inferior crop unlike teff or maize.

The most influential factor for adoption next to land is the price of maize. Price of maize affects allocation of land negatively and significantly[7]. One birr increase in price of maize is associated with 0.17 points decline in allocation of land. Another policy relevant variable that is associated with adoption of castor is farmer's access to formal sources of information such as radio, tv, news papers. Participants tend to depend more on formal sources of information for their information on agricultural prices and practices unlike non-participants who found to be reliant on friends, local markets and informal networks as their primary sources of information. Like most findings in the literature, gender of the household head is negatively and significantly associated with adoption i.e. women headed households tend to adopt less.

Unlike our expectation and most previous findings for other crop technologies, exposure to government extension services does not seem to be an important factor for adoption. Distance to the extension centers which are often located at the center of each village is also not significant. During the survey, we learned that the spread of the castor seed even to remote location in some villages and farmers willingness to try the technology are worth to mention here. The dissemination of the crop was widespread into remote villages and distance was not as such a barrier to adoption. The incentive mechanisms of technology dissemination through a private company and its potential outcome is expected to be different from the predominant public extension system in our context. In the literature, the impact of access to road and infrastructure has been perceived as vital in technology adoption. Our observation, in contrast, highlights the

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[7] Our price data is the average annual market prices in each village in the preceding crop year. In villages where complete data was absent for some months, we have taken the nearby closest villages price as a proxy.

potential role a privately organized extension systems can play in overcoming physical barrier.

6.2. Determinants of food security

We estimate endogenous switching regression using the FIML method. This model can control for unobservable selection bias under a structural assumption (i.e. the error terms exhibit independent trivariate distribution). The food equation specifies the food security outcome variable on the left hand side and endogenous dummy variable for participation. Control variables include income by type, household characteristics, asset indicators and district dummies. The FIML estimation results of food gap are reported in table 8. Households reported the number of months, during the two main preceding seasons, that they had "serious food shortage and thus they failed to satisfy the food needs of the household".

<<Insert table 8>>

For both participants and non-participants, off-farm job participation of a family member is significantly linked with lower food gaps on equal magnitudes. Literacy of household head is associated with lower food gaps in both groups, but it is only significant for non-participant groups. Borrowing of more cash during the year, is correlated with higher level of food gaps in both groups. Households that are food insecure may tends to borrow more during the year. Estimates of the remaining coefficients, strongly suggests the presence of heterogeneous effect between the two groups. For example, family size is significantly associated with lower level of food gaps for participants than non-participants. Livestock holding are also reduce food gaps significantly for non-participants than participants.

The implication of some of the determinant variables differ between the food gap equation and the food consumption equation. Agricultural income determines the level of food consumption strongly and significantly. However, in terms of narrowing intra year food gap it contributes relatively less compared to off-farm income. This is an indication that factors pertinent to reduce food gap may not always be same as factors that determine total annual food supply at household level. Identifying significant sources of mitigating seasonal food gap contains relevant policy implication.

<<Insert table 9>>

The last row of table 8 and table 9 show the Log likelihood Ratio (LR) test of the independence of equations. At a 90% confidence level, it confirms that it was appropriate to assume effects of covariates on the two groups are significantly different. The opposite signs of the correlation coefficient (ρ) of the two groups imply sorting behavior of farm households into which they would be better off i.e. participants have higher returns under adoption while non-participants are better off not participating. The correlation coefficient of the non-participant outcome equation under the participation equation is positive and significant; suggesting that individuals who choose not to participate in the castor program would have had higher food gaps than a random individual from a sample would have, had they participated in the program..

6.3. Impact of participation

A summary table of impact simulations of food consumption and food gap are presented in table 10. The values across the diagonals in cell (a) and (d) represent the expected mean values of participants and non-participants in the sample. The values in cell (b) and (c) are the counterfactual expected values. A positive mean difference of (c)

from (a) indicates that participant farmers gain under participation. A negative mean of (d) from (b) on the contrast, implies that non-participant farmers perform better under non-participation.

<<Insert table 10>>

Participation in castor program results in 37% month (i.e. about 11 days) less food gap days among participant households. This could be attributed to the cash smoothing nature of the castor contract and to the indirect spillover effect of castor on food crop. In general, participation in the castor contract provided higher food security gains for adopter households which they would not fair it had they been excluded from the program. But for non-participants the food gab days would increase had they decided to grow biofuel crop. The potential underling economic reason for this would be that farmers who have other better income generating alternatives - which they are more productive at than being involved in the castor program- tend to lose if they shift their resources to castor production. Hence, they tend to fare better under non-participation scenario.

Participating in castor outgrower scheme contributed to increased food consumption by approximately 27% for participant households while non-participants show a reduction in food consumption under adoption decision scenario (table 10). This suggests the presence of heterogeneity and sorting based on comparative advantages. Our findings are in line with other results (Suri, 2011; Zeitlin, 2010) who show farmers with low net returns do not adopt a technology but the once who have higher expected returns continue to apply them. However, we need to be cautious not to excessively extrapolate from such simulated counterfactuals as they are only indicatives of the potential underlying sorting process of households into different regimes. They should not be taken as a substitute for panel (comparative) data (Mare and Winship, 1987). In the absence of

such data, nevertheless, they serve well to understand the effects of selection process to comparative regimes and differentials in outcomes.

7. Conclusion

This paper presents micro- evidence on the impact of the cultivation of a biofuel crop - castor on food security by presenting survey data and analyzing the effects on poor households in rural Ethiopia. The study is based on data collected in early 2011 from 478 randomly selected households. We use endogenous switching regression with exclusion restriction to control for endogenous selection issues in consumption and adoption decisions. Our choice of the instrument is based on the eligibility criteria used by the contracting company and the pre evaluation period intensity of the program intervention at the village level.

There are several important findings. We find that land and non land assets are key determinants of castor adoption, while physical accessibility such as distance from village centers appears not significant for adoption. These findings also offer interesting insights on the dissemination of new technologies in poor rural areas. Privately promoted technologies appear to be more efficient in this aspect compared to (other) government promoted technologies. This is an important insight about the efficiency and the potential role of supply chains in technology dissemination.

In terms of their impact on food security, our findings indicate improvements in food security (as measured by the "food gap") and food consumption levels. For rural farmers where liquidity constrains are detrimental to food security, castor programs timed to coincide slack seasons can contribute to mitigate seasonal food availability. This is suggestive of the complementarities between "fuel" and "food" at the micro-level in castor production in Ethiopia.

Our analysis also suggests that, not surprisingly, there the impact is heterogeneous across households. We find rational sorting based on comparative advantage from the technology where participants gain significantly from adopting which they may not otherwise. The presence of sorting in adoption decision of farmers, may be based on expected payoffs, observable and unobservable characteristics.

In summary, our empirical results provide evidence that participating in biofuel supply chains increased farmers food consumption significantly and narrowed their food gap period.

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Table 1 Private biodiesel projects in Ethiopia

Type of business model	No of project	Type of feedstock specialized	Total area (ha)	
			Total alloted/or leased ('000 ha)	Under cultivation ('000 ha)
Large scale plantations*	3	Jatropha, Pongamia, Castor	66.7	8
Outgrowers	1	Castor	NA	NA
PPP	1	Jatropha, Candlenut, Croton	15	7
Mixed outgrower with plantation	2	Castor	3	.08

Source: own survey 2010

*all are foreign firms

Table 2: Mean land size allocated (ha) to major annual crops and Castor

Season	Long (Sila)		Short (Gaba)	
	Land size in ha	Cumulatieve %	Land size in ha	Cumulatieve %
Teff	0.26	27.07	0.15	15.51
Maize	0.27	55.11	0.40	55.87
Harricot beans	0.18	73.83	0.16	72.41
Sweetpotato	0.12	85.92	0.14	86.36
Castor	0.13	98.97	0.12	98.71
Other	0.01	100.00	0.01	100.00
Total	0.97		0.99	

Table 3: Characteristics of sampled villages and castor seed distribution

Village name	Adopters (% in the population) 2008 (ave.20%)	2010 (ave. 33%)	Distance to the nearest town (km)	Land size per capita (ha) (ave. .14)	Fixed telephone network availability (Yes=1)	Mobile Network availability (Yes=1)	Access to Electricity	Other dominant cash source
Ade Dewa Mundeja	0.11	0.37	16	0.12	✓	✓	✗	Cereal retail
Anka Duguna	0.24	0.50	42	0.11	✓	✓	✗	Limited
Degaga Lenda	0.19	0.36	12	0.12	✗	✓	✗	Cereal retail
Fango Sore	0.52	0.54	90[a]	0.14	✗	✗	✗	Limited
Sura Koyo	0.13	0.55	14	0.12	✓	✓	✗	Cereal retail
Tura Sedbo	0.19	0.63	35	0.18	✗	✓	✗	Limited
Mundeja Sake	0.17	0.49	42	0.09	✓	✓	✗	Cereal retail
Olaba	0.01	0.13	25[a]	0.10	✗	✗	✗	Cereal retail
Mayo Kote	0.31	0.41	16	0.09	✓	✓	✗	Cereal retail
Hanaze	0.26	0.36	61	0.10	✗	✓	✗	Avocado
Tulicha	0.07	0.32	73[a]	0.13	✗	✓	✗	Ginger
Sorto	0.14	0.30	69	0.13	✗	✓	✗	Fruit trees
Bade Weyde	0.10	0.31	70	0.11	✗	✗	✗	Fruit trees
Bola Gofa	0.48	0.28	9	0.10	✓	✓	✓	Dairy
Sezga	0.08	0.28	4	0.20	✗	✓	✗	Pottery
Uba Pizgo	0.17	0.30	17[b]	0.18	✓	✓	✗	Limited
Zenga Zelgo	0.54	0.28	18	0.14	✓	✓	✗	Limited
Suka	0.09	0.29	3	0.16	✓	✓	✗	Dairy
Tsela Tsamba	0.05	0.12	7[b]	0.13	✗	✓	✗	Dairy
Lotte Zadha Solle	0.17	0.33	15[a]	0.17	✓	✓	✗	Retail
Gurade	0.08	0.20	11	0.17	✗	✓	✓	Dairy
Bala	0.07	0.41	65	0.22	✓	✓	✗	Live animal
Shalla Tsito	0.04	0.31	80	0.22	✓	✓	✗	Live animal
Zaba	0.17	0.35	68	0.18	✓	✓	✗	Live animal

[a] all weather road but portion of it inaccessible during heavy rain
[b] only dry season road

Table 4: Descriptive summary of selected variables

Variables	All samples	Participants	Non-participants	t-stat (diff)
Outcome Variables				
Crop income ('000 Birr)	4.621	5.141	4.491	1.33* (14%)
Log crop income	8.05	8.22	7.98	2.36*** (23%)
Food gap (months)	1.40	1.02	1.58	-0.56**(17 days)
Per capita food consumption (kcal/person/day)	2515	2772	2407	1.43*(15%)
Household characteristics				
Age of the head (years)	41.811	42.707	41.550	0.75
Gender of the household head (1=female)	0.120	0.058	0.137	2.89***
No schooling (1=yes)	0.42	0.41	0.43	0.28
Elementary education (1=yes)	0.23	0.17	0.26	2.42*
Junior education (1=yes)	0.23	0.28	0.21	1.70*
High school education (1=yes)	0.11	0.13	0.10	1.11
Proportion of labour force (productive age group) in the family	0.505	0.486	0.510	0.99
Proportion of dependents in the family	0.495	0.514	0.490	0.99
Family in polygamy (1=yes)	0.090	0.084	0.074	0.10
Family with a widow member (1=yes)	0.080	0.031	0.114	3.25***
Household wealth variables				
Owned land size (in ha)	0.80	0.95	0.74	4.00***
Per capita owned land size (in ha)	0.14	0.15	0.13	1.00
Family have member who have non agricultural income source	0.509	0.436	0.530	1.20
Owned number of Enset trees (Number)	26.710	31.221	25.444	0.86
Own pair of ploughing oxen (1=yes)	0.231	0.31	0.21	1.62**
Own donkey for transport (1=yes)	0.168	0.216	0.154	1.40*
Access related variables				
Access to fertilizer (1=yes)	0.553	0.683	0.517	2.23***
Total fertilizer use during the year (kg)	20.794	30.124	18.174	1.71***
Borrowed money during the year (1=yes)	0.372	0.424	0.357	1.14
Amount of birr borrowed (birr)	446.619	571.587	411.520	1.20
Distance from extension center (Minutes)	27.738	27.532	27.796	0.10
Contact with extension agent (Number)	11.680	12.816	11.365	0.98
Access to media (1=yes)	0.21	0.27	0.18	1.73***
Access to Telephone	0.260	0.249	0.263	0.34

Note: t-statistics are in absolute terms *significance at 0.1, ** significance at 0.05 *** significance at 0.01;

summary statistics variables are weighted stats.

Table 5: Perceptional food security by participation (%)

Food gap (months)	Non-participants	Participants	Pearson chi2
No food gap	47.45	52.11	5.82***
Less than one month	13.51	19.01	0.82
One to three months	18.32	19.01	1.35
More than three months	20.72	9.86	1.24**
Total	100	100	

Table 6: Food consumption by participation (%)

Food security level (kcal/day/per)	Non-participants	Participants	Pearson chi2
Food secure (>2100)	37.43	49.30	8.14***
Marginally food insecure (1,800 -2,100)	9.88	7.75	0.18
Moderately food insecure (1,500 -1,800)	10.78	7.04	2.55**
Chronically food insecure (<1,500)	41.92	35.92	5.90**
Total	100	100	

Table 7: Determinants of household decisions to plant castor seeds

	Jointly estimated probit Participation in castor (yes=1)[a]		Marginal effects (dy/dx) Probit		Tobit	
Land per capita (ha)	6.570**	(2.618)	1.649**	(0.705)	1.801***	(0.679)
Land per capita squared	-10.337**	(5.002)	-2.776*	(1.472)	-2.772*	(1.502)
Pr of maize before planting is made (birr)	-0.366**	(0.178)	-0.139**	(0.058)	-0.165***	(0.056)
Pre program asset indicator	0.629**	(0.262)	0.094**	(0.046)	0.048*	(0.025)
Farmers choice indicator	0.066	(0.172)	0.063	(0.061)	0.099*	(0.059)
Main info source (1=formal media)	0.320**	(0.157)	0.086	(0.055)	0.084*	(0.051)
Log of number of extension visits	0.022	(0.063)	-0.007	(0.020)	-0.006	(0.018)
Log of distance to extension service	-0.075	(0.088)	-0.011	(0.027)	-0.014	(0.028)
Log of number of Enset trees	0.023	(0.040)	0.006	(0.013)	0.005	(0.012)
Gender of household head	-0.450**	(0.228)	-0.141**	(0.057)	-0.132**	(0.061)
Household attended schooling (yes=1)	0.25	(0.153)	0.063	(0.048)	0.081*	(0.044)
Age of the head	0.03	(0.028)	0.017*	(0.010)	0.017**	(0.009)
Age squared	0.000	(0.000)	-0.000*	(0.000)	-0.000*	(0.000)
At least one family member works off-farm (yes=1)	-0.229*	(0.137)	-0.054	(0.043)	-0.066	(0.041)
Access to own pair of oxen(yes=1)	0.217	(0.192)	-0.002	(0.057)	0.032	(0.057)
Distance to the furthest plot from home	0.003	(0.003)	0.001	(0.001)	0.000	(0.001)
Constant	-0.578	(0.968)	1.649**	(0.705)	1.801***	(0.679)
District dummy	Yes		Yes		Yes	
Wald chi2	160.71		61.99		85.29	
N					476	

* p<0.1, ** p<0.05, *** p<0.01; bootstrap standard errors in parentheses

[a] This is selection equation is jointly estimated with the regime equation shown in the next table 8.

Table 8: Full information maximum likelihood estimates of the Switching regression model (Dependent variable=Log of food gap months)

	Participant		Non-participants	
Land per capita (ha)	-2.799**	(1.392)	-0.221	(0.637)
Land per capita squared	2.066	(2.550)	-0.177	(0.757)
Log of agricultural income per capita	-0.063	(0.057)	-0.074*	(0.039)
Log of non-agricultural income per capita	-0.013	(0.019)	-0.014	(0.017)
Age of the head	0.004	(0.003)	-0.002	(0.002)
Gender of household head	0.128	(0.126)	-0.034	(0.083)
Household attended schooling (yes=1)	-0.030	(0.064)	-0.140**	(0.059)
Family size	-0.053***	(0.019)	-0.014	(0.015)
At least one family member works off-farm (yes=1)	-0.109*	(0.062)	-0.113**	(0.055)
Family in polygamy (yes=1)	0.412***	(0.135)	0.177	(0.113)
Log of number of extension visits	0.025	(0.027)	0.029	(0.023)
Log of distance to extension service	-0.033	(0.037)	-0.003	(0.033)
Own livestock (TLU) per capita	-0.092	(0.066)	-0.165**	(0.073)
Log of number of Enset trees per capita	-0.015	(0.032)	0.011	(0.027)
Borrowed cash during the year (yes=1)	0.212***	(0.063)	0.100*	(0.055)
Constant	1.438***	(0.431)	2.030***	(0.273)
District dummy	Yes		Yes	
Sigma (δ)	-1.09***		-0.77***	
ρ	-0.22*		0.40**	
N			476	
Likelihood ratio test of independent equations (X^2)			2.98*	

Table 9: Full information maximum likelihood estimates of the Switching regression model (Dependent variables: Log food consumption kcal/capita/day)

	Participants		Non-participants	
Land per capita(ha)	0.384	(2.289)	2.030*	(1.042)
Land per capita squared	-1.090	(3.984)	2.780**	(1.255)
Log of agricultural income per capita	0.334***	(0.083)	0.186***	(0.067)
Log of non-agricultural income per capita	0.036	(0.030)	0.037	(0.029)
Age of the head	0.005	(0.004)	0.001	(0.004)
Gender of household head	-0.272	(0.188)	0.356**	(0.142)
Household attended schooling (yes=1)	0.010	(0.092)	-0.052	(0.100)
Family size	-0.150***	(0.034)	-0.162***	(0.025)
At least one family member works off-farm (yes=1)	0.246***	(0.093)	0.266***	(0.093)
Family in polygamy (yes=1)	0.150	(0.199)	-0.330*	(0.193)
Log of number of extension visits	0.094**	(0.039)	0.100**	(0.040)
Log of distance to extension service	0.005	(0.056)	0.100*	(0.055)
Own livestock (TLU) per capita	0.073	(0.107)	-0.061	(0.124)
Log of number of Enset trees per capita	-0.050	(0.046)	-0.018	(0.046)
Borrowed cash during the year (1=yes)	0.145	(0.092)	0.172*	(0.094)
Constant	5.432***	(0.802)	5.987***	(0.512)
District dummy	Yes		Yes	
Sigma (δ)	-0.71***		-0.18***	
ρ	0.23*		-0.34***	
N				476
Likelihood ratio test of independent equations (X^2)				5.28**

Table 10: Simulated net impact of participation in biofuel crop contract

Sub-sample	Decisions stage		Treatment Effect
	To participate	Not to participate	
Log of food gap (months)			
Households who participated	(a) 0.84	(c) 1.20	(treated) -0.37***
Households who did not participate	(b) 1.04	(d) 0.98	(untreated) 0.06***
Log per capita annual food consumption (kcal/capita/day)			
Households who participated	(a) 7.86	(c) 7.59	(treated) 0.27***
Households who did not participate	(b) 7.23	(d) 7.41	(untreated) -0.18***

*significance at 0.1, ** significance at 0.05 *** significance at 0.01 level

Figure 1: Sampled villages in SNNP (South Nations and Nationalities) region, the dots indicate the villages surveyed
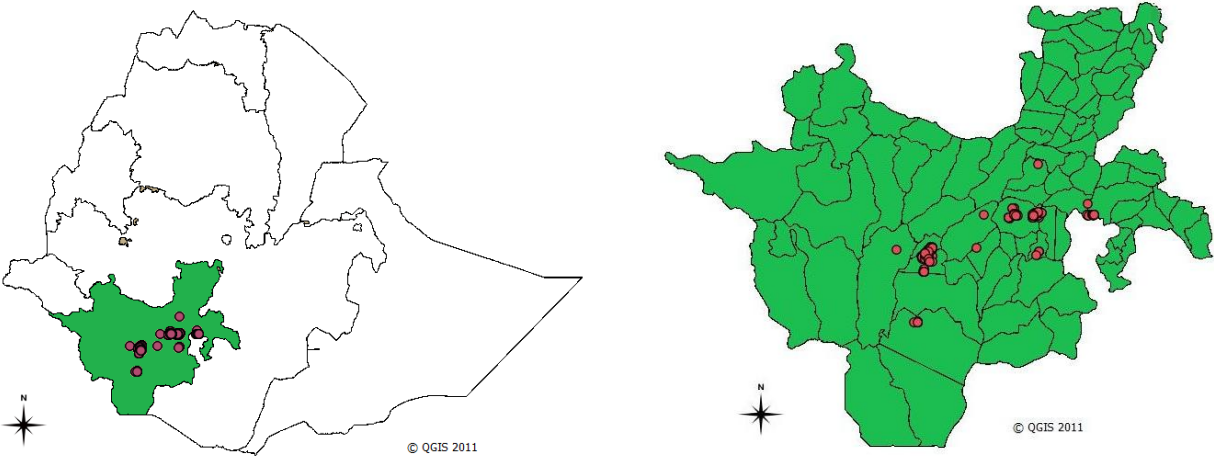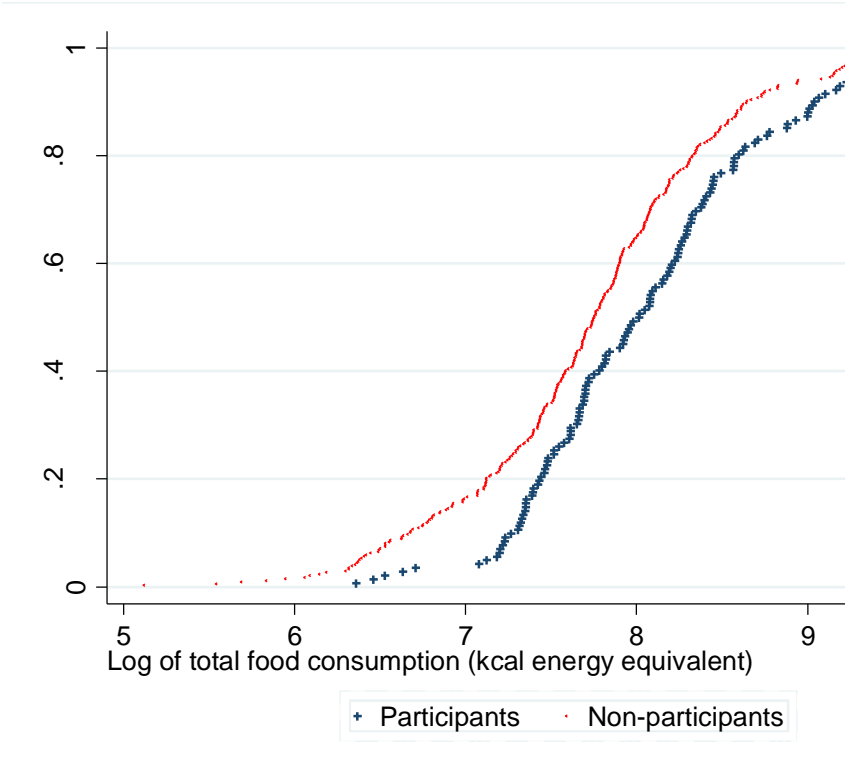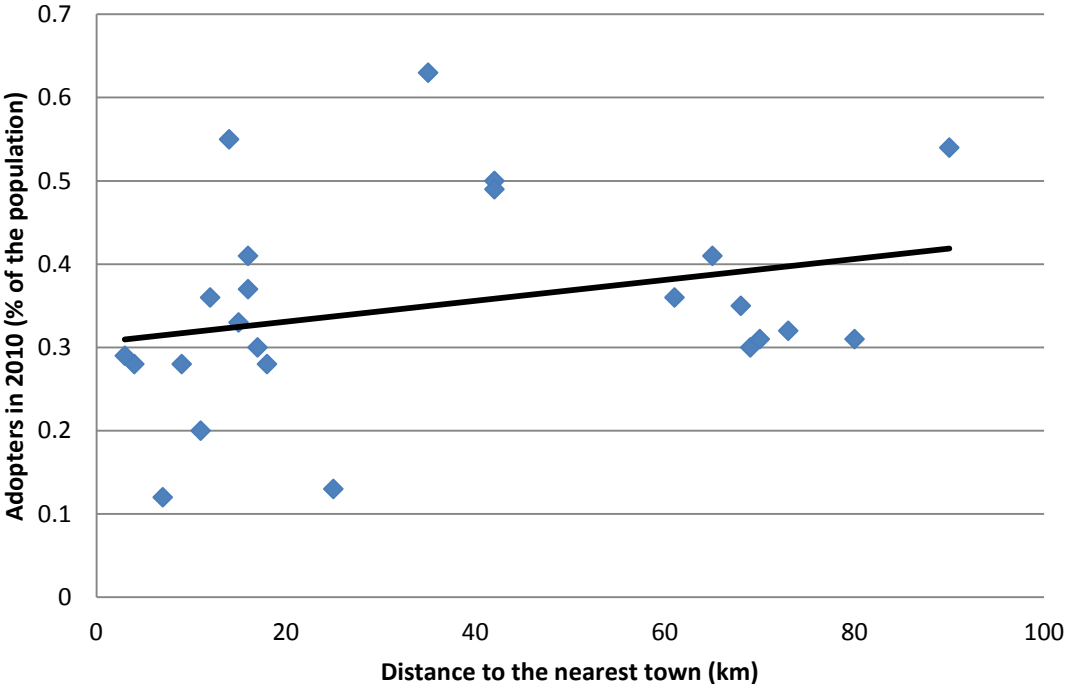

Figure 2: Distribution of per capita food consumption

Appendix 1 :

Figure 1A: Adoption and distance to the nearest town

Appendix 2

Estimation of endogenous switching regression model

The system of simultaneous equations for adoption and impact of adoption can take the form:

$$d_i = \begin{cases} 1 \ if \ \gamma Z_i \geq \ u_i \\ 0 \ if \ \gamma Z_i < \ u_i \end{cases} \tag{1}$$

where the latent equation for d_i given by $d_i^* = \gamma' Z_i + \ u_i$
and the outcome equation for each regimes of adoption defined by:

Regime 1:	$y_{1i} = \beta_1 X_i + \ \varepsilon_{1i}$	$if \ d_i = 1$	(2)
Regime 2:	$y_{2i} = \beta_2 X_i + \ \varepsilon_{2i}$	$if \ d_i = 0$	(3)

where y_{ji} are the dependent variables in the continuous equation, X_1 and X_2 are vectors of exogenous variables, β_1, β_2 and γ are parameters to be estimated. ε_{1i} ,ε_{2i} and u_i are assumed to have a trivariate normal distribution, with a mean vector zero and a covariance matrix say δ.

$$\delta = cov(\varepsilon_{1i} \ ,\varepsilon_{2i} \ , \ u_i) = \begin{pmatrix} \delta_{\varepsilon 1}^2 & . & \delta_{\varepsilon 1u} \\ . & \delta_{\varepsilon 2}^2 & \delta_{\varepsilon 2u} \\ \delta_{u\varepsilon 1} & \delta_{u\varepsilon 2} & \delta_u^2 \end{pmatrix} \tag{4}$$

Identifying the *Average Treatment Effect* (ATE = $E\{y_{1i} - y_{2i}\}$) or the Treatment effect on the treated (TT=$E\{ \ y_{1i} - y_{2i}\}| \ d_i = 1\}$) from observations on y_i, X_i and d_i is problematic. We can easily find E$\{ \ y_{1i}| \ d_i = 1\}$ = E$\{ \ y_i| \ d_i = 1\}$ and E$\{ \ y_{2i}| \ d_i = 0\}$ = E$\{ \ y_i| \ d_i = 0\}$. But we can not find E$\{ \ y_{1i}| \ d_i = 0\}$ and E$\{ \ y_{1i}| \ d_i = 1\}$ from observational data since individual observations are only observed in either of the regiems once (Verbeek, 2010). When an endogenous disecret variable is added into the structural equation (equation 1), equation 2-3 can be represented in a linear form as:

$$y_i = \beta_2 X_i + \ \varepsilon_{2i} + \ di[X_i'(\ \beta_1 - \beta_2) + \ (\varepsilon_{1i} - \ \varepsilon_{2i} \ )] \tag{5}$$

The term in square brackets denotes the gain from participating in castor program. When the outcome equation depends upon the position ($d_i = 0 \ or \ d_i = 1$) it can be represented by a Swiching Regresstion Model. The individual specific gain from participating in the program consists of a component related to observable characterstics and unobservable error component. We can rewrite equation 5 as:

$$y_i = \beta_2 X_i + diX_i'\theta + \varepsilon_i \tag{6}$$

Where $\theta = (\ \beta_1 - \beta_2)$ and $\varepsilon_i \ = (1 - di)\varepsilon_{2i} + di\varepsilon_{1i}$ The average treatment effect of participating in the castor program with characteristics $X_i$is given by:

ATE $(X_i)= X_i'\theta$ $\tag{7}$

while the TT is:

TT$(X_i)= X_i'\theta + E\{(\varepsilon_{2i} - \varepsilon_{1i} \ )|X_i, di = 1\}$ $\tag{8}$

ATE and TT are equal when the second term in 8 is equal to zero. If there is 'selection upon unobservables', we need to account for it to consistently estimate the TT. This can be done through eastimating an endogenous regresstion model.

The logarithmic likelihood function for the system of equations (1-3) is:

$$\ln L\left(\beta_{1i},\ \beta_{2i}, \delta_{\varepsilon 1}^2, \delta_{\varepsilon 2}^2, \delta_{\varepsilon 1u}\ \delta_{\varepsilon 2u}\right) = \sum_{i=1}^{N}\left\{ d_i \left[ln\emptyset\left(\frac{\varepsilon_{1i}}{\delta_{\varepsilon 1}^2}\right) - \ln\delta_{\varepsilon 1}^2 + ln\Phi(\eta_{1i})\right] + \right.$$
$$\left. (1 - d_i)\left[\ln\emptyset\left(\frac{\varepsilon_{2i}}{\delta_{\varepsilon 2}^2}\right) - \ln\delta_{\varepsilon 2}^2 + \ln\left(1 - \Phi(\eta_{2i})\right)\right]\right\} \qquad (9)$$

where δ_u^2 is the variance of the error term in selection equation, $\delta_{\varepsilon 1}^2$ and $\delta_{\varepsilon 2}^2$ are variances of the error terms in the continuous equation. $\delta_{\varepsilon 2u}$ and $\delta_{\varepsilon 1u}$ is the covariance of u_i with ε_{2i} and ε_{1i} respectively. $\eta_{ji} = \frac{\left(\gamma Z_i + \rho_j \varepsilon_{ji}/\delta_j\right)}{\sqrt{1-\rho_j^2}}, j = 1,2$ and ρ_j denotes the correlation coefficient between the error term (u_i) of the selection equation and the error term in outcome equation (ε_{ji}) in the outcome equations 2 and 3 (Lokshin and Sajaia, 2004).

If estimated values of $\delta_{\varepsilon 2u} = \delta_{\varepsilon 1u} = 0$, we have the switching regression model with exogenous switching. If the estimated covariance of these terms are statistically significant, then the decision to adopt and the welfare outcome variables are correlated. And thus we reject the hypothesis that sample selection bias is absent. Thus, we have endogenous switching (Maddala, 1999). The correlation coefficients ε_{1i} and u_i (ρ_{1i}) can be computed as $\left(\frac{\delta_{\varepsilon 1u}}{\delta_{\varepsilon 1*}\delta_u}\right)$; and between ε_{2i} and u_i (ρ_{2i}) as $\left(\frac{\delta_{\varepsilon 2u}}{\delta_{\varepsilon 2*}\delta_u}\right)$.

As outlined in Cadot and Ross (1999), the estimation procedure can be implemented in steps by maximum likelihood methods:

Step (1): Equation 1 is estimated through a non-linear estimation (Probit model in this case), yielding an initial estimate for $\hat{\gamma}$. This estimates gives the predicted value of the participation position if i[th] individual in j[th] position.

Step (2): Estimates from the first step are used in OLS regression for the reduced structural equation of (2 and 3) to estimate the $\widehat{\beta_1}, \widehat{\beta_2}$,$\delta_{\varepsilon 2u}$ and $\delta_{\varepsilon 1u}$. Plugging the former into (2) and (3) yields a residuals $\widehat{\varepsilon_{1i}}$ and $\widehat{\varepsilon_{2i}}$ and estimates of $\delta_{\varepsilon 1}^2$ and $\delta_{\varepsilon 2}^2$ are obtained

Step (3): All estimated parameters are used as initial values for the maximization of the logarithmic likelihood function defined in (9). The procedure starts again from step 1 and is repeated until the maximum of this function is found.

Alternatively, the STATA command (*movestay)* written by Lokshin and Sajaia (2004) estimates the binary and continuous part of the model simultaneously using FIML in order to yield consistent standard errors.

Equations of impact of participation

<div align="center">Participation decision position</div>

	Regime 1 (participate)	Regime 2 (Not participate)	Treatment effect
Participant	(10a) $E(y_{1i}|d_i, x_{1i} = 1)$ $\beta_1 X_{1i} + E(\varepsilon_{1i}|di = 1)$ = $\beta_1 X_{1i} + \left(\frac{\delta_{\varepsilon 1u}}{\delta_u^2}\right)\left(\frac{\phi(\hat{z}_i)}{\Phi(\hat{z}_i)}\right)$	(10c) $E(y_{2i}|d_i, x_{2i} = 1)$ $\beta_2 X_{1i} + (\varepsilon_{1i}|di = 1)$ = $\beta_2 X_{1i} + \left(\frac{\delta_{\varepsilon 2u}}{\delta_u^2}\right)\left(\frac{\phi(\hat{z}_i)}{\Phi(\hat{z}_i)}\right)$	(10a)-(10c) = TT
Non-participant	(10b) $E(y_{1i}|d_i, x_{1i} = 0)$ $\beta_1 X_{2i} + E(\varepsilon_{2i}|di = 0)$ = $\beta_1 X_{2i} - \left(\frac{\delta_{\varepsilon 1u}}{\delta_u^2}\right)\left(\frac{\phi(\hat{z}_i)}{1-\Phi(\hat{z}_i)}\right)$	(10d) $E(y_{2i}|d_i, x_{2i} = 0)$ $\beta_2 X_{2i} + E(\varepsilon_{2i}|di = 0)$ = $\beta_2 X_{2i} - \left(\frac{\delta_{\varepsilon 2u}}{\delta_u^2}\right)\left(\frac{\phi(\hat{z}_i)}{1-\Phi(\hat{z}_i)}\right)$	(10b)-(10d)=TU

Source: Di Falco et al, 2011

Equation (10a) $E(y_{1i}|d_i, x_{1i} = 1) = \beta_1 X_{1i} + E(\varepsilon_{1i}|di = 1) = \beta_1 X_{1i} + \left(\frac{\delta_{\varepsilon 1u}^2}{\delta_u^2}\right)\left(\frac{\phi(\hat{z}_i)}{\Phi(\hat{z}_i)}\right)$ is the expected outcome of the ith individuals if they enter position 1. The second part in is a function of the estimated covariance between the outcome residuals in position 1 and the chance of occurring in position 1 ($\delta_{\varepsilon 1u}$) and the estimated probability of occurring in position 1 $\left(\frac{\phi(\hat{z}_i)}{\Phi(\hat{z}_i)}\right)$. Equation (10a) and (10d) above represent the actual expected values observed in the data, while the other two terms (10b & 10c) represent the hypothetical counterfactual expected outcomes[8].

From the estimated values above, we can calculate the effect of participation (the treatment) on the treated farm households as the difference between Equation (10a) and (10c). And the effect of the participation of the non-participants by the difference between Equation (10b) and (10d). The first difference (10a − 10c) compares a sample adopter farmer i's average gain under the participation to the gain of a general farmer (with the same characteristics) under the contract. A positive mean of this difference for crop income indicates that under the participation, farmers who actually adopted the crop tend to have higher gain than those who did not. And the second difference (10b - 10d), compares a sample adopter farmer i's average performance without the contract to the gain of a general farmer without the contract.

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[8] Estimates of this terms can be obtained from STATA post estimation options for each of these equations (the STATA postestimation option uses the notations -yc1_1, yc2_2, yc1_2and yc2_1 respectively for each equation) Lokshin and Sajaya (2004).