Drivers of bioenergy crop adoption: evidence from Ethiopia's castor bean contract farming

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Abstract

Smallholder farmers in poor economies like Ethiopia dominate the agriculture sector. Energy crop supply for biofuel processing will likely depend on the adoption behavior of farmers. The drivers of energy crop adoption at household level are predicted to include access related factors, assets and household characteristics. Using data from castor outgrower scheme in Ethiopia and applying a double-hurdle model, we analyze adoption as a two-step decision process. The results show that higher price of maize (a major staple crop) is strongly associated with lower size of land allocation to castor. Contrary to the widely accepted notion, access indicator variables such as distance from village centers (where most decentralized public service centers are located) and number of visits by public extension agents do not influence the decision to adopt. But interestingly, conditional on positive participation, farmers who live furthest from the village centers tend to allocate bigger proportion of their land to the energy crop.

Keywords: adoption, biofuels, castor, Ethiopia

JEL: Q42, Q16, O13, Q12

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1. Introduction

Farming energy crops has become increasingly important in the global agriculture. The introduction of energy crops may alter or replace existing farming activities, requiring rural farmers to adjust their farming decisions. The production of crops dedicated to energy can be organized either as a large-scale commercial plantation activity or as an integrated operation within traditional smallholder farming systems. Under the integrated system, the potential supply of feedstock to the processer or exporter firm depends on farmers' willingness to adopt the energy crop.

Under what terms do smallholder farmers participate in contract farming is a policy relevant question. Farmers' participation in the value chains through contract farming has been increasingly viewed as a means of overcoming market imperfections (Gow et al., 2000 and Grosh, 1994). Under limited or irregular functioning of the public agricultural input delivery system, farmers may find it attractive to engage in contracts with private firms that offer a contract to purchase the household's production of some agricultural commodity jointly with credit services or other agricultural inputs. There is also evidence to suggest that such contracts provide new agricultural skills that motivate farmers to participate. Access to new production skills not only help farmers to improve the productivity of the contracted crop but may also have spillover effects on the production of other food crops (e.g. Minten et al., 2009; Masakure and Henson, 2005).

From the perspective of the feedstock buyer firms, pursuing an agreement to supply the necessary inputs to farmers allow them to monitor the right input levels, the essential agronomic practices and also lets them ensure quality in procurement. Through visiting farmers' fields and supervising when, how, and under what conditions farmers undertake production tasks, firms collect information that allow them to persuade farmers to respect the contract terms (Wolf et al., 2004).

The degree to which participating smallholders benefit from biofuel contract farming is a subject of debate (Negash and Swinnen, 2013). Despite that, it is commonly accepted that farmers indeed participate if there is an expected gain from engaging in contracts (Bellemare, 2012). Farmers' willingness to enter into contract schemes does not always guarantee them participation. There are a number of barriers that limit smallholders' access to contract farming and agricultural value chains (Barrett et al., 2012). Institutional constraints and accesses related factors—such as limited access to credit, insurance, and market information, and uncertainties regarding new risks—may reduce the feasibility and attractiveness of contract farming participation for smallholders.

Transaction costs associated with weak physical infrastructure are said to substantial distort farmers' marketing behaviors (Barrett et al., 2008). The marginal payoffs to private firms is long perceived to be better in areas where infrastructure is developed, hence, private investment would locate their business close to towns (Chamberlin and Jayne, 2013). This leaves farmers residing in the remote rural areas with no inputs, technical assistance and marketing services. In contrast to that, there is now an increasing understanding about the increasing role of private firms in improving smallholders' access to services in distant locations (Chamberlin and Jayne, 2013).

In line with this growing literature, the purpose of this paper is to explore in what way physical distance from village centers (which in most cases are the economic and service hubs) affect the degree to which farmers adopt a biofuel crop. To examine these important questions, we draw data from Ethiopia and analyze which factors are closely associated with farmers' engagement with a privately organized biofuel contract farming scheme. This makes additional contributions to the literature, since the current studies on economics of bioenergy give limited attention to adoption processes and technology diffusion (Rajagopal and Zilberman, 2007).

The remaining part of the paper is organized as follows. Sections two presents the empirical estimation method. Section three describes the study area, the data sampling method and presents descriptive statistics. Section four presents the regression results and section five outlines the conclusions.

2. Empirical analysis framework

We draw our framework of analysis from the extensive literature on agricultural technology adoption or innovations to provide new insights about adoption of energy crops in developing countries (Feder, 1980; Feder et al., 1985; Foster and Rosenzweig, 2010; Rogers, 1995). These studies have been widely used to predict factors that influence an individual's decision to adopt or reject a technology or an innovation (e.g. Carlettoa et al., 2010; Doss, 2006).

Roger (1995) defines adoption as the process through which an individual (or other decision-making unit) passes from first knowledge of an innovation to forming an attitude toward the innovation, to a decision to adopt or reject. The process leads to a decision stage that the individual either (1) adopt, a decision to make full use of an innovation as the best course of action available, or (2) reject, a decision not to adopt an innovation. Feder (1985) provides a quantitatively measurable definition by distinguishing adoption at individual (farm-level) and aggregate level. Accordingly, adoption at individual level is defined as the degree of use of a new technology in long-run bases when the farmer has full information about the new technology.

Aggregate level adoption is measured by the aggregate level use of a specific new technology within a given geographical area (e.g. a village or a region) or given population. Since adoption is a process it also refers to the intensity of use of a technology as a quantitative measure of the extent of adoption. The intensity of adoption in a given time period at the individual level can be measured by the amount or share of farm area utilizing the technology (Feder, 1985; Feder, 1980).

Adoption decisions can be estimated using standard limited dependent variable models such as probit or logit. These conventional models treat adoption as a dichotomous choice variable. When the dependent variable is continuous (e.g. proportion of land allocated to new crop), a Heckman selection model can be applied. However, the Heckman approach is designed for incidental truncation where the zeros are unobserved values (Heckman, 1979). This suggests that a corner solution model (such as Tobit model) is more appropriate. But one shortcoming of the Tobit model is that the probability of a positive value (e.g. the probability of adopting new crop) and the actual outcome (e.g. the extent the new crop is adopted) are determined by the same underlying process, i.e. the same parameters (Wooldridge, 2010).

To overcome the limitations of the conventional limited dependent variable estimations methods, recent adoption studies widely use a double-hurdle model (Mariano et al., 2012; Noltze et al., 2012; Rao and Qaim, 2013). The double-hurdle model is a class of selection model in which two separate stochastic processes determine the decision to adopt and the intensity of adoption stepwise (Cameron and Trivedi, 2010). These two hurdles of decision are as follows. First, the farmer decides whether to adopt castor (status of adoption) or not; second, the farmer decides how much of her/his land to allocate to castor cultivation (intensity of adoption). The double-hurdle model is more flexible than the Tobit model because it accounts for the possibility that factors influencing castor contract participation and factors influencing proportion of land allocated to castor may be different.

The two different latent variables used to model each decision process can be represented as:

$$d_i^* = \gamma z_i + u_i \quad (1)$$

$$l_i^* = \beta_i x_i + \varepsilon_i, \quad (2)$$

$$l_i = \beta_i x_i + \varepsilon_i, \text{ if } d_i^* > 0 \text{ and } l_i^* > 0, \text{ otherwise } l_i = 0 \quad (3)$$

Equation 1 refers to the latent form of the first stage decision of whether to participate or not with a vector of variables represented by z_i. Equation 2 is the second stage decision of how much land to allocate with a vector of variables x_i. Equation 3 is the representation of the double-hurdle model; u_i and ε_i are error terms that are independently distributed. The dependent variable in the first stage is the farmer's participation decision in the castor contract offered by the firm, taking a binary value 1 if the farmer participates and 0 otherwise. In the second stage, the dependent variable is the proportion of land allocated to castor (the ratio of plot size a farmer allocated to castor to the total own land) conditional on participating in the contract.

The choice of the explanatory variables included in z_i and x_i is guided by previous empirical literature on adoption. These variables include household characteristics, physical and social capital indicators, access to road, and district dummies. Demographic characteristics identified from the literature that are relevant across adoption studies include age of the household head (as a proxy for experience), education of the household head, gender of the household head, and other socio-economic characteristics (Rogers, 1995; Tatlidil, 2009). A number of factors (beyond the immediate nominal returns) are predicted to influence a farmer's decision to adopt castor or allocate land. This decision is usually based on: own skills and preferences; availability or access to seeds, inputs, prices of close substitutes and government policies. The adoption of cash crops (which are potentially rewarding but as same time are risky enterprises) among smallholders may be constrained as a result of their limited risk-bearing ability, access to credit, asset position, and level of human capital and management skills (Bandiera and Rasul, 2006; Barham et al., 1995; Lee, 2005).

Farm size and asset holdings in general are hypothesized to have a positive influence on the adoption process, as is contact with extension agents (Feder et al., 1985; Doss, 2006). Infrastructures (in particular proximity to markets) are reported to favor adoption (Abdulai and Huffman, 2005; Dadi et al., 2005). In terms of food-versus-fuel crop choices, we expect an inverse relationship between food prices and allocation of land to energy crops. The direction of the relationship between access to non-farm employment and adoption can be ambiguous since it depends on the degree of complementarities between the off-farm income and farming activities.

In order to determine how each of these variables relates with adoption, we apply the Cragg's double-hurdle maximum likelihood estimation method to run the regression and compute the marginal effects. For computing the marginal effects and the corresponding bootstrapped standard errors we adopted a step-by-step user-written estimation program given by Bruke (2009).[1]

[1] This method was initially proposed by Cragg (1971) and known as 'Cragg's Double hurdle model'. But Bruke (2009) elaborates the model with accessible STATA user command that can specifically be applied when the outcome variable of second tier is in continuous form.

3. Data and descriptive statistics

3.1. Case study of the castor contract farming

The predominant farming system of the study area is a mixed crop-livestock system. Most important food crops farmers cultivate include enset (commonly called "false banana"), diverse types of cereals and root crops. [2] Some farmers produce local cash crops such as fruit, ginger, coffee, and cotton. Crop production entirely depends on rainfall, which is often erratic and unpredictable and which leaves many vulnerable to food insecurity.

Castor production in the Southern region started in 2008 with castor seed distribution to more than 10,000 farm households in Wolaita and Gamo Gofa. Participation in the program was based on voluntary farmers who agreed to allocate portion of their land to cultivate castor. Farmers traditionally recognize that crop rotation with castor enhances soil fertility, but no one was interested to cultivate it on large scale because there was no market for the crop before 2008. The company had to undertake extensive promotion activities to encourage farmers to grow the crop as cash crop. It resulted in relatively 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 (that live close to each other) signs a contract to receive all the necessary inputs such as fertilizer, herbicide, and technical assistance. Each farmer signs the contract individually but the group is formed to facilitate input distribution and loan repayment. The company provides the fertilizers in loans but the herbicide and technical assistance for free of charge. In return farmers 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 the village level are responsible for training farmers, facilitating group formation, input distribution and for following up the cultivation and output collection. The promoters of the crop are mainly extension agents hired by the

[2] Enset is a perennial and relatively drought-resistant plant, maturing at around four years and grows up to seven years, serves as a food store for most households.

company (83%), but government extension workers have also been involved in disseminating the information.

3.2. Data collection

Four districts (woredas) were chosen as representatives of the Wolaita 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.

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 represents smallholder farmers in castor growing areas of the region. We used a sampling frame that is derived from three set of information sources: (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 intervals equal 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 questions on crop production, revenue, input use, income by type, and food security. Except for general household characteristics, we disaggregated our data enquiry over the two main crop seasons. In most 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.

3.3. Descriptive statistics

The dataset contains 476 households. On average a farmer owns 0.8 ha of land and 2.6 units of livestock. 12% of the households are women headed. 50% of the households have at least one family member who has a non-agricultural income source. Farmers who have access to telephone are 26% and 12% of the farmers use formal information sources such as radio, TV and newspaper. Access to electricity is almost non-existent in the study area. Only 8% of households (40 households out of the total 476 in the sample) have access to electricity.

Adopters represent 30% of the households. An adopter or a participant farmer in our analysis is defined as a farm household that signed a castor supply contract with the company and allocated land to grow castor in the planting season of the year 2010. To understand the farmers' reasons for choosing to participate or not to participate in the castor program, we summarized their responses in Table 1 and Table 2. An issue of profitability is described as farmers' most important reason in their decision to participate. 83% of participants households responded that they planted castor in the expectation of higher income and close to 14% of them responded it was mainly to benefit from higher soil productivity associated with planting castor. Some farmers are aware of the soil improvement benefit of castor specially when used in crop rotation or intercropping.

Many non-participant farmers (about 45%) reported their main reason not to participate is because they thought castor is not a profitable crop to them (see Table 2).

The fact that the issue of profitability being emphasized by both participant and non-participant households suggest that households sort themselves based on their expected gains from growing the biofuel crop.

The second most important reason of non-participation is lack of access to resources such as land and labour. Households that did not participate because of lack of information comprise only 6%. This is not surprising given the intensive promotion activity that the company conducted in pursuit of more castor supply to meet export demand.

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 from towns and constrained by a limited availability of markets for alternative commodities, the adoption intensity is above the average rate (54%) (Figure 2). Villages that are close to the nearby district towns (villages at the right bottom of Figure 2) enjoy access to big roads that connects the district with the region's capital. These villages have better access to other agricultural cash sources (such as livestock raring, dairy farming etc.). Castor adoption is relatively low in these villages. One possible explanation is that economic incentives may vary spatially and farmers who live close to district towns may find it more attractive to engage in non-castor agricultural activities. There are villages that are not far from district towns but have higher number of adopters. For example the village called Uba Pigazo is only 17km away from the nearby town but its intensity of adoption equals the regions average. Although villages like that are close to the district centers in terms of the absolute distance, it takes farmers more time to reach to nearby towns due to poor quality of the infrastructure or absence of transport services. Availability of other cash sources in these villages is also very limited (Table 3). The company deploys inputs and other necessary materials to these villages using motorbikes.

Table 4 provides the list and definitions of the variables that are included in the household level analysis. Access-related variables include households' use of formal media, size of social contact, distance from village, number of government extension agents access to off farm employment' visit. Distance is measured by the time it takes to walk (in minutes) from the village centers to farmer's houses. On average farmers spend half an hour to walk from the village centers to their places. There is no significant difference between participant and non-participant households in terms of distance from village centers.

It was important to include a price indicator of the major food crop to analysis the interaction between food and biofuel production. Maize is one of the major staple in the area and covers the largest cultivated area of annual crops. Therefore, we included the average maize price before the planting season of the evaluation period. Another important food crop in the area is enset. Finding a standardized unit and price data of enset product was not possible in our survey. Therefore, we include the number of enset trees the household owns to control for the effect of access to other food crops on land allocation for biofuel crops. The rest of the variables are socio-economic related such as age, gender, and literacy status of the household head and the family size of the household.

Land holding is a key eligibility criteria for participation, and is necessarily higher for participants. On average, adopters own larger farms and more livestock than non-adopters. Participants and non-participants do not differ significantly in terms of access to public services including extension centers or contact with government extension agents. Land is an important criterion when recruiting farmers. Farmers need to have enough land to grow the crop and keep adequate land for other crops. 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 is also confirmed by our data. The average allocation of land to castor is 15% of total land covered by annual crops (Table 5). The maximum land that farmers allocate does not exceed 25% of their total land holdings. 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 despite its wide coverage of areas it was extremely challenging for the company to obtain sufficient supply to meet the export demand. In the following years (2009 and 2010) the land size for eligibility was therefore reduced to 0.75ha.

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 (negligible in number) that participated but did not satisfy the eligibility criteria.

On average 27% of participants get information about markets, prices and agricultural practices primarily through formal media sources such as radio. Only 18% of non-participants make use of the formal media sources. In contrast, non-adopters have larger social connections and friends that they regularly spend time together, unlike participants.

Participants and non-participants are similar in a number of characteristics (such as age of the household head, education of the head, and proportion of working age group) but differ in terms of gender of the household head, number of social contacts, and family size (Table 6). Female-headed households, household heads with large number of social contacts and smaller family sizes are less likely to participate. There is no strong correlation between education and adoption. Overall, schooling is low: 50% of the total sample never attended school.

3.4. Castor contracted plots

We further explore the adoption pattern at the plot level. We sample all plots cultivated by the participant household in the long rainy season (namely *sila*) and the short rainy season (namely *gaba*). The sample comprises 837 plots, of which 19% are castor contracted plots, i.e. in either of the two seasons, each participant farmer cultivates on average one castor plot and three non-contracted plots. Farmers cultivate range of crops (sometimes up to 14 types of different cereals, pulses, fruit trees, cash trees such as coffee and eucalyptus, or perennial non-food trees) simultaneously on the same plot. Intercropping castor with other crops is also the dominant way of castor cultivation as 54% of castor contracted plots are intercropped with maize, haricot beans, pulses or other crops (Table 7).

The contracted plots may not be randomly chosen i.e. households may assign plots for growing castor based on plot characteristics. We present the descriptive statistics in Table 8 to show the characteristics of castor contracted and non-contracted plots. Castor contracted plots are significantly larger in size by about 0.06 ha. and they are farther from home. There are four major type of soils identified in the data (Table 8). We adopt farmers' soil classification to measure soil quality given the evidence that farmer's soil classifications strongly associates with those of soil scientists in terms of fertility and physical characterization. Description and classification of soils of the study area are available in Ponda and Jonfa (2005). *Gobo* soils are identified as red color, with deep depth fine topsoil and poor water moisture retention characteristics. The most fertile soil is Kareta. It is clear that farmers do not plant castor on plots with best soil type like Kareta. Table 8 show farmers grow castor mostly on plots with soil type locally called *talla*. As described by Ponda and Jonfa (2005), *talla* soils are hard to plough in dry and wet condition, become sticky during rainy seasons and leave crack in dray seasons. While these soils are difficult to manage for cultivation, but are reported to be responsive to fertilizers. The reasons why farmers tend to contract out *talla* soil plots to the castor program can be because such plots are difficult to plough and castor requires less ploughing compared to other crops.

4. Results

We first run the double-hurdle model to analyze adoption as a process that involves a two steps decision. The first step estimates the probability that a farmer adopts castor (status of adoption); and the second estimates the intensity of adoption. In the second part of the estimation, a positive coefficient means that, conditional on a positive participation to the contract scheme, the corresponding variable increases the proportion of land allocated to castor.

In order to verify the use of the double-hurdle model as outlined in section three, the preferred specification is tested against the alternative which is generalized Tobit specification. Because the Tobit model is nested in the double-hurdle model (Burke, 2009), we tested the use of double-hurdle model over Tobit using a likelihood-ratio (LR) test. The test result (LR statistics equals to 286; and X^2 critical value equals 44.03) strongly rejects the hypothesis at the 95% confidence level that the Tobit model is appropriate. In our setting, there is strong evidence that farmers who decide not to allocate land do so deliberately, so that the observed zeros represent rational or intentional choices instead of censored zeros (or missing data) implying the regression result of the double-hurdle model is preferred.[3]

We run three different estimations controlling for key variables including household characteristics, land size, livestock assets, the price of maize (at the beginning of the year before planting decisions are made), access to information and district dummies. Table 9 displays the results. The first two columns report the coefficients of the first and second stage estimation results of the double-hurdle model, and the third column shows the computed average marginal effects of the covariates to land allocation given a positive probability of adoption. The last two columns are the probit and Tobit results.

Across all models land size significantly affects both adoption and land allocation, but at a decreasing rate as the squared term is negative and significant. The combined effect (direct and squared) is positive for the domain up to 1.9 hectares per household for the average household. This is more than twice the eligibility criteria (0.75 hectares per household) and includes almost all the households since 93% of households are in this domain.

The results further show that a higher price of maize significantly reduces the allocation of land to castor.[4] One birr increase in the price of maize is associated with 0.12 points decline in allocation of land. The impact of price on adoption of castor may depend on whether the household is a net food producer or not but our result do not confirm this.

The adoption of castor is also positively correlated with a farmer's access to formal sources of information such as radio, TV, and newspapers. Adopters tend to depend more on formal sources of information for their information on agricultural prices and practices than non-participants who are more reliant on friends, local markets and informal networks as their primary sources of information. While the underling mechanisms should further be explored, the higher the number of social

[3] From Table 2, we see that more than 94% of the farmers are aware of the program but decided to not take part because they think that castor is not profitable crop or they have no sufficient resources to grow castor.

[4] 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.

contacts and friends that a farmer regularly interacts with the lower is the probability of participation as well as land allocation to castor. One possible explanation is that larger farmers (who are largely adopters) may have less time to spend on social activities compared to small farmers. Unfortunately our data does not contain information about the adoption behavior of one's social network. The 'social network' variable in our analysis simply measures 'how many close friends other than close family member there are that the household regularly interacts to consult agricultural issues'. Therefore, it is only a partial measure of the social capital. It cannot be considered as a proxy to determine 'social learning' since it does not contain information on how many individuals adopted castor within the household's network.

We found that the gender of the household head is negatively and significantly associated with adoption, meaning that women-headed households are less likely to adopt. Being a female farmer and living in a female-headed household can affect the adoption decision in different ways. We admit that simply identifying the gender of the household head does not completely allow us to capture that distinction. Female headed household does not always mean that the farming decisions are made by a female farmer. Having in mind that drawback of the data, we presume there are two main reason for low adoption of castor by female headed households. First, women and men may have dissimilar needs. In our case female headed households may prefer cultivating food crops instead of cash crops. Second, differential rates of adoption arise because men and women face different constraints, especially unequal access to land, labour or market information that affect adoption indirectly. Both can be reasons behind low participation of female headed households in castor contract scheme. However, the results from the double-hurdle estimation shows that once the condition for probability of adoption is taken into account the effect of gender disappears in allocation of land. This means male and female headed households do not differ in the intensity of their adoption.

Exposure to government extension services (measured by the number of extension agent's visit to the farmer) does not seem to be an important factor for adoption. Since the promotion of the castor crop is primarily undertaken by the company's employed workers, the insignificant coefficient of government extension variable in line with what we expect. Distance to village centers is also not significant. The dissemination of the crop was widespread, even in remote villages. Distance does not appear to be a barrier to adoption.

We also note that there are important differences between the double-hurdle estimation results (column 3) of Table 9 and the Tobit estimation (column 5). The effect of distance to towns (where most public services are located) is insignificant when estimated using Tobit but it is positive and significant when estimated using the double-hurdle. The result suggests that given participation in a castor contract, farmers that live furthest from towns tend to allocate larger proportions of their land to castor. Distance is expressed in natural logarithm terms so we can approximate the marginal effect as an elasticity. The average marginal effect of 0.021 indicates that for farmers who live furthest from the village center (say in location that requires 100% additional minutes of walking), the average proportion of land devoted to castor would be greater by 0.021%. Our result are in line with the findings in Chamberlin and Jayne (2013), which report a marketing agent (in this case a biofuel company) can improve specific access to agricultural inputs and markets conditions of farmers that are located in remote and low potential areas. This is counter to the commonly accepted notions that claim private service providers tend to confine their business close to towns or and market hubs where infrastructure is relatively developed.

Finally, the estimates from the plot level are given in Table 10. The major plot characteristics that are associated to castor contracted plots are bigger in sizes and are largely soil type *talla*. The property of the of soil type *talla* as described in the previous section are more suited for crops that require less ploughing. Farmers tend to choose plots of *talla* soil for castor and reserve plots with good soil like Kareta for food crops.

5. Conclusion

This paper provides empirical evidence on factors that influence the extent and intensity of biofuel crop adoption. A better understanding of the characteristics of biofuel adopters can inform biofuel promotion strategies and possibly support their implementation.

In the outgrower scheme we study, the company offers a contract to small farmers and agrees to provide the necessary inputs. In return farmers can sign up to allocate part of their land to castor production. The firm distributes castor together with other inputs (such as chemical fertilizers, improved haricot bean seeds for intercropping, etc.) through village level assigned extensions workers. The extension workers often distribute inputs door to door and demonstrate applications to farmers, collect castor seeds and effect payments. Farmers get paid in cash for the castor beans they sell during harvest after they pay their fertilizer debts in seeds.

The results from the double-hurdle analysis reveal that conditional on positive participation, farmers tend to allocate a bigger proportion of their land to castor the furthest they live from the village centers. We presume that such a result may be an outcome of the firm's pan-territorial pricing. Distributing castor seeds and fertilizers with a same price through village stores without differentiated transport cost in principle encourages adoption in more remote areas. In Ethiopia, extension is mostly provided by the public sector, operating in a decentralized manner and implemented at the woreda (district) level. The public sector is the single most important player at the local level for smallholders, especially in terms of inputs and agricultural advisory services. Despite being known to have innovative and progressive approaches, the private sector plays a minimal role in agricultural input delivery system. Our results show that adoption of biofuel crops is likely to be effective in distant locations. In view of the presence of large number of remote villages in Ethiopia, contract farming can be an important arrangement to enhance input delivery services.

Introduction of new commercial crops such as castor may require farmers to bear certain risk. Therefore, similar to most adoption studies our result suggests that land is an important asset to support adoption of the biofuel crop. However, we cannot conclude that resource poor farmers are excluded from the biofuel chain since land possession alone may not be an indicator of wealth (particular in distant villages).

In general, we conclude that a successful participation of farmers in the biofuel value chain requires reductions in farm-level input constraints and innovations in distribution of inputs. The same energy crop can have different returns for different people in different locations. A strategy to organize bioenergy productions needs to incorporate the fact that adoption patterns vary across locations and explore optimal ways of location targeting.

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Tables

Table 1. Farmers reasons to plant castor

	Freq.	Percent
Higher income	75	83.85
Higher soil productivity	12	13.98
Guaranteed market	2	1.24
Other (specify)	1	0.93
Total	**142**	**100.00**

Source: Own survey

Table 2. Reason for not growing castor by non-participant households

Why did you decide to not grow castor?	Freq	Percent
I don't know about the program	19	5.69
I was not accepted to join the program	18	5.39
I don't think castor is profitable	151	45.21
I don't have enough land to grow castor	53	15.87
I don't have enough labour to grow castor	41	12.28
I was not interested in castor	32	9.58
Other	5	1.50
Total	**334**	**100**

Source: Own survey

Table 3. Characteristics of sampled villages and castor seed distribution

Village name	Adopters (% in the population)		Distance to the nearest town (km)	Land size per capita (ha) (ave. 0.14)	Fixed telephone network availability (Yes=✓)	Mobile Network availability (Yes=✓)	Access to Electricity	Other dominant cash source
	2008 (ave.20%)	2010 (ave. 33%)						
Ade Dewar	0.11	0.37	16	0.12	✓	✓	×	Cereal retail
Ana Dugong	0.24	0.50	42	0.11	✓	✓	×	Limited
Degage Linda	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
Mandela Sake	0.17	0.49	42	0.09	✓	✓	×	Cereal retail
Olaba	0.01	0.13	25[a]	0.10	×	×	×	Cereal retail
Mayo Kite	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 Weyden	0.10	0.31	70	0.11	×	×	×	Fruit trees
Bola Gofa	0.48	0.28	9	0.10	✓	✓	✓	Dairy
Sega	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 Zahra Sole	0.17	0.33	15[a]	0.17	✓	✓	×	Retail
Gurade	0.08	0.20	11	0.17	×	✓	✓	Dairy
Baal	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. Definition of variables and measurement

Variable	Type	Definition and measurement
Land holding per capita	Continuous	Size of per capita land holding in hectare
Land per capita squared	Continuous	Size of land holding in hectare squared
Maize price	Continuous	Maize price before planting is made (in birr)
Net food producer	Dummy	1 if the household produces more annual food crops (measured by calorie equivalent) over what the household consumes
Maize price X Net food producer	Continuous	Interaction term between maize price and net food producer group
Livestock holding before the program	Continuous	Livestock holding in TLU a year before the program
Farmer eligibility	Dummy	1 if land size >=0.75ha and lives in village where initial adoption rate has been more than the average, 0 otherwise
Formal media	Dummy	1 if primary source of agricultural information is formal media (radio, TV or newspaper), 0 if informal
Social contacts	Continuous	Logarithm of number of social contacts
Extension agent visits	Continuous	Logarithm of the frequency of DA visits during the year
Distance from town	Continuous	Walking distance to the center of the village in minutes
Number of enset trees	Continuous	Logarithm of the number of matured enset trees the household owns
Gender of the head	Dummy	1 if the household head is female-headed, 0 otherwise
Literacy of the head	Dummy	1 if the household head has ever attended any schooling, 0 otherwise
Age of the head	Continuous	Age of the household head in years
Age squared	Continuous	Age of the household head in years squared
Family size	Continuous	Number of total family members that currently live together
Work off-farm	Dummy	1 if there is a family member employed off-farm, 0 otherwise
Distance to plot from home	Continuous	The average distance from home to all plots in minutes

Table 5. Mean land size allocated (ha) to major annual crops and Castor

Season	Long (Sila)		Short (Gaba)	
	Land size in ha	Cumulative %	Land size in ha	Cumulative %
Teff	0.26	27.07	0.15	15.51
Maize	0.27	55.11	0.40	55.87
Haricot beans	0.18	73.83	0.16	72.41
Sweet potato	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**	

Source: Own survey

Table 6. Descriptive statistics

	Mean (sd)						
	All sample		Adopters		Non-adopters		
Outcome variables							
Adopters			0.298				
Proportion of land allocated to castor			0.185	(0.017)			
Household wealth variables							
Land holding per capita	0.142	(0.110)	0.157	(0.094)	0.135	(0.115)	***
Livestock holding before the program	2.627	(2.889)	2.908	(3.641)	2.338	(2.451)	**
Formal media	0.212	(0.409)	0.275	(0.448)	0.184	(0.389)	*
Work off-farm	0.509	(0.500)	0.436	(0.498)	0.530	(0.501)	
Farmer eligibility	0.197	(0.399)	0.289	(0.455)	0.159	(0.366)	***
Log number of social contacts	1.756	(0.842)	1.651	(0.841)	1.801	(0.840)	**
Food crop related variables							
Maize price	3.040	(0.452)	3.020	(0.399)	3.048	(0.473)	
Log number of enset trees	1.615	(1.944)	1.845	(2.073)	1.517	(1.882)	
Proportion net food producer	0.237	(0.019)	0.218	(0.034)	0.245	(0.023)	
Access related variables							
Log of number of extension agent	1.963	(1.176)	2.067	(1.184)	1.919	(1.171)	
Distance from village centers	27.46	(0.934)	27.67	(1.725)	27.37	(1.112)	
Log distance from village centers	2.967	(0.925)	2.959	(0.959)	2.971	(0.911)	
Distance to plot from home	28.880	(33.389)	28.775	(33.667)	28.925	(33.321	
Household characteristics							

Gender of the head	0.120	(0.312)	0.0583	(0.245)	0.137	(0.335)	***
Literacy of the head	0.500	(0.501)	0.556	(0.499)	0.476	(0.500)	
Age of the head	41.811	(12.776)	42.707	(12.034)	41.550	(13.076	
Family size	6.330	(2.326)	6.725	(2.476)	6.162	(2.242)	**
Religion of the head							
Orthodox	0.158	(0.016)	0.147	(0.029)	0.162	(0.024)	
Protestant	0.804	(0.018)	0.802	(0.022)	0.809	(0.033)	
Other	0.036	(0.019)	0.036	(0.010)	0.042	(0.017)	
Number of observation	476		142		334		

The mean difference between adopter and non-adopters * p<0.1, ** p<0.05, *** p<0.01

Table 7. Main forms castor cultivation on contract plots

Patterns of castor cultivation	No. of obs.	%
Castor mono crop	82	44.6
Castor with maize	44	23.9
Castor with haricot beans	26	14.1
Castor, maize and haricot	17	9.2
Castor with annual cereals or pulses other than maize and haricot beans	11	6.0
Total	180*	100

Source: Own survey

*There are some households who have more than one castor plot, as a result total number of plot are more than the total number of castor growers in the sample (which is only 142)

Table 8. Plot level descriptive statistics

	All samples		Contracted plots		Non-contracted		
Outcome variable							
Castor contract plot (1=yes)			.187				
Plot size	0.272	(0.009)	0.322	(0.021)	0.260	(0.009)	***
Presence of perennial tree on the plot (1=yes)	0.289	(0.016)	0.223	(0.033)	0.305	(0.018)	***
Plot distance from home (in minutes)	13.622	(0.862)	17.994	(2.269)	12.596	(0.919)	***
General plot fertile	0.466	(0.017)	0.439	(0.040)	0.472	(0.019)	
Plot slope							
Flat	0.383	(0.017)	0.376	(0.039)	0.384	(0.019)	
Steep	0.617	(0.017)	0.624	(0.039)	0.616	(0.019)	
Soil type							
Kareta	0.386	(0.017)	0.318	(0.037)	0.402	(0.019)	**
Talla	0.288	(0.016)	0.369	(0.039)	0.269	(0.017)	***
Gobo	0.104	(0.011)	0.121	(0.026)	0.100	(0.012)	
Shafe	0.222	(0.014)	0.191	(0.031)	0.229	(0.016)	
Season plot cultivated (1=Sila, long rainy season)	0.499	(0.017)	0.554	(0.040)	0.486	(0.019)	*
N	837		157		680		

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

Table 9. Maximum likelihood estimates for double-hurdle model, probit, and Tobit

	(1) First hurdle Decision to adopt Coefficient		(2) Second hurdle Decision to allocate land Coefficient		(3) Double-hurdle Marginal effect Decision to allocate land conditional on participation		(4) Probit Marginal effect Decision to adopt		(5) Tobit Marginal effect Decision to allocate land	
Per capita land holding	5.991**	(2.475)	6.135**	(3.181)	3.085*	(1.152)	1.870***	(0.528)	1.567**	(0.761)
Per capita land holding squared	-8.708*	(4.807)	-6.522	(6.440)	-4.307	(3.101)	-2.721*	(1.514)	-2.571*	(1.522)
Maize price	-0.276**	(0.142)	-0.479**	(0.228)	-0.232**	(0.121)	-0.118**	(0.051)	-0.155***	(0.056)
Net food producer (1=yes)	-0.608	(1.049)	0.224	(0.085)	0.059	(0.065)	0.190	(0.631)	-0.520	(0.568)
Maize price X Net food producer	0.010	(0.051)	-0.010	(0.053)	-0.167	(0.320)	0.003	(0.016)	-0.000	(0.017)
Livestock	0.050*	(0.027)	-0.000	(0.026)	0.021	(0.016)	0.015*	(0.008)	0.012	(0.008)
Farmer eligibility	0.102*	(0.082)	0.178**	(0.089)	0.070**	(0.030)	0.027*	(0.018)	0.098*	(0.060)
Formal media	0.286**	(0.141)	0.071**	(0.035)	0.058**	(0.029)	0.152**	(0.076)	0.066*	(0.037)
Log of number of social contacts	-0.196**	(0.081)	-0.216**	(0.095)	-0.087**	(0.043)	-0.060**	(0.025)	-0.077***	(0.025)
Log of number of extension agent	-0.154	(0.132)	0.002	(0.064)	-0.011	(0.017)	-0.006	(0.019)	-0.005	(0.019)
Log of distance from village	-0.041	(0.080)	0.140**	(0.086)	0.021**	(0.011)	-0.008	(0.025)	-0.017	(0.027)
Log of number of enset trees	0.023	(0.040)	-0.047	(0.043)	0.005	(0.000)	0.007	(0.012)	0.003	(0.013)
Gender	-0.449*	(0.235)	-0.296	(0.296)	-0.164	(0.157)	-0.137**	(0.071)	-0.142**	(0.061)
Literacy	0.169	(0.142)	0.126	(0.147)	0.081	(0.057)	0.052	(0.045)	0.060	(0.043)
Age	0.022	(0.029)	0.012	(0.030)	0.007	(0.008)	0.007	(0.009)	0.015**	(0.009)
Age squared	-0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)
Family size	0.103**	(0.048)	0.099**	(0.048)	0.035**	(0.015)	0.019**	(0.009)	0.011	(0.012)
Work off-farm	-0.185	(0.133)	-0.247*	(0.139)	-0.084*	(0.049)	-0.057	(0.040)	-0.077*	(0.040)
Distance to plot from home	0.001	(0.003)	-0.001	(0.003)	0.000	(0.000)	0.000	(0.001)	0.000	(0.001)
District dummies	Yes		Yes		Yes		Yes		Yes	
Sigma	53.01						62.72		97.51	
N	476						476		476	

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

Table 10.	Plot choice for castor contract (probit estimation)

Dependent variable = Dummy for castor plot (1 if yes 0 otherwise)	Probit			
	(Population average effect)		(Random average effect)	
Plot size (in ha)	0.430*	(0.237)	0.416*	(0.220)
Perennial tree planted on the plot (1= yes)	-0.264**	(0.133)	-0.250**	(0.124)
Walking distance of the plot from home (in minutes)	0.001	(0.003)	0.001	(0.003)
General plot fertility	-0.016	(0.094)	-0.028	(0.109)
Slope (1=gentle slope)	-0.005	(0.118)	0.116	(0.124)
Soil type Kareta	0.098	(0.141)	0.047	(0.150)
Soil type Talla	0.310**	(0.142)	0.335**	(0.149)
Soil type Gobo	0.368**	(0.166)	0.355*	(0.198)
Season (1=sila, long rainy season)	0.124	(0.078)	0.130	(0.103)
Constant	-1.626***	(0.312)	-1.422***	(0.221)
District dummy	Yes		Yes	
N	826		826	
chi2	161.743		27.484	

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

Figures

Figure 1. Sampled villages in SNNP (South Nations and Nationalities) region

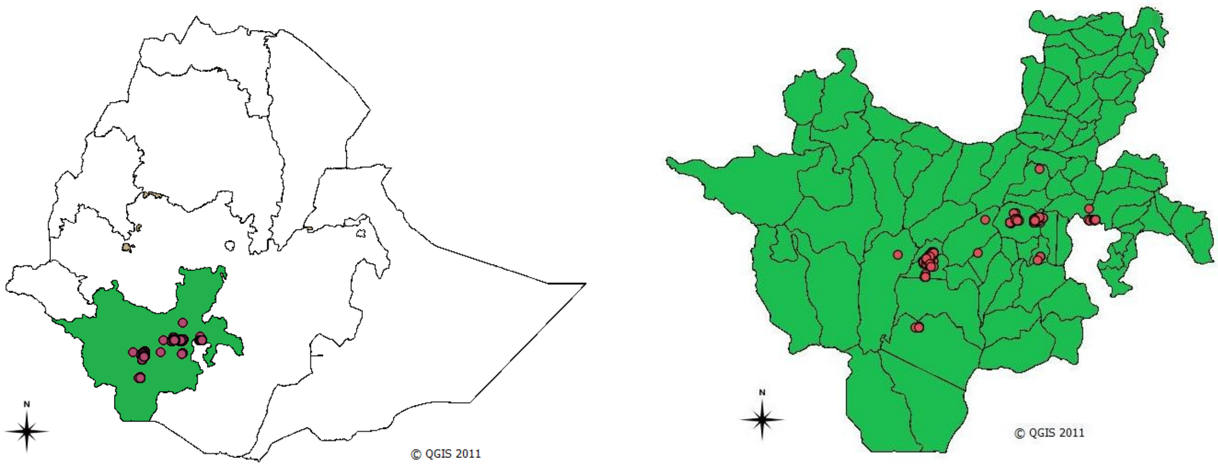

Figure 2. Adoption intensity by distance to the nearby town