Adoption determinants and welfare impact of agroforestry technologies in Ethiopian highlands

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Abstract

Deforestation and land degradation are one of the major causes of low and declining agricultural productivity and continuing food insecurity and rural poverty in Ethiopia. To reverse the problems of land degradation and to make farmlands more resilient, the government of Ethiopia and various development partners have promoted agroforestry trees and land rehabilitation technologies since 1970s. Despite continued efforts, several studies in Ethiopia show persistently low adoption of agroforestry trees and land rehabilitation technologies. This paper applies the counterfactual outcome framework that models technology adoption as a selection processon a cross-sectional data from 416 farm households to explore adoption constraints and welfare impacts of agroforestry technologies in Ethiopia. Empirical findings show that gender of household head being male, high proportion of male family members, larger family size, larger land holding and household location being in higheraltitudesare positively associated with adoption of agroforestry technologies. The result suggest that large scale adoption of agroforestry technologies requires addressing the disparity between men and women in access to farm resources, and land and labour constraints. Furthermore, treatment effect estimates from matching and weighting estimators show that adopting agroforestry technologies confers additional household income and reduces food insecurity in this context. The result suggests that investment in land rehabilitations interventions such as agroforestry merits greater attention in the discourse on rural development.

Key words: *Agroforestry; Technology Adoption; Food security; Propensity Score Matching; Ethiopia*

Highlights

- *We examine adoption constraints and welfare impacts of agroforestry technologies.*
- *Maleness, larger family labour and land holding facilitate adoption of agroforestry technologies.*
- *Adoption of agroforestry technologies is affected by agro-ecology.*
- *Adopting agroforestry technologies increases household income and reduces food insecurity.*

1. Introduction

Deforestation and land degradation are one of the major causes of low and declining agricultural productivity and continuing food insecurity and rural poverty in Ethiopia(Shiferaw and Holden, 1998, pp. 233-247, Ehui and Pender, 2005, pp. 225-242, Tefera and Sterk, 2010, pp. 1027-1037). Identifying effective strategies for raising the use of soil conservation and land rehabilitation technologies has been a longstanding policy priority in Ethiopia. The government of Ethiopia and various development partners have madelarge scale investments in soil conservation and land rehabilitation measures to overcome the problem. For example, rehabilitation of degraded lands, which started through food-for-work relief assistance following the 1974-1975 famine, has become a major component of the government's approach to mitigate the impact of soil degradation in many regions of Ethiopia (Asrat, et al., 2004, pp. 423–438, Azene and Kimaru, 2006).In recent years, Sustainable Land Management Program (SLM) and Productive Safety Net Program (PNSP) have been implementedto disseminate watershed rehabilitationtechnologies and sustainable land management practices among smallholder farmers in many parts of Ethiopia.The activities that are undertaken by these programs include watershed management and communal land rehabilitation, reforestation by plantingagroforestry trees and support for alternative livelihood assets. Agroforestry trees can make farmlands and landscapes more resilient. Numerous field experiments have demonstrated agroforestry trees make farmlands and landscapes more resilient. For example, there are a number of successful agroforestry trees that prevent soil erosion, fast-growing trees for fuel wood, indigenous trees to provide nutritious food, livestock feed and medicinal plant products (Ajayi et al., 2016; Dawson et al., 2014; Mbow et al., 2014; Verchot et al., 2007). Some species fix nitrogen from the air on their root systems, which helps maintain and improve soil fertility. Trees also play a key role in mitigating the negative effects of climate change. Furthermore, high-value fruit trees like apple, mango, avocado and indigenous medicinal trees such as Moringa tree were promoted as one way of empowering rural households to improve their livelihoods (Leone et al., 2015; Megerssa, 2013; Tesfaye et al., 2015). While this has led to *commendable success in certain pockets, yet the country is struggling to scale up promising agroforestry technologies to a large number of farmers and pastoralists. These interventions were intended to reverse the problems of land degradation and desertification and to make farmlands and landscapes more resilient(Bishaw, et al., 2013).*

Yet several studies in Ethiopia have reported low adoption of land rehabilitation technologies among the majority of smallholders(Asfaw, et al., 2011, pp. 436-447, Beshir, et al., 2012, pp. 39-49, Iiyama, et al., 2016, pp. 1-23, Teklewold, 2016). This poses a question as to why the majority of smallholders have not adopted the land rehabilitation technologies in Ethiopia. Both external factors, such as access to basic infrastructure and services, common pool resources and social stability, as well as internal factors, such as asset endowments, interests and power, could determine the extent to which poor households adopt a specific technology. Poor households and smallholder enterprises require minimum assets to successfully implement technologies in agriculture, forestry,environment and climate change(Bryan, et al., 2013, pp. 26-35, Wunder, et al., 2014, pp. S1-S11). Smallholders often have heterogeneous access to land, credit and technical advice, basic knowledge of the market system, and current information on market prices and conditions— all of which restrict their capacity to invest, expand their market surplus and add value to their produce (Asfaw, et al., 2011, pp. 436-447). Despite the evidence that poor households vary in their asset levels, income flows, social networks and abilities to cope with shocks, many technology dissemination initiatives treat poor rural households as a uniform farmer group with the same response capacity(Spielman, et al., 2011, pp. 195-212). Furthermore, technology scale up programs requires adequate policies to improve overall investment conditions, attract investment and provide better business services to increase farmer's competitiveness. Although several studies have been conducted to determine factors affecting technology adoption in Ethiopia, still there are issues where more evidence and consensus are needed (Taddese, 2001, pp. 815-824, Holden, 2004, pp. 369-392 , Poulton, et al., 2006, pp. 243-277, Adimassu, et al., 2012, pp. 191-198, Asfaw, et al., 2013, pp. 1-7). Despite advances in our understanding of factors affecting technology adoption, there are a number of crucial issues on which our knowledge is still insufficient. In fact, the constraints to agricultural *technology adoption and exploring options for change in smallholder farming systems remain elusive (Giller, et al., 2011, pp. 468-472).*

Agricultural household models have been used as a standard framework for technology adoption studies in developing countries (Feder and Umali, 1993, pp. 215-239, Adesina and Baidu-Forson, 1995, pp. 1-9, Shiferaw and Holden, 1998, pp. 233-247, Abdulai and Huffman, 2005, pp. 645-659, Doss, 2013, pp. 52-78). Yet adoption estimates derived from the application of standard techniques such as the probit and tobit yield biased estimates. Furthermore, there is limited evidence on whether previous projects have achieved the intended outcomes on the landscape and farmer's livelihoods. A review of previous studies on the impacts of large-scale degraded land rehabilitation initiatives show that local livelihoods impacts are not clear for many situations and lack clear indicators for monitoring (Adams, et al., 2016, pp. 731-744). Program evaluations are often based on before-after comparisonsof case studies, occasionally relying on observations by rounding out the field and expert opinion. They often use subjective methods such as performance management and participant evaluation approaches. Such evaluation approaches poorly predict causal relationship between the interventions and livelihood outcomes.For instance, too little is known about the impact of agroforestry technologies on household income and on household food security. Another limitations of previous adoption and impact studies has been that they treat technology adoption and impact evaluation as separate entities. Using a counterfactual outcome framework that models technology adoption as a selection processon a cross-sectional data from 416 farm-households in Ethiopian highlands, this paperexamines the binding constraints to adoption of agroforestry technologies and adoption impacts on household welfareas measured in terms of household income and food security in Ethiopian highlands. We also use a combinations of identification strategies to check internal validity of impact estimates. On the basis of research findings, we provide recommendations on interventions and investments that can improve the uptake of agroforestry technologies in Ethiopian highlands.

2. Materials and Methods

2.1. Description of the study sites

The data used for this study were collected from 416 sample households in four districts in Ethiopia. The four districts were selected based on the representativeness of the target areas of Sustainable Land Management Productive Safety Net Program (PSNP)-public works interventions and suitability for fruit and vegetable production.This study was conducted in Sinan, Sekela and AnkashaGuagusa districts located in Amhara region and Chencha district located in the Southern region.

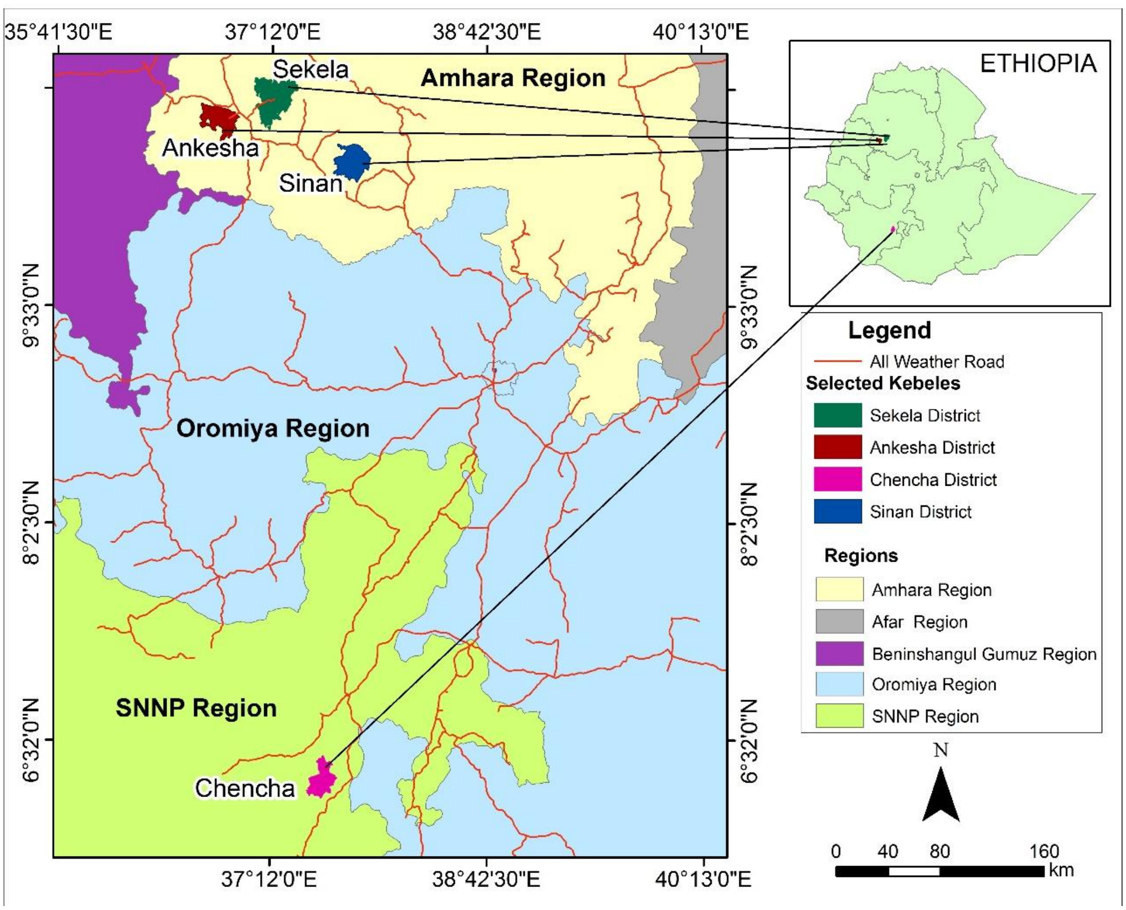

Figure 1: Map of the study sites

2.2. Conceptual framework

Our guiding principle in exploring the determinants of household technology adoption and impact evaluation is grounded in the theoretical model of the agricultural household (Singh, et al., 1986, pp. 149-179, De Janvry, et al., 1991, pp. 1400-1417). Theoretically, the decision to adopt technologies is considered under the general framework of utility maximization. It is assumed that farmers are expected to choose enterprises or adopt the technology that gives the largest expected discounted net return, or utility. Here we focus on the adoption of agroforestry technologies (e.g., planting multipurpose trees and fruit trees). We assume that a farmer chooses agroforestry technology that maximizes utility subject to household demographic characteristics, household resource endowments and other determinants. The feasibility and attractiveness of any alternative within the choice set depends on access to livelihood assetsas well as on the technical and financial performance of each alternative.The inclusion of the explanatory variables in the empirical model is based on a review of theoretical work and previous empirical adoption studies(Feder, et al., 1985, pp. 255-298, Knowler and Bradshaw, 2007, pp. 25-48). Factors that are likely to affect adoption and impact of agroforestry technologies include household and individual characteristics (age, gender, household size, education, etc.), household asset ownership (livestock, land, number of major farm equipment and household furniture, etc.),access to institutional services (distance to extension office and number of contacts with extension agents); and location characteristics (e.g., distance to nearest market place and differences in agro-ecological zones) are included in the adoption analysis.

2.3. Estimation strategy

Probit model

In this paper, we use a probit model (Wooldridge, 2010) to estimate the influence of explanatory variables on adoption of agroforestry technologies. The probit model specification employs a latent variable y_i^* to an observable dependent variable y_i according to the rule:

$$y_i^* = x_i\beta_i + \varepsilon_i$$

$$y_i = \begin{cases} 1 \; if \; y_i^* > 0 \\ o \; otherwise \end{cases} \qquad (1)$$

where x_i is a vector of explanatory variables, β_i is a vector of coefficients, and ε_i is a stochastic disturbance term.

Propensity score matching

Project impact is defined as the difference between observed outcome of project participants and the outcome that would have been obtained if the project participants did not participate in the project (i.e., counterfactual outcome) (Rosenbaum and Rubin, 1983, pp. 41-55, Heckman, et al., 1998). As it is well known in the program evaluation literature, however, counterfactual outcomes are unobservable as an individual is either in one state or the other at a point in time. In non-experimental intervention, project participants and non-participants are not randomly assigned to the project. Propensity score matching (PSM) has been widely used to examine the impacts of technology adoption on household welfare using data collected through non-experimental study designs (Mendola, 2007, pp. 372-393, Ali and Abdulai, 2010, pp. 175-192, Wu, et al., 2010, pp. 141-160, Abebaw and Haile, 2013, pp. 82-91, Takahashi and Barrett, 2013, Imbens, 2014). Propensity score matching method strives to overcome the selection bias that may arise due to non-random assignment of project participants by creating a comparison group of non-project participants that are as similar as possible in all relevant pre-project participation characteristics to the group of project participants (Rosenbaum and Rubin, 1983, pp. 41-55). The PSM method controls for observable characteristics and test for the robustness of results to handle the unobservable characteristics. The PSM approach balances the observed *distribution of covariates across the project participants and non-participants based on observables.*

More formally, we define two outcomes and a treatment indicator:

Y_{1i} *denotes the outcome for a household ï" with treatment*

Y_{0i} *denotes the outcome for household "ï" without treatment*

$T_i \in \{0, 1\}$ *indicates treatment status for household "ï"*

Because a given household can only experience one of the two outcomes, we have the observation equation

$$Y_i = T_i Y_{1i} + (1 - T_i) Y_{0i} \qquad (2)$$

Where Y_i *denotes the observed outcome for household ï". We use "treatment" as a generic term for programs and policies.*

For treated household, we observe the treated outcome while the untreated outcome remains counterfactual. For the untreated household, we observe the untreated outcome while the treated outcome remains counterfactual. The difference between the treated outcome and untreated outcome defines the unobserved treated (or causal) effect for each household:

$$\delta_i = Y_{1i} - Y_{0i} \qquad (3)$$

The literature focuses on particular average of δ_i*, where the choice of which average depends on the policy question of interest, subject to constraints following from the identification strategy and the data. The most common causal estimand is the average Treatment Effect on the Treated (ATT), given by:*

$$ATT = E(Y_1 - Y_0 | T = 1) \qquad (4)$$

This parameter informs a cost-benefit analysis that addresses the question of whether to keep or scrap a program in its present form. Another common estimand is the Average Treatment Effect (ATE), defined as:

$$ATE = E(Y_1 - Y_0) \quad (5)$$

The ATE equals the expected impact in the entire population of eligible households, whether or not they actually participate.

Kernel matching (KM) was used in this studyas it is known to produce the best balance statistics (Caliendo and Kopeinig, 2008, pp. 31-72, Becerril and Abdulai, 2010, pp. 1024-1035). Kernel matches are based on a weighted average of the individuals in the comparison group, and the weight is proportional to the propensity score distance between the treated and untreated. The advantage of kernel matching is greater efficiency, as more information is used; however, the disadvantage is that matching quality may be limited, due to use of observations that may be bad matches (Caliendo and Kopeinig, 2008, pp. 31-72).

Inverse probability weighting with regression adjustment estimator (IPWRA)

The PSM is a base-case estimator. The PSM method is basically built on a strong assumption that observable covariates account for the selection process into the treatment and control individuals' conditions (un-confoundedness assumption. While propensity score matching is the most common method of estimating treatments effects, PSM estimates could be sensitive to bias when the treatment model or the outcome model is affected by confounding unobservable factors (Imbens, 2004, pp. 4-29, Abadie and Imbens, 2006, pp. 235-267, Imbens, 2014). The key limitation of PSM method is that if unobservable factors affect adoption decisions, estimated ATT may be biased due to those unobservable factors (Rosenbaum, 2002, pp. 286-327, DiPrete and Gangl, 2004, pp. 271-310). Furthermore, propensity score matching does not perform well in small samples in comparison with other estimators. In light of the emerging literature on these issues (Rosenbaum, 2002, pp. 286-327, DiPrete and Gangl, 2004, pp. 271-310), we had concerns that the estimated treatment effect by PSM may be biased due to unobservable factors. Therefore, we checked the validity of PSM estimates using inverse probability weighting with regression adjustment estimator (Cattaneo, 2010, pp. 138-154).The IPWRA estimator has the double-robust property, which means that the estimates of the effects will be consistent if either the treatment model or the outcome model are miss-specified (Cattaneo, 2010, pp. 138-

154). The doubly robust estimators give us an extra shot at correct specification. The IPWRA estimator models both the outcome and the treatment to account for the non-random treatment assignment (Cattaneo, 2010, pp. 138-154, Abadie and Imbens, 2011, pp. 1-11). The IPWRA estimators use weighted regression coefficients to compute averages of treatment-level predicted outcomes, where the weights are the estimated inverse probabilities of treatment (detailed model derivation is given in Cattaneo, 2010).

2.4. Sampling scheme and data

The survey was conducted by researchers from Ethiopian Environment and Forest Research Institute during April -May, 2016. A multistage sampling procedure was employed to select villages from each district and households from each village. First, one village was selected from each of the four districts: Senan, Ankesha and Sekela in East Gojam Zone province Amhara regional state, and Chencha district in Gamo-Gofa Zone province Southern region. Second, based on proportionate random sampling, sample households were selected from the list of farm households in each village. The data were collected using a paper-based structured questionnaire through interviews with the household head or in his/her absence, the most senior household member available. Trained enumerators with experience in conducting farm household surveys collected the data. The variables of interest included information on household demographic characteristics, household farm resources and household assets, the inventory of crop, forest and livestock production activities, use of modern technologies, marketing practices, household access to credit and extension services, the distance a household resides from input and output markets and household monthly expenditure. The questions on monthly expenditure was used for measuring household cash income. The total monthly expenditure was computed by aggregating all expense categories (e.g. expenses for food items, clothes, school fees, weddings, funerals, loan repayment, membership fees to local organizations, church donations, etc.). Household dietary diversity scores (HDDS) are increasingly used as measures of food security and as a useful indicator for capturing some aspects of diet quality, as it correlates with adequacy of nutrient intake in recent years (Ruel, *2002, Swindale and Bilinsky, 2006, pp. 1449S-1452S, Thorne-Lyman, et al., 2010, pp. 182S-188S, Beegle, et al., 2012, pp. 3-18, Behnassi, et al., 2013, pp. 203-215). We included questions about the number of food types or food groups consumed during the last seven days in the questionnaire to estimate HDDS. Household Food Insecurity Access Scale (HFIAS) was calaculated and used as proxy measures of household food insecurity (Swindale and Bilinsky, 2006, pp. 1449S-1452S). The HFIAS was assessed by asking a series of questions reflecting different domains of food security as experienced by the respondents (Swindale and Bilinsky, 2006, pp. 1449S-1452S).The HFIAS calculates as sum of the frequency-of-occurrence during the most food insecure month for the nine food insecurity-related conditions. In addition to the quantitative household survey, we conducted focus group and key informant interviews to triangulate with the information obtained from empirical exercise.*

3. Results and Discussion

3.1. Descriptive statistics

Table 1 reports results for the mean differences in various characteristics for adopters and non-adopters of agroforestry technologies, using the t-test to test the null hypothesis of equality of means. It is apparent that households who adopted agroforestry technologies have a higher and significant education level. On the other hand, farm-households who adopted agroforestry technologies have lesser number of livestock animals and reside close to nearest major market place in comparison with non-adopters. Farmers without a nearby major market place to sell their produce from fruit trees are less likely to adopt agroforestry technologies liker fruit trees. Furthermore, technology adopters have significantly higher monthly consumption expenditure and lesser food insecurity scale.

Table 1. Descriptive summary of selected variables used in estimation (Standard errors in parentheses)

Variable	*Adopters*	*Non-adopters*	*Diff*
Age of household head (Years)	*51.85(1.28)*	*52.24(0.81)*	*-0.40(1.50)*
Sex of household head	*0.89(0.03)*	*0.87(0.02)*	*0.02(0.04)*
Education of household head (Years)	*6.97(0.28)*	*5.53(0.14)*	*1.43(0.28)****
Family size (adult equivalent)	*1.79(0.51)*	*2.93(1.48)*	*-1.19(2.07)*
Total land holding (ha)	*2.49(0.12)*	*13.92(8.01)*	*-11.43 (11.01)*
Total livestock holding (TLU)	*0.93(0.04)*	*1.12(0.04)*	*-0.19(0.07)****
Distance to nearest major market center	*0.44(0.03)*	*0.6(0.03)*	*-0.15(0.04)****
Total monthly expenditure ($/month)	*392.75 (33.09)*	*273.80 (14.82)*	*118.95 (18.27)****
Household dietary diversity score (HDD)	*4.21(0.21)*	*4.46(0.13)*	*-0.25(0.24)*
Household food insecurity access score (HFIAS)	*5.6(0.49)*	*7.13(0.37)*	*-1.53(0.63)***
N	*144*	*272*	*416*

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

3.2. Estimation results

The Wald chi square test strongly rejected the null hypothesis of no association between adoption decision of agroforestry technologies and explanatory variables included in the model at 1% level [χ^2 (13) =74.17, Prob > χ^2= 0.00], indicating the validity of estimating the adoption equations jointly using probit model.

An analysis of new data from a survey of 416 smallholder farmers in Ethiopian highlands shows that gender of household head being male, proportion of male family members, family size and total land holding and district dummy for Chenchahighlands are positively associated with adoption of agroforestry trees.Adoption of this technology increases consumption expenditure *and reduces food insecurity of households significantly. This study also confirmed our expectations and previous adoption studies that adoption of agroforestry practices demands more labour and availability of land resources, which female headed and resource poor farmers often lack in adequate amounts. The finding contributes to the emerging literature on gender-related technology adoption gaps. Empirical results also pointed out that the disincentive created by distance to nearest major market and differences in agro-ecological zones (AEZs) in predicting technology adoption decision (Thompson and Scoones, 2009, pp. 386-397, Dillon and Barrett, 2016).*

Table 2: Factors affecting adoption of agroforestry technologies*(Standard errors in parentheses)*

Variables	*Adoption of agroforestry trees*
Age of household head (Years)	*-0.01(0.01)*
Sex of household head	*0.83(0.38)***
Education of household head (Years)	*0.01(0.09)*
Family size	*0.12(0.04)****
Proportion of male family members	*0.26(0.13)***
Total land holding (ha)	*0.28(0.14)***
Land fragmentation (number of plots)	*0.09(0.08)*
Total livestock holding (TLU)	*0.03(0.07)*
Distance to nearest major market center	*-0.16(0.19)*
Distance to extension office	*-0.25(0.31)*
Membership in village credit association	*-0.42(0.42)*
Ankesha (if farmer is located in Ankeshadistrict, 0 otherwise)	*0.07(0.53)*
Sinan(if farmer is located in Sinan district, 0 otherwise)	*-0.35(0.47)*
Chencha(if farmer is located in Chencha district, 0 otherwise)	*1.12(0.40)****
Constant	*-2.74(0.80)****

Observations	*210*

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

The clear message of Tables 1 and 2 is that farmers are more likely to adopt agroforestry technologies in Ethiopian highlands the wealthier they are in terms of family labour and land and have better access to input and output markets. The findings in this study echoes the results of previous studies on adoption of agroforestry practices in different parts of Africa (Ayuk, 1997, pp. 189-206, Franzel, 1999, pp. 305-321, Franzel, et al., 2001, pp. 37-62, Lee, 2005, pp. 1325-1334, Nkamleu and Manyong, 2005, pp. 135-148, Gyau, et al., 2012, pp. 265-274, Meijer, et al., 2015, pp. 40-54, Mwase, et al., 2015, pp. 148, Kabwe, et al., 2016, pp. 4704-4717). Significance of district dummy suggests that households' production choices are constrained by various agro-ecological factors, such as climate and terrain. This is particularly true for Ethiopia as there are no private land markets in Ethiopia, households are restricted in terms of where they can live(Gebremedhin and Swinton, 2003, pp. 69-84, Abdulai, et al., 2011, pp. 66-78).Smallholders who operate in areas near provincial towns with growing incomes, markets and employment are likely to have more market opportunities and take better advantage of them than farmers in less economically dynamic areas. In contrast to development approaches that focus narrowly on improving the capacities of smallholders to increase their productivity or better manage natural resources, significance of access to market challenges development organizations to work with diverse stakeholders to understand the performance of the value chain and identify mutually beneficial options for improving chain performance. The results found in this study is consistent with the findings of other studies in developing countries (Faltermeier and Abdulai, 2009, pp. 365-379), which report that households who do not meet minimum asset thresholds require specific, non-market-based interventions to create the necessary preconditions for their participation in technology scale up initiatives. These include, investments in basic infrastructure and services and resolution of land-tenure conflicts where they exist. The results suggest that research and development efforts in land rehabilitations interventions such as agroforestry technologies should target farmers who have farm assets and better market access. Blanket technology scale up strategy does not seem to be appropriate in smallholder settings. These *interventions fall outside the realm of extension, but are critical for its success if the poorest sections of the rural population are to benefit.*

The estimates for the average treatment effects on the treated (ATT)by PSM and IPWRA show that adopting agroforestry technologies has a positive effect on household income and reduction of household food insecurity.Investment in agroforestry technologies result in $43.48 more average monthly income or by 163.87% for households who adopted the technologies than the households in the control group. The result further shows that adaptors of agroforestry technologies reduces household food insecurity by a scale of 2.2 or 73.08 %. This result suggests that households who adopt agroforestry technologies are more likely to achieve better livelihood outcomes relative to non-adopters.

Table 3: PSM results on household welfare effects of adopting agroforestry technologies

Household welfare indicator	*ATT*	*P>|t|*
Household income ($/month)	*107.82*	*0.00****
Dietary diversity score	*-0.18*	*0.51*
Household Food Insecurity Access Scale	*-2.20*	*0.002****

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

Table 4: Results of IPWRA estimator on household welfare effects of adopting agroforestry technologies

Household welfare indicator	*ATT*	*P>|t|*
Household income ($/month)	*40.99*	*0.01****
Dietary diversity score	*0.12*	*0.68*
Household Food Insecurity Access Scale	*- 2.04*	*0.00****

*Notes: *** p<0.01, ** p<0.05, * p<0.1*

The results in Tables 3 and 4 suggests that investment in land rehabilitations interventions such as agroforestry practices are economically efficient and socially fair. The resultsarerobust across *different econometric methods used for impact evaluations. A lower magnitude of ATT estimate by IPWRA, as compared to the ATT estimate by PSM, can be attributed to selection bias arising from unobservable characteristics that may have affected adoption decision and outcome. The higher ATT values by PSM suggest that ATT estimates based on PSM alone can potentially lead to erroneous conclusion about the effect of technology adoption. These findings are consistent with the view that adoption of agroforestry technologies can improve household income and food security. This is a very strong evidence for supporting agroforestry based degraded land rehabilitation programs going forward.*

4. Conclusionand policy implications

This paper examines the binding constraints to adoption of agroforestry technologies and adoption impacts on household welfare as measured in terms of household income and food security in Ethiopian highlands. Using a theoretically-grounded counterfactual outcome framework, we have shown that persistently low adoption of agroforestry technologies are associated with individual household's access to productive assets—such as availability of family labour and size of land holding—and access to input and output markets.Empirical findings demonstrate that gender of household head being male, high proportion of male family members, larger family size and total larger land holding size and district dummy for Chencha highlands are positively associated with adoption of agroforestry trees. Moreover, the results reveal that adoption of agroforestry technologies significantly increases household income and reduces food insecurity. The result suggests that investment in land rehabilitations interventions such as agroforestry technologies are economically efficient and socially fair. The result of this study, however, does not support the large technology scale up strategy passionately followed by the government of Ethiopia. The technology scale us programs make an implicit assumption that household characteristics and the relationship between farmers' production goals and preferences are homogenous. On the other hand, the result supports the widespread wisdom among the development community that agricultural input and output markets function poorly for many smallholder farmers. Thissuggests that the issue of low technology adoption is mostly *associated with structural (institutional and policy) barriers – often related to failures of accountability in public service delivery, rent seeking, uncertain and expensive contract enforcement and weak physical infrastructure that results in high transactions costs that systematically reduce the gains for poor farmers from adopting technologies.The high transaction costs involved in accessing the technologies and marketing outputs may lead to higher cost of using technologies greater than the potential benefits gained from the technologies. Many of the constraints to technology adoption identified in this paper are not limited to agroforestry technologies but relevant to most technologies intended to increasing productivity of smallholder systems in developing countries. Technological interventions that support small-scale farmers will have little impact unless they are complemented with policy changes that create a more conducive environment that help smallholders gain a fair share in profitable value chains. As the development community and Ethiopian governments increasingly strives to reverse land degradation in the highlands, the onus now falls on the government to addressinstitutional and policy barriers that impede thescaling up of agroforestry technologies in rural Ethiopia.*

Acknowledgements

Financial support for the field work of this research was obtained from Ethiopian Environment and Forest Research Institute. We are grateful to participants of household questionnaire interview, focus group discussion and key informant interviews for providing insightful information and viewpoints.

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