International Journal of Agricultural Science, Research and Technology in Extension and Education Systems (IJASRT in EESs)
Available online on: http://ijasrt.iau-shoushtar.ac.ir
ISSN: 2251-7588 Print
ISSN: 2251-7596 Online
2018: 8(3):139-146

Received: 14 March 2018
Reviewed: 4 April 2018
Revised: 5 April 2018
Accepted: 23 August 2018

Smallholder Farmers' Participation in Agricultural Training and Demonstration in Ethiopia: Implications for Inclusive Targeting by Agricultural Extension Services

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Abstract

Small farms and smallholder farming systems play crucial roles in agricultural development in many developing countries. From the various rural development programs designed to support such farming systems, agricultural extension services are of at most importance. However, the benefit that farmers obtain from these services and the resulting impact depends, to a great extent, by their direct and indirect participation in the services. In this research, we examined the predictors of participation in agricultural training and demonstration in Haramaya district of eastern Ethiopia. By collecting data from 180 rural households, and employing the Poisson regression, we found that several factors explain farmers' differential participation in agricultural training and demonstration. In particular, financial capital (farm income, credit), physical capital (value of livestock, value of household asset), and access to services (e.g., veterinary, experience with extension) were significant predictors of participation in agricultural training. Concerning demonstration, human capital (age), physical capital (asset, land), financial capital (farm income, off-farm employment), social capital (networks), and access to services had a significant effect. Based on the findings, some implications for inclusive targeting by agricultural extension programs were put forward.

Keywords: Agricultural extension, participation, training, Poisson regression, Ethiopia

1. Introduction

Small farms and smallholder farming systems play crucial roles in agricultural development in many developing countries. This is clearly evident in the context of Ethiopia where smallholder mixed-farming systems support the livelihoods of majority of the rural population (Abro et al., 2014; Berhanu & Poulton, 2014). Although there are some studies showing the importance of such farms in sustainable agricultural development and poverty reduction (e.g., Devendra, 2007; Rocha et al., 2012), only a small body of empirical literature documents challenges facing agricultural advisory services in addressing their problems (Rauniyar & Goode, 1992; Marsha,l 2012).

Agricultural Advisory Services (AASs)[1] encompass the entire range of rural services designed to foster the access of smallholder farmers to technical knowledge and information, improve their skills through agricultural training and demonstration, and facilitate their access to a range of other rural services (Birner et al., 2006; Swanson, 2008). In the case of Ethiopia, the provision of formal and organized AASs dates back to the 1950s. Since then, AASs have gone through a number of transformations: from models dominated by on-farm/general AAS provision to the recent farmers' training centers (FTCs) based approaches.

[1] In this study, AASs were used to refer to agricultural extension services.

In general, available research suggests that AASs play significant roles in improving farmers' skills (Tripp et al., 2005), knowledge level (Godtland et al., 2004), production, productivity and income (Birkhaeuser et al., 1991; Godtland et al., 2004; Davis., et al 2012), as well as improving consumption (Dercon et al 2009) and food security (Larsen & Lilleør, 2014) and reducing poverty (Dercon et al., 2009). Nevertheless, the benefit that farmers obtain from AASs and the resulting impact depends, to a great extent, by their direct and indirect participation in these services.

Similar to the case with impact of AASs, there is a scarcity of empirical evidence in relation to farmers' participation in on-farm AASs (especially agricultural training and demonstration). Although some studies (such as, Kalinda et al., 1998; Rehman et al., 2013; Anaglo et al., 2014; Baloch & Thapa, 2014) attempted to address the issue, there are some concerns. First, many of the studies deal with lower access to agricultural information. However, since agricultural activities are seasonal and have many phases (i.e., land preparation, sowing/planting, fertilizer application, harvesting, etc.), they require a continuous follow-up and support from AAS providers. Hence, having a one-time access to AASs may not have the same effect as getting frequent services.

Second, the studies attempt to provide explanations on the factors affecting access to advisory services. None of them address the issue of access to agricultural training and/or demonstration services that are equally, if not more, relevant to smallholder farmers. Finally, there are some limitations associated with the methodological approaches employed, including sample size, adequacy and choice of explanatory variables, and empirical strategy to analyze data. In order to respond to these issues in the context of Ethiopian AASs, the present research was initiated to investigate the determinants of farmers' participation in on-farm agricultural training and demonstration in Haramaya district of eastern Ethiopia.

The remainder of the paper is structured as follows. In the next section, a brief review of the literature pertaining to the issue of farmers' access to AASs in developing countries is provided. What follows this is a discussion on data and methods used in the study, including the choice of empirical strategy. After this is the result and discussion section where the main findings of the study are presented and discussed. Finally, some conclusions and recommendations are provided.

2. Materials and methods

Data for this study comes from a field-based household survey conducted in Haramaya district of East Hararghe zone, Oromia region, Ethiopia. From the ten rural kebeles1 that have fully functional Farmers' Training Centers (FTCs) in the district at the time of the survey, three kebeles (i.e., Ifa Oromia, Adele Waltaha and Biftu Geda) were purposively selected in such a way that they are representative to the rest of the kebeles with functional FTCs in terms of biophysical (topography, weather, etc.) and socio-economic characteristics. The list of households was obtained from the district Bureau of Agriculture and Rural Development (BoARD). The list contained 450 household heads that were registered for agricultural training at the FTCs. However, only 180 of them actually completed the training (i.e., 60 households in each kebele). Hence, all of them were included in our study sample. Using trained enumerators, a survey questionnaire was pre-tested and administered to gather primary data on socio-demographic characteristics, agricultural production and extension.

To analyze data, both the Poisson regression and the Negative Binomial regression are used because of the nature of the outcome variables (i.e., count outcome data). Count outcome variables, such as the number of training or demonstration, are often modeled using the Poisson regression, under the assumption that the variance of the outcome variable is constrained to equal the mean, which is referred to as equi-dispersion (Greene, 2008; Cameron & Trivedi, 2013).

According to Agresti (2007), for instance, the Poisson loglinear model can be given as $\log(\mu) = \alpha + \beta_x$, where μ is the non-negative count outcome variable (also denoted as $E(Y)$ – the expected value of the outcome variable Y), α is the constant, and x is a vector of explanatory variables with the corresponding coefficient estimates β.

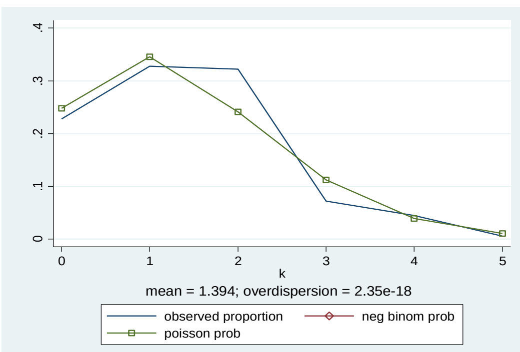
However, since it is a common encounter that observed outcome data will exhibit over-dispersion (Agresti 2007; Green 2008) and violate the key assumption, some scholars stress the use of alternative models that can account for over-dispersion. One such model is the Negative Binomial, which includes a disturbance/error term (Agresti 1996, 2007, 2014; Byers et al 2003; Cameron & Trivedi 2009) – an additional parameter such that the variance can exceed the mean (i.e., $E(Y) = \mu, Var(Y) = \mu + D\mu^2$). The non-negative index D is called a dispersion parameter (or the over-dispersion parameter α). When there is greater heterogeneity in the Poisson mean values, this heterogeneity results in

[1] These are the smallest administrative units in Ethiopia (i.e., region, zone, district, and kebele).

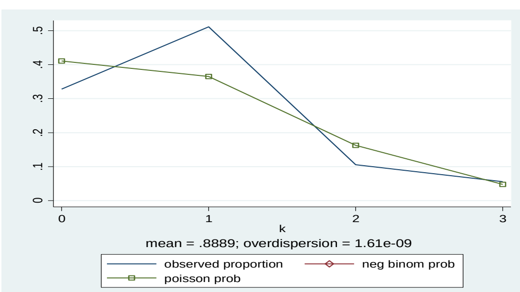
larger values of D. However, as D approaches to 0, $Var(Y)$ converges to μ and the Negative Binomial distribution reverts to the Poisson distribution. The farther D falls above 0, the greater the over-dispersion relative to Poisson variability (Hilbe, 2011).

The usual functional form of the negative binomial regression (e.g., Byers et al 2003) can be given as $\log(\mu_i) = \beta_0 + \beta_{1x1i} + \cdots + \beta_{kxik} + \sigma\epsilon_i$, where μ_i is the expected value of the outcome variable (i.e., number of training or demonstration per year) for farmer i, x_i are the independent variables with the corresponding regression coefficients β, and $\sigma\varepsilon_i$ is the disturbance term.

This study takes into account two discrete outcome variables – number of training and number of demonstrations farmers take part in per year. Table 1 presents the frequency of training and demonstration.



(1) Training



(2) Demonstration

Figure 1. Graphical inspection of model fit
Note: (1) Observed distribution of training reasonably fits the Poisson distribution. (2) Observed distribution of demonstration reasonably fits the Poisson distribution.
Source: Own elaboration using survey data

The data in Table 1 appear to fit more the Poisson than the Negative Binomial distribution. Nonetheless, in order to confirm these observations, there are some more outcome data inspections required. Figure 1 displays the observed distribution of the outcome variables in relation to the Poisson and Negative Binomial distributions. This confirms that the data fit the Poisson distribution.

In addition, a post-estimation test of model fit was carried out. The goodness-of-fit χ^2 test for Poisson regression (Table 3) indicates that the use of the Poisson regression is appropriate. In relation to data collection, before embarking on the actual data collection, we carried out the selection and training of seven research assistants/enumerators. These research assistant were given training on how to use a questionnaire to gather socio-economic, biophysical, and institutional data related to agricultural extension. Likewise, to ensure the collection of good quality data, we employed two supervisors from Haramaya University to closely supervise the enumerators and provide feedback. Prior to the actual survey, the questionnaire was pre-tested on a sample of 15 farmers. Modifications to the questionnaire were made based on their response. Hence, we confirmed the validity and reliability of our data collection tool through pre-testing. The variables presented in table 2 were selected based on previous empirical research and our own experience with the study setting. The variables were measured as follows: education (years of schooling), age (year), household size (number of people sharing the same dwelling unit), farm experience and experience in AASs (year), value of asset, livestock and farm income (currency unit), network (number of people available in time of need), and land size (hectare). All dichotomous variables were coded as one if the farmers had access and zero otherwise.

3. Results and discussion

The descriptive statistics on demographic characteristics of the farmers is given in Table 2.

3.1 Determinants of participation in agricultural training

One of the major findings indicates that two types of physical capital (value of asset and value of livestock) affect participation in agricultural training. It is found that the expected log count of training increases with an increase in value of asset. This implies that asset-constrained farmers, i.e., the majority (44%) of households with low asset portfolios (Table 2) may not take part in agricultural training. This is contrary to the very aim of agricultural extension in the country. Regarding livestock, the result shows that the expected log count of training decreases as the value of livestock increases. This suggests that households with a few livestock are encouraged to participate in training. From the descriptive statistics (Table 2), however, it is evident that about two-third of the respondents possess livestock whose value is between 10,000 and 60,000 birr. Historically, AASs have been biased against the livestock sector in the country (Belay, 2002, 2003) and more so is with households possessing higher valued livestock. On the other hand, it may be the case that households with many livestock may not seek out for training due to their better financial position.

An important aspect related to livestock production and management is animal health care/veterinary service. It is found in this study that having access to veterinary services significantly increases the expected log count of training. This may be because farmers who interact with veterinary service providers are more likely to establish good relationships with them and may end up being selected for training. The role of development agents in selecting farmers into extension services is a long documented truth in the country (e.g., Belay, 2003).

Another key finding of the study concerns the role of economic/financial capital (farm income and microfinance credit). It is found that farm income has a positive and significant association with the number of training. This shows that households in the low-income category are left out of training in the study area. Concerning credit, the study shows that access to microfinance credit significantly increases the expected log count of training. However, since only a few proportion (9%) of the respondents are currently beneficiaries of microfinance services (Table 2), promoting farmers' access to credit should be encouraged, given its importance to achieving increased agricultural productivity and poverty reduction in the study area (Brehanu & Fufa, 2008). Microfinance credit is also shown to result in increased consumption and housing improvements in the country (e.g., Berhane & Gardebroek, 2011). Moreover, since many farmers in the study area also save irrespective of their level of income (Teshome et al., 2013), a mechanism that combines efficient credit provision and saving can be relevant. This calls for increased coordination between AAS providers and credit and saving institutions operating at various levels.

Experience in AASs is found to increase the expected log count of training. Although working with more experienced farmers is useful in relation to accelerated adoption and diffusion of agricultural innovations, the providers of AASs should also aim to build up the confidence of younger and energetic farmers to try out new technologies and practices. One way of doing so can be by providing frequent training to these farmers. Such targeting can help to retain and engage the rural youth in agricultural activities and reduce the migration of them to urban areas in search of non-farm employment. The issue of diffusion of agricultural technologies is especially important considering the generally low rates of adoption of modern varieties of staple food crops (e.g., sorghum) in the study area (Cavatassi et al., 2011).

Finally, the effect of FTC-based formal training (i.e., rural agricultural school) shows that the more the number of FTC training a farmer receives, the better the involvement in on-farm/field training. This may imply the apparent lack of coordination between the school based and field/farm based agricultural training in terms of targeting. There is redundancy in AAS provision. Regarding geographical location, it is found that whereas residing in Adele Waltaha increases the expected log count of training, living in Biftu Geda decreases the log count of training (compared to the reference, i.e., Ifa Oromia, in both cases).

3.2 Determinants of participation in agricultural demonstrations

The extent of farmers' participation in on-farm demonstration is given in Table 3. The first key finding relates to the relationship between human capital (household size, age, education) and extent of participation in method and result demonstrations of improved agricultural technologies and best practices. Concerning household size, it is found that it positively predicts farmers' participation, suggesting that large sized households are targeted better. It is also evident from the study that the expected log count of demonstration decreases for every one year increment in age. This indicates that younger farmers are in a better position of getting more demonstration services.

The second finding relates to physical capital (value of household asset and land holding). The coefficient of household asset is positive and significant, suggesting that household asset levels matter in participating in demonstrations. In relation to the area of land cultivated by the farmers, the coefficients indicate that for each one hectare increment in land holding, the expected log count of demonstration increases. It is long documented that development agents frequently work with farmers who have large land holdings in order to use part of the land for demonstration purposes (Belay, 2003).

The third result relates to the influence of economic/financial capital (farm income and off-farm employment). Regarding farm income, an increase in farm income has a negative effect. This may suggest that as household income improves, farmers are unlikely to seek out for more on-farm demonstration services. It may also imply that development agents in these areas choose to work more with those farmers who have a lower farm income, which is consistent with the very aim of AASs. In relation to income from off-farm employment, the analysis shows that an increased participation in off-farm activities significantly reduces the intensity of involvement in on-farm demonstrations. This may be due to the fact that such farmers may not have enough time to frequently take part in demonstrations since their time is spent elsewhere. It may also be because of a deliberate effort by development agents to avoid such farmers and support the ones who are devoted full time in their farm. More generally, however, since off-farm employment requires households to adjust their employment portfolio to changing circumstances and challenges (Bezu & Barrett, 2012; Bezu & Holden, 2014), it may pose difficulty to frequently participate in agricultural demonstrations.

A fourth major result illustrates the role of social capital (networks). The analysis reveals that networks are important. Concerning network size, i.e., the number of people/farmers in one's network, it appears from the regression that an addition of one network member increases the expected log count of demonstration. In general, social relationships among network members are important channels of information flow, which can play significant roles in agricultural technology adoption and diffusion (Maertens & Barrett, 2013; Jensen et al., 2014; Krishnan & Patnam, 2014).

Finally, the study shows that participating in FTC-based demonstration positively and significantly affects the expected log count of on-farm demonstration. This implies the existence of a weak link between FTC-based services and on-farm AASs. Regarding geographic location, farmers residing in Biftu Geda have a lower expected count of on-farm demonstration compared to the reference group.

Table 1. Frequency of training and demonstration (n=180). Standard deviation (SD) in parenthesis.

	Training	**Demonstration**
Mean (SD)	1.4 (1.1)	0.9 (0.8)
Variance	1.2	0.6

Source: Calculated based on survey data

Table 2. Descriptive statistics of socio-demographic characteristics of respondents

Variable	Mean (SD)	Variable	Mean (SD)
Age (years)	38.11 (5.49)	Land size (ha)	0.72 (0.31)
Female household head [a]	0.02	Certified land [a]	48.33
Education [a]		Value (Birr) of livestock [a]	
No formal education	79.89	< 10,000	11.67
Primary	6.7	10,000 – 30,000	28.89
Primary & lower secondary	11.11	30,000 – 60,000	47.78
Secondary	3.33	> 60,000	11.67
Household size [a]		Household farm income (Birr)	20,370.78(11,929.76)
< 5 members	10.56	Off-farm employment [a]	22.22
5 – 10 members	86.67	Microfinance [a]	9.44
> 10 members	2.78	Membership in *iddir* [a]	96.11
Experience in farming (years)	24.01 (5.18)	Network (no. of people)	5.22 (1.40)
Experience in AASs (years)	19.22 (7.14)	Access to basic facilities [a]	
Household assets (Birr) [a]		Daily market	25.0
< 5,000	43.89	Drinking water	61.67
5,000 – 10,000	26.67	Human health center	7.78
10,000 – 15,000	13.89	Veterinary	68.89
15,000 – 20,000	6.67		
> 20,000	8.89		

Standard deviations (SD) in parenthesis.

[a] Proportion of households possessing the specific characteristics.

Table 3. Poisson regression estimation results with robust standard errors in parenthesis

	Training	Demonstration
Age (years)	– 0.002 (0.01)	– 0.06 (0.02) ***
Primary education (grades 1 – 4)	0.21 (0.19)	– 0.002 (0.20)
Primary and lower secondary education (5 – 8)	0.05 (0.14)	– 0.23 (0.15)
Secondary education (9 – 12)	0.17 (0.15)	– 0.19 (0.25)
Family size (5 – 10 members)	0.13 (0.22)	0.57 (0.28) **
Family size > 10 members	0.55 (0.43)	0.18 (0.80)
Value (Birr) of household assets	0.0000068 (0.0000033) **	0.000011 (0.000005) **
Land size (ha)	0.20 (0.18)	0.60 (0.18) ***
Value of livestock (reference: < 10,000 birr)		
10,000 – 30,000	– 0.49 (0.16) ***	– 0.16 (0.16)
30,000 – 60,000	– 0.56 (0.20) ***	– 0.32 (0.26)
> 60,000	– 0.46 (0.26) *	– 0.18 (0.36)
Farm income (birr) per year	0.0000058 (0.0000030) **	– 0.000010 (0.000005) **
Off-farm employment	0.03 (0.12)	– 0.32 (0.13) **
Microfinance	0.30 (0.11) ***	0.08 (0.13)
Network	0.01 (0.03)	0.11 (0.04) **
Member of iddir	0.31 (0.21)	0.12 (0.27)
Access to animal health center	0.75 (0.16) ***	0.34 (0.27)
Experience in AASs (years)	0.02 (0.01) *	0.02 (0.01)
FTC-based training (reference: 1 training/year)		
2 – 3 training/year	0.01 (0.18)	
> 3 training/year	0.90 (0.28) ***	
FTC-based demonstration (reference: 1 demonstration/year)		
2 – 3 demonstrations/year		0.42 (0.17) **
> 3 demonstrations/year		0.35 (0.25)
PA/Kebele reference (Ifa Oromia)		
Adele Waltaha	0.87 (0.32) ***	– 0.05 (0.32)
Biftu Geda	– 0.76 (0.21) ***	– 0.82 (0.28) ***
Constant	– 1.45 (0.59) **	0.26 (0.74)
Number of observations	180	180
Log Likelihood	– 218.04	– 179.58
Pseudo R2	0.17	0.15
Alpha (α)	2.35e–18 [a]	1.61e–09 [a]
Likelihood-ratio test of α = 0	0.00 [a]	0.00 [a]
Goodness-of-fit χ^2 test b	97.98	95.59

***, **and * denote significance at 1%, 5%, and 10% level, respectively.

[a] Based on Negative Binomial regression Likelihood-ratio test of α = 0: chibar2(01) = 0.00 Prob ≥ chibar2 = 1.000. This reinforces that the Poisson distribution fits the data better than the Negative Binomial distribution.

[b] Since the χ^2 values are not statistically significant, this indicates that the Poisson regression is appropriate for this set of data.

4. Conclusion and recommendations

In this study, an investigation is undertaken on the predictors of smallholder farmers' participation in on-farm AASs (training and demonstration) in Haramaya district of eastern Ethiopia. The study shows that a host of factors affect farmers' involvement in these services. Specifically, financial capital (farm income, credit), physical capital (value of livestock, value of household asset), and access to services (FTC-based training, veterinary, experience in AASs) are significant predictors of participation in agricultural training. Concerning demonstration, human capital (age), physical capital (asset, land), financial capital (farm income, off-farm employment), social capital (networks), and access to services (FTC-based demonstration) have a significant effect.

On the basis of these findings, some recommendations are suggested. First, an area-specific targeting and selection criteria should be followed by the implementers of AASs in the study area. Second, the possibility for a reorientation of service provision should be explored. This can be achieved, for example, by focusing training efforts on asset-constrained and low-income households. Third, there is a need to improve coordination between the FTC-based services and the on-farm AASs. This can be achieved through coordinated planning, implementation, and evaluation of AAS activities. Fourth, since the findings indicate that farmers residing in Biftu Geda have lower expected counts of both training and demonstration, the activities of AASs need to be strengthened in these kebeles. Finally, the relationship between participation and outcome variables (such as farm income, food security, poverty, consumption, etc.) should be investigated in future studies. More rigorous impact evaluations (e.g., as in Wordofa and Sassi 2018) should be conducted.

Acknowledgments

The authors would like to thank the anonymous reviewers, data collectors, survey respondents, and local administrators for their time and enthusiastic cooperation.

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