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FARMERS' TECHNOLOGY ADOPTION DECISION AND USE INTENSITY IN THE AGRICULTURAL SECTOR: CASE OF MASHA DISTRICT (DOUBLE HURDLE MODEL)

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Abstract

Convinced with the importance of full understanding of the determinants of technology adoption in agricultural sector in planning technology-related policies and programs, this research aimed to critically analyze the determinants of technology adoption as well as the use intensity by small farm households in the study area (Masha District). To achieve the set-out objectives of the study, 6 kebelles were randomly selected from the district and 251 sample households were proportionally and randomly identified from the selected kebeles. The data collected from the sample households have been analyzed using both descriptive as well as inferential analysis. For inferential analysis, the Double Hurdle model was adopted to estimate the technology adoption decision as well as use intensity of small farm households in the study area. Results of the findings show that technology adoption decision was associated with household-specific characteristics such as sex, education, extension and family size which increases the likelihood of technology adoption whereas rigidity with the old technology is highly correlated with the age of the Household head, where old age farmers are not inclined towards new technology. On the other hand, institutional factors such as access to extension service and access to credit facilities have a significant impact where the latter has contributed negatively to the farmers' decision regarding technology adoption. Besides, the government should engage in awarness creation regarding new technology in the area along with ensuring fair and timely access for those technologies.

Keywords: *technology adoption, Masha woreda, Double Hurdle model, Agricultural Productivity*

1. Introduction

The report by African Union (2014) recognized that there has been little improvement in agricultural production and factor productivity (labor and land) while Agricultural growth in Africa is generally achieved by cultivating more land (land intensive) and by mobilizing a larger agricultural labor force (labor-intensive), which produces very little improvement in yields. On average, cereal yields are 50 percent less as compared to those obtained in Asia per a given plot. In the last three decades, Africa's population has doubled, which implies the continent now has more mouths to feed and less per-capita land to cultivate. However agricultural output has been unable to keep growing side by side. This resulted in being food self-insufficiency which puts the continent to be a net importer of cereals from the rest of the world.

The dimension of African's agricultural growth has been recognized to be different as compared to Asia and South America. It was through intensification that agricultural growth was registered in Asia, while growth in South America, was driven largely by improvements in labor productivity which is resulting from mechanization. Opposed to these, area expansion was responsible for the increase in production in the agricultural sector along with predominant intensification of cropping system in sub Saharan countries (NEPAD, 2014; Brink and Eva, 2009). As SSA is generally endowed with abundant land and most of this arable land is still unexploited, area expansion in the decades to come may not seem problematic. But since in rural SSA there is uneven distribution of land while a considerable share of its rural population resides in smallholder farming areas that are densely populated and face land shortages (OECD/FAO, 2016; Jayne et al., 2014).

In countries with constrained land size, area driven growth may come at the expense of fallows. Rapid growth of rural populations and associated land would result in continuous cropping in many African countries, with fallows largely disappearing in densely populated areas. The repeated cultivation will not be a problem only if sufficient use of new agricultural technologies (such as fertilizers, improved seed verities, soil amendment practices and other related investments on farm land) are promoted and coupled with continued teaching and awareness creation to maintain and improve soil quality (Stoorvogel and Smaling, 1990; Drechsel et al., 2001; Tittonell and Giller, 2012). The above arguments can be summarized as; if Africa need to attain food self sufficiency as well as sustainable development, it need to improve its practice in terms of technology adoption and those backward cultivation practices should progressively be transformed into relatively modern way and any attempt to boost production and productivity should be environmentally friendly.

Despite its critical implication for food security, information with regard to adoption of agricultural technologies on the factors influencing adoption and use intensity of improved seed technologies being promoted in the districts was not thoroughly studied and documented in the study area. Hence, the specific objectives this study is aimed to address are;

- Assessing the technology adoption practices of small farm households in the study area
- Estimating the determinants of farm households' decision in participating in the technology adoption
- Estimating the determinants of the use intensity of technology adoption by the farm households in the study area.

2. Methods

2.1. Description of the Study Area

Masha woreda is one of the three woredas in Sheka Zone of the South Nation Nationalities and Peoples Region (SNNPR. Masha woreda shares borders on the South by the Andracha woreda on the West and North by Oromia regional state and on the East by Keffa zone (CSA, 2007).

Concerning demographic characteristics, Masha woreda has a total population of 40810 of whom 20,116 are men and 20,694 women. About 6787or 16.63% of its population is urban dwellers. Religion wise majority of the inhabitants (56.5%) were Protestant followers followed by Ethiopian Orthodox Christian (32.82%) while the remaining 7.15% practiced traditional belief and 1.56% were Muslim (Census 2007 Tables). It receives mean annual rain fall about 2000m and its mean monthly temperature ranges between 18 – 21oC. Total area of the woreda is 217,527.15 hectare (CSA, 2007) (Benyam and Fayera, 2018).

2.2. Data Types, Sources and Methods of Data Collection

This study used the data both from primary and secondary sources. Primary data was collected directly from randomly selected farmers in the study area using structured questionnaire while the secondary data was obtained from different published and unpublished government reports especially from Sheka Zone agricultural and rural development office. The secondary data is used for triangulation purpose so as to validate the primary data obtained from the farmers. More to this, data is collected through group discussion with concerned parties like Woreda agriculture and natural resource management offices, site supervisor and through key informant interview with Development agents.

2.3. Sampling Techniques and Sample Size

Regarding the method used to draw the sample units from the target population (farmers in Masha woreda), a multi-stage sampling technique was adopted. In the first stage, Sheka Zone is purposively selected based on the observed degree of reluctance in technology adoption by the farm households, from the three woredas in the zone, Masha woreda is randomly selected in the second stage. In stage three, out of 19 kebeles in the woreda, five kebeles (Yina, Degelle, Wello, Ateso and Gatimo) are randomly selected and the final stage (stage 4) deals with selecting a total of 251 farm households proportionally from the selected kebeles as a representative sample and hence the final questionnaire was distributed to these farm households so as to get the relevant data. These 5 kebeles have a total of 2,613 farm households and the aforementioned sample size is determined by using the statistical formula forwarded by Yemane (1967) by choosing the precision level to be 7 percent.

$$n = \frac{N}{1 + N(e^2)}$$

Where, n = sample size, N = total (target) population and for this study it is 2613

$$n = \frac{2,613}{1 + 2,613(0.07^2)} = 251$$

Table 2.1 Distribution of sample households in selected Kebeles

Kebele	Total farm household	Sample size
Yina	463	45
Degele	590	57
Wello	710	68
Ateso	450	43
Gatimo	400	38
Total	2613	251

Source: own data (2019)

2.4. Method of Data Analysis

Regarding the data analysis techniques, the researcher used both descriptive and inferential analysis methods so as to answer the research question and associated objectives mentioned above. The descriptive analysis make use of the usual methods such as computing mean and frequency distributions using tables and graphs basically to support the inferential analysis. In inferential analysis on the other hand, Double Hurdle model is used to estimate factors influencing the farmers' decision as well as intensity to adopt agricultural technologies in the study area. The estimate the aforementioned model, stata software version 14 was used in this study.

Regarding Econometric Model specification; the Double-Hurdle Mode; most adoption studies have used the Tobit model to estimate adoption relationships with limited dependent variables. Tobit model is, however, very restrictive for statistical reasons, which makes this model unsuitable for certain empirical applications. Tobit model is also statistically restrictive because it assumes that the same set of variables determine both the probability of non-zero adoption and intensity use level. That is why recent empirical studies have shown the inadequacy of the Tobit model in cross-sectional analysis, stressing the relevance of alternative approaches.

Therefore, the appropriate model considered in this study is Double-Hurdle model, which was initiated by Cragg (1971). DH model assumes farm households faced with two hurdles in any agricultural decision making processes such as, participation decision (the decision to adopt) which is followed by use intensity (the decision regarding the level of production). Double-hurdle model hence, allows for the simultaneous consideration of the determinants of technology adoption decision of the HHs as well as the determinants of use intensity through two separate stages.

This model make use of both probit regression and truncated regression at different stages where it involves running a probit regression to determine factors affecting the decision to participate given all the sample population in the first stage and a truncated regression model on the individuals who passed the first hurdle (i,e the one who decided to participate) to analyze the intensity of adoption in the second stage.

Double hurdle model is helpful as it allows a subset of the data to pile-up at some value without causing bias in estimating the determinants of the continuous dependent variable in the second stage hence, it can be possible to obtain all the data in the remaining sample for the participants. Thus, there are no restrictions regarding the elements of explanatory variables in each decision in double hurdle model. Stated differently, it is possible to separately analyze the determinants of adoption decision and the extent of adoption decisions. Due to this separability, the estimates of production decisions can be obtained by a means of probit regression and that of the level of adoption decision can be analyzed by use of a truncated regression. According to Burke, the separability in estimation may not be mistaken.

The general form of the double -hurdle model employed for analyzing for farm households' decision for adoption and intensity of adoption of technologies in term of area coverage in hectare based:

$$D_i = z'\gamma + \varepsilon_i \quad \text{..(1)}$$

$$y_i^* = x'\beta + \varsigma_i \quad \text{..(2)}$$

$$y_i = \begin{cases} y_i^* \ if \ z'\gamma + \varepsilon_i > 0 \ and \ x'\beta + \varsigma_i > 0 \\ 0 \ if \ z'\gamma + \varepsilon_i \le 0 \ and \ x'\beta + \varsigma_i > 0 \text{ or} \\ \quad if \ z'\gamma + \varepsilon_i > 0 \ and \ x'\beta + \varsigma_i \le 0 \text{ or} \\ \quad if \ z'\gamma + \varepsilon_i \le 0 \ and \ x'\beta + \varsigma_i \le 0 \end{cases} \quad \text{.........................(3)}$$

$$where, \ (\varepsilon, \varsigma) \sim BVN(0, \Sigma), \ \Sigma = \begin{bmatrix} 1 & \sigma\rho \\ \sigma\rho & \sigma \end{bmatrix}$$

Where, z and x respectively are the set of explanatory variables which enter in the first and second hurdle. Di represents a latent variable indicating the household's participation decision while Y* is a latent variable as well measuring the intensity of adoption. Lastly, y indicates the actual (observable) amount of intensity which can only be observed if the household is a potential adopter (D>0) as well as the actual adopter (Y*>0).

2.4.1. Measurement and Definitions of Variables

The dependent variable of the model takes a censored value depending on the farmers' decision either to adopt or not to adopt the improved technologies as well as the intensity of adoption if they decide to adopt the technology. In this case, it indicates the amount of fertilizer per hectare cultivated in the year 2018. A farmer is said to be adopter if he/she use inorganic fertilizer on his/her farm land.

2.4.2. The Independent Variables and Their Definitions in the DHM

Adoption literatures provide a long list of factors that may influence the adoption of agricultural technologies. Generally, farmers' decision to use improved agricultural technologies and the intensity of the use in a given period of time are hypothesized to be influenced by a combined effect of various factors such as farm household specific characteristics, socioeconomic and physical environments in which farmers operate. Based on the previous study done on the adoption of improved crop technologies and the experience of the farming system of the study area, farm household specific characteristics' such as marital status and age of the household head, education level of the household head, religion of the farmer are considered. As a institutional factors access to road, access to credit facilities and extension services are considered. Additionally variables such as previous output level as well as farm size were selected for this study as a potential variables hypothesized to affect the adoption decision as well as extent of adoption.

3. Results and Discussion

The figure caption should begin with an overall descriptive statement of the figure followed by additional text. They should be immediately after each figure. Start this caption with a short description of your table. Format tables using the Word Table commands and structures

Needless to state, agriculture sector in Ethiopia is and continue to be the base of the country's economy accounting for more than one third of gross domestic product (GDP), and more than 80 percent of exports, as well as total employment (NBE, 2018). Ethiopia's agriculture is highly exposed to natural phenomena and beleaguered by periodic drought, soil degradation caused by overgrazing, deforestation and poor infrastructure. Yet agriculture is the country's most promising resource as well a possible means for self-sufficiency in food.

The controversy of Ethiopia's resource structure (labor and land abundance) and self insufficiency in food remains unsolved regardless of policy directions by the government. Though 80 percent of the labor force has been engaging in the sector, the country has continued to import food items from the rest of the world.

3.1. Descriptive Analysis

Table 1 Mean output (in quintal) by adoption status

Adoption	freq	Mean output	Std. deviation
Non participant	85	26.95	21.59
Participant	166	82.38	53.82
Combined	251	63.61	52.53
Difference	-	-55.43	-
	Ho: mean diff = 0 .00	Prob = 0.000	

Source: own computation (2019)

As can be shown from the table, out of 251 sampled farm households, 166 individuals are agricultural technology adopters and the remaining 85 individuals are non users. Average outputs produced by technology users is about 82.38 quintal per hectare with the standard deviation of 53.82 where as those how didn't use any technology on average produce about 26.95 quintal per Hectare with associated deviation of 21.59. The mean productivity difference between the two groups is about 55.43 quintal per Hectare and this difference is statistically meaningful as can be checked using t-test. The non users can be treated as the one who are less ready to take risk (risk averse farmers) as the mean deviation for the users is relatively higher as compared to the mean deviation of the output for non users. The argument is in line with the fact that technology in any sector is more risky as well as more return. Obviously, farmers are reluctant to practice new technology on their farm as they are afraid to take risk because they want to be safe and avoid failure. But those who are constantly involved in risk-taking activities have the probability to become successful. Therefore the risk-return trade off associated with new technology adoption can be taken as one factor behind the reluctance of some farmers from adopting agricultural technologies on their farm land.

Table 2. average output distribution across various attributes

	Non-Adopter		Adopter	
Education	**freq**	**Mean output**	**freq**	**Mean output**
Illiterate	25	34.36	13	61.46
1-4	4	33	7	90.14
5-8	23	21.13	38	58.87
9-12	27	24.30	59	90.86
>12	6	26.33	49	94.86
Total	**85**	**26.95**	**166**	**8238**
Marital status				
single	3	35	3	94
married	77	26.92	148	85.12
Divorced	4	20.75	12	53.42
Widowed	1	30	3	51.67
Extension Access				
yes	36	26.69	146	89.67
No	49	27.14	20	92.20
Credit Access				
No	40	30.85	63	72.17
Yes	45	23.49	103	88.63

Sex				
Female	6	19.67	10	46.10
Male	79	27.51	156	84.71

Source: Own computation, (2019)

Across their educational attainment, farmers' technology use improves. That means, farmers' with higher educational attainment are ready to use agricultural technology as compared to individuals with lower educational background. On the other hand there is no evidence that education improves agricultural productivity for non-users of technology. Illiterate non-adopters on average produce 34.36 quintal per hectare and this output declines to 33 quintal for 1-4th grand individuals and as education increases, the mean output level of the non-adopters is almost constant with no major change. Opposed to non-adopters, technology adopters' average productivity improves with educational attainment. Illiterate farmers' average productivity is about 61.46 quintal per hectare and this figure rises to 94.86 quintal per hectare for grand 12 and above.

In terms of marital status, single farmers are the most productive group with average output of 35 quintal per hectare for non-adopters and 94 quintal per hectare for adopters followed by married farmers (whose average output ranges about 27 quintal for non-users and 85 quintals for users.

Access to extension service on the other hand improves the decision to participate in the technology adoption whereas it doesn't have any significant implication on the average productivity for both adopters and non-adopters. As can be seen from the above table, out of 85 non-adopter farmers 49 (58%) farmers do not have access to extension whereas only 36 (42%) farmers have access to extension service. In terms of average productivity of non-adopters, the one who have access to extension service produce 27 quintal per hectare and this figure is almost similar to the farmers who do not have access to extension service. On the other hand, out of the total technology adopters (166 farmers), 146 (88%) farmers have access to extension service and the remaining 20 (12%) farmers have not. In terms of their average productivity, farmers who adopt technology as well as have access to extension service on average produce 90 quintal per hectare and farmers with no access to extension on average produce 92 quintal per hectare.

Regarding farmers' access to credit facilities, out of the sampled households 103 (41 %) farm households do not have access to credit facilities whereas 148 (59%) have access to credit. In terms of technology use, out of the non-users, 40 (47%) have no access whereas 45 (53%) have access to credit facilities. From the other side, among the technology users 63 (38%) have no access to credit and the remaining 103 (62%) have access to it. One can conclude from the above figure that access to credit is not the inessential determinants of technology adoption decision in the study area as about 47 % of non-adopters have access to it and still decides not to adopt the technology on their farm land

The adoption decision of farm households are split in gender wise in the above table and accordingly, 16 (6.37%) of the farm households are female headed and the remaining 235 (93.63%) farm households are male headed. Out of the total female headed farm households, 6 (37.5%) are non-adopters and the remaining 16 (62.5%) engage in technology adoption. In terms of average productivity, male headed households are more productive as compared to female headed households in the study are (27.51 vis-à-vis 19.67 quintal for non-adopters and 84.71 vis-à-vis 46.1 quintal per hectare for adopters).

3.2. Inferential Analysis

3.2.1. Double Hurdle Model)

In this part the data is estimated using DH model after taking care of all the priori tests on the collected and managed data. To address the researcher's objective of measuring the decision as well as use intensity of technology in the study area, the researcher chooses double hurdle model because of its superiority as discussed in the previous sections.

Table 3. Determinants of technology adoption (DH Model)

	1st Hurdle (participation decision)		2nd Hurdle (intensity)	
Agri_Tech	**Coefficients**	**P-values**	**Coefficients**	**P-values**
Sex	0.48**	0.02	0.07	0.86
Education	0.04	0.35	0.07**	0.01
Extension	0.39**	0.01	1.11*	0.00
Age	-0.01*	0.00	-0.01	0.75
Farmers' perception	0.41**	0.04	0.37*	0.00
Family Szs	0.07*	0.00	0.01	0.74
Land ownership	0.05	0.84	0.13	0.15
Off-Farm income	0.151*	0.00	0.61	0.21
Credit	-0.21**	0.02	-	-
Farm Size	-0.03	0.17	0.07	0.14
Ln_sigma	-0.60	0.92	0.00	
/sigma	0.55	0.03	-	
N = 251	LR chi2(6) = 104.52	P > Chi2=0.00	pseudo R2=0.52	

Source: Own Estimate, (2019)
* Significant at 1% level, ** significant at 5% level, *** significant at 10% level. Significance levels are based on significance levels of the underlying marginal effects.

To estimate the determinants of adoption decision and use intensity of agricultural technology the Double Hurdle estimates are reported in table 3 above. Accordingly, the overall significance of the model is checked given the likelihood ration test statistics (LR chi2(6) = 104.52) and its respective p-value (P > Chi2=0.00) which indicates the model is statistically meaningful. Whereas out of the total variation of the dependent variable, about 52 percent is explained by the variation of the variables included in the model (Pseudo R2=052).
Sex of the household head does significantly affect farm households' decision to adopt the agricultural technologies whereas once if the household decides to adopt the technology, to the extent to which the farmers decide to adopt is not influenced by genderwise differences of the household head. Accordingly, as compared to female headed households, male headed households have higher likelihood to participate in the technology adoption. On the other hand, education level of the household is estimated to affect farm households' decision to participate in the technology market and doesn't have any significant impact on the intensity of technology use in the study area. Farm household with better educational attainment have relatively higher probability to participate in the technology market while the variable is statistically significant at 5 percent level.
Other variables such as extension access and family size have a positive impact on the use intensity of agricultural technology in the study area whereas age of the household head and credit access have a negative and significant impact on the use intensity of the technology in the study area. All variables but access to credit have their respective expected sign and access to credit is happen to be negative which is against the theory as well as intuition.
Empirically access to extension services has been found to be among the key determinants of technology adoption. Extension agents have a critical role in providing information to farmers about the access as well as the benefits of new technology along with giving guidance on the farm land how and how much to use. Extension agent are assumed to serve as a bridge between technology innovators (research and development) and users of the same technology through facilitating information flow and reducing the transaction cost (Genius et al., 2010), (Margaret Mwangi Samuel Kariuki 2015). Apart from this finding, access to credit has been believed to facilitate technology adoption (Mohamed & Temu, 2008) by promoting the adoption of risky technologies through lessening of the financial constraint of farm households and boosting household's-risk bearing ability (Simtowe & Zeller, 2006).
Farm households' decision to adopt as well as their intensity of adoption is highly influenced by their subjective opinion about the technology they have access to. Thus, as can be checked from the table above, farmers with

positive preference to the technology and their associated (positive) judgment concerning the compatibility of the technology with their environment (such as the soil type and temperature) are likely to adopt such technology expecting positive reward from those investment.

Farm size owned by the farm households is generally believed to play a significant role in on technology adoption decision of the farmers (Margaret Mwangi and Samuel Kariuk, 2015). Many researchers have argued land size as one of determinant of technology adoption as land size can influence other factors determining the adoption decision (Lavison 2013). Opposed to many studies who have reported a positive impact of farm size and technology adoption (Kasenge, 1998; Gabre-Madhin and Haggblade, 2001 Ahmed, 2004; Uaiene et al., 2009) this study has revealed no significant impact of land size on farmers' adoption decagons as well as the intensity of adoption. This finding is generally against the arguments of previous researches that farmers who have ownership of large farm size are likely to use new technology as they can be able to put aside part of their land to practice a new technology so as to avoid crop failure if used in their entire land. On the other hand, large farm size facilitates the use of other farm technologies (such as tractor) as it requires economies of scale to make sure profitability (Feder, and Zilberman, 1985). But the latter argument doesn't work specially for the study area as land size in the study area is more or less distributed symmetrically and relatively small.

Regarding the off-farm income, we find positive and significant association to farmers' technology adoption decision whereas, when once the adoption decision is made, off-farm income doesn't influence the intensity of adoption. This study partly confirms the findings by Banker and MacDonald, (2005) and Uaiene, R et al (2009).

3.2.2. Impact of Adoption on Productivity

Farmers in the study area claim that technology has an adverse impact on the productivity of their land, as one of the reason behind low rate of technology adoption. Aiming to test the impact of technology on productivity, Cobb-Douglas production function was estimated where technology use is entered as one of the explanatory variable.

Table 4. Determinants of productivity

Output	Coefficients	Std. Error	P-values
M. status	-0.04	0.12	0.72
Religion	-0.00	0.08	0.98
Lnd size	0.13*	0.02	0.00
Education	0.09**	0.04	0.04
Extension	0.46*	0.12	0.00
Age	-0.01	0.05	0.38
Family Szs	0.07*	0.02	0.00
Distance_Road	0.01	0.49	0.76
Credit	0.02	0.99	0.81
FtlZr	0.85*	0.11	0.00
N = 251	F(10, 240) = 22.93	P > F=0.00	R2=0.49

Source: Own estimation (2019)

* Significant at 1% level, ** significant at 5% level, *** significant at 10% level.

The objective under this part is to empirically test whether the claims by most of the small farm households in the study area about the ineffectiveness of agricultural technology is true, by estimating the production function including the technology adoption as one of the determinants of productivity. They argue that the technology they are supplied by the government is incompatible with the nature of the soil and has been contributing adversely to the productivity of their land. Apart from this claim, as can be seen from the table above, fertilizer use is one of the statistically significant determinants of productivity in the study area. Accordingly as compared to non-users, output increases by about 85 percent for technology users.

Along with technology, output in the study area is determined by land size, education level of the household head, access to extension service and family size. On the other hand household characteristics such as marital status, religion and age of the household head as well as institutional factors such as access to road and credit facilities have no significant impact on productivity in the study area.

4. Conclusions and Recommendations

Population growth, land fragmentation and associated over-utilization of land has been one of the serious cause of low productivity, food self insufficiency and mal nutrition in developing country in general and Ethiopia in particular. Access to new and improved technological has been recognized as a vital part at both micro level (productivity) and macro level (economic growth and development) (Solow, 1994; Kasenge, V. 1998). The readiness associated with new technology supply and diffusion remains critical for sustainable agricultural productivity and self food sufficiency (Franklin Simtowe, 2011). Use of agricultural technology such as fertilizer and improved seeds has been advocated as a cure to loss of natural fertility of the soil and associated low productivity. Apart from these consensuses the degree of technology adoption varies spatially as well as temporally. Among others, the study area (Masha district) is the one where farmers remain reluctant for agricultural technologies. Some of the possible explanations for the variation are capacity constraint (lack of credit access and high technology price) and low educational attainment of the farm households.

Apart from the low rate of technology adoption, the productivity difference between adopters and non adopters is very significant and positive while the variability of productivity (the standard deviation of output) is very large (about 53) within the technology adopters, which implies that the uniformity of the adoption is still a problem which might be emanated from farmers' low education level as well as constrained access to extension service. One and the most imperative thing to be noted in this study is that the negative perception towards adoption in the study area is merly from lack of knowledge as well as a loose relation between extension agents and the farm households in the study area. Therefore government's assignment in awareness creation is not accomplished yet in the study area in addition with timely and faire distribution of the agricultural technology. Thus local government should pay attention in building confidence in the farm households concerning the technology they provide by integrating the farmers and local development agents (extension agents) while demonstrating the fruits of the technology adoption (the productivity difference with in the same community) through peer to peer assessment.

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