

Determinates of the Adoption of Rust Resistant Wheat Technology:The Case of Misha District, Southern Ethiopia

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Abstract
Wheat rusts are the Major biological constraint to wheat production in Ethiopia. The main objective of the study was to examine factors influencing the adoption of rust-resistant improved wheat varieties by households in Misha district. Descriptive statistics and logistic regression were used for data analysis to achieve the objectives of the study. Binary logistic regression was used to examine factors influencing the adoption of rust-resistant improved wheat varieties. The study has found that age and education level of household head, land size, livestock holding, frequency of extension contact, and access to credit services were factors that significantly affected the adoption of rust-resistant improved wheat varieties. The findings of this study have the implication that any development intervention through improved wheat technology should take into account the aforementioned socioeconomic characteristics to enhance the adoption rate of new technologies.
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1. Introduction

Wheat is one of the major staple and crucial food security crops in Ethiopia. Next to maize wheat is the second most consumed cereal crop in Ethiopia. It is a staple food in the diets of several Ethiopians, providing about 15% of the caloric intake (FAO, 2015), placing it second after maize and slightly ahead of teff, sorghum, and enset, which contribute 10-12% each (Minot et al., 2015). It has multipurpose uses in making human foods, such as bread, biscuits, cakes, sandwich, and others. Besides, wheat straw is commonly used as a roof thatching material and as feed for animals (Mesfin, 2015).

Demand for wheat is growing rapidly in Ethiopia, reflecting the population growth, and shifting dietary patterns linked to urbanization that are mirrored across other eastern and southern African countries (Mason et al., 2015). Despite this low productivity, the demand for wheat has been increasing in both urban and rural areas of the country(Bekele et al., 2014). Although there are recent productivity gains, shortfalls remain and drastically can be narrowing the gap between supply and demand; self-sufficiency in wheat production is a high national priority. For the government of Ethiopia, issues with food security and the necessity to stop wasting precious foreign currency reserves on expensive wheat imports are of the utmost priority (Hodson et al., 2020).

During the 2019 production season, the national average wheat productivity of Ethiopia was 2.97 tons per hectare (t/ha), which was lower than the average productivity of Zambia and Egypt whose productivity was 6.68 t/ha and 6.38 t/ha, respectively (FAOSTAT, 2019). The low productivity is attributed to several factors including biotic (diseases, insects, weeds, and others) and abiotic (low and high rainfall, temperature, and low adoption of new agricultural technologies). Among the biotic factors, wheat rust has been the most devastating disease in Ethiopia causing up to 100% yield losses on susceptible varieties during the epidemic year (Belayneh et al., 2012; Alemayehu et al., 2020). The adoption of improved wheat varieties and improved agricultural practices are some of the mechanisms for productivity enhancement. Rust-resistant improved wheat variety is among wheat technologies for improving wheat productivity. Therefore, to increase wheat productivity in disease-prone areas there is a need to adopt rust-resistant wheat varieties. There is limited empirical evidence on factors affecting the adoption of rust-resistant wheat varieties. Moreover, although there are related studies on factors that affect the adoption of improved wheat technologies, their findings vary across time and places for instance:

Bekele et al. (2000) and Chilot et al. (2013) reported that access and use of credit significantly and positively influenced the adoption of improved wheat varieties and intensities of use. On the other hand, Tesfaye et al. (2001) and Tesfaye et al. (2016) found that access to credit did not affect the adoption of improved wheat varieties.

Chilot et al. (2013) and Hiwot (2018) reported that the education level of the head of the household positively and significantly influenced both the likelihood of adoption and the intensity of improved wheat variety use. On contrary, Tesfaye et al. (2016) reported that the education level of household heads negatively and significantly affected the adoption of improved wheat varieties. Bekele et al. (2000) reported that the education level of the household has not affected the adoption decision of improved wheat varieties.

Tesfaye et al. (2001) reported that extension contact and participation of farmers in on-farm demonstrations had positively and significantly affected the adoption of improved bread wheat varieties. On the other hand, Hiwot (2018) reported that contact with extension agents has not affected the adoption of improved wheat varieties.

Tesfaye et al. (2016) reported that livestock ownership had a significant and positive effect on the adoption of improved wheat varieties. On the other side, Bekele et al. (2000) and Hiwot (2018) reported that Livestock numbers did not affect the adoption of improved wheat varieties.

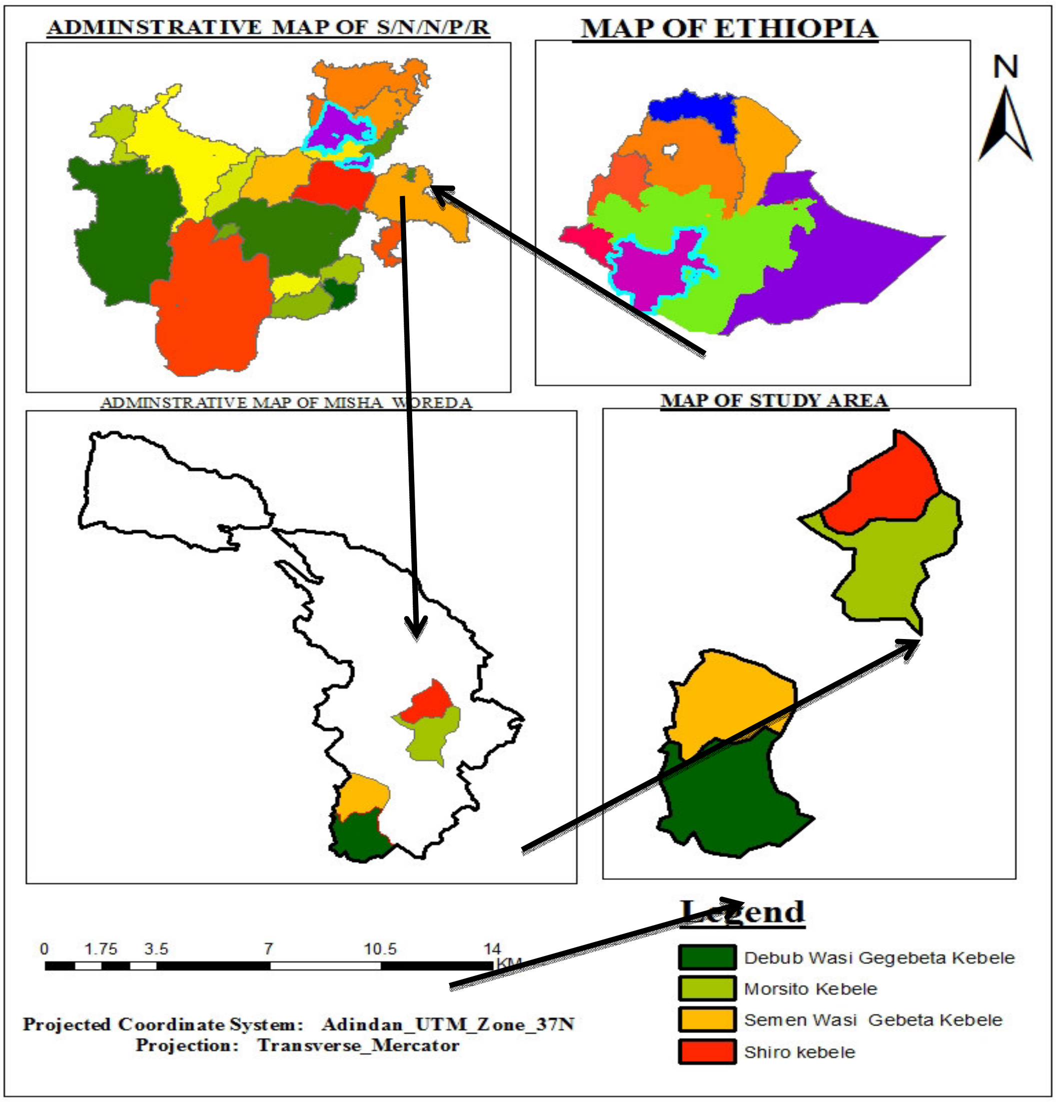
The aforementioned findings indicated that practical problems and factors that prevent the farmers from adopting these improved technologies of production differ across time and place. Thus, this study aims to assess factors affecting the adoption of rust-resistant wheat technologies in Misha district.

2. Materials and Methods

2.1. Description of the Study Area

This study was conducted in Misha district, which is found in Hadiya administrative zone of the Southern Nations Nationalities and Peoples Regional State of Ethiopia. The district is located 253 km away from Addis Ababa, 207 km from Hawassa, and 18 km from Hossana. The geographic location of the district is at 7°08' N latitude and 37°81' E longitude. Agricultural activity is the main means of livelihood for the majority of Misha district population. In terms of economic activities, the Woreda community fully experienced animal rearing and crop production (mixed farming system). The most dominant cereal crops produced in this district are wheat, teff, maize, sorghum, bean, pea, and other cash crops like chat, coffee, and vegetables (Shigute and Anja 2018; Girma et al., 2019).

Map of the Study Area



Source: Ethio_map of Shapefile

2.2. Sampling procedure

A cross-sectional study design was used. A household survey questionnaire was administered to collect data from the farmers drawn from the study area. The sampling method used for this study was a mixed method of purposive and simple random sampling, which involves three stages. First, purposive selection of potential wheat production kebeles of the woreda was conducted based on the data on the production potential of each kebeles. In the meantime, four wheat potential production kebeles were selected. Then in the second stage these four selected kebeles: households were grouped into two strata: That is households that cultivate rust-resistant improved wheat varieties and non-rust-resistant wheat varieties. Finally, samples of households from each stratum were selected through a simple random sampling technique based on probability proportional to the size of the population for each kebeles. The required sample size was determined by using Yamane's (1967) sample size determination formula. In Misha district, there were about 11,683 wheat-producer households. Using a 95% confidence level, and 5% (0.05) level of precision. Thus, the sample size was 387 households. The sample size for each kebele was determined using the proportional sample size of four kebeles.

2.3. Sources of data collection

Primary data were collected using a structured questionnaire that comprises information related to household demographic, socioeconomic characteristics, and institutional factors. On the other hand, secondary data were collected, from Woreda and Kebele agricultural and development office reports.

2.4. Method of Data Analysis

In this study, both descriptive and econometric models were used to assess the relationship between explanatory and dependent variables. Descriptive statistics involving mean, and percentage of frequencies were used to assess the characteristics of the sample households. Also, t-tests and tests were employed to assess the relationship among the variables of interest. For the econometrics model logistic regression model was used to analyze factors affecting the farmer's decision to adopt rust-resistant improved wheat variety.

Adoption of agricultural practice is a dummy dependent variable (adopt or not adopt), which is influenced by some explanatory variables. It is possible to compute Ordinary Least Squares for binary choice models, however, this results in heteroscedastic error terms, that is, the variance of the error term is not constant for all observations so that parameter estimates obtained are inefficient, thus classical hypothesis tests, such as t-ratios, are inappropriate. All parameter estimates of models are asymptotically consistent, efficient, and normal if the models use maximum likelihood estimation (MLE) procedures (Gujarati, 2004; Greene, 2012).

Demographic, socio-economic characteristics, and institutional factors or variables were used, in the logistic regression analysis of this study aiming to identify factors affecting the decision to use or not to use rust-resistant improved wheat varieties. If the response of the ith farmer to the question of adoption is denoted by a random variable Yi and a corresponding probability (i.e., probability of adopting rust-resistant improved variety by pi such that the probability of adoption (Yi = 1) = pi and the probability of non-adoption (Yi = 0) = 1 – pi.
The logistic model is specified by:

……………………………………………………… (1)

Where: Yi: be a dichotomous outcome random variable with categories 1 (adopter) and 0 (non-adopter).
Xi: denotes the collection of predictor variables
Ui: denotes the error term, which has an independently distributed random variable with a mean of zero.
In the regression model, because the dependent variable in this case adoption is taking the value 1 or 0, the use of LPM has a major problem that the predicted value can fall outside the relevant range of 0 to 1 probability value. Therefore, the model was estimated through using Maximum Likelihood Estimation (MLE). So, the logistic cumulative probability function for adopters is represented by:

…………………………………………… (2)

Where:
Pi is the probability that the ith farmer adopted the rust-resistant improved wheat varieties and that Pi is non-linearly related to Zi (i.e., Xi and βs). , 'e', represents the base of natural logarithms: Then, (1-P), the probability of non-adopter of rust-resistant improved wheat varieties is presented as:

……………………………………………………………….. (3)

And then, by dividing equation (2) by equation (3), the odds ratio in favor of adopting the rust-resistant improved variety obtained as follows:

.... (4)

Then the dependent variable is transformed by taking the natural log of Equation 4 specified by:

…………………………. (5)

Where: Li is the log of the odds ratio, L is the logit, Zi: is a function of n-explanatory variables, i.e., , Pi probability of adoption which, ranges between 0 and 1.

Definition of variables and hypothesis

Dependent variable: the dependent variable is the adoption of rust-resistant improved wheat varieties. The variable takes the value of 1 for the household that cultivated rust-resistant improved wheat varieties during the 2020/2021 production year and 0 for a household that did not cultivate rust-resistant improved wheat varieties.

Independent variable: for this study independent variables were selected based on the literature of past research findings on the adoption and impact of agricultural technology. Major variables expected to influence the adoption of improved wheat varieties were selected. The list of variables and their expected signs were listed in Table 1.

Table 1. Description of independent variables and expected signs

Variables	Description of the variable	Variable type	Expected sign of variables
Sex_hh	Sex of household head; 1 if household head is male 0, otherwise	Dummy	+
Age_hh	Age of household head in years	Continuous	-
Educ_level	Education level of household head in years of schooling	Continuous	+
TFAMSIZE	Total number of family size/members of a household	Continuous	+
Landsize	Total landholding or ownership in hectares	Continuous	+
Farm_Exp	Farming experience of household head in years	Continuous	+
LHTLU	Livestock ownership of household in tropical livestock unit (TLU)	Continuous	+
FRQEXN	Frequency of extension contact during cropping season in numbers	Continuous	+
MCOP	membership of farmers' cooperative 1, if a household is a member of farmers' cooperative, 0 otherwise	Dummy	+
ACRD	Access and availability to credit services, 1 if there is access to credit, 0 otherwise	Dummy	+
Mrk_Dist	Walking distance to the nearest market in walking minutes	Continuous	-
DPR	Dependency ratio in percent	Continuous	-

CHAPTER TREE

3. RESULTS AND DISCUSSION

The chapter was structured into two sections. Section one presented and discussed descriptive statics results of household demographic, socio-economic, and institutional variables. Section two presents an econometric estimation of factors affecting the adoption of rust-resistant improved wheat varieties.

3.1. Descriptive Statistics of Variables

Table 2 shows the result of descriptive statistics for dummy variables. The chi-square test was computed for the dummy variables and it was found to be statistically significant for membership farmers' cooperatives and access to credit services at a 1% level of significance. This indicates that there was a proportional difference between adopters and non-adopters in these variables.

Table 2. Summary of frequency of dummy variables

Variables		Adopters		Non-adopters		Total		χ^2 (chi2)
		Frequency	Percent	Frequency	Percent	Frequency	Percent	
Sex_hh	Female	37	23.57	69	30.00	106	27.39	1.942
	Male	120	76.43	161	70.00	281	72.61	
ACRD	Yes	120	76.43	131	56.96	251	64.86	15.529***
	No	37	23.57	99	43.04	136	35.14	
MCOP	Yes	100	63.69	114	49.57	214	55.30	7.535***
	No	57	36.31	116	50.43	173	44.70	

Source: Own computation using survey data (2021).

*Note: **, and *** represent significance at 5%, and 1% levels of significance respectively.*

Table 3 shows the result of descriptive statistics for continuous variables. As shown from the table, t-statistics were computed for all continuous variables and it was found to be statistically significant for age of household head, education level of household head, distance to nearest market in walking minutes, land size, livestock holding, and frequency of extension service at 5% and 1% level of significances. This implies that there was a significant difference in all these variables between adopters and non-adopters.

Table 3. Summary and mean comparison of continuous variables

Variables	Adopters	Non-adopters	Combined sample	t-stat.
Age of household head	41.35	43.78	42.79	2.524**
Education level	7.78	6.27	6.89	6.713***
Farm experience	17.22	17.65	17.48	0.496
Distance to market	33.43	36.57	35.29	2.230**
Family size	7.42	7.1	7.23	1.668
Land size (ha)	0.80	0.68	0.72	5.213***
Livestock holding (TLU)	6.74	5.62	6.08	4.068***
Frequency of extension service	4.29	3.60	3.88	5.871***
Dependency ratio	76.23	80.87	78.99	0.675

Source: Own computation using survey data (2021).
Note: **, and ***, indicate significance at a 5% level of significance, and 1% level of significance respectively.

3.2. Estimation of Econometric Models.

3.2.1. Diagnostic test of the logistic regression model

This study used logistic regression to assess factors affecting the adoption of rust-resistant wheat varieties. For the analysis to be valid, the model has to satisfy the assumptions of logistic regression. Therefore, before using the model to make any statistical inference, the study checked that the logistic regression model used fits sufficiently well using major diagnostic tests of the logistic regression model. According to Hosmer and Lemeshow (2000), homoscedasticity and normality of error terms are not assumptions that should be fulfilled for logistic regression. The details of model diagnostic tests of the logistic regression model used in the study are presented as follows.

1. Goodness of logistic regression

The goodness-of-fit (GOF) tests can help us to decide whether the model is correctly specified. This study used the Hosmer-Lemeshow goodness-of-fit test to examine the overall model fit. The Hosmer & Lemeshow test provides a global fit test, testing the 'estimated model to one that has a perfect fit. If this test is not significant, then you have evidence of a correctly specified model. If it is significant, then you have evidence that the model is miss-specified (Pituch and Stevens, 2016). Table 4 shows that (Hosmer-Lemeshow chi2 (8) = 8.07, Prob> chi2 = 0.4267), prob chi2 is greater than the critical value 0.05 which was insignificant; this result revealed that the model had an acceptable fit or correctly specified.

Table 4. Hosmer-Lemeshow chi-square model specification test

Goodness-of-fit test of logistic regression
(Table collapsed on quantiles of estimated probabilities)
number of observations = 387
number of groups = 10
Hosmer-Lemeshow chi2(8) = 8.07
Prob> chi2 = 0.4267

Source: Own computation using survey data (2021)

2. Multicollinearity test

Multicollinearity test of continuous explanatory variables

For continuous explanatory variables, multicollinearity was detected with the help of tolerance and its reciprocal, called variance inflation factor (VIF). Values of VIF exceeding 10 are often regarded as indicating the existence of multicollinearity. All continuous explanatory variables had tolerance values closer to one, and variance inflating factors of all explanatory variables were below 2, which indicates that the VIF of all these explanatory variables was less than the critical VIF value 10 (Table 5). So, by using the rule of thumb (that is if the VIF of a variable exceeds 10, that variable is said to be highly collinear) there was no multicollinearity problem between explanatory variables.

Table 5. Multicollinearity test for continuous variables

Variable	VIF	Tolerance	R-Squared
Age_hh	1.29	0.7758	0.2242
Educ_level	1.11	0.9046	0.0954
Farm_Exp	1.36	0.7332	0.2668
Mrk_Dist	1.19	0.8389	0.1611
TFAMSIZE	1.05	0.9509	0.0491
Landsize	1.14	0.8749	0.1251
LHTLU	1.19	0.8423	0.1577
FRQEXN	1.16	0.8635	0.1365
DPR	1.14	0.8769	0.1231
Mean VIF	1.18		

Source: Own computation using survey data (2021)

Multicollinearity test for discrete variables

This study used a contingency coefficient to detect the existence of multicollinearity between desecrates variables. The contingency coefficients between explanatory variables where is less than 0.75 (Table 6). So, using this rule of thumb method of detecting multicollinearity, there is no multicollinearity problem between these desecrates variables.

Table 6.Contingency coefficient for discrete variables

	Sex_hh	ACRD	MCOP
Sex_hh	0.707		
ACRD	0.112	0.707	
MCOP	0.039	0.121	0.707

Source: Own computation using survey data (2021).

3.3. Determinants of adoption of rust-resistant improved wheat varieties

The dependent variable was the adoption of rust-resistant improved wheat varieties. The variable is binary with two outcomes. If a farmer participated in the planting of rust-resistant improved wheat varieties the variable assumes a value of 1 or, 0 otherwise. Table 7 shows that the Wald chi-square test with 12 degrees of freedom (Wald chi2 (12)) = 91.20, prob> chi2 = 0.0000). This implies that the null hypothesis which indicates all coefficients are simultaneously equal to zero is rejected at 1% level significance (Wald chi2 = 91.20 df = 12, prob> chi2 = 0.0000; $p < 0.01$). According to Pituch and Stevens (2016), Pseudo-R2 between 0.2 and 0.4 indicates the model has a good fit. Rosenbaum and Rubin (1985) suggested that the low value of Pseudo-R2 indicates there is no systematic difference in covariate distribution between program participants and non-participants. Pseudo-R2 had a value of 0.2277, based on the aforementioned reason; the model has a good fit and no systematic differences in the distribution of covariates between adopters and non-adopters.

The explanatory variables that were assumed to affect the adoption of rust-resistant improved wheat varieties were age, sex (gender), educational level, farming experience, distance to the nearest market in walking minutes, family size, land size owned, livestock ownership in tropical livestock unit, frequency of extension contact, access to credit service, membership of farmers cooperatives, and dependency ratio of households.

Age of household head: age of the household negatively affected the adoption of rust-resistant improved wheat varieties and was significant at a 1% level of significance. Keeping other factors constant, as the age of household head increases by one year the probability or likelihood of adopting rust-resistant improved wheat varieties decreases by 1.2% (Table 8). This result is congruent with the studies by Sosina et al. (2014), Berihun et al. (2014), Moti et al. (2015), and Udimal et al. (2017), confirming the younger age households are adopters as compared to their counterparts elders. This impels older people reluctant to accept new technologies because they are afraid of the risks of new technologies.

Education level of household head: education level of household head positively affected the probability of adoption of rust-resistant improved wheat varieties and was significant at a 1% level of significance. Keeping other factors constant if the schooling of household head increases by one year the probability of adopting rust-resistant improved wheat varieties increase by 8.4% (Table 8). This result is in line with the findings of Bekele (2014); Leake and Adam (2015); and Hiwot (2018) reported that an increase in the level of education of a household increases the probability of adopting improved wheat varieties. But it is in contrast with a study by Tesfaye et al. (2016) reported that the level of education of a household head decreases the likelihood of adoption of improved wheat varieties. This implies farmers who attained high-level formal education gain better skills for gathering information from different sources as a result; it has a significant positive contribution to the adoption of new technologies as compared to non-educated farmers.

Land size owned (landholding): having more farmland size is one option whereby farmers could be prompted in diversifying their crop production and adopting newly emerging improved crop technologies. Land size owned by a household positively affected the probability of adoption and was significant at a 1% level of significance. An additional hectare increases in land size for households increase the probability of adopting rust-resistant improved wheat varieties increase by 41% keeping other factors constant (Table 8). This result is inconsistent with the study by Regassa and Degye (2019) which reported that having a large farmland size increases the probability of adopting high-yielding wheat varieties. Similarly, Solomon et al. (2011), Bekele et al. (2014), and Degefu et al. (2017) reported that as farm size increases the likelihood of adoption of the improved technology by farmers increases. This implies that farmers who have large farm sizes had the opportunity to produce more crops if needed. It indicates that farmers who have more land holdings are more likely to take the risk of new technologies.

Livestock holding: livestock holding by a household has positively affected the adoption of rust-resistant improved wheat varieties and was significant at a 5% level of significance. An additional unit increases in tropical livestock unit in livestock holding for a household increases the likelihood of adopting rust-resistant improved wheat varieties by 2.3% keeping other factors constant (Table 8). This finding is in line with a study by Regassa and Degye (2019) which reported that an increase in tropical livestock units increases the probability of adopting high-yielding wheat varieties. Similarly, this result is in line with studies by Solomon et al. (2011), Hassen et al. (2012), Berihun et al. (2014), Tolesa (2014), and Milkias (2020) who confirmed that livestock holding positively and significantly affect adoption. This implies that having more livestock enables households to increase family income from the sales of livestock. Thus, farmers can easily meet their agricultural needs from sales income of livestock and livestock products. Thus, this increases the probability of the adoption of improved agricultural technology.

Frequency of extension contact: Frequent extension contact positively affected the probability of adoption of rust-resistant improved wheat varieties and was significant at a 1% level of significance. Keeping other factors constant, one additional day increase in the number of extensions contact increases the probability of adopting rust-resistant improved wheat varieties by 8.5% (Table 8). This result agrees with the studies conducted by Solomon et al. (2011), Moti et al. (2013), Leake and Adam (2015), Sisay (2016), and Regassa and Degye (2019) who found that frequency of extension contacts with extension agents positively and significantly influenced the adoption decision of agricultural technologies. This is because farmers who have more frequent extension contact get more new information regarding new agricultural technologies and associated agricultural practices; therefore they are more likely to adopt these improved agricultural technologies.

Access to credit services: access to credit positively affected the adoption of rust-resistant improved wheat varieties and was significant at a 1% level of significance. Keeping other factors constant having an access to credit service increased the probability of adopting rust-resistant improved wheat varieties by 18.2% (Table 8). This result agrees with the study by Milkias (2020),who reported access to credit had positively and significantly influenced the likelihood of adoption of improved wheat technology. Studies by Namwata et al. (2010), and Leake and Adam (2015) also confirmed access to credit facilities positively affects the adoption of improved agricultural technology. From the discussion in focus groups and key informant surveys, most farmers reported that agricultural inputs or technologies costs were high, as a result, there was a lack of enough money to purchase improved farm technologies. This implies having access to credit services solves such type of problem. Therefore, having access to credit services increases the likelihood of adopting improved agricultural technologies.

Table 7.Maximum likelihood estimation logistic regression

Variables	Coef.	RobustSt.Err.	Z	P>z
Age_hh	-0.053***	.015	-3.59	0.000
Sex_hh	0.224	.294	0.76	0.446
Educ_level	0.364***	.076	4.77	0.000
Farm_Exp	0.017	.017	0.98	0.326
Mrk_Dist	-0.011	.011	-1.00	0.317
TFAMSIZE	0.103	.069	1.50	0.133
Landsize	1.772***	.621	2.85	0.004
LHTLU	0.102**	.051	1.99	0.046
FRQEXN	0.366***	.119	3.06	0.002
ACRD	0.823***	.288	2.85	0.004
MCOP	0.215	.277	0.78	0.438
DPR	-0.003	.002	-1.33	0.183
Constant	-5.391	1.146	-4.71	0.000
Number of obs	387			
Wald chi2(12)	91.20			
Prob> chi2	0.0000			
Pseudo R2	0.2277			

*Note: **and *** indicate significant at 5 %, and 1%, levels, respectively.*

Table 8. Marginal effects after logistic regression

Variables	dy/dx	Std. Err.	Z	P>z
Age_hh	-0.012***	0.003	-3.570	0.000
Sex_hh*	0.051	0.066	0.770	0.439
Educ_level	0.084***	0.017	4.930	0.000
Farm_Exp	0.004	0.004	0.980	0.325
Mrk_Dist	-0.002	0.002	-1.000	0.317
TFAMSIZE	0.024	0.016	1.500	0.134
Landsize	0.410***	0.145	2.830	0.005
LHTLU	0.023**	0.012	2.000	0.045
FRQEXN	0.085***	0.027	3.080	0.002
ACRD*	0.182***	0.060	3.050	0.002
MCOP*	0.050	0.064	0.780	0.435
DPR	-0.001	0.000	-1.330	0.185

*Note: **and *** indicate significant at 5 %, and 1%, levels, respectively.*

CONCLUSION AND RECOMMENDATION

The most crucial component for increasing agricultural productivity and farm households' access to food security in Ethiopia is the deployment of improved varieties. Thus, Adopting rust-resistant improved wheat technology is one way of improving farmers' wheat production and decreasing yield loss due to currently occurring wheat rust diseases. However, adoption of improved variety remains very low, especially among small-scale farmers of the country. Variables such as the education level of the household head, land size, livestock holding in TLU, extension contact and access and availability of credit services of household affect the adoption of rust-resistant improved wheat variety positively and significantly. On the other hand, the age of the household head affects the adoption of rust-resistant improved wheat varieties negatively and significantly.

The fact that access to extension services has a positive and significant effect on the adoption of rust-resistant improved wheat varieties indicates that; the crucial role that extension workers played in influencing farmers' attitudes and raising farmers' understanding of the advantages of better wheat technology. This suggests that to increase the production of sustainable food, farmers' perceptions of the benefits and uses of better wheat technology must be increased. Therefore, the government and other stakeholders should encourage access to extension agents to enhance the dissemination of improved rust-resistant wheat varieties among the farmers.

Access to credit facilities is one of the key factors that influence the adoption decision of households. Access to credit services enhances the adoption of improved inputs particularly those unaffordable to smallholder farmers through its effect of reducing the existing cash constraint for undertaking agricultural decisions and accessing high-value inputs. Therefore it is recommended that credit services should be made available to farmers at an affordable rate to increase the adoption of improved wheat technologies.

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