Adoption of diversified farm technology in a semi arid of northern Ethiopia: A Panel Data Analysis

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Abstract:

Technological change in agriculture in climate risk exposed developing countries requires for three major reasons: First, the increased climate risk and increase the need for new agricultural technologies that are more robust to such variability. Second, a need for land use intensification to feed the growing populations and third, economic transformation that creates an opportunity for market-oriented production that is more focused on the production of crops for market. This study emphasizes to assess factors associated with the extent of and intensity of adoption of three farm technologies (high yield wheat, drought tolerant teff, and cash crops) in the semi-arid of northern Ethiopia. We estimate determinants of adoption of the three technologies using double hurdle models. We apply correlated random effects with control function approach to control for possible endogeneity associated with access to the technologies. Results show that high population density has a positive and significant effect on the adoption decision of improved wheat and, irrigation has positive and significant effect on adoption of cash crops. Adoption of drought-tolerant teff is access constrained. Hence, increasing access to drought-tolerant teff and promoting irrigation appears to be adoption stimulants of drought-resistant teff and cash crops in a climate risk environment.

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Keywords: Technology adoption; double hurdle; control function; northern Ethiopia.

1. Introduction

There is a wide consensus that improved agricultural technologies are essential components in a pro-poor development in a changing climate, improving agricultural productivity, and facilitates the transition from subsistence to high value and market-based farming (Bezu et al., 2014; De Janvry & Sadoulet, 2002; Mendola, 2007; Minten & Barrett, 2005; Yu et al., 2011; Zilberman et al., 2012). Technological change in agriculture in climate risk exposed developing countries requires mainly for three reasons. First, climate change may cause increased climate risk and increase the need for new agricultural technologies that are more robust to such variability. This implies that the continual increasing of global temperature may enhance weather uncertainty and affects the productivity of rain-fed agriculture in developing countries(Holden & Fisher, 2015; Zilberman et al., 2012). Second, continued population growth implies a need for land use intensification to feed the growing populations and high yielding crop varieties are adopted more rapidly than other agricultural innovations (Wale & Chianu, 2015). Third, economic transformation through promotion of growth packages such as irrigation, physical infrastructure (i.e, market, improved road, and communication) may create an opportunity for market-oriented production that is more focused on the production of crops for market (Gebremedhin et al., 2009).

Farmers have certain demands and expectations from adoption of modern farming technologies. These in turn, explain their decision behavior whether to adopt or not. Producer-consumer-farmer often has multiple selection criteria of technology adoption including production, food, feed and uncertainty which is in contrast to adopters who focus on a single trait, for-profit (Singh et al., 1986). Depending on the preference, resource endowment, risk, and constraints that an individual farmer encounters, a beneficial attribute to one farmer may be unfavorable to another. The technology with the desired benefit (s) can then reach out to farmers who are accessed and demanding (Amare et al., 2012). Hence, understanding the factors affecting farmers' adoption decision of improved farm technologies has an important implication on prioritizing of technology improvement such as crop varieties and targeted agricultural extension.

Ethiopia is the second most populated country in Africa, with more than 75 % of the population work in a highly diversified agro-ecology with erratic weather condition (Croppenstedt et al., 2003). The subsistence farming system, with limited landholding less than one ha per household Gebremedhin et al. (2009) and rapidly declining this size is a challenge to meet the food requirement of the high population growth (Verkaart et al., 2017). The existence of missing or poor insurance and credit markets and low off-farm employment opportunity, the traditional agricultural system lacks to improve the well-being of the rural society and may stagnate the transformation process of subsistence agriculture to a market-based economy. Addressing these problems, the Ethiopian government enacts pro-small farmer strategies allowing the agriculture sector responsive to food security, weather uncertainty, and rural transformation. As part of the strategies, provision of extension programs on adoption of agricultural technologies has launched since the mid of the 1990s (Wubeneh & Sanders, 2006). High yield wheat variety, drought tolerant *teff* and cash crops were among the technologies that were widely adopted by highland farmers of the country (Zilberman et al., 2012).

In this paper, we analyze the extent to which we observe these types of technological changes in the climate-changing agriculture of Tigrai regional state, northern Ethiopia. This is a densely populated semi-arid area dominated by smallholder agriculture. Over the last twenty years, the Ethiopian economy has had a take-off in economic growth and the economic transformation may also open the possibilities for further agricultural transformation through adoption of modern farming technologies. We employ three rounds of household panel data collected in 2005/06, 2009/10 & 2014/15 to assess the extent to which we see signs of technology adoption in response to climate change, population pressure, and transformation in the data. To stimulate our analysis, first, we apply constrained technology adoption framework in the imperfect factor market agriculture. Next, we estimate adoption, generally measured as a discrete choice and intensity of adoption, associated with a continuous indicator as shares of fixed resources (land) that utilize newly adopted technology using double hurdle model. We use correlated random effect models with a control function approach to fix the probable access endogeneity in modeling adoption decisions of the technologies. Agroecology and community level factors were used to instrument the endogenous access variables.

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The remaining parts of the paper is organized as follows. The next section presents constrained technology adoption theoretical framework. The empirical model part comprises the study area, data, estimation method, and strategies are presented in section three. Section four presents the main research findings and discussions. Finally, section five presents the conclusion and provides some inferences.

Theoretical model

Constrained technology adoption

Technology adoption literature proposes various econometric methods that can be used in modeling the behavior of household's demand for modern farming technology and identify the factors that can explain adoption decision (Heckman, 1979; Maddala & Nelson, 1975; Wooldridge, 2010). Household's adoption decision of new technology is usually modeled as a choice between the traditional and the new technology. A farmer adopts the technology when the discounted expected benefit is higher from adoption than without adoption (Amare et al., 2012; Bezu et al., 2014; Ma & Shi, 2015). If adoption of the new technology is profitable, the speed of diffusion is high and demand for the new technology is derived from profit function. This infers that the number of aggregate adopters of technology is below the saturation point (Amare et al., 2012).

In this case, data are collected on whether a given technology is adopted or not, without additional information on the constraints that some farmers might face in accessing the technology. Under this circumstance, the censored Tobit model allows for modeling both the adoption choices and their intensity (Tobin, 1958). The underlying assumption of Tobit specification is that a farmer demands the new technology with unconstrained access and the non-adoption is rational decision-making. Practically, however, some farmers with positive demand have faced access problem. This might be due to violation of the full information assumption, i.e., farmers may lack the information at all or obtained insufficient information to allow them to adopt. Likewise, farmers may not adopt the new technology due to credit constraint, limited supply of the technology or underdeveloped the supply system (Amare et al., 2012). Thus, Tobit specification lacks to distinguish between households with a constrained positive demand and those with unconstrained positive demand for the new technology and yields inconsistent estimates (Amare et al., 2012; Bezu et al., 2014; Croppenstedt et al., 2003).

In developing countries including Ethiopia, due to imperfect or missing factor markets, farm household decides production and consumption simultaneously (Singh et al., 1986). In this perspective, access to improved technology is a key point to overcome for farmers with positive desired demand. To this end, consistent estimates for models exhibited constrained demand specification can obtain using the double hurdle (DH) model (Croppenstedt et al., 2003). There are two possible reasons that farmers declined to adopt new technology in a climate risk environment. First, farmers with full information and fully accessible to the new technology while, they are unwilling to adopt. This is because adoption may be risk full, expensive or less profitable at the current price (Amare et al., 2012; Antle, 1987). Second, farmers want the new technology but, they faced difficulty to get it either due to limited supply or poor supply system (transport is too difficult). Therefore, the DH model allows us to separate the sample of households into three groups. (1), some farmers are fully informed and access to the technology and, have positive demand and adopt it. (2), some farmers have an access but unwilling to adopt because they may be less benefited from adoption. (3), some farmers have the desire to adopt the new technology but, difficult to get it due to supply-side constrained.

In this study, we have information whether or not farmers are access constrained to the technology. The information is prompted from macro level possibly measured by collective behavior with the diverse performance of strategy determined at agroecology or community-level. This presumes that access to technology differs according to the feature of the agro-ecology and accessibility of public services. Following this, households were characterized into three target groups. First, households residing in the mid and high land agro-ecologies were accessed to high yield wheat variety. This is because wheat is mid and high land crop. Second, households live in drought-affected agro-ecologies (districts) were accessed to drought-tolerant *teff*, implies the new crop variety grows with small rainfall intensity and matures early[1]. Third, households live in a community with irrigation were also accessed to get cash crops, as adoption of water-conserving technologies increases total water use and is an important input to grow cash crops. The availability of this information allows us to specify the technology demand equations using DH model in a better way than Tobit model. Assume that a farmer i with unobservable desired demand ($D*$) for new technology *j* where j = 1, 2, &3[2] at time *t*, in a panel data set represented as follows:

$$D*_{ijt} = \beta' X'_{it} + \pi' A*_{ijt} + U_{ijt} \tag{1}$$

Where the vector X' comprises the predetermined household features and endowment variables of the demand function. A refers access dummy with value one if household i is accessed at least one technology, zero otherwise. β and π denote the vector of parameters and U is the unobservable effect of the model, assumed with zero mean and constant variance. Considering access to the specific improved technology, it is expressed as:

$$A*_{ijt} = \vartheta' Z'_{it} + \mu_{ijt} \tag{2}$$

Where A is an access to technology and we can identify only whether an individual has an access or not. Z is a vector of variables directly affect access to technology but indirectly affect technology demand decisions. ϑ is a vector of parameters in the access equation, and μ is random error term with mean zero and constant variance. The interaction of equation (1) and (2) reveals the observed model of technology that comprises three sub-sample groups. The first group is with farmers passed the positive demand threshold (D* > 0), providing that they have an access to the technology (A* > 0) and individuals are in a positive use of the technology (G1). The second group in the sample is households unwilling to demand the technology whether they are accessed or not (D* < 0, A* > 0 or A*≤ 0) (G2). Finally, individuals desired the technology while, they cannot adopt it as they do not have an access to the technology (D* > 0, but A*< 0) (G3). Therefore, the DH model applied here follows as of Amare et al. (2012); Croppenstedt et al. (2003); Ricker-Gilbert et al. (2011); Verkaart et al. (2017) and we assume that the access and demand equations are independent. Based on this assumption, the likelihood function for the sample- separated data can be specified as follows:

$$\begin{aligned} lnL = & \sum_{G1=1} \ln[\Phi(\frac{\vartheta Z'_{it}}{\delta_u}) * \phi(\frac{D_{it} - \beta' X'_{it}}{\delta_u})] \\ & + \sum_{G1=2} \ln[1 - \Phi(\frac{\beta' X'_{it}}{\delta_u})] \\ & + \sum_{G1=3} \ln[\Phi\left(\frac{\beta' X'_{it}}{\delta_u}\right) * 1 - \Phi\left(\frac{\vartheta Z'_{it}}{\delta_u}\right)] \end{aligned} \tag{3}$$

Where ϕ and Φ are the probability density function (*pdf)* and cumulative distribution function (*cdf*) of the standard normal variable, respectively; G_1, G_2, and G_3 are indicator functions showing whether a given observation belongs to group one, two or three, respectively, as described above. Based on this, we hypothesized the following for empirical tests:

H$_1$*: Farm households live in a community with irrigation are more likely to adopt cash crops. The testable implication is that the dummy irrigation increases land use efficiency, tends to increase yield and will have a positive and significant effect on adoption of cash crops (high-value crops).*

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H$_2$ *: Households live in a dense population area are more likely to adopt yield enhancing wheat. The implication is that the higher population density, the lower per capita land size leads to apply land use intensification to meet the food requirement at the household level and the higher adoption rate of the improved wheat.*

H$_3$: *Lower average rainfall leads to less use of drought-tolerant teff. The implication is that the coefficient of mean rainfall of the previous three years production seasons is negative and statistically significant in both probability and intensity models of drought-tolerant teff.*

3. Empirical model

3.1 Description of the study area

The study area is Tigrai regional state located in the northern part of Ethiopia where smallholder agriculture is the main livelihood of the rural society. Agriculture contributes 38.7 % of the Regional Gross Domestic Product (RGDP) (BoFED Tigray 2010). Arable land of the study region accounts 1.03 million ha where 83 % of this area was covered with cereals in the 2013/14 production season. Wheat and *teff* take the major share in cereal harvesting. Population growth rate of the study region reaches 2.5 % per year and an average population density of 327 persons /km^2 (BPF, 2014). About 41 % of the region's population living in extreme poverty, defined as less than one dollar per day in purchasing power parity and the per capita income of the region reaches 234 dollars in the real term by 2009/10. The rainy season of the region is mid of June to mid of September (BOARD, 2014). The occurrence of recurrent drought due to weather variability is the feature of the region's agriculture and using local crop variety is less robust to such climate shock and deters productivity of smallholder agriculture. As a result of public and developmental agents' effort on irrigation, the proportion of irrigated land from the total arable land of the study region has increased from 7.5 % in 2005/06 to 15 % in 2013/14 (BoARDTigray, 2014).

3.2 Method of data collection and data type

The data used in this study come from a panel of three survey rounds conducted in 2005/06, 2009/10 and 2014/15 production seasons. The sampling frame bases on a two-stage approach as defined by Hagos and Holden (2003). In the first stage, communities were selected from the rural districts of the region based on agricultural potential, population density, agro-ecology diversification and accessibility of public services. In the second stage, about 24 to 25 households were randomly sampled from a list of farm families in the selected communities. The surveys collected useful information on several factors including household composition and characteristics, land, and non-land endowments, adoption of improved farm technologies, land used and technology-induced income, indicators of access to infrastructure (marketplace and road), and community level characteristics like population density and rainfall. Rainfall data were captured from monthly satellite record of the study communities.

As the survey time difference is just about four to five years, it is expected that some households were left out in the subsequent surveys. On the other hand, additional households were included in the subsequent surveys and finally, the data end up with an unbalanced panel. Hence, attrition biased is an issue of unbalanced panel data and it should be handled to avoid biased estimates in the adoption models. We estimate a probit attrition model to assess and control the attrition bias through exploiting the baseline data from 2005/06. The dropout and remaining households in each survey round were used to construct attrition dummy dependent variable (attrite =1 and 0, otherwise) and estimated on household and community level control variables. If the explanatory variables explain the attrition dummy significantly (at the 5 % level), attrition is an issue in the analysis implying that it is systematic. Detail explanation is presented in the estimation method section.

3.3 Estimation method

Beginning from theoretical model equation (1), all farmers do not have equal access to the technologies. This implies that households belong to group one (G1) would have positive demand while households belong to group two and three (G2 &G3) would have zero demand. Then, the outcome variable is censored at zero. In this case, the adoption equation is best explained in the framework of corner solution model (Wooldridge, 2010). Therefore, farmer *i* extent of adoption (area used for the adopted technology j *)* at time *t* is formulated as follows:

$$D_{ijt} = \max(0, D*_{ijt}) \tag{4}$$

Where the latent variable $D*_{ijt}$ refers to non- linear specification of the technology adoption equations. The censored Tobit model is popular for corner solution estimation (i.e., the probability and intensity of adoption). The is because the dependent variable of the linear regression is observed only for some part of the sample households and assumed that the error term is normally distributed $\varepsilon_{ijt}|X_{it} \sim normal(0, \delta^2)$ (Tobin, 1958). However, Tobit model has a limitation[3]. An alternative to the standard Tobit model, the Double Hurdle (DH) model allows the initial decision of positive demand $D > 0$, versus $D = 0$ to be handled separately from the decision of how much D wanted providing that $D > 0$ by the two separate equations (Burke, 2009). This was based on the likelihood ratio test that whether the censored Tobit model is nested in the two stage model. The likelihood ratio test rejects the censored Tobit molded in favor of the double hurdle model on the improved wheat adoption ($\chi^2_{(27)}$=981. Pr=0.0000), drought tolerant *teff* ($\chi^2_{(27)} = 740$, $Pr = 0.0000$), and cash crop ($\chi^2_{(27)}$ =998, Pr =0.0000). Therefore, the separate estimation comprises the probit model in the first hurdle and the truncated normal regression in the second hurdle. This allows the likelihood of the positive outcome and the value of a given positive outcome to be determined by separate process. We apply this method to estimate the model specification in equation (5) as of Amare et al. (2012); Ricker-Gilbert et al. (2011).

The non –leaner adoption equation (4) more specifically, can be expressed as a function of individual unobservable heterogeneity and other exogenous variables as follows:

$$D^*_{ijt} = \beta_0 + \beta_1 L_{it} + \beta_2 H_{it} + \beta_3 W_{it} + \beta_4 D_t + \beta_5 Y_t + \beta_6 A*_{ijt} + C_i + \varepsilon_{ijt} \tag{5}$$

Where L is household labor endowment proxy by the number of male and female active labor force. The human productive element of household presents the capability of undertaking the laborious task, apply their effort in rapidly adoption of modern farm technology and exploit new market opportunities. H refers household's composition and characteristics such as age and gender of household head. The variable W included the land and non-land endowments expressed in terms of Oxen and non-oxen livestock (in Tropical Livestock Units) that have a risk neutralize effect and expected to enhance the likelihood of farmer's technology adoption decision. *D* refers district dummy that captures across agro-ecological difference in the distribution of technologies among the adopters. The variable Y refers the time dummy to see adoption variations across time in reference to the 2005/06 survey. The term C is the unobservable heterogeneity of farm households which is captured to the adopter but not observed by the researcher. A* is the specific access dummy variable where, a given farmer is accessed at least to one of the technologies with value one and zero, otherwise. This is an endogenous variable and assumed correlated with error term in the adoption equation. ε refers the unobservable effect of the model, assumed with mean zero and constant variance. i, j & t are individual, technology type and time identifiers, respectively.

To handle the problem of attrition biased, a probit model was estimated in the baseline survey of 2005/06 and the subsequent survey rounds (i.e., 2009/10 and 2014/15). The probit attrition results are included in Appendix table 1. The results indicate that several of the variables are significant and attrition is therefore non-random and leads to bias estimates. To correct the bias, we construct an Inverse Millis Ratio (IMR) and included as a regressor in the Mundlack-Chamberlin specification. The insignificance of IMR in the adoption model results (Table 3) indicate that attrition does not have an effect on the adoption results.

3.4 Estimation challenges and remedial

While estimating the causal relationship between the control and the outcome variables using a panel data, there are two important issues take into consideration i.e., unobservable and observable household heterogeneities. The next section deals with these.

The first estimation issue is the existence of unobservable individual heterogeneity. This affects adoption decisions by creating selection bias as some farmers are more likely to adopt the technology compared to the others. The intuitive is that the unobservable individual heterogeneity effect C_i in equation (5) is correlated with the explanatory variables and creates biased estimates. If we assumed that the unobservable household heterogeneity effect is uncorrelated with all of the control variables (strict exogeneity assumption), we estimate the model using random effect estimator considering a composite error term (i.e.,$u_{it} = C_i + \varepsilon_{it}$) of equation (5). Nevertheless, this is a strong assumption and we are not guaranteed that the unobservable individual heterogeneity is orthogonal and uncorrelated to the other explanatory variables. On the other hand, the fixed effect model can fix the problem of correlation between individual unobservable heterogeneity effect and the explanatory variables through the demeaning process. However, fixed effect model is a workforce for linear models but not applicable for nonlinear model due to the incidential truncation problem (Verkaart et al., 2017). Therefore, for nonlinear panel data models, the Correlated Random Effects (CRE), model of Mundlak (1978) and Chamberlain (1982) eases the assumption of strict exogeneity. This implies that the CRE approach expresses the unobservable heterogeneity variable (C_i) as a function of the avearge of the time variant household i variables denoted by $\bar{X}i$ and includes as a regressor in the adoption model (Wooldridge, 2010). We rewrite equation (5) as follow:

$$D^*_{ijt} = \beta_0 + \beta_1 L_{it} + \beta_2 H_{it} + \beta_3 W_{it} + \beta_4 D_t + \beta_5 Y_t + \beta_6 A *_{ijt} + \beta_7 \bar{X}i + \varepsilon_{ijt} \quad (6)$$

Intuitively, averaging the time-varying household i variables make the same value within households in each year whereas, varying across households. Thus, the Mundlack - Chamberlin approach solves as with fixed-effects while, avoiding the problem of incidential parameters in nonlinear models (Ricker-Gilbert et al., 2011). Finally, both the reduced form of access equations and the technology adoption equations are estimated using the Double hurdle -CRE estimator.

The second estimation issues is related to the problem of endogeneity. Referring to the theoretical model section, not all farmers have access to the specific technology as access is based on some agro-ecology or community-level factors, which is non-random. Hence, the access variable in the adoption equation (5) is possibly correlated with the error term i.e., cov $(A *_{ijt,}\ \varepsilon_{ijt}) \neq 0$. We apply a control function approach to handle for possible endogeneity of access variable. More specifically, we rewrite the adoption equation (5) as a system of two equations, (i.e., the access equation, first stage and the adoption equation, second stage) separately.

$$A *_{ijt} = \beta' X'_{it} + \vartheta' Z'_{it} + \overline{\emptyset X} i + \mu_{ijt} \quad (7)$$

$$D_{ijt} = \max[0, \beta(X'_{it} + A *_{ijt} + \bar{X}i + \widehat{\mu j_{it.}}) + \varepsilon_{ijt}] \quad (8)$$

The control function approach requires exclusion restriction at least one variable (Z'_{it}) in the first stage equation (7), that is not in the adoption equation and uncorrelated with the error term in equation (8), $cov\left(Z'_{it}\,, \varepsilon_{ijt}\right) = 0$, but correlated with the potentially endogenous variable, $cov\left(Z'_{it}, A *_{ijt}\right) \neq 0$. Following the work of Smith and Blundell (1986) for testing and controlling the endogeneity in a censored adoption models of each technology in equation (8), there are two steps. First, estimate the reduced form access model of each technology in equation (7) using correlated random effect probit model and captured the generalized residual. Second, include the generalized residual in the adoption equation (8) along with the endogenous access variable.

A significance test on the coefficient of the residuals test for the endogeneity of the access variable. As in a two-stage- instrumental variable model, the control function approach requires exclusion restrictions as discussed above. In this case, a dummy variable mid and high land altitude, a dummy variable agroecology with high rainfall variability in the previous three years rainy season, and an interaction of dummy irrigation and community dummy were used as an instrument for accessibility of high yield wheat variety, drought tolerant *teff* and cash crops, respectively. The intitutive is that wheat is mid and high land crop and households live in mid and high land were access to the improved wheat. Drought tolerant *teff* is low land crop since low land is often characterized as drought exposed agroecology (high rainfall variability) and households live in this agroecology were also deserve to access the drought-tolerant *teff*. We see particular reason that in areas with existence of irrigation, there is less likely to adopt drought-tolerant *teff* as the crop is adaptable to moisture stress environment. Furthermore, access to cash crop is associated with the presence of irrigation. We tested the statistical validity of this by including the instrument in the adoption equation in one specification. If the instrument was insignificant in the adoption equation but significant in the access equation, and if the error term from the first stage access model is significant in the adoption model, then endogeneity is an issue and was corrected for with the control function.

4. Results and discussions

4.1 Descriptive analysis

The mean and distribution of the outcome and explanatory variables used in the econometric analysis are presented in Table 1. Choice of explanatory variables is based on previous literature suggestions that a wide range of socio-economic, technical, and physical factors influence adoption and extent of adoption of farm technologies in developing countries (Feder et al., 1985). Table 1 also presents the adoption and extent of adoption of high yield wheat variety, drought tolerant *teff* and cash crops by survey year. The adoption rate is measured in terms of the average households growing improved crop variety. For instance, we observe that the adoption rate of improved wheat increased from 13 % in 2005/06 to 19 % in 2009/10 and decreased to 14 % in 2014/15. Likewise, the adoption intensity is measured in terms of area used for improved wheat variety in the production season. The pattern of adoption intensity of improved wheat is similar to the adoption rate and it increased from 0.15 *tsimdi* in 2005/06 to

Table 1: Descriptive statistics of variables used in the analysis (mean value)

	Survey year			
Varibale description (average households)	**2005/06**	**2009/10**	**2014/15**	**Total**
Technology variables				
HYV_ Wheat adoption (yes =1)	0.13	0.19	0.14	0.15
HYV_ Wheat area planted (*tsimdi*)	0.15	0.31	0.20	0.22
Drough Tolerant *Teff* adoption (yes=1)	0.06	0.04	0.11	0.08
Drough tolerant *Teff* area palnted (*tsimdi*)	0.09	0.08	0.22	0.14
Cash crops adoption (yes =1)	0.11	0.19	0.16	0.15
Cash crop area planted (*tsimdi*)	0.04	0.19	0.21	0.14
Irrigated area (*tsimdi*)	0.11	0.44	0.61	0.38
Cash crop area planted/ irrigtaed plot (ratio)	0.36	0.43	0.34	0.37
Household feature and endowment variables				
Gender of head (female =1)	0.27	0.27	0.28	0.27
Age of head (year)	54.0	54.4	57.8	55.9
Male adult (count)	1.44	1.55	1.93	1.69
Female adult (count)	1.39	1.38	1.54	1.45
Oxen own (count)	0.92	1.09	1.08	1.04
TLU total (tropical livetsock unit)	2.11	2.52	4.39	3.25
Own land (tsimsid)	5.26	5.56	5.34	5.39
Community-level variables				
Distance to farmers training center (walking hr)	1.02	1.27	0.97	1.07
Distance to district office (walking hr)	2.87	2.80	2.76	2.83
Distance to market (walking hr)	0.32	1.27	1.27	1.04
Access to irrigation (yes =1)	0.08	0.28	0.25	0.22
Population size in a community (count)	5145	6128	9161	7233
Previous three years rainy season mean rainfall (mm)	52.19	56.95	54.43	56.5
Previous three years rainy season mean rainfall variability (Std.dev) (mm)	9.8	8.25	9.14	9.03

Source: NMBU and MU household panel survey.

0.30 *tsimdi* in 2009/10 and decreased to 0.20 *tsimdi* in 2014/15. This indicates that adoption and extent of adoption of improved wheat in the study region remain small. Limited supply, poor infrastructure, remoteness to the distribution and development area and land size disparity to test the technology may be the possible reasons for lower adoption and intensity of adoption of improved wheat. One can also observe the pattern of adoption rate and area used for drought tolerance *teff* and cash crop in each year from the same table (Table1).

4.2 Econometric results

The results from the first stage access equation of the three technologies are presented in Table 2. The strength of the exclusion restrictions (instruments) in the first stage correlated random effect probit model is tested as of Ricker-Gilbert et al. (2011). These tests verify the significant relationship between the exclusion restrictions and the potential endogenous access to technology variables. In this context, the exclusion restrictions in the access of improved wheat variety is altitude. The access probit model result shows statistically significant and positive coefficient of altitude dummy (mid and high land = 1, 0 otherwise) at the 1 % level. That is expected. Wheat needs long growth period with humidity and it is suitable in the mid and high land agroecology. Therefore, households reside in the mid and high land area are associated with positive access to the improved wheat variety. Likewise, access to drought-tolerant *teff* model results depict that households reside in agroecology experienced with high rainfall variable (1= yes, 0 otherwise) in the previous three years rainy season are accessed to drought-tolerant *teff* and the correlation is significant at the 1% level. Households live in a community with irrigation has positive and significant correlation with access to cash crops.

Table 2: Correlated Random Effect probit models of access to technologies [a]

	Technology type		
Variables	HYV Wheat	Drought tolerant Teff	Cash crop
Altitude is mid and high land (1=yes)t (hr)[b]	3.281*** (0.329)		
Drought-exposed districts (high rainfall variability in the previous 3yrs, yes=1)[b]		0.538***(0.151)	
Interaction of Irrigation and community dummy			0.088***(0.016)
Head sex (Female =1)	0.091 (0.213)	0.034 (0.265)	0.077 (0.185)
Head age (Year)	0.005 (0.006)	-0.005 (0.009)	-0.007 (0.006)
Male adult (count)	0.024 (0.080)	-0.046 (0.094)	0.042 (0.063)
Female Adult (count)	0.047 (0.089)	-0.245** (0.105)	-0.023 (0.072)
Oxen_qty (count)	0.178 (0.113)	-0.184 (0.141)	-0.114 (0.091)
Tropical live stock (TLU)	0.095*** (0.032)	0.042 (0.044)	-0.020 (0.021)
Own land(*tsimdi*)	-0.032** (0.016)	0.001 (0.021)	0.025** (0.013)
Year dummy=2009/10	0.922***(0.139)	0.336** (0.165)	(0.110) (0.119)
Year dummy =2014/15	1.631***(0.183)	1.590***(0.219)	0.831***(0.123)
Constant	-4.403*** (0.585)	-0.099 (0.647)	1.450***(0.321)
Wald chi2(16)	163.21	102.20	123. 93
Pro >chi2	0.0000	0.0000	0.0000
Observation	1419	1419	1419

a.*The mean of time-varying variables is included as additional regressors in the correlated random effect model. The base year dummy is 2005/06.*
*b .These variables are instruments. The significance of the coefficients indicates that these variables are appropriate instruments for accessibility of these technologies. Number in parenthesis are standard errors. ***, **, & * refers to 1, 5, & 10 % significant level, respectively*.
Source: NMBU and MU household panel survey.

We also test whether smallholder farmers make demand decisions (adoption and extent of adoption of technology) simultaneously versus sequentially by examining how well the Tobit model fit to our data compared to the DH model. We conduct a likelihood ratio test and the test favors the DH model over Tobit (see the estimation method section). Moreover, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) estimates also substantiated the same DH model to be better fit the data. Henceforth, we base our discussion on the results of the DH model and states adoption of the technologies need to be estimated conditional on technology access threshold. This proposes that farmers in northern Ethiopia make technology demand decision sequentially that first deciding to adopt or not and then deciding how much to adopt.

The comprehensive results of the double hurdle models for adoption and intensity of adoption of the three technologies are presented in Table 3. The Wald chi_2 test for instance, ($\chi^2{}_{(34)}$= 57.62, Pr = 0.0000) in hurdle 1 for the improved wheat is significant at the 1 % level. This indicates that the subset of coefficients of the hurdle 1 model is jointly significant and that the explanatory power of the variables comprised in the model is satisfactory. Hence, the model fits the data nicely. We observe the same model fitness for the other technologies also. As we mentioned earlier, we use a control function approach to handle sample selection bias related to accessibility of the technologies left out in the second stage model. Altitude dummy, dummy high rainfall variability in the previous three years rainy season and interaction of community dummy with irrigation were instruments in the first stage and included in the second stage model to assess the statistical validity.

As shown the instruments are significant on the first stage model at the 1 % level (Table 2) while, insignificant in the standard test levels in the second stage mode (Table 3). Furthermore, the double hurdle mode results include the generalized residuals from the first stage access equations of these technologies along with the observed access variable. The inclusion of the residuals test and control for the endogeneity of access to the technologies. Standard errors are estimated using the bootstrap method to account for the two-stage estimation in this control function procedure.

Table 3: Double hurdle models of factors affecting demand for farm technologies (access to technology treated as endogenous variable)

Explanatory variables	Improved Wheat		Drought Tolerant *teff*	
	Hurdle 1 Probability of Adoption Probit estimator	Hurdle 2 Log of area planted upon adoption Truncation normal estimator	Hurdle 1 Probability of Adoption Probit estimator	Hurdle 2 Log of area planted upon adoption Truncation normal estimator
IV from first stage	0.312(0.367)	0.040 (0.256)	0.146 (0.228)	-0.123 (0.280)
Generalized error term	-1.841***(0.708)	-0.702 (0.542)	-0.918 (0.829)	-1.361* (0.825)
Access to technology	8.396(440.921)	0.000(0.040)	2.188** (0.910)	1.481 (0.977)
Head sex (Female=1)	-0.152(0.211)	0.167 (0.143)	-0.088 (0.239)	-0.266 (0.179)
Head age (year)	-0.015**(0.008)	-0.003 (0.005)	0.047 (0.029)	-0.073** (0.036)
Male adult (count)	0.071(0.082)	-0.047(0.054)	0.010 (0.086)	-0.132 (0.083)
Female Adult (count)	-0.023(0.088)	0.068 (0.057)	0.028 (0.099)	-0.005 (0.082)
Tropical Livestock (TLU)	-0.033(0.033)	0.029 (0.026)	0.016 (0.022)	0.027 (0.018)
Oxen_qty (count)	0.176*(0.105)	-0.069(0.081)	0.118 (0.104)	0.063 (0.095)
Mobile own (yes=1)	0.792***(0.192)	0.039 (0.135)	0.530* (0.271)	0.033 (0.112)
Own land (*tsimdi*)	-0.020(0.019)	0.022 (0.014)	0.000 (0.017)	0.009 (0.017)
Population density (Highy=1)	0.237**(0.119)	-0.054 (0.107)	0.033 (0.116)	-0.066 (0.111)
Access to irrigation (yes =1)	0.279**(0.123)	-0.06(0.078)	0.092 (0.129)	-0.089 (0.109)
Previous three years rainy season mean rainfall (mm)	-0.015**(0.006)	0.015 (0.009)	0.018***(0.004)	0.009 (0.007)
Previous three years rainy season rainfall variability (std dev) (mm)	0.006 (0.011)	0.004 0.011)	-0.017 (0.019)	-0.001 (0.026)

Table 3 Continue ….

Inverse Millis Ratio (IMR)	4.589 (5.309)	1.587 (3.396)	-6.247 (5.363)	7.591* (4.444)
Year dummy=2010	-0.326 (0.227)	-0.015 (0.178)	-0.467**(0.190)	0.071 (0.202)
Year dummy =2015	-0.832***(0.252)	-0.055 0.204)	-0.146 (0.209)	-0.126 (0.193)
Constant	-13.923 (331.4	0.395***(0.025)	-0.902 (4.038)	-7.731**(3.255)
Wald chie2 (34)	57.62	223.10	44.24	69.45
District fixed effect	yes	yes	yes	yes
Prob<chi2	0.0000	0.0000	0.0000	0.0000
AIC		224.36		147.4
BIC		339.64		127.86
Observation	1419	213	1419	108

*Note: Regressions include the mean of time-variant variables but not reported. Numbers in parenthesis are standard errors bootstrapped at 400 replications for the truncation estimation. ***, **, & *, refers to 1, 5, & 10 % level of significance, respectively.*

Source: NMBU and MU household panel survey.

Table 3: continue….

Explanatory variables	Cash crop	
	Hurdle 1 Probability of Adoption Probit estimator	Hurdle 2 Log of area planted upon adoption Truncation normal estimator
IV from first stage	0.018 (0.016)	0.016 (0.018)
Generalized error term	2.352** (1.121)	0.643 (1.219)
Access to technology	-1.357 (1.135)	-0.265 (1.358)
Head sex (Female=1)	0.184 (0.212)	-0.004 (0.231)
Head age (year)	-0.004 (0.007)	-0.009 (0.007)
Male adult (count)	0.010 (0.088)	0.033 (0.111)
Female Adult (count)	0.069 (0.086)	-0.038 (0.095)
Tropical Livestock (TLU)	0.021 (0.024)	-0.007 (0.022)
Oxen_qty (count)	-0.043 (0.098)	-0.100 (0.091)
Mobile own (yes=1)	0.129 (0.187)	0.199 (0.165)
Own land (*timid*i)	0.021 (0.016)	-0.012 (0.018)
Population density (high=1)	0.056 (0.124)	0.079 (0.151)
Access to irrigation (yes= 1)	0.950***(0.314)	-0.143 (0.460)
Previous three years rainy season mean rainfall (mm)	0.000 (0.009)	-0.038***(0.011)
Previous three years rainy season rainfall variability (std dev) (mm)	0.006 (0.015)	0.005 (0.023)
Inverse Millis Ratio(IMR)	2.145 (5.430)	1.058 (6.482)
Year dummy=2010	-0.010 (0.171)	0.407 (0.272)
Year dummy =2015	-0.292 (0.200)	0.676* (0.387)
Constant	-2.867 (4.173)	0.960 (5.199)
District fixed effect	yes	yes
Wald chie2 (34)	123.93	107.01

Prob<chi2	0.0000	0.0000
AIC		104.08
BIC		226
Observation	1419	222

*Note: Regressions include the mean of time-variant variables and district dummies but not reported. Numbers in parenthesis are standard errors bootstrapped at 400 replications for the truncation estimation. ***, **, & *, refer to 1, 5, & 10 % level of significance, respectively. Source: NMBU and MU household panel survey.*

The coefficient for the generalized residual is significant in the improved wheat, drought-tolerant *teff* and cash crop technologies, at the 1, 10 and 5% level, respectively. This implies that access to improved technology in the adoption model is potential endogenous as expected and, therefore, our approach works nicely. The coefficient of access to drought-tolerant *teff* is positive and significant in the probit component, while positive but insignificant in the linear component. This suggests that access to drought-tolerant *teff* affects positively the probability of adoption but not important in explaining the extent of adoption. This shows that access to drought-tolerant *teff* has a direct implication on *teff* production in areas with rainfall stress.

Examining the other variables in the double hurdle model typify the variation of adoption and intensity of adoption of the three technologies among farm households. The model allows different explaining power of variables in the probit and linear component implies that a variable with a significant effect in Hurdle 1 may not necessarily significant in Hurdle 2. This confirms our assumption that the probability and degree of adoption are performed in a separate process.

Citrus paribus, we observe a negative and statistical significance relation between household head's and the likelihood of improved wheat adoption and adoption intensity of drought-tolerant *teff* at the 5% level. The possible justification could be the risk aversion and a technology distrust behavior is widely associated with older headed households. This may also consider as a lifecycle hypothesis in which older people are less likely to adopt technologies that are embodied with capital goods or that require extra knowledge. We found similar results on the inverse relationship between head's age and adoption of improved Maize verities in Malawi Bezu et al. (2014) and improved Chickpea variety adoption in Ethiopia (Verkaart et al., 2017).

The presence of irrigation significantly and positively explains adoption of improved wheat, revealing a statistically significant effect at the 5 % level. As far as cash-crop is concerned, irrigation stimulates adoption significantly at the 1 % level. This suggests that promoting irrigation is an important factor in adoption of cash crop. Thus, we do not have solid evidence to reject the first hypothesis (**H_1**). This is because households in a semi-arid economy become more willing to adopt the new technology that makes better to handle the weather uncertainty they faced.

We wanted to test whether the households live in the community with high population density starts to make a visible positive impact on the adoption of improved wheat. Here, there are two competing arguments. On the one hand, the food security issue. In highly populated but land scarce economy like Ethiopia, there are more mouths that need continuous feeding. To do this, there should be land use intensification to increase productivity via adopting yield-enhancing crop varieties. Then, high population density is an important factor for adoption of farming technology. On the other hand, the prevalence of endowment heterogeneity affects the timing and magnitude of technology adoption. The intuitive is that, in the land-scarce economy, higher population density means lower per capita farm size and is a great barrier to adoption of technologies due to risk aversion behavior. Therefore, the impact of population density on technology adoption is an empirical issue. *Citrus paribus*, the double hurdle results did indicate a positive and significant effect of population density on adoption of improved wheat. This is consistent with the descriptive finding (Table 2) and we fail to reject the second hypothesis (**H_2**).

Our third hypothesis stated that adoption of drought-tolerant *teff* is more likely when rainfall is low. However, we found that high rainfall has a positive and significant effect on adoption of drought-tolerant *teff*. This indicates that although households with good rain in the previous three years rainy season were not accessed to drought-tolerant *teff*, but they adopted it. Thus, the result contradicts to the prior expectation that drought-tolerant *Teff* was anticipated to adopt in areas with minimum rainfall. Hence, we reject the third hypothesis (**H_3**).

5. Conclusion and policy implications

The implementation of Agricultural Development Led Industrialization (ADLI) policy of Ethiopia brought a significant reduction in the extent of poverty at country level. As part of this national policy, extensive rural development packages in response to food security, climate change and rural transformation were introduced since the mid of 1990s. The purpose of this study is to assess the pattern and determinants of demand decisions (probability and extent) of farm technologies in a semi-arid region of northern Ethiopia. Using unbalanced household panel data collected in 2005/06, 2009/10 & 2014/15, we estimate the demand decision of the three technologies using double hurdle model with correlated random effects estimator. A control function approach is applied to account for the endogeneity of access to technology in the adoption models. The data showed that several households were constrained from adopting the technologies and thus, adoption rate of these technologies is relatively low.

The access estimation results show that the district or community level variables appear to have a significant effect on the supply-side of the three technologies as expected. We include the residuals from the first stage access estimations in the adoption models. The significance of the residual coefficients in the adoption models revealed that access variable is endogenous and fixes the problem of endogeneity. We include the exclusion restriction variables in the second stage model to assess the statistical validity and coefficients are strongly insignificant and thus, the control function approach works nicely. The DH results show that adoption of improved wheat is positively and significantly explained by high population density, suggest the food security implication of the crop. The result also shows a positive and significant relationship between young headed households and adoption probability of improved wheat and adoption level of drought-tolerant *teff*. The effect of irrigation on adoption of cash crop is positive and significant, suggest that public investment in irrigation stimulates the production of high-value products in a climate-changing environment.

For policy implication, increase access to drought-tolerant *teff* and promoting irrigation appears to be a major adoption stimulants of drought-resistant *teff* and cash crop in a climate risk environment.

Endnotes

[1]According to the discussion with the experts of the agricultural research institute of Tigrai, they used historical rainfall data of agro-ecologies (districts). Agro ecologies with a shortfall in rain in the previous production years used as a criteria for distributing the Drought tolerant *teff*. We compute the mean of rainfall variability of the previous three years rainy season of each district and used as a yardstick to identify a district with lower than the mean value is with low rainfall variability while above the mean is a district with high rainfall variability (drought exposed district).

[2] 1 = refers improved Wheat, 2= Drought tolerant *Teff* and 3 = Cash crops. We used the same notations throughout the paper.

[3] The probability of a positive value (y > 0) and the actual value (y = 0), are estimated in a single equation and lacks to accommodate two nature equation suggest that the directional effect of the explanatory variables on the probability and intensity of adoption of the technology is identical.

[3] Since the bootstrapped models used to correct the standard errors for possible heteroscedasticity in Stata 13 do not allow with Inverse probability Weight (IPW), we use IMR to correct for attrition biased.

[4] The benchmark for sorting population density of the study region is 200 persons/km2. Above this number noted as high population density area while, below this number refers low population density area. See Fitsum (2002) at https://www.researchgate.net/publication/35211639.

[5] Distance to marketplace also defined as household live in areas above an hour walking time to reach the market palace refers long distance whereas, below an hour is short distance. See Fitsum (2002) at https://www.researchgate.net/publication/35211639

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Appendix

Annex table 1**:** Probit estimation of attrition biased for panel data (Attrite=1)

Explanatory variables	Coeffi.	Std.error
Head's sex (Female=1)	0.011	(0.162)
Head's age (year)	-0.001	(0.005)
Male adult (count)	-0.148**	(0.070)
Female Adult (count)	-0.134	(0.082)
Oxen own (count)	0.153	(0.188)
Tropical Livestock (TLU)	-0.063	(0.040)
Land holding (*tsimdi*)	-0.017	(0.019)
Distance to district office (hr)	-0.136**	(0.054)
Distance to nearby market (hr)	-0.074	(0.082)
Distance to farmer's training center (hr)	0.109	(0.077)
Constant	-1.006***	(0.351)
Prob >chi2	0.0000	
Number of observation	1419	

***, **,* are 1, 5, & 10 % level of significance, respectively. Numbers in parenthesis are robust standard errors. Source: NMBU and MU household panel survey.