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## Article

# Determinants of adopting improved bread wheat varieties in Arsi Highland, Oromia Region, Ethiopia: A Double-hurdle approach

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## ECONOMETRICS | RESEARCH ARTICLE

# Determinants of adopting improved bread wheat varieties in Arsi Highland, Oromia Region, Ethiopia: A Double-Hurdle Approach

Bedilu Demissie Zeleke<sup>1\*</sup>, Adem K. Geleto<sup>1</sup>, Hussien H. Komicha<sup>2</sup> and Sisay Asefa<sup>3</sup>

**Abstract:** The improvement of agricultural productivity using technology is an important avenue for increasing output and reducing poverty in sub-Saharan countries. However, the low adoption of high yield varieties has been identified as one of the main reasons for low productivity in sub-Saharan Africa. Consequently, the study examined the effect of demographic, socioeconomic and institutional factors affecting adoption and adoption-intensity of improved wheat varieties (IWVs), using data obtained from randomly selected farm households in the Arsi Highland of Ethiopia. We estimated a Double hurdle model to analyze the determinants of the intensity of IWVs adoption, as adoption and use intensity were two independent decisions influenced by different factors. The results also show that Double hurdle model is more appropriate than the Tobit model. Empirical estimates of the first hurdle reveal that wheat farming experience, distance to cooperatives, renting a tractor and combine harvester, Urea application, and net income from the wheat grain sale all significantly increased the likelihood of IWVs adoption. Estimates of the second hurdle revealed that the

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### PUBLIC INTEREST STATEMENT

Over the last decades, International Agricultural Research Centers have been collaborating with the Ethiopian Institute of Agricultural Research in the development and dissemination of improved bread wheat varieties for cultivation by farmers in Ethiopia. However, unlike many Green Revolution-type systems whose success have been manifested in the widespread adoption of high yield varieties across millions of hectares, the adoption of improved varieties has not been fully embraced by the smallholder farmers in Ethiopia. Hence, the study aims at the investigation of the determinants of adoption and adoption intensity of improved wheat varieties in Arsi Highland of Ethiopia. Empirical findings confirm that access to improved varieties, access to farm machinery, row planting, Urea application, and net income from wheat grain significantly influence the adoption and the adoption intensity of improved varieties. Cognizant policy interventions that are informed about such factors are required to accelerate adoption and adoption-intensity of improved wheat varieties in Ethiopia, to realize a Green Revolution.

decision to use the optimal intensity of IWVs by smallholder farmers was influenced by seed availability, row planting, and distance to cooperative all significantly and positively. The intensity of adoption was also found to be negatively related to the proportion of farmland allotted for wheat production. Accordingly, policies and interventions that are informed about such factors are required to accelerate the adoption and adoption-intensity of IWVs in Ethiopia to realize a wheat Green Revolution and fight food insecurity in a sustainable manner.

**Subjects:** Agricultural Technology; Business and Economics; Development Studies; Seed Industry & Finance

**Keywords:** Adoption; improved wheat varieties; tobit model; double hurdle model; Ethiopia

### 1. Introduction

Large econometric literature (Dixon et al., 2006; Irz et al., 2001; Kassie et al., 2011; Shiferaw et al., 2008) find high poverty reduction elasticities for agricultural productivity growth, through generating high incomes for the farmer, reducing food price, and generating more tax<sup>1</sup> revenues. For instance, it has been estimated that each 1% increase in crop productivity reduces the number of poor people by 0.48% in Asia (Thirtle et al., 2003). In Africa, each dollar investment in the agricultural sector has a multiplier effect ranging from 1.5 to 2.7% (UNECA, 2009). In sub-Saharan Africa, the contribution of agriculture to poverty reduction was estimated to be 4.25 times the contribution of equivalent investment in the service sector (Christiaensen et al., 2011), and every 1% increase in wheat productivity reduced the extent of poverty by 0.5–1.0% (World Bank, 2005).

Even though the adoption of improved technologies for staple crop production is fundamental to the transformation of rural Africa, thereby to achieve food security, reduce poverty (Teklewold et al., 2013), and improve the well-being of millions of African poor households. Unlike many Green Revolution-type systems whose success has been manifested in the widespread adoption of high yield plant varieties and associated packages across millions of hectares, adoption of improved technology has not been fully embraced by the smallholders in Africa (Dethier & Effenberger, 2012; Langyintuo & Mulugetta, 2008; Moser & Barrett, 2003; Spielman et al., 2010). This is because of the lack of correctly identifying the factors that prevent substance farmers from adopting improved, high yielding crop varieties in the continent (Langyintuo & Mulugetta, 2008).

Despite its vast agricultural potential, Africa's low-income countries have remained a net importer of agricultural products in the last decades, especially cereals (Rakotoarisoa et al., 2012) implying that cereal import has been increasingly important in ensuring food security. For instance, in 2010 alone, sub-Saharan Africa countries imported a total of 18.2 million MT of wheat, valued at nearly US\$ 5.1 billion (Rakotoarisoa et al., 2012). Most drivers of wheat consumption in sub-Saharan Africa include an increase in the country's GDP, growing populations, and women's participation in the labor force and government policy<sup>2</sup> (Mason et al., 2015).

Hence, it is sine qua non to improve wheat production and productivity in Africa through the development, dissemination, and adoption of better responsive high-yielding wheat varieties in order to promote African Green Revolution. For instance, the semi-dwarf wheat varieties were the backbone of the overwhelming success of the Indian Green Revolution during the late-1960s and early-1970s (Singh, 1993). The varieties were more resistant to both rust diseases and lodging. Moreover, the varieties were attractive to small farmers because they were in general risk-reducing and scale-neutral (Smale et al., 2008). However, there is a debate that the Green Revolution technology being capital-intensive suits rich farmers much better than small-scale and marginal farmers, and created new kinds of inequalities, and at times exacerbated the old ones (Dhanagare, 1988; Patel, 2013).

Wheat is among the most important crops grown by smallholder farmers in the Ethiopian highlands, at altitudes ranging from 1500 to 3000 m.a.s.l. Even though wheat ranks fourth in total cereal production next to maize, sorghum, and *teff* (CSA, 2015), the country falls short of being self-sufficient in wheat production and continually remains a net importer (FAO, 2015), especially, in a drought year when food deficits are large. To overcome this problem, one of the key strategies pursued by the Government of Ethiopia was to expand the availability of high-yield improved wheat varieties that are also resistant to common insects, pests, and diseases for farmers.

Over the last decades, International Agricultural Research Centers have been collaborating with Ethiopian Institute of Agricultural Research (EIAR) in the development and dissemination of improved bread wheat varieties with associated technological packages. Despite strenuous government and nongovernment efforts, farmers' adoption rates of these technologies have remained low (Asrat et al., 2010; Solomon et al., 2014; Tesfaye et al., 2016; Yirga et al., 2013) and have not been analyzed systematically (Ali et al., 2015; Shiferaw et al., 2014; Yirga et al., 2013). Although the literature on the adoption of crop technologies is large, most studies have looked at other crops such as maize (Danso-abbeam et al., 2018; Feleke & Zegeye, 2006), rice (Fisher et al., 2012; Ghimire et al., 2015; Mariano et al., 2012), pigeonpea (Asfaw et al., 2011), groundnut (Ahmed et al., 2016), and sorghum (Wubeneh & Sanders, 2006) and much less is known about the factors affecting adoption probability and intensity of IWVs in the study area, particularly at the household level.

Furthermore, there is relatively very scant recent information on the adoption of improved wheat technology in the study region. The studies of Tesfaye et al. (2016), Shiferaw et al. (2014), Solomon et al. (2014), Yirga et al. (2013), and Kotu et al. (2000) are few of the latest addition to improved wheat varieties adoption studies in the country. For instance, Shiferaw et al. (2014) suggest that farmers fail to adopt improved wheat varieties either because they lack variety information or because they are access constrained (despite wanting to) or because of lack of economic incentives (such as attractive price) or because they cannot adopt due to high input cost. Thus, this analysis has dealt more with barriers to technological adoption.

Whereas other studies have given more consideration to why farmers adopt when others do not. Solomon et al. (2014) found gender, participation in field day, access to weather roads, and active labor force as important factors associated with improved wheat varieties adoption. Yirga et al. (2013), and Kotu et al. (2000) showed that access to credit, education, as well as labor saving technologies are the major determinants affecting improved wheat varieties adoption in Ethiopia. Zegeye et al. (2001) in their research on the adoption of improved varieties in Northwestern Ethiopia found that farm size, on-farm demonstrations participation, access to credit, education level and extension contact are the main determinants of improved wheat varieties adoption by farmers. However, aside from analyzing the adoption levels of improved wheat varieties, in these studies, researchers had been confined to examine just a few numbers of explanatory variables due to limited data. Thus, leaving gaps in the literature that this study intends to fill. Unlike the previous adoption studies, we include access to improved varieties as a covariate in the adoption model as seed access constraint limit the quick spread of the technology to wider areas (Shiferaw et al., 2008). In addition, we include variables such as farm machine rent (such as tractor and combine harvester), row planting, distance to cooperative, non-wheat income and net return. The parsimonious model<sup>3</sup> result using only the additional sets of explanatory variables to those commonly used in the existing adoption literature demonstrates that IWVs availability in local store, renting farm machinery, and row planting significantly and positively affects both adoption and adoption intensity of IWVs in Arsi Highland of Ethiopia.

Most importantly, in contrast to most improved wheat varieties adoption studies in Ethiopia that adopt categorical dependent variables qualitative choice models of adoption either Probit, Logit or Tobit (Kotu et al., 2000; Tesfaye et al., 2016; Yirga et al., 2013; Zegeye et al., 2001), we employ a Double Hurdle (DH) model. This model, originally due to Cragg (1971), has been

extensively applied in a variety of area, including consumption (Aristei & Pieroni, 2008; Gao et al., 1995; Rossini et al., 2015; Yen & Huang, 1996; Yen & Su, 1995), conservation agriculture (Martínez-Espiñeira, 2006), gambling behavior (Humphreys et al., 2010) and technology adoption (Aryal et al., 2018; Bokusheva et al., 2012; Croppenstedt et al., 2003; Mal et al., 2012). However, the model has been rarely used in the area of improved wheat varieties adoption, exceptions would be Solomon et al. (2014).

For the empirical analysis, DH model proposed by Cragg (1971) was chosen to identify the factors affecting the adoption and intensity of IWVs use by farm households. First, we tested Tobit model versus the DH models for our data. The Tobit estimator proposed by Tobin (1958) assumes that the decision to adoption and the extent of adoption are determined by the same factors and in the same process. Hence, in the Tobit model, a variable that increases or decreases the probability of adoption also increases or decreases the intensity of use. Given the shortcomings of Tobit procedure as a corner solution, DH model is used in the current study to examine the probability and extent of IWVs adoption. The DH model allows more flexibility assuming that the decision to adopt and intensity of use of IWVs may be influenced by different variables. In the Cragg (1971) model, for the first hurdle corresponds to household choice of whether to adopt or not, we estimate a Probit model and for the second stage corresponds to the extent of adoption, we estimate a truncate regression.

For comparison, we applied the likelihood ratio test because the Cragg (1971) model nests the censored Tobin (1958) model. In the case of improved wheat varieties adoption, the adoption specification likelihood ratio test leads us to reject the Tobit model in favor of the more flexible DH model. Hence, this study provides further empirical evidence that the Tobit model may in some case, be an inappropriate representation of adoption. This study is aimed at analyzing the socioeconomic and institutional determinants of adoption and intensity of use of IWVs to provide information for consortium of sub-Saharan African Green Revolution partners comprised of sub-Saharan Africa governments, philanthropic donors, multilateral institutions and the private sectors. To improve the efficiency of agricultural research, extension services, and design better adoption programs that will address factors determining the adoption of IWVs at the national and sub-Saharan Africa level.

We hypothesise that the socioeconomic, demographic, and institutional characteristics of the farm households have no influence on their adoption of IWVs. The remainder of the article is organized as follows. A brief description of the data and IWVs adoption decision models to assess the determinants of adoption is presented in the next section. In section 3, findings from the econometric models are presented. Finally, the concluding section highlights the key findings and implications for policy to enhance IWVs adoption.

## 2. Material and method

### 2.1. Data sources and methods of collection

The survey was conducted in Arsi zone, Oromia Regional State of Ethiopia. For the study, both primary and secondary data were collected. The field survey was conducted during 2014/2015 to collect qualitative and quantitative data, from primary and secondary sources. Primary data were collected from the bread wheat-based farm households (HH)<sup>4</sup> by using a structured questionnaire and employing trained enumerators under the supervision of the researcher. The questionnaire was pretested and amended based on the feedback obtained to ensure validity and reliability. Secondary data were collected from Central Statistical Agency (CSA), Food Security Research Project, Office of Agriculture and Rural Development, FAO, International Research Institution Report, and On-line publications.

## 2.2. Sampling procedure

A multi-stage random sampling technique was employed to collect data. The first stage involves the purposive selection of districts noted for bread wheat production, based on information obtained from Arsi Zone Agricultural and Rural Development Office, based on the information wheat-based farming system area which includes Digalu and Tijo, Lemuna Bilbilo, Munessa, Lode Hetosa, Hetosa, Tiyo, Shirka, and Arsi Robe.

The second stage involved the purposive selection of two high bread wheat-producing *kebeles*<sup>5</sup> Gonde Finchama and Gadissa Derara from Hetosa and Lemuna Bilbilo districts, respectively. Finally, the list of households growing bread wheat was obtained from Agricultural and Rural Development office records for the selected “*Kebeles*” and finally 140 farm HHs were selected based on the proportional random sampling method. Data collected include the socioeconomic and institutional variables such as gender, schooling, marital status, experience, farm size, wheat grain price, seed availability, row planting, receive training, extension contact, take credit, distance to cooperative, rent machinery, DAP application, Urea application, net return from the wheat sale and household size to provide the most up-to-date information on improved bread wheat technology adoption to policymakers and researchers.

These variables are defined in [Table 1](#) along with their expected signs on their coefficients. These sets of variables were tested for collinearity. The estimated maximum tolerance level was 0.6717 between the variables net income from wheat and total wheat land planted; we can conclude that multicollinearity is not a serious problem. As a tolerance level of close to 1 means, there is little multicollinearity, whereas a value close to zero suggests that multicollinearity may not be a threat. While we seek to minimize concerns about multicollinearity, we cannot eliminate all potential concerns about endogeneity. Hence, to attenuate such endogeneity concerns, we also estimate a more parsimonious model (see [Appendix Table A1](#)) that only contains variables that are arguably endogenous to the probability or intensity of IWVs adoption using the Tobit and DH model. For instance, net income from the wheat grain sale could be endogenous to the probability or intensity of IWVs adoption as more income facilitates access to new technology. This parsimonious model, also presented in [Appendix Table A1](#), is used for a robustness analysis of the additional set of explanatory variables to those commonly used in the existing adoption literature (including access to improved varieties, farm machine rent, row planting, distance to cooperative and net return from wheat sell).<sup>6</sup>

## 2.3. Econometric specification

Unlike the typical binary dependent variable models such as Logit and Probit models applied for studying the dichotomous issue of the probability of adopting new agricultural technology or not like the case of Ahmed (2015), Finger and El Benni (2013), Mariano et al. (2012), and Wafula et al. (2016) our objective goes beyond that and helps in understanding the intensity of adoption of improved bread wheat varieties. Consequently, we applied the DH model developed by Cragg (1971) for this purpose.

Several studies used the DH approach to study adoption of a given technology such as Asfaw et al. (2011), Legese et al. (2009), and Shiferaw et al. (2008) as it has an advantage over the dichotomous model by permitting to determine the intensity of use of agricultural technology once adoption has taken place. This study uses the DH model which is a parametric generation of the Tobin (1958) model due to the presumption that factors that influence the household’s decision to the adoption of bread wheat varieties are different from those that affect the extent of adoption (Greene, 2013).

The limitation with the Tobin (1958) model is that it allows one type of zero observation, called a *corner solution* since it is based on the assumption that zero observations are due to respondents’ non-participation decision, which arise from other factors such as economic, institutional and demographic characteristics (Martínez-Espiñeira, 2006). For instance, under Tobit model farm households with positive desire to adopt a given agricultural technology have unconditional access to the new technology; however, in most of the sub-Saharan countries like Ethiopia where seed supply system is



**Table 1. Definition of variables and hypothesized effects for IWWs adoption model**

<b>Variables</b>	<b>Definition</b>	<b>Hypothesis associate with the explanatory variable</b>
<b>Dependent variable</b>		
IWWs adoption	1 = farmer plants IWWs, 0 = otherwise	
IWWs area	Area allotted for IWWs	
<b>Independent variable</b>		
Gender	1 = HH head is male; 0 = otherwise	Male-headed HH are expected to have higher adoption probability (e.g., Dixon et al., 2006) & intensity of use.
Schooling	Years of formal education by the HH head	Better educated farmers are expected to have higher adoption probabilities (e.g., Ahmed, 2015; Feleke & Zegeye, 2006) & intensity (e.g., Nkonya et al., 1997).
Marital Status	1 = HH head is married; 0 = otherwise	Married households are expected to have higher adoption probability & intensity of IWWs.
Experience	Years of wheat farming experience of the HH head	Farmers with better farming experience are expected to have higher adoption probabilities & use intensity (e.g., Mariano et al., 2012).
Farm size	Total wheat area planted in ha	Large area under wheat tend to have higher adoption probabilities (e.g., Ransom et al., 2003) & intensity (e.g., B. A. Shiferaw et al., 2008)
Wheat grain price	Market price of wheat grain in ETB <sup>10</sup> /kg	Higher wheat grain price increase adoption probability & intensity.
Seed availability	1 = Availability of IWWs in local store; 0 = otherwise	Availability of IWWs in local store increase adoption probabilities & intensity (e.g., Ghimire et al., 2015; Ransom et al., 2003)
Row planting	1 = Farmer sow IWWs by row planting; 0 = otherwise	Planting IWWs by row is expected to have higher adoption probability & intensity of use (e.g., Abay et al., 2016).
Receive training	1 = Farmer received training; 0 = otherwise	Farmers who receive training on IWWs management have higher adoption probability (e.g., Mariano et al., 2012) & intensity.
Extension contact	1 = Farmer have access to advise from extension agents; 0 = otherwise	Farmers who have access to extension service have higher adoption probability & intensity of use (e.g., Mariano et al., 2012; Ransom et al., 2003).
Take credit	1 = Farmer received any credit; 0 = otherwise	Farmers who have access to credit are more likely to adopt IWWs than constraint farmers (e.g., Dixon et al., 2006; Feleke & Zegeye, 2006)
Distance to cooperative	Distance to the nearest cooperative in kilometers	The distance of the farm to the nearest input supplier cooperative is expected to favor technological adoption (e.g., Mariano et al., 2012).
Rent machinery	1 = Farmer rent any tractor or harvester; 0 = otherwise	Renting farm machinery tend to have higher adoption probability (e.g., Mariano et al., 2012; Wafula et al., 2016) & use intensity as machinery are complementary farm asset.
DAP application	DAP application/ha in kg	DAP application increase adoption probabilities & use intensity (e.g., Nkonya et al., 1997)

(Continued)

**Table 1. (Continued)**

<b>Variables</b>	<b>Definition</b>	<b>Hypothesis associate with the explanatory variable</b>
Urea application	Urea application/ha in kg	Urea use increases adoption probability & use intensity (e.g., Nkonya et al., 1997).
Net return	Net return from wheat sales in ETB	High net return from IWVs cultivation favor technology adoption (e.g., Feder & Umlai, 1993).
Family size	Number of family members	Large HHs adopt new technologies more often than small HHs (e.g., Abdulai et al., 2008; Mariano et al., 2012) due to the availability of more labor to use the new technology.
Non-wheat income	Total income from source other than wheat farming in ETB	Farmers who have high non-wheat income are more likely to adopt seed technology than those who do not (Mariano et al., 2012).

underdeveloped, this is often untenable as farmers wanting to plant new varieties often face seed access constraints (Shiferaw et al., 2008; Asfaw et al., 2011) and the Tobit model has no mechanism to distinguish such farm households from those with unconstrained ones and consider a zero amount of land under agricultural technology; hence, yield inconsistency parameter estimation (Croppenstedt et al., 2003). The other limitation to the Tobit model is that the probability of a positive value and the actual value, are determined by the same parameters (Burke, 2009); however, the DH model allows for the possibility that participation and intensity decisions are affected by a different set of parameters.

Although Heckman's (1979) model addresses the problem associated with the zero observations by considering the respondents' self-selection, which means that all the zero comes from the respondents' deliberate choices. This model differs from the Tobit model by assuming that sets of different variables could be used in the two-step estimations; however, this makes the Heckman model similar to the DH model. Also the Heckman and DH model are similar in identifying the rules governing the discrete outcomes, which are determined by the selection and level of use decisions. However, the Heckman model assumes that there will be no zero observations in the second stage once the first-stage selection is passed. In contrast, the DH model considers the possibility of zero outcomes in the second-hurdle which arise from the individuals' deliberate choices or random circumstance. However, if sample selection bias is an issue, the Heckman model<sup>7</sup> is favored over the DH model, but the sample-selection bias is not an issue in this study as Mills ratio is insignificant, thus the Cragg DH model is optimal.

The DH model is a parametric generation of the Tobit model, whereby two separate stochastic processes determine the decision to adopt and the level of adoption of technology. In our case, the two decisions are the decision to adopt and the decision about the intensity of adoption.<sup>8</sup> The first decision variable ( $y$ ) takes the value 1 for farmers who have adopted IWVs and 0 otherwise. However, the expected utility of adopting a technology ( $y_i^*$ ) is a latent variable.<sup>9</sup> Hence, the first decision (adoption hurdle) of the households is formulated as:

$$y_i^* = x_i' \alpha + \varepsilon_i$$

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if otherwise} \end{cases} \quad (1)$$

where  $y_i^*$  is the latent adoption variable that takes the value of 1 if a household grew IWVs and 0 otherwise,  $x_i$  is a vector of household characteristics and  $\alpha$  is a vector of parameters. Not all improved bread wheat adopters grow IWVs at the same level of intensity. As stated previously, the intensity of adoption is measured in terms of the proportion of farm areas allocated to IWVs. The intensity of adoption (intensity hurdle) of IWVs is given as in a Tobit like function:

$$t_i^* = z_i' \beta + \mu_i$$

$$t_i = \begin{cases} t_i^* = z_i' \beta + \mu_i & \text{if } t_i^* > 0 \text{ and } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where  $t_i$  is the observed response on how much land one allocated to IWVs,  $z$  is a vector of the household characteristics and  $\beta$  is a vector of parameters. Sampled households grow a wide range of bread wheat cultivars, including local seeds. Out of the total respondents, 33.9% sowed the most popular variety Digalu, 30.4% sowed more than one variety but less than three cultivars to avoid the risk associated with improved seed attributes subject to maximizing crop harvest. While the remaining 16.5% sowed only Kubsu, 10% sowed only Kakaba, 7.6% sowed only Danda'a, 1.3%

sowed only Shorma and 1.3% sowed Pavan. According to the respondents, Kubsu and Galema were preferred for their high yield, but both varieties are susceptible to yellow rust. Digalu variety is resistant to stem rust comparatively from Kubsu and Galema but now it has become susceptible even including Danda'a and Kakaba (Alemu et al., 2018).

The decision of whether or not to adopt IWVs and how much land to allocate to IWVs can be jointly modeled if they are made simultaneously by the farmers; independently, if they are made separately; or sequentially, if one decision is made first and affects the other one (this is the *dominance* model) (Martínez-Espiñeira, 2006). If the independence model applies, the error terms are distributed as follows:  $\varepsilon_i \sim N(0, 1)$  and  $u_i \sim N(0, \delta^2)$ . If both decisions are made jointly (the Dependent DH) the error term can be defined as  $(\varepsilon_i u_i) \sim BVN(0, Y)$  where

$$Y = \begin{bmatrix} 1 & \rho\delta \\ \rho\delta & \delta^2 \end{bmatrix}$$

The model is said to be a dependent model if there is a relationship between the decision to adopt and the intensity of adoption. This relationship can be expressed as follows:

$$\rho = \frac{\text{COV}(\varepsilon_i u_i)}{\sqrt{\text{var}(\varepsilon_i)\text{var}(u_i)}}$$

If  $\rho = 0$  and there is dominance (the zeros are only associated to non-participation, not standard corner solutions), then the model decomposes into a Probit for participation and standard OLS for  $Y$ .

Following Smith and Brame (2003) we assume that the error terms, and  $\varepsilon_i$  and  $u_i$  are independently and normally distributed and thus we have the following expression:

$$\begin{pmatrix} \varepsilon_i \\ u_i \end{pmatrix} \sim N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & \delta^2 \end{pmatrix} \right]$$

And finally, the observed variable in a DH model is  $t_i = y_i t_i^*$  and the log-likelihood function for the DH model is:

$$\text{LogL} = \sum_0 \ln \left[ 1 - \Phi(x_i' \alpha) \Phi \left( \frac{z_i'}{\delta} \right) \right] + \sum_+ \ln \left[ \Phi(z_i' \alpha) \frac{1}{\delta} \varphi \left( \frac{y_i - x_i' \beta}{\delta} \right) \right] \quad (3)$$

Thus, in this study, we estimate the decision to adopt and the extent of adoption using a DH model. A simple specification test that evaluates for Cragg's DH-model against the Tobit model can be used using the same set of explanatory variables, through a comparison of the log-likelihood function values of the Tobit, Probit and Truncated models estimated. Assuming that the same set of independent variables appears in all the three equations, the following value  $\lambda$  will be distributed as a chi-square random variable with degrees of freedom equal to the number of explanatory variables under the null hypothesis that the Tobit model is the correct (Goodwin et al., 1993):

$$\lambda = -2 (f_{\text{Tobit}} - f_{\text{Probit}} - f_{\text{Truncated}}) \quad (4)$$

where the  $f_i$ 's represent the respective estimated log-likelihood function values.

Studies on factors influencing the adoption and intensity of use of agricultural technologies such as (B. A. Shiferaw et al., 2008; Asfaw et al., 2011; Finger & El Benni, 2013; Mariano et al., 2012; Nkonya et al., 1997; Ransom et al., 2003) have pointed out the influence of the following factors for the adoption decision and use intensity: socioeconomic (e.g., age of head, household size, sex of

head, literacy, household asset, wealth and off-farm activities etc.), farm characteristics (such as fertilizer use, oxen per capital, farm size and land tenure, distance from market, distance to nearest agricultural office etc.), technology characteristics (e.g., grain yield, drought resistance, disease tolerance, etc.), institutional environment (e.g., contact with extension agent, membership of a social group, farm experience, rural finance through credit, access to improved technology etc.), market attributes (e.g., grain color, grain size, test, price etc.) and environmental factors (such as demographic location etc.). (See [Table 1](#) for hypotheses associated with these variables). Moreover, risk attitudes, farmers’ environmental preferences as well as attitudes and behavioral norms have been indicated as potentially important.

### 3. Results and discussion

#### 3.1. Socioeconomic characteristics of bread wheat farming households

In this subsection, the socioeconomic and institutional characteristics of the sample households will be presented comparatively for adopters and non-adopters of IWVs. Some of these characteristics are the explanatory variables of the estimated models we present further on. [Table 2](#) presents the t-value comparison of means of selected variables by adoption status for the surveyed sampled households. The dataset contains 140 farm households and of these, about 55% were adopters, that is, planted at least one of the IWVs on their farmland during 2014/15 cropping season. The analysis of the data shows that there is no significant difference between the mean age of adopter ( $44 \pm 10.75$ ) and non-adopters ( $45.19 \pm 10.77$ ) although the group varies significantly ( $p < 0.05$ ) in terms of their education level, suggesting the importance of education for the adoption of new technologies. No significant difference is observable between mean farm experience among adopter ( $25 \pm 11.29$ ) and non-adopter ( $25.79 \pm 10.93$ ). The area planted of IWVs is about ( $2.26 \pm 1.46$ ) and  $2.23 \pm 1.75$ ha for adopter and non-adopter, respectively.

IWVs had superior yields over the local landraces, at a significance level of 1%. The average yield from the local varieties was about  $3.04 \pm 0.5$ ton/ha, which compares with  $3.85 \pm 0.89$ ton/ha for

Table 2. Mean of farm and farmers’ characteristics of adopter and non-adopter				
Variable	Unit	Adopter (N = 77)	Non-adopter (N = 63)	t-value
<b>Dependent variables</b>				
IWVs used per ha	tons	8.95 (6.17)	0.00	
Adoption	1/0	1.00	0.00	
<b>Dependent variables</b>				
Age	years	44.01(10.75)	45.19(10.77)	-0.64
Schooling	years	3.29 (3.29)	2.49 (2.49)	1.14**
Experience	years	25.12 (11.27)	25.79 (10.93)	-0.36
Farm size	ha	2.26 (1.46)	2.23 (1.75)	0.12
Wheat production	tons	3.85 (8.9)	3.04 (5.0)	6.44***
Price of wheat grain	birr	665.13 (91.12)	661.48 (53.74)	0.26
Distance to cooperative	km	4.83 (3.52)	4.23 (2.72)	1.10*
Rental cost of machine	birr	3241.9 (43,334.7)	2330 (3702.19)	1.32
DAP application	Kg	101.76 (106.9)	112.6 (122.3)	-0.56
Urea application	Kg	19.4 (29.2)	7.9 (15.4)	2.83***
Net income	birr	20,175 (28,504)	14,686.5 (17,065.9)	1.34
Family size	no	7.09 (2.56)	7.63 (3.01)	-1.15
Non-wheat income	birr	7188.25 (13,861)	4687.7 (8574.5)	1.23

Source: Own survey, 2014/15

improved varieties. This represents an average yield gain of 79% in switching to IWVs. Furthermore, IWVs adopter ( $665.13 \pm 91.12$ ) sold their wheat produce at a higher price than non-adopters ( $661 \pm 53.74$ ) per quintal, because IWVs have a higher market preference than the local seed by consumers. The average distance to input supplier cooperative where input is purchased was considerably greater for an adopter ( $4.83 \pm 3.52$  km) of IWVs as compared to non-adopter ( $4.23 \pm 2.72$  km) at a significance level of 1%. Since this distance was based on farmers' responses and not on direct measurement, it may not be very accurate. However, it is a sine qua non for comparing the relative distance between adopters and non-adopters.

All farmers surveyed in both districts applied DAP fertilizer to the optimal amount, the mean application was  $101.76 \pm 106.9$  kg/ha for adopter and  $112.6 \pm 122.3$  kg/ha for non-adopters, and did not differ significantly. However, the application of Urea fertilizer per ha for both adopter ( $19.4 \pm 29.2$  kg) and non-adopter ( $7.9 \pm 15.4$  kg) was very low relative to the recommended rate, and it was statistically significant at 1% level, supporting the importance of Urea application for IWVs adoption. No significant differences between adopters and non-adopters are indicated for the rental cost of farm machines (such as tractors and harvester), net income from wheat grain sell, family size, and income other than wheat.

Sampled respondents were composed of both male and female households (Table 3). The majority (79.3) were male-headed while 20.7% were female-headed. The female-headed households' proportion for adopters and non-adopters were 15.7% and 5%, respectively. The variable is statistically significant ( $p < 0.1$ ) for adopters and non-adopters. In many cases, data are collected on whether a given technology has been adopted or not, without considering farm households are seed access constrained or not.

However, the study revealed that the availability of IWVs at the local input supplier cooperative was highly significant ( $p < 0.01$ ) between adopter and non-adopter. Revealing that sampled households who have access to IWVs tend to adopt the technology more than those who are access constrained. Even though row planting is one of the technology package introduced by Ethiopian Agricultural

**Table 3. Socioeconomic characteristics of the respondents for discrete variables in %**

Variable		Adopter (N = 77) %	Non-adopter (N = 63) %	Chi-square
Gender	Female	15.7	5	6.432*
	Male	39.3	40	
Marital Status	Married	50.7	43.6	1.371
	Other wise	4.3	1.4	
IWVs availability	Yes	19.3	1.4	21.456***
	No	35.7	43.6	
Row planting	Yes	5	13.6	4.216**
	No	40	41.4	
Received Training	Yes	34.3	15.7	10.418***
	No	20.7	29.3	
Extension visits	Yes	50.7	35	5.892***
	No	4.3	10	
Credit	Yes	7.9	7.9	0.264
	No	47.1	37.1	
Rent farm machine	Yes	37.9	32.6	3.957**
	No	17.7	21.4	

Source: Own survey, 2014/15

Transformation Agency (ATA) Wheat Initiative, few of the sampled respondents (18.6%) used a reduced-wheat seed rate through row planting, while the remaining 81.4% did not, the variable is also significantly different between adopter and non-adopter at 5% level. As far as institutional variables are concerned, about 50% of respondents got training specific to wheat production while regarding extension service, except for 14.3% of the sampled respondents all of them indicated that they get the extension service with different frequency. Out of the total sampled households, greater percentages of respondents (70.5%) used a labor-saving complementary asset (such as tractor and combine harvester) and the difference is statistically significant ( $p < 0.5$ ) between adopter and non-adopter supporting the importance complementary farm assets for the adoption of new agricultural technologies. No significant differences between adopters and non-adopters are indicated for marital status and credit.

### 3.2. Determinants of adoption of improved bread wheat varieties

The results for the Tobit model are reported in two first columns of Table 4, while the other columns show the results of the DH model using the same set of explanatory variables. Assuming that, the same set of explanatory variables appears in Tobit, Probit, and Truncated models. Following the specification test ( $\lambda = -2(f_{Tobit} - f_{Probit} - f_{Truncated})$ ) that evaluates the Tobit model against the DH model, our case has a value of  $\lambda = 32.084$ , whereas  $\chi^2_{tail}(19, 32.084)$  has a significance value of  $\alpha = 0.03$  accordingly we reject the Tobit model as it is not appropriate, in favor of the Probit and Truncated regression model (DH model) over the Tobit model. Confirming that, some variables predict the decision to adopt IWVs, but not the intensity of adopting IWVs, making the Tobit model inappropriate to explain why some respondents state a zero value.

The Tobit model indicates that IWVs availability at a local seed store positively and significantly ( $p < 0.01$ ) influenced adoption, as was expected. The partial derivate for this variable suggests that the adoption of IWVs rises by 36.77 kg for each additional increase in the availability of seed in a local store of input supplier cooperatives. This is consonance with Langyintuo and Mulugetta (2008) that explained the reluctance of seed companies to expand their retail networks is a disincentive for increased adoption rates. Likewise, a study conducted by Ghimire et al. (2015) and Lunduka et al. (2012) revealed that the availability of seeds in the local stores eases the households to purchase and cultivate new improved varieties in their field.

Another interesting significant ( $p < 0.1$ ) institutional variable is extension visits, the result revealed that the higher the extension contact, the higher the adoption of IWVs by the sampled households. In fact, the partial derivate for extension visits shows that these households have 19.55 Kg more adoption rate than farmers who have fewer visits of extension. The plausible explanation for this is that such institutional settings critically promote the adoption of agricultural technologies by counterbalancing the negative effects of lack of formal education thereby facilitating adoption. This result is consistent with early literature Feleke and Zegeye (2006) and Ransom et al. (2003).

Contrary to the expected distance to input supplier cooperative had a positive and significant ( $P < 0.1$ ) effect on the adoption of IWVs. The finding revealed that the marginal effect of a kilometer increase in farmers' distance from the input supplier cooperative results in increasing adoption of IWVs by a factor of 2.42 kg, keeping other factors constant. This result is contrary to Asfaw et al. (2011) and Mariano et al. (2012), which had revealed a negative influence of distance from the office of agriculture on technology adoption. The main reason for the positive coefficient is that most of the input supplier cooperatives in Ethiopia are located near to district town or main road where most of the households have limited land holding and engage themselves in other non-farm activities.

Use of farm machinery such as a tractor or combine harvester is a common labor-saving complementary asset used by sampled farmers while farming bread wheat, that is why we use farm machinery as an explanatory variable in our adoption model. The result suggests that adoption of IWVs will be increased by a factor of 16.76 kg if sampled farmers rent farm machines

**Table 4. Tobit model versus Double-Hurdle model**

	Tobit analysis		Double-Hurdle analysis			
	Tobit coefficients	Marginal effects	Probit coefficients	Marginal effects	Truncated coefficients	Marginal effects
Gender	-31.38*(-1.68)	-13.13	-1.25(-2.63)	-.46***	-14.34(-.75)	-8.57
Schooling	1.87(.91)	.78	.07(11.41)	.03	-.19(-.06)	-.12
Marital status	-16.1(.60)	-6.73	.07(.10)	.03	-28.83(-.88)	-17.24
Experience	1.08(1.41)	.45	.05(2.62)	.02***	.84(.77)	.50
Farm size	-7.49(-1.17)	-3.14	-.07(-.42)	-.03	-30.19(-2.6)	-18.1***
Price of wheat	-.01(-.10)	-.004	.002(.56)	.001	.014(.13)	.01
Seed availability	87.87(4.84)	36.77***	0(omitted)		57.69(2.5)	34.48***
Row planting	20.52(.98)	8.59	.44(.82)	.17	56.35(2.04)	33.69***
Training	19.10(1.06)	7.89	.31(.90)	.12	-4.75(-.17)	-2.84
Extension	46.71(1.80)	19.55*	.50(1.15)	.18	60.83(1.06)	36.36
Take credit	13.27(.63)	5.55	.41(.92)	.16	40.14(1.40)	24
Distance to cooperative	5.78(2.24)	2.42**	.12(2.14)	.05**	7.76(2.2)	4.64***
Rent machine	40.05(2.5)	16.76**	.99(2.74)	.36***	29.85(1.27)	17.84
DAP application	-.01(-.14)	-.004	-.01(-1.38)	.003	.06(.67)	.03
Urea application	0.55(1.85)	.23*	.03(2.58)	.01**	.14(.42)	.85
Net return	5.17e-05(.12)	2.16e-05	3.0e-05(2.01)	1.1e-05**	4.43e-05(0.09)	2.7e-05
Family size	-0.33(-.14)	-1.14	.05(.98)	.02	-4.13(-.95)	-2.47
Non-wheat income	5.94e-04(.99)	2.49e-04	7.75e-06(.59)	2.9e-06	9.4e-04(1.22)	5.6e-04
Cons	86.17(-1.02)		-3.96(.13)		-.02(-.01)	
	No. of obs. = 140		No. of obs. = 111		No. of obs. = 78	
	LR chi2(18) = 68.83		LR chi2 = .0003		Wald chi2(18) = 20.18	
	Prob>chi2 = 0.000		Pseudo R2 = .2904		Prob>chi2 = 0.3227	
	pseudoR2 = 0.07		Log likelihood = -54.06		Log likelihood = -404.6	

Note: Some variables are omitted from the hurdles due to a lack of convergence during estimation. This could arise due to identification problem; t-values are shown in parenthesis; Asterisks indicate the level of significance: \*\*\* = 0.01; \*\* = 0.05; \* = 0.10,  $\chi^2$  test Double-Hurdle versus Tobit  $\lambda = d1 * ((probl + trunc) - tobit) = 32.084$ ,  $d1 \chi^2_{tail}(19, 32.084) = 0.03$ , level of significance. We use 19 degrees of freedom because the Tobit uses 18 parameters, Probit 18 and Truncreg 19, the difference in the number of parameters used is 19. We reject the null at  $\alpha = 0.03$  the level of significance. Thus rejects the Tobit model as it is not appropriate, in favor of the probit and truncated regression models.



to plow their wheat land. This result is in agreement with Mariano et al. (2012) who revealed that farmers who own labor-saving assets are more likely to adopt certified seed technology. Similarly, every increase in the application of Urea fertilizer would increase the adoption of IWVs by a factor of 0.23 kg, *ceteris paribus*. This is in line with the result of Nkonya et al. (1997) who found that adopting Urea and improved seed technologies together provides synergetic benefits as improved varieties have high responses to fertilizer application.

In the DH model, the Probit coefficients estimated, and the implied marginal effects, are contained in the third and fourth columns of Table 4, respectively, while the last two columns contain those coefficients that relate to the Truncated model. The decision to adopt or not is explained by the same set of variables as in the Tobit model. However, in this case, extension contact variable, although exhibiting the same sign, it is not significant in the DH model. The marginal effects of the Probit show changes in the probability of adoption of IWVs for an additional unit increase in the independent variables.

Contrary to expectation, the marginal probability results (fourth column) indicate that the probability of adopting IWVs raises by 46% if the household is female-headed, revealing that male-headed households are less likely to adopt IWVs than female-headed, which suggests success in targeting vulnerable female households in Ethiopia by the government and NGOs. Likewise, each additional wheat farm experience, since farmers become a decision-maker on his/her field raises IWVs adoption probability by 2%, subsequently increased farming experience furnished farmers with more knowledge that increases their rationality in the use of IWVs. As in the Tobit model, another interesting, and unexpected result is that the farther the distance between sampled respondents and the input supplier cooperatives, the higher the probability of adopting IWVs. For this variable, a unit increase in distance from the input supplier cooperative raises the probability of adoption by 5%. Moreover, it is also possible that even after the decision to adoption has been made, farmers further away from the input supplier cooperatives (and with sufficient capital) might prefer to adopt more (to minimize the *ex ante* and *ex post* transaction costs) IWVs than farm households who is closer to the input supplier cooperatives.

Labor-saving farm machinery such as tractor and combine harvester is a complementary asset used by sampled farmers while farming wheat. The study revealed that farmers who use labor-saving farm machinery are more likely to adopt IWVs at 1% significance level and the probability of adoption of IWVs increases by 36% if a farmer has rented farm machinery. A similar result was found by (Wafula et al., 2016). Likewise, the result indicates that the probability of adopting IWVs increase by 1% for each additional increase in Urea application. Implying that the decision to plant IWVs was concurrent with fertilizer application decision. Similarly, according to Dhanagare (1988) use of farm machinery (as labor-saving, efficient devices), and large quantities of fertilizers has been the essence of the Green Revolution.

Net return being an indicator of farmer's judgment that the new varieties offers some returns or loss of a particular crop; it is a useful tool for a farmer chooses to adopt a new varieties to replace an older variety (Mazid et al., 2009). Since the higher the expected net return of technology, the higher the risk a farmer will normally accept (Dercon & Christiaensen, 2011; Fisher et al., 2012). The effect of each additional net return from wheat grain on the probability of adopting IWVs is the lowest, only 0.001%. This is in agreement with the finding of Feder and Umali (1993) and Kebede et al. (1990) who revealed the positive effect of extra income or net benefit on the probability of technological adoption.

In the DH model, the Truncated model estimated shows in contrast with the Tobit model, the variables representing Gender, Extension visit, Renting farm machines (such as tractor and combine harvester), and Urea application are not significant. However, important variables such as land allotted to wheat, IWVs availability, row planting, and distance to input supplier cooperatives are all significant at 1%. The result revealed that each additional hectare of land farmed reduced IWVs adoption intensity by a factor of 18.05 kg per ha. This is in agreement with the idea that the

Green Revolution in India started with large farm households who had the initial wherewithal and capacity to take risks, and moved over time to small farm households (Dhanagare, 1988; Patel, 2013).<sup>11</sup> Moreover, studies from Asia also revealed that during the Green Revolution first, large farmers adopted high-yielding variety package in the 1970s, small farm households caught up in the 1980s, causing an inverse relationship between the intensity of adoption and landholding size. However, this result was inconsistent with the finding of Ransom et al. (2003).

The adoption of agricultural technology by the poor can be limited by lack of access to inputs (Irz et al., 2001), especially for poor farmers with positive desire demand because of the imperfection in local seed markets (Asfaw et al., 2011). For this variable, if the respondent interviewed had access to IWVs in the local seed store, the level of IWVs adoption intensity raises by a factor of 34.48 kg per ha, a result that is very similar to one obtained in the Tobit model. The finding agrees with Ghimire et al. (2015) and Mignouna et al. (2011). Likewise, the African Green Revolution efforts predominately support increasing availability of improved varieties to smallholder farmers (Shilomboleni, 2017) by fostering input market as a way to increase crop productivity.

The result shows that if sampled respondents use a reduced-wheat seed rate through row planting, the adoption of IWVs increases by 33.69 kg per ha. The plausible reason for this is that using a reduced wheat seed rate through row planting is one of the pieces of the agricultural technology package introduced by the Agricultural Transformation Agency Wheat Initiative. This finding is in agreement with Abay et al. (2016) who revealed that the effectiveness of complementary package interventions supports smallholders' to adopt agricultural technology. Contrary to the expectation, the marginal effects show that each addition kilometers from input supplier cooperatives raises the adoption intensity of IWVs by 4.64 kg per ha. Revealing that, farmers who live far from the input supplier cooperative are more likely to use IWVs compared to farmers who live near to the technology source once they adopt the technology, a result that is similar to the one obtained in the Tobit model.

#### 4. Conclusion and policy implication

This study investigated the factors affecting the adoption and adoption intensity of IWVs in Arsi Highland of Ethiopia. The choice of IWVs technology adoption and use intensity was assumed to have affected by a combination of demographic, socioeconomic, and institutional factors. Unlike the typical binary dependent variable models (such as Logit and Probit) applied for studying the dichotomous issue of the probability of adopting improved wheat varieties, our objective goes beyond that and helps in understanding the intensity of adoption. Even for the Tobit model, the specification test performed has strongly rejected the Tobit model in favor of the more flexible DH model. Confirming that, some variables predict the decision to adopt IWVs, but not the intensity of adoption, making the Tobit model inappropriate to explain why some respondents state a zero value.

We assumed the same set of explanatory variables in Tobit, Probit and Truncated models and most of the results are reasonably consistent between methods. Besides, the result is in line with previous empirical results in the literature. In addition to the DH and Tobit model, the Heckman method allowing correlation between the participation decision and intensity of adoption is also proposed. Unlike many adoption studies, comparisons between the DH and Heckman model suggest that the DH model better explains the sequential decision process of household adoption decision.

The probability of IWVs adoption on the DH Probit model increases with the level of wheat farming experience, renting farm machinery (such as tractor and combine harvester), distance to input supplier cooperatives, urea application and net return, but it is a decreasing function of male headship of the household. Based on the Tobit model adoption intensity of IWVs increase with the level of seed availability, extension visits, distance to input supplier cooperatives, renting farm machineries, urea application and decreases with male-headed household while the Truncated DH model result revealed that adoption intensity of IWVs increase with seed availability, row planting, distance to input supplier cooperative and it is a decreasing function of farm size.

We can derive several policy implications from the above results of this study to consortium of sub-Saharan African Green Revolution partners to support the implementation of African Green Revolution. First, similar to other studies of technology adoption among smallholder farmers in developing countries, farm experience plays a central role in the adoption of IWVs by furnishing farmers with more knowledge that increase their rationality in the use of agricultural technology. Second, addressing the lack of labor-saving farm machinery assets such tractor and/or combine harvester though renting at the lowest cost or increasing access to the farm machinery with the help of government or NGOs at credit or subsidy base at a village will increase the probability and intensity of adopting IWVs.

Third, IWVs technologies should be made available to farmers who reside within a long distance from rural *kebeles*, through availing farm service centers within a reasonable distance from farmer's farm or else encourage farmers to form seed multiplier cooperatives which will in turn multiply and supply IWVs to farmers. Hence, to ensure IWVs availability at a distant place. Fourth, there is a need to develop high yielding IWVs that reduce associated cost of production and simultaneously increase the financial benefit, as farmers perceive such innovation are profitable they will adopt for the high net benefit they earn from the technology.

Fifth, application of Urea fertilizer was concurrent with the IWVs application decision since the two technologies together provide synergetic benefits as IWVs have a high response to Urea fertilizer. Hence, there is a need to avail such types of complementary inputs with the required quantity and quality to enhance adoption and adoption intensity of IWVs. Sixth, the result revealed that some success has been achieved in targeting vulnerable rural female-headed households by the Ethiopian Government and NGOs unlike many developing countries. As a result, female-headed households had high probability and intensity of adopting IWVs as compared to male-headed households.

Seventh, the government should consider long-term strategies that promote intensive promotion and utilization of reduced-wheat seed rate through row planting and increase the availability of IWVs in local seed stores by strengthening public and private partnership to increase the adoption intensity of IWVs, ones the technology is adopted. Since lack of IWVs in the nearest seed multiplier cooperative is the major constraint which impedes the adoption of improved varieties, government system should take the lead in seed technology promotion and dissemination at the initial stage and create an enabling environment for effective participation of the private seed sector as there are no private seed supplier companies who supply IWVs for the farmers in the study area during the survey period.

Moreover, there is a need to develop a bottom-up seed distribution approach that can enhance and accelerate the adoption of new technology by the very poor people of the study area rather than target only the model farmers as it empowers the poor farmers as seed traders and increases the availability of IWVs at the local area. Finally, extension service should be strengthened to expose farmers to modern farming techniques and improved technologies through enhancing and institutionalizing the role of ICT in disseminating field trial results and facilitating farmers' access to government programs and services.

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## Notes

1. For instance, in Japan in the last decades of the 19<sup>th</sup> century, early industrialization was financed by land tax, accounting over 80% of fiscal revenues at the time (Ghatak & Ingersent, 1984).
2. Government policies that increase wheat consumption in sub-Saharan Africa probably is keeping wheat price low relative to the price of domestically produced staple crops (*ibid*).
3. We thank an anonymous reviewer for this useful suggestion.
4. Household refers to agricultural HH when at least one member of the HH is engaged in growing crops and/or livestock in private or in combination with others.
5. Kebele refers to the smallest administrative unit in Ethiopia.
6. We thank an anonymous reviewer for this useful suggestion.
7. The results of the Heckman's two-step approach estimations are not reported but are available (see Appendix Table A2) to see if sample selection bias is an issue based on the inverse Mills ratio ( $\lambda$ ).
8. Intensity of adoption is the share of farmland utilizing the technology (Feder & Umali, 1993).
9. Latent variable occur when farmers decide to adopt but are prevented from doing so because of various circumstances.
10. Ethiopian birr(ETB); ETB 21.56=US\$ 1 at the time of the survey and it highly varies, 2014/15.
11. Though, that poor smallholders soon found themselves sitting on goldmines after the Green Revolution took off. Hence, the poorest residents of rural areas smallholders such as landless, semi-landless and extremely land-poor- might have been ignored by the Indian Green Revolution (Patel, 2013). However, the East Asian Green Revolution has tended to reduce poverty, and achieved growth-with-equity which has inspired so many-poverty architects (Mosley, 2002).

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**Appendix**

**Table A1. Estimation Tobit model and Double-hurdle model (robustness analysis result)**

	Tobit analysis			Double hurdle analysis			
	Tobit Coefficients	Marginal effects	Probit Coefficients	Marginal effects	Truncated coefficients	Marginal effects	
Seed availability	<b>96.6***</b> (4.9)	<b>96.59***</b> (4.9)	<b>1.5***</b> (3.7)	<b>.48***</b> (4.2)	<b>63.97**</b> (2.6)	<b>63.97*</b> (2.6)	
Row planting	<b>46.1**</b> (2.2)	<b>46.11**</b> (2.2)	<b>.58 *</b> (1.7)	<b>.19*</b> (1.7)	42.7(1.6)	42.7(1.6)	
Distance to cooperative	3.25 (1.3)	3.25(1.27)	.033(0.9)	.01(0.87)	3.32(0.97)	3.32(0.97)	
Rent machine	<b>29.37*</b> (1.8)	<b>29.35*</b> (1.8)	<b>.51**</b> (2.1)	<b>.17**</b> (2.3)	-7.7(-0.03)	-7.7(-.03)	
Net return	-0.0003 (-.9)	-0.0003(-.9)	2.4e-06(0.3)	7.7e-07(0.3)	-0.0007(-1.4)	-0.0007(-1.4)	
Cons	-37 (-1.9)*				23.59(0.7)		
No. of obs.	139	No. of obs.	139	No. of obs.	= 77		
LR chi2(5)	= 38.57	LR chi2 (5)	= 31.61	LR chi2(5)	= 9.87		
Prob > chi2	= 0.000	Pseudo R2	= 0.165	Pron > chi2	= 0.079		
PseudoR2	= 0.0377	Log likelihood	= -79.73	Log likelihood	= -409.9		

Note: t-values are shown in parenthesis; Asterisks indicate the level of significance: \*\*\*=0.01; \*\*=0.05; \*=0.10.

**Table A2. Estimation of the Heckman two-step model result**

**Heckman selection model - - two-step estimation Number of obs. = 140**

**Wald chi2 (18) = 32.94**

**Prob> chi2 = 0.0170**

	Coef.	Std. Err.	Z	P> Z	[95% Conf. Interval]	
IWVs used per hector						
Gender	-12.84	18.371	-0.70	0.485	-48.847	23.165
Schooling	0.124	1.899	0.07	0.948	-3.597	3.845
Marital status	-28.895	23.659	-1.22	0.222	-75.265	17.475
Experience	0.459	0.738	0.62	0.534	-0.988	1.907
<b>Farm size</b>	-27.461	10.798	-2.54	<b>0.011</b>	-48.625	-6.297
Price wheat	-0.562	0.052	-1.08	0.281	-0.158	0.045
<b>Seed availability</b>	53.553	21.424	2.50	<b>0.012</b>	11.562	95.544
<b>Row planting</b>	31.876	17.481	1.82	<b>0.068</b>	-2.385	66.138
Training	13.049	18.846	0.69	0.489	-23.888	49.986
Extension	16.699	30.380	0.55	0.583	-42.846	76.243
Take credit	10.451	19.621	0.53	0.594	-28.005	48.907
<b>Distance to cooperative</b>	4.120	2.377	1.73	<b>0.083</b>	-0.538	8.779
Rent machine	16.111	16.937	0.95	0.341	-17.085	49.307
DAP application	0.017	0.065	0.27	0.787	-0.109	0.144
Urea application	0.317	0.251	1.26	0.209	-0.177	0.808
Net return	0.0005	0.0004	1.05	0.292	-0.0004	0.0014
Family size	-2.214	2.652	-0.84	0.404	-7.412	2.983
Income other than wheat	0.0008	0.0005	1.55	0.121	-0.0002	0.0017
Cons	92.040	64.463	1.43	0.153	-34.305	218.385
Dy						
<b>Gender</b>	-1.108	0.416	-2.66	<b>0.008</b>	-1.924	-0.291
Schooling	0.066	0.042	1.58	0.113	-0.016	0.147
Marital status	0.730	0.552	1.32	0.1860	-0.351	1.812
Experience	0.024	0.150	1.58	0.115	-0.006	0.053
<b>Farm size</b>	-0.508	0.174	-2.92	<b>0.003</b>	-0.849	-0.168
Price of wheat	-0.0004	0.0009	-0.41	0.678	-0.002	0.001
<b>Seed availability</b>	1.798	0.533	3.37	<b>0.001</b>	0.752	2.843
Row planting	-0.0543	0.458	-0.12	0.906	-0.953	0.844

(Continued)



**Heckman selection model - - two-step estimation Number of obs. = 140**

**Wald chi2 (18) = 32.94**

**Prob> chi2 = 0.0170**

Training	0.561	0.326	1.72	0.085	-0.077	1.199
Extension	0.234	0.413	0.57	0.571	-0.575	1.043
Take credit	-0.107	0.382	-0.28	0.778	-0.855	0.641
Distance to cooperative	0.656	0.049	1.33	0.183	-0.031	0.163
<b>Rent machine</b>	0.942	0.309	3.05	<b>0.002</b>	0.338	1.552
DAP application	-0.002	0.002	-1.05	0.294	-0.005	0.001
<b>Urea application</b>	0.014	0.007	1.93	<b>0.053</b>	-0.0002	0.029
<b>Net return</b>	0.0003	0.00001	2.75	<b>0.006</b>	9.68e-06	0.00006
Family size	-0.013	0.0497	-0.26	0.794	-0.1105	0.0845
Income other than wheat	0.00001	0.00001	-1.70	0.088	-3.9593	0.2763
Cons	-1.841	1.080	-1.70	0.088	-3.959	0.276
<b>Mills</b>						
lambda	39.993	28.372	1.41	<b>0.159</b>	-15.615	95.601
rho	0.731					
sigma	54.723					

Censored obs. = 64; Uncensored obs. = 76



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