Adoption and Impact of Improved Wheat Technology package on Household Livelihood: A Case Study of Misha Woreda, Hadiya Zone, SNNPR, Ethiopia.

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Abstract
Wheat is the most widely consumed cereal crop and its productivity was low in Ethiopia, which are mainly associated with poor adoption and low implementation of improved wheat farm inputs, were among the major problems. Adoption and intensity of improved wheat crop technologies is one of the most promising ways to increase wheat production, productivity and enhance food insecurity in study area. However; the adoption of new technologies was constrained by various factors. Therefore, the aim of this study was to analyze adoption and impact of improved wheat technology package on wheat yields and consumption expenditure of wheat growers in Misha Woreda. A multi-stage sampling technique was employed to select 216 sample household heads and they were interviewed using semi-structured interview schedule. In order to analyze data, Propensity score matching method, Binary logit and Tobit models were employed to analyze impact of improved wheat technology adoption on farmers yield and consumption expenditure; determinants of adoption and intensity of improved wheat technology package respectively in study area. Binary logit model result revealed that sex, education level of household head, tropical livestock holding, access to credit service, availability of farm labor and extension services were positively and significantly influenced adoption whereas family size and farming experience were significant and negatively influence wheat technology package adoption. Tobit model regression results revealed that education level of household head, tropical livestock holding, access to extension service and cultivated land size were significant and positively affect intensity of improved wheat technology package adoption. The propensity score matching showed adoption of wheat technology package has a robust and positive effect on farmers' wheat crop yield and consumption expenditure per capita. The average treatment effect on the treated (ATT) was 20,237.67 birr per capita in given year for consumption expenditure and about 21.86 quintals yield-per-hectare increase for adopters as compared to non-adopters which indicate that efforts to disseminate existing of wheat technology package highly contribute to increasing wheat yield among farm households. The findings suggest that the government and stakeholders should need to focus on promoting improved wheat productivity through strengthening the provision of farmers' education, encouraging extension services and facilitating access to credit in the study area. Finally, further support of improved wheat production technology package adoption should be given due attention for its impact on wheat yield produced by smallholders.

Keywords: *Adoption, Impact, Intensity, Binary logit, Tobit model, Propensity Score Matching, Wheat.*
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Introduction

The challenges of food insecurity and poverty can be solved in significant part by increasing wheat yield, which will also advance Ethiopia's agricultural growth (Negesa,et al 2021;). This is attainable if farmers are effectively taught how to deepen and enhance their production using new wheat crop technologies (Melkamu,2022; Degefa,2019). The yields of important crops like wheat, maize, and Teff, which average 2.45 tons per hectare, 3.25 tons per hectare, and 1.47 tons per hectare, respectively, are still low despite the widespread technology generation and dissemination efforts, indicating that the country has not fully reaped the rewards of the investments made in agricultural technology generation and dissemination efforts (CSA,2014). Due to the sector's dominance by subsistence-oriented, the developing economy of Ethiopia is not utilizing all of its agricultural potential.

Furthermore, many area-specific research pieces revealed that the country's and the study area's adoption of enhanced wheat crop technology is low. Ethiopia cannot fulfill the high demand due to the low output; as a result, it is a net importer of wheat (Degefa,2019). This poor adoption rate of farmers is typically influenced by a number of factors, including socioeconomic, institutional, demographic, and psychological ones (degefa,2019; Negesa,2021). High yielding crop varieties are especially crucial when it comes to using enhanced agricultural inputs to boost agricultural output production and productivity, income, and food security.

Additionally, there were little research on how these technologies affected farmers' livelihoods (Bekele et al., 2014; Tesfaye et al., 2016). Although Misha woreda is one of the Hadiya zone's most promising wheat-producing woredas and is familiar with the adoption of improved wheat technologies, to the best of the research's knowledge, there is less information regarding the impact evaluation study on the adoption of improved wheat crop technologies in Misha woreda as well as Ethiopia. Therefore, the goal of this study was to assess how improved wheat technology adoption has affected household output and consumption spending in Misha woreda. Despite this intervention, farmers in the study area still grow both local and improved wheat crops, and there is little information available about the adoption of cereal crops in general and wheat production in particular, locally specific factors that affect adoption, and farmer variation in the intensity of adoption of improved wheat crop technology. Meanwhile, it is discovered that the research area's weak adoption and intensity of improved wheat crop technology is insufficient and poorly understood. In the study area, there have only been a few studies on the uptake and intensity of usage of improved wheat crop technology. As a result, the study aims to support these claims.

There has also been some empirical research on the adoption and impacts of improved wheat crop technology, however the majority of these have focused on the impacts of improved wheat on output or other outcome variables by using only a single improved wheat crop technology. For instance:

Negesa (2017) investigated the adoption and impact of row wheat planting technology on household livelihood in Hadiya zone, Duna woreda; Negesa (2021) examined the adoption and impact of chemical fertilizer on wheat productivity, income, and food expenditure of farmers in Hadiya zone, Soro woreda; Fitsum (2018) investigated the impacts of the adoption of improved wheat seed on productivity in various agroecological zones of Ethiopia; and Hiwot (2018) investigated the imp

In addition, as per the knowledge of the researcher, there was limited study on factors that affect the adoption and intensity of improved wheat crop technologies, although there exist related studies on factors that affect the adoption of improved wheat technologies, their findings disagree across time and places for example:
Bekele *et al*. (2000) and Chilot *et al*. (2013); reported that access and use of credit significantly and positively influenced the adoption of improved wheat varieties and intensities of use. On the other hand, Tesfaye *et al.* (2001) and Tesfaye *et al.* (2016); found that access to credit did not affect the adoption of improved wheat crop technologies.

According to Chilot et al. (2013) and Hiwot (2018), the head of the household's education had a favorable and significant impact on both the likelihood of adoption and the intensity of use of improved wheat crop technology. Tesfaye et al. (2016), on the other hand, found that the adoption of increased wheat crop production was negatively and considerably impacted by the education level of household heads. Others, as Bekele et al. (2000), claimed that education had no influence on people's decisions to apply enhanced wheat crop technology.
According to Tesfaye et al. (2001), farmers' adoption of improved wheat crop technology utilization was positively and significantly impacted by their involvement in on-farm demonstrations and extension contact. The adoption of the improved wheat crop technology package, on the other hand, was not impacted, according to Hiwot (2018), who reported on this.

According to Tesfaye et al. (2016), owning cattle has a large and advantageous impact on the uptake of improved wheat crop technology. On the other hand, Bekele et al. (2000) and Hiwot (2018) reported that the adoption of improved wheat crop technology was unaffected by the amount of livestock. We can infer from the aforementioned findings that the practical issues and variables that discourage farmers from implementing these improved wheat production technologies vary depending on the period and location. In order to better understand what influences the adoption of improved wheat crop technology in Misha Woreda, this study also sought to identify such aspects.

Moreover, most studies fail to accurately define the region of common support during the implementation of the propensity score matching method of impact evaluation. According to Heckman *et al*. (1997a), a violation of the common support condition is a major source of evaluation bias. In addition to this, most studies measured the impacts of improved wheat crop technology packages using propensity score matching, did not test estimated average treatment effects were free from unobserved bias (example studies by: Tsegaye and Bekele, 2012; Tesfaye *et al*., 2016; Hiwot, 2018; Tesfaye *et al*., 2018; Fitsum, 2018; Baye *et al.,*2019), the afro-mentioned empirical studies used propensity score matching for impact evaluation but those studies did not accurately define the region of common support and did not conduct sensitivity test for unobserved factors that affect treatment and outcome variables. Unlike previous studies this study had correctly defined common support region and test the existence of unobserved variables. Therefore, this study is designed to analyze an adoption and impacts of improved wheat production technology package on household wheat yield and consumption expenditure with a specific focus on the role of socio-economic, demographic characteristics and institution variables in Misha woreda.

Objectives of the study

1. To determine factors affecting the adoption of improved wheat crop technology package in Misha woreda;
2. To determine factors affecting the intensity of adoption of improved wheat crop technology package in Misha woreda;
3.To evaluate the impact of adopting improved wheat crop technology package on wheat yield and consumption expenditure of households in Misha woreda;

Theoretical Review of the Literature

Theoretical Models for Adoption

Development economists are interested in the adoption of technological advancements in agriculture in less developed nations. This is because a large portion of the population relies on agriculture for a portion of its income, and successful adoption of enhanced technologies presents a potential to raise production and productivity as well as ensure the sustainability of revenue (Dorosh and Rashid, 2013). Investigating the theoretical outcomes of the adoption of agricultural innovations can help identify adoption variables, establish precise relationships for estimate, and propose ideas that can be empirically evaluated. A deeper comprehension of the interconnectedness of adoption decisions can also come from theoretical analysis (Feder et al., 1982).

Feder et al. (1982) assert that adoption choices in a given era are predicated on the maximization of predicted utility under the conditions of land availability, loan availability, and other limitations. The advantage is a trait of the farmer's crop and technological decisions in every time cycle. As a result, it depends on a variety of technologies, including traditional technology and a combination of new technology packages, to accomplish its specific goals. The utility function of the farmer is typically assumed to have one argument, such as perceived income or consumption, but in other circumstances, the utility function is supposed to contain additional components, such as leisure time.

Of course, maximizing temporal anticipated utility oversimplifies the dynamic problems that an experienced planner might produce. But instinct says that this "myopic optimization" strategy might be a good reflection of how farm households make decisions. Analytical evidence has shown that, given appropriate conditions, the results of myopic optimization are a good approximation of those of the more difficult inter-temporal optimization issue (Leigh,1980).

The first thing to think about when analyzing technology adoption is whether it is a continuous measure or a discrete state with binary variables. The percentage of farmers who use the technology is often used in studies to gauge acceptance. Another indicator of acceptance is the percentage of land devoted to new technology (Langyintuo, 2008). In order to analyze adoption, a variety of statistical and econometric techniques can be applied. They consist of binomial choice models, linear regression, correlation analysis, frequency tables, contingency tables, and tables of frequencies. Comparing technology adopters and non-adopters is made easier with the use of tables. Binomial choice models are used when there is a qualitative response or regressand variable, in this case the adoption of new wheat technology. There are many techniques available for studying qualitative response models. These include the double hurdle, Tobit, and linear probability models as well as the logit, probit, and multinomial logit and probit models (Gujarati, 2004; Greene, 2012).

In these models, the dependent variable was dummy characteristics or qualitative values, such as whether or not a person adopts or selects a technology. The qualitative variables often show whether a trait or attribute, such as adopter or non-adopter, is present or absent. Dummy variables are variables that assume values of 1 and 0 when an attribute is present or absent in order to quantify that attribute (Gujarati, 2004). Finding the likelihood that something will happen, like the adoption of better wheat crop technology, is the goal in models when the dependent variable is qualitative. Consequently, probability models are used with qualitative response regression models (Maddala, 1992; Gujarati, 2004). The most used statistical technique in regression models is the linear regression model when the dependent variable is continuous. However, linear regression models are inappropriate when the dependent variable is a discrete or categorical result (Wooldridge, 2010).

There are issues with using the linear probability model in adoption studies. The issues include the error term's heteroskedasticity, non-normality, and potential for the estimated value of the qualitative dependent variable to lie outside the 0–1 probability range. They also include the lower R2 values. However, the heteroskedasticity problem can be solved using weighted least square, and the non-normality problem can be reduced by increasing the sample size. The main issue with the linear probability model, however, is that it assumes that the probability or expected value of the dependent variable being equal to one, given the independent variable, increases linearly with the independent variable, indicating the independent variable's marginal effect is constant (Gujarati, 2004).

Therefore, a model must contain two fundamental characteristics, which include: In addition, the relationship between Pi and Xi is nonlinear. First, when the independent variable (X) rises, the probability Pi = E (Y = 1 | X) increases but never lies outside the 0 - 1 probability region. A sigmoid or S-shaped curve that mimics the cumulative distribution function of a random variable is the model with a probability that ranges from 0 to 1 and varies nonlinearly with the X variable (Gujarati, 2004; Greene, 2012). The logistic and the normal cumulative distribution functions, which result in the logit and probit models, respectively, reflect the 0 and 1 response models. The two models are similar overall, with the exception that the logistic distribution (the logit) has flatter tails. The two models differ in the definition of the distribution of the error term (Maddala, 1992). If the distributions of the sample values of Yi are not too skewed, the two models will yield findings that are equivalent. Maximum likelihood is employed to estimate the parameters of these nonlinear models; however, the choice of the cumulative distribution function will be sensitive to a sample in which the proportion Yi = 1 (or the proportion Yi = 0) is relatively small. The slope coefficients of a variable in the logit model, while leaving all other variables constant, provide the change in the log of the probabilities associated with a unit change in the variable. jPi (1- Pi), where j is the partial regression coefficient of the jth regressor, calculates the rate at which the chance of an event occurring. However, each of the variables used in the analysis is used to determine Pi (Gujarati, 2004).

For categorical dependent variables, there exist numerous nonlinear models, according to Wooldridge (2010) and Greene (2012). The multinomial logit model is the model specification that is most frequently used for nominal outcomes with more than two categories that are not sorted (Greene, 2012). In practical econometrics and social sciences, multinomial logistic regression is employed in a variety of contexts. The likelihood that the estimations of the parameters predicting each category of the dependent variable may produce the observed sample data is jointly maximized by multinomial logistic regression. The multinomial logistic regression results are reduced to binary logistic regression estimates when the dependent variable only contains two categories. Since qualitative response models cannot be reliably estimated using linear regression techniques, the method of maximum likelihood is used in the estimation of all categorical dependent variable models (Wooldridge, 2010; Greene, 2012).

Theoretical Models for Impact Evaluation

Interventions and development strategies often try to alter the knowledge or behavior of homes, people, or organizations. An explicit or implicit theory comprising social, behavioral, and institutional presumptions explaining why a specific policy action will be effective in addressing a specific development challenge underlies the design of the intervention. Understanding this notion is essential for determining the type and direction of an impact (Leeuw and Vaessen., 2009). The same study claims that theories require some reconstruction and articulation. The assumptions of how an intervention will affect outcomes and impacts must be stated and then tested. This can be accomplished by explicitly testing the intervention or by carefully creating the causal story about how the intervention has achieved results.

Theories are brought to life by interventions. They include an anticipation that the implementation of a program or policy intervention will contribute to the amelioration of a persistent social issue as well as an assumption or set of assumptions about how and why program activities and resources will result in improvements. A graphic representation of boxes and arrows, a table, a narrative explanation, and other visual representations can all be used to identify and explain program or intervention concepts. The process used to create intervention theory, as well as its level of complexity and delicacy, differs greatly (Trochim, 1989; Rogers et al., 2000).

An approach logical strategy, which focuses on interviews, archives, and argumentation examination; a key appraisal strategy, which focuses on gather elements and exchange; and an elicitation strategy, which focuses on cognitive and organizational brain research are all strategies for remaking the fundamental suspicions of arrangement theories (Leeuw, 2003). An approach logical strategy, which focuses on interviews, archives, and argumentation examination; a key appraisal strategy, which focuses on gather elements and exchange; and an elicitation strategy, which focuses on cognitive and organizational brain research are all strategies for remaking the fundamental suspicions of arrangement theories (Leeuw, 2003). Through a better understanding of why the observed results have occurred and the roles played by the intervention and other circumstances, the ultimate goal is to reduce the ambiguity regarding the contribution the intervention is making to the observed results.

What percentage of changes in outcomes of interest can be attributable to a certain intervention is the key question (Leeuw and Vaessen, 2009). Program implementation is not the focus of program impact evaluation; rather, it examines how an intervention affects final welfare outcomes. Program impact evaluation often determines whether the intervention has a welfare effect on people, households, and communities and whether this effect can be connected to the intervention in question.

We must compare the observed outcome with the outcome that would have occurred had the participant not taken part in the program if we are to understand the effect of an intervention on a participating individual. However, the same person cannot have two different results. In other words, just the actual result may be seen. Therefore, the problem of missing (non-existence of counterfactual) data is the essential issue in any evaluation of an intervention (Bryson et al., 2002; Ravallion, 2007). To determine a program's effectiveness, it is necessary to distinguish its effects from other variables that may be related to the outcomes but were not brought about by the program. Impact evaluation must estimate the counterfactual, or what would have happened if the intervention hadn't occurred, in order to assure methodological rigor (Baker, 2000).

Impact evaluation techniques might be experimental (the evaluator collects data proactively and plans evaluations in advance) or quasi-experimental (data are gathered to simulate an experimental situation). Ex-ante and ex-post measures of participant and control groups can be combined in a variety of ways. The optimum method for establishing comparable groups is thought to be randomizing intervention participants. With the exception of the intervention, groups formed by random assignment to participant and control groups have comparable average characteristics for both observables and non-observables. When creating treatment and control groups through experimental design is not practicable, quasi-experimental procedures might be utilized to conduct an evaluation. These methods produce comparison groups that, at least in terms of observed attributes, resemble the treatment group.

When neither a baseline survey nor randomizations are practical possibilities, a quasi-experimental approach is the only choice, according to Jalan and Ravallion (2003). The fundamental benefit of quasi-experimental designs is that, if there is adequate existing data, they may be undertaken after a project has been established and are frequently quicker and cheaper to implement. It contains double-difference approaches and matching procedures. The effect evaluation techniques most frequently employed in non-randomized experiments are:

The difference in difference (Double Difference)

A comparison of participants and nonparticipants before and after the intervention is the foundation of the Double Difference (DD) estimator. It requires comparing observed outcomes changes for a sample of participants and nonparticipants before and after the initiative. A follow-up survey of both groups can be done after the intervention following an initial baseline survey of both non-participants and (subsequent) participants. The difference between the observed mean outcomes for the treatment and control groups before and after program intervention is determined using this information. Thus, assuming that unobserved heterogeneity is time-invariant and uncorrelated with the treatment across time, one can estimate impacts when baseline data are available. given a two-period setting where t = 0 before the program and t = 1 after program implementation, letting YtT and YtC be the respective outcomes for a program beneficiary and nontreated units in time t, the DD method can estimate the average program impact as follows:

$$\mathrm{DD} = E\left(Y_1^T - Y_0^T \mid T_1 = 1\right) - E\left(\mathrm{Y}_1^C - Y_0^C \mid T_1 = 0\right)$$

Where: T1 = 1 denotes treatment or the presence of the program at t = 1, whereas T1 = 0 denotes untreated (Becker and Ichino, 2002; Khandker *et al*., 2010). To apply a DD approach or method, baseline data need to be collected on a program (intervention) and control before program implementation. Therefore, for this study since the data collected will be cross-sectional, this method of impact evaluation is not preferred.

Regression Discontinuity

The alternative impact evaluation method is regression discontinuity design. As the appropriate sample for measuring the treatment impact, participants and nonparticipants within a specific neighborhood of the eligibility threshold are used to ensure comparison. Known as regression discontinuity (RD) this method allows observed as well as unobserved heterogeneity to be accounted for. Although the cut-off or eligibility threshold can be defined nonparametrically, the cut-off has in practice traditionally been defined through an instrument. then contrasts the outcomes of a group of people just above the eligibility cut-off with a group of those just below it. The main technical issue with this approach is that it only evaluates the program's marginal impact around the eligibility cut-off point and says nothing about people who live further away. Due to the fact that there are typically less observations than in a randomized trial with the same sample size, the effect is assessed at the discontinuity. It also results in local average therapeutic effects that cannot be generalized (Khandker et al., 2010).

Instrumental Variable Estimation

Endogeneity is made possible by instrumental variable (IV) methodologies in terms of program placement and person involvement. Finding a variable (or instrument) with a high correlation to program placement or participation but no correlation to unobserved variables influencing outcomes is the goal of the IV approach. Instruments for IV impact evaluation methodologies implementation should be properly chosen. If weak instruments are connected with unobserved traits or omitted factors that affect the outcome, the bias may be worsened even further than when estimated by ordinary least squares (OLS). Finding a decent instrument may be challenging, which is a disadvantage of the IV method (Z). The estimates of the program effect will be inaccurate if the instrument is correlated with the unobserved factors influencing the result (i.e., cov (Z,) 0). Additionally, because the projected impact on the outcome will be evaluated less precisely, the standard error of the IV estimate is likely to rise if the instrument only weakly correlates with the treatment variable T (Khandker et al.

Propensity Score Matching

The propensity score matching (PSM) method is a quasi-experimental method to estimate causal treatment effects. PSM is a method to match program participants with non-participants typically using individual observable characteristics. Each program participant is paired with a small group of non-participants in the comparison group that is most similar in the probability of participating in the program (Becker and Ichino, 2002). Based on observed traits or propensity scores, it pairs control groups with treatment groups; the closer the score, the better the match. In contrast to econometric regression methods, PSM compares only comparable observations and does not impose a functional form on the outcome, avoiding assumptions on functional form and error term distributions, such as linearity imposition, multicollinearity, and heteroskedasticity issues. PSM also does not rely on parametric assumptions to identify the impacts of programs.

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5. Research Design and Methodology

According to Creswell (2009), researcher employed an explanatory study design to explain and quantify the relationship between two or more variables. Therefore, the study was intended to use an explanatory research design in order to explain the causes and effects of variables that correlated to estimate the integrated influence of explanatory variables such as age of household head, sex of household head, educational level of household head, farming experience of household head, family size of household head, access to credit service, access to extension service, availability of farm labor and tropical livestock holding.

Furthermore, the research was deployed descriptive research design in order to describe the frequency with which an event occurs (Creswell,2009). Hence, the study was intended to the describe the nature and influence of demographic, social, economic, institutional characteristics of wheat growing farmers on adoption and intensity of use of improved wheat crop technology through frequency, percentage, chart, table and figures.

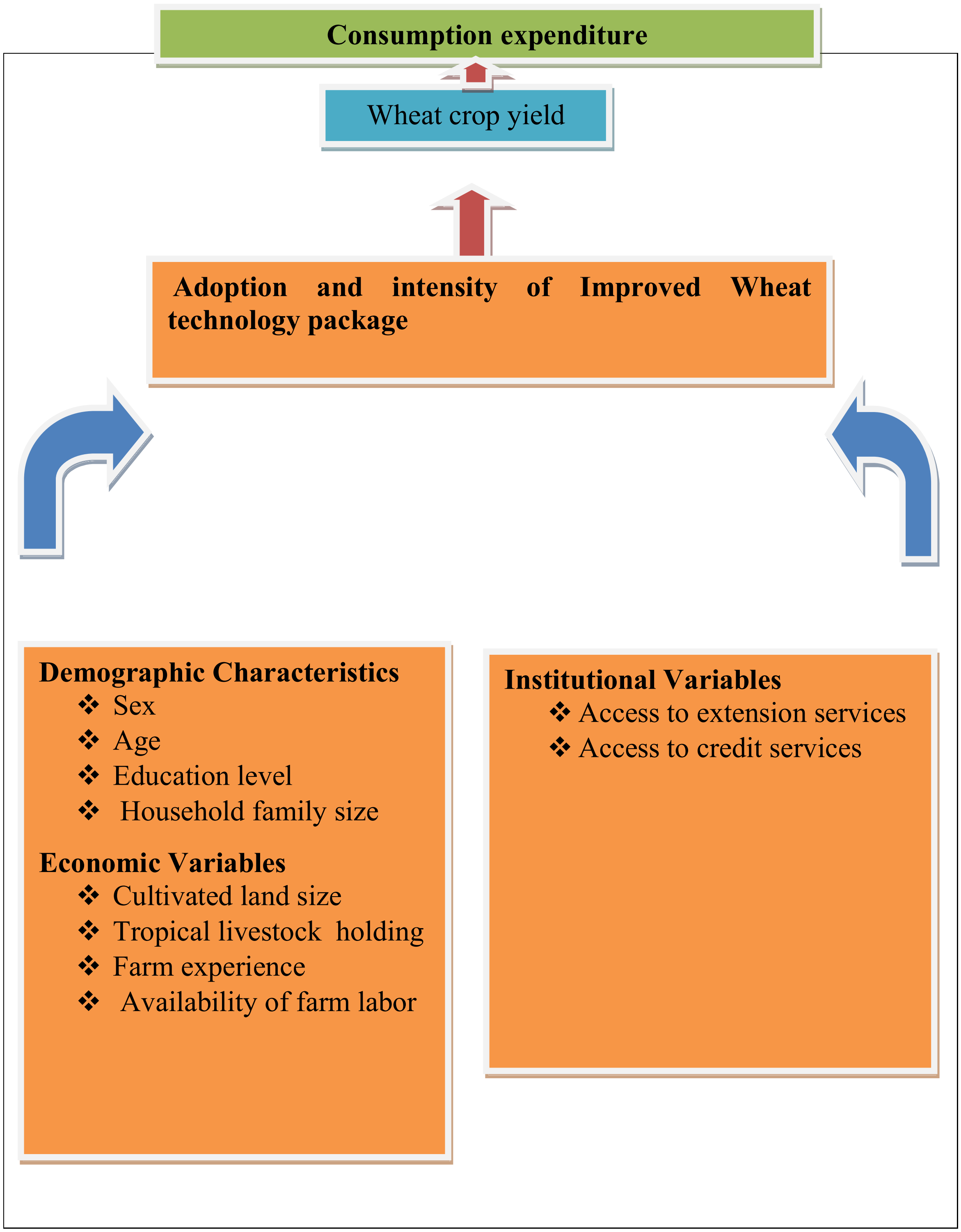
Research Approaches

To examine the variables influencing adoption and adoption intensity, a quantitative research methodology was used (Silverman, 2005). Descriptive, inferential, and econometric analysis tools were used to describe demographic, socioeconomic, and institutional variables. Semi-structured questionnaires were used as a research tool to compare groups like adopter and non-adopters. This helped the quantitative approach gain a thorough understanding of the issues and reveal the potential.

Data Types, Sources and Methods of Data Collection

This study is mostly based on primary data collected through a cross-sectional survey conducted throughout the production season of 2020/21. Since a longitudinal survey would require repeated measurements on a continuous basis, which would have ramifications for both cost and time, the research chose a cross-sectional survey instead. Consequently, it becomes challenging to use this form of design in research of this nature. However, cross-sectional survey requires one-time data collection and analysis which in turn is time-saving and cost effective (Kothari, 2004).

Hence, this study is designed to undertake a cross-sectional survey. The cross-sectional survey was conducted using semi-structured questionnaire. Because, the semi structured questionnaire was used to collect data on household demographic, socio-economic structure, institutional factors and production activities. Secondary data were also collected from woreda agricultural and rural development office in order to get potential wheat growers from the list of farmers to analyze the sample size.



Sample Size Determination

To choose the appropriate sample size for analysis, there are various general formula that can be employed. In this study, a representative sample size was chosen using Kothari's [2004] sample size determination formula. Use of this sample determination is recommended for two primary reasons: first, it is the most recent sample determination technique, and second, it considers both success(adopter) and failure (nonadopter) groups.

There are two circumstances to think about (population proportion of success). First, the formula can be applied to a value if an approximation is known (from a previous study). Second, use 0.5 if no estimate is known. Given the confidence interval and the estimate error, this value will provide a sample size large enough to ensure an accurate forecast [G.B. Allan, 2007]. This is because when each is 0.5, the product is at its maximum. The population proportion for each kebele was used to pick 216 wheat grower farmers based on the following equation:

$$n=\frac{(z)^2 pqN}{(e)^2(N-1)+(z)^2 pq}=\frac{(1.96)^2(0.2)(0.8)(1711)}{(0.05)^{2(1711-1)+}(1.96)^{2(0.2)(0.8)}}=216$$

where we have the following:

(1) n = estimated sample size

(2) e = the allowable error, where e = 0.05

(3) N= total *wheat* grower farmers (N= 1711)

(4) p = the estimated proportion of an adopter that is present in the population, which is 0.2 (from a previous study by Tamir. A [2020].

(5) q = the population proportion of nonadopter in the population. q =1 – p, where q = 1 − 0.2; therefore, q =0.8

(6) $Z\alpha/2$ = standard variate for given confidence level (as per normal curve area). It is 1.96 for a 95% confidence interval.

Methods of Data Analysis

To analyze the research data, descriptive and a combination of both inferential and econometric approaches were used. The characteristics of the respondents were described using descriptive statistical methods like mean, standard deviation, frequency, and percentage. Tables are used to present the findings. The inferential statistics like t-test (help to see difference between households in relation to independent variables); c2 tests were administered to see the influence of independent variables on the dependent variable; Chi-square and F-tests were used to evaluate the significance of the relationship between adoption groups; for the categorical variables chi-square test was used while for the continuous variables F-test was used by classifying the respondents into different classes of adoption groups. In the econometric part, binary logit model and a combination of both Tobit model and propensity score matching methods were used to analyses the determinants of adoption, intensity of adoption and impact of adoption of improved wheat technology package on wheat yield and consumption expenditure respectively. The data were also analyzed using STATA 13 software.

Econometric Model Specification

The intensity of adoption, adoption choice, and impacts of technology adoption on farmers' wheat yield and consumer expenditure in the research area were all examined using Tobit and a mix of binary regression model and propensity score matching techniques.

Tobit model

It's vital to evaluate the level or estimation of the adoption index for each farm household before delving into the factors that affect adoption intensity. Utilizing an adoption index, which reveals the degree to which the respondent farmer has embraced the most set of packages, the survey's adoption level for numerous packages was measured at the time of the survey. The adoption indices for wheat production technology package were initially computed from five technology components including uses of row planting, herbicides application, use intensities of NPS, urea, and improved wheat varieties. The dependent variable for wheat production technology adoption package was an index computed from the intensity of use of technologies related to improved wheat varieties, herbicides, row planting, Nitrogen ,Phosphporous and sulphur (NPS) and Urea in wheat production. It is a weighted index, censored between 0 and 1, which is computed based on these five technology components as follows.

Only five of the improved agronomic methods are presently used by wheat crop producers in the research area: row planting, better wheat seed, herbicides, NPS, and UREA. The adoption quotient of each practice is added up and divided by the total number of practices embraced by each respondent to arrive at the adoption index score.

The ratio of the actual rate applied to the suggested rate is used to compute the adoption quotient for each practice. In this study, the adoption index is used to measure the degree of adoption for various practices (packages) at the time of the survey. It demonstrates the degree to which the respondent farmer has embraced the greatest number of packages. Each respondent farmer's index is calculated as follows:

$$AIi = \frac{\frac{ARPWi}{RRPWi} + \frac{AISWi}{RISWi} + \frac{ANPSi}{RNPSi} + \frac{AUREAi}{RUREAi} + \frac{AHERB}{RHERB}}{NP} \text{ ---------------- Equation (1)}$$

Where:

AIi = Adoption index

ARPWi= area covered by row planting of wheat crop per hectare of the ith farmer.

RRPWi=Recommended area to cover by row planting of wheat crop per hectare of the ith farmer.
AISWi= area under improved seed of wheat crop of the ith farmer.
RISWi= Total area allocated for wheat crop production (improved seed,if any) of the ith farmer.
AHERBi= number of herbicides applied per unit of area in the cultivation of improved variety of wheat crop by ith farmer
RHERBi= Number of herbicides recommended for application per unit of area in the cultivation of improved variety of wheat crop
NPSi= amount of NPS fertilizer applied per unit of area in the cultivation of improved variety of wheat crop by ith farmer,
RNPSi= Amount of NPS fertilizer recommended for application per unit of area in the cultivation of improved variety of wheat crop
AUREAi=amount of UREA fertilizer applied per unit of area in the cultivation of improved variety of wheat crop by ith farmer,
RUREAi=Amount of UREA fertilizer recommended for application per unit of area in the cultivation of improved variety of wheat crop
Thus, the adoption index is a continuous dependent variable calculated using the formula presented above with a value ranging from zero to one. Once the adoption index was calculated, respondent farmers were classified into three categories, viz., low, medium, and high adopter
NP = Number of practices.
Farmers' usage of enhanced wheat crop production technologies may vary depending on a variety of institutional, social, and demographic variables that may be examined using the Tobit model. These variables may also affect how well the household functions.
Tobit model was to determine the relative influence of various explanatory variables on the dependent variable. The Tobit model was applied for analyzing factors influencing intensity of adoption of an improved wheat crop and its agronomic practice. This model was chosen because; it has an advantage over other analytical models in that, it reveals the intensity of use of the technology (Maddala, 1992; Johnston and Dandiro 1997). Production and productivity of farm households depend not only on adoption but also on the intensity of use of the technology.

The farmer may adopt only some part of the recommended package and may also do this on1% or 100% of his/her farm. So, Tobit model is more appropriate to give reliable output of both discrete and continuous variable combination. Examining the empirical studies in the literature, many researchers have employed the Tobit model to identify factors influencing intensity of technology use. For example, Nkonya *et al*. (1997), Lelissa(1998), and Getahun *et al*., (2000) used the Tobit model to estimate the intensity of technology use. Furthermore, according to Adesina and Zinnah (1993, cited in Shivani *et al.;* 2000), the advantage of the Tobit model is that, it does not only measure the probability of adoption of technology but also takes care of the intensity of its adoption.
Tobit model specification: The Tobit model (McDonald and Moffitt, 1980; Maddala 1983) which tests factors affecting the intensity of use of technology adoption, can be specified as follows:
The equation for the model is constructed as:
$AIi^* = B0 + BiXi + Ui$
$AIi = AIi^*$ if $B0 + BiXi + Ui > 0$..(2)
$=0$, if $B0 + BiXi + Ui \leq 0$

Where:
AIi*= is the latent variable and the solution to utility maximization problem of intensity of adoption subjected to a set of constraints per household and conditional on being above certain limit,
AIi= is adoption index for ith farmer
Xi= Vector of factors affecting adoption and intensity of adoption,
Bi= Vector of unknown parameters, and

Ui= is the error term which is normally distributed with mean 0 and variance σ

The Tobit model shown above is also called a censored regression model because it is possible to view the problem as one where observations of Y* at or below zero are censored (Johnston and Dinardo, 1997).

The dependent variable in the model is index value ranging from 0 to 1. A value of 0 indicates non-adopter, index value 1 represents the full adopter of the technology component (adopted without discontinuity), and the values between 0 and 1 indicate the level of the adoption within the range of the Tobit model Limit.

Before running the Tobit model all the hypothesized explanatory variables were checked for the existence of multi-collinearity problem. There are two measures that are often suggested to test the existence of multicollinearity. These are: Variance Inflation Factor (VIF) for association among the continuous explanatory variables and contingency coefficients for dummy variables. In this study, variance inflation factor (VIF) and contingency coefficients were used to test multicollinearity problem for continuous and dummy variables respectively. The larger the value of VIF, the more troublesome. As a rule of thumb, if the VIF of a variable exceeds 10 (this will happen if Ri exceeds 0.95), that variable is said to be highly Collinear (Gujarati, 1995). Similarly, contingency coefficients were computed for dummy variables. If the value of contingency coefficient is greater than 0.75, the variable is said to be collinear (Healy, 1984 as cited in Mesfin, 2005)

Binary Logistic Regression Model

In this study, a farmer was defined as an adopter if he or she cultivates improved wheat crop. The adoption variable was defined as 1 if a farmer was an adopter of improved wheat crop technology and 0 if farmers didn't adopt improved wheat crop technology. The logistic regression model was selected for this study to determine factors that affect farmers' adoption status. The response variable was binary, taking values of one if the farmer adopter and zero otherwise. The logistic regression can help us to predict a response variable on the basis of continuous, discrete, dichotomous, or a mix of these predictor variables to determine the percent of the variance in the response variable explained by the predictor variables, to rank the relative importance of predictor variables and to assess interaction effects.

According to Hosmer and Lemeshew (2000), the logistic distribution (logit) has an advantage over the competition in the analysis of dichotomous outcome variables because it is a very flexible and user-friendly mathematical model that yields a coherent interpretation. The model's parameter estimates were accurate and asymptotically consistent. A few explanatory variables can affect adoption of wheat crop technology practice, which is a qualitative or categorical dependent variable (adopt or not adopt). Although Ordinary Least Squares (OLS) can be used to calculate parameter estimates for binary choice models, doing so produces heteroscedastic error terms, meaning that the variance of the error term is not constant across all observations.

Therefore, in this study, the decision to utilize or not use improved wheat crop technology was determined by using a logistic regression model. If a random variable Yi and a related probability (i.e., the likelihood of adopting improved wheat) are used to represent the ith farmer's response to the adoption question, then the probability of adoption (Yi = 1) = pi and the probability of non-adoption (Yi = 0) = 1 - pi.

Additionally, the improved wheat technology package is used as the dependent variable in the model, and socioeconomic, demographic, and institutional factors are used as the explanatory or independent variables that have an impact on how the wheat technology package is used, as well as the outcome variable known as wheat yield and consumption expenditure. The dependent variable is a binary variable that takes values of 1 (one) if the farmer planted improved wheat seed at least among wheat production technology package in production season 2020/2021 G.C and zero otherwise.

The function form of model or logit model is specified as follows:

$$P=E(Y=1/Xi) = \frac{1}{1+e^{-(\beta o+\beta iXi)}} \quad \ldots\ldots (1)$$

This will be writing as follows, z_i is equal to $\beta_0 + \beta_i X_i$

$$P_i = \frac{1}{1+e^{-zi}} \quad \ldots\ldots (2)$$

$$1 - P_i = \frac{1}{1+e^{zi}} \quad \ldots\ldots (3)$$

The probability that a given household is user of improved wheat seed at least among wheat technology is expressed in equation two, while the probability for a non-user of improved wheat seed is expressed in equation three.

Therefore, we can write as

$$\frac{P_i}{1-P_i} = \frac{1/1+e^{-zi}}{1/1+e^{zi}} = \frac{1+e^{zi}}{1+e^{-zi}} = e^{zi} \ldots\ldots (4)$$

The ratio of the probability that household is user of improved wheat seed at least among wheat technology package to the probability of that it is a non-user of improved wheat seed.

$$L_i = \ln \frac{P_i}{(1-P_i)} = z_i = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n \ldots\ldots (5)$$

Where L is the log of the odds ratio and it is called the logit.

The above equation with disturbance term can be written as:

$$z_i = \beta_0 + \sum_{i=1}^{n} (\beta_i X_i) + U_i$$

Where z_i= function of explanatory variables (X).

β_0 = an intercept,

$\beta_1, \beta_2, \beta_3 \ldots\ldots \beta_n$ are the slope of the equation in the model

L_i = log of the odds ratio = z_i

X_i= vector of a relevant characteristic or independent variable.

U_i = disturbance term

Propensity Score Matching (PSM)

The impact of improved wheat technology on household production and consumption spending was examined in this study using propensity score matching. Since adopters and non-adopters may not be directly comparable and since participants and non-participants typically differ even in the absence of therapy, the propensity score matching method is utilized. As a result, outcomes of the two groups differ even in the absence of the treatment. This problem is known as selection bias. Therefore, before proceedings to future counterfactuals, first need for comparability establishment to avoid initial difference (Caliendo and Kopeinig, 2008). The PSM approach tries to capture the effects of different observed covariates *X* on adoption, in a single propensity score or index. Then, outcomes of adopters and non-adopters with similar propensity scores are compared to obtain the adoption effect. PSM constructs a statistical comparison group that is based on a model of the probability of participating in the treatment *G* conditional on observed characteristics *X*, or the propensity score: $P(X) = \Pr(G = 1|X)$. Under certain assumptions, matching on $P(X)$ is as good as matching on *X* (Rosenbaum and Rubin, 1983).

The validity of the outputs of the PSM method depends on the satisfaction of two basic assumptions namely: The Conditional Independence Assumption (CIA) and the Common Support Condition (Khandker *et al*., 2010). CIA states that the potential outcomes are independent of the treatment status, given *X*. Or, in other words, after controlling for *X*, the treatment assignment is “as good as random”. This allows the non-adopters to be used to construct a counterfactual for adopters. The common support condition entails the existence of sufficient overlap in the characteristics of the adopters and non-adopters to find adequate matches (or common support). Two fundamental assumptions—the Conditional Independence Assumption (CIA) and the Common Support Condition—must be satisfied for the PSM method's results to be legitimate (Khandker et al., 2010). According to CIA, given X, the outcomes could differ depending on how one is being treated. Or, to put it another way, the treatment assignment is "as good as random" after adjusting for X. In order to create a counterfactual for adopters, the non-adopters can now be used. To locate suitable matches, the adopters' and non-adopters' attributes must sufficiently overlap for there to be a shared support condition (or common support). The treatment assignment is deemed to be strongly ignorable if these two suppositions are met (Caliendo and

Kopeinig, 2008). When these two assumptions are satisfied, the treatment assignment is said to be strongly ignorable (Caliendo and Kopeinig, 2008).
The propensity score-matching method summarizes the pre-treatment characteristics of each subject into a single index variable and then uses the propensity score to match similar individuals (Rosenbaum & Rubin, 1983).

Impact evaluation implementation

Propensity Score Estimation
Estimating propensity scores is the initial step in the propensity score matching process. There are two options to consider when estimating the propensity score. The first one focuses on the estimate model, and the second one on the variables that will be part of this model. Logit and probit models typically produce similar findings for the binary treatment situation, where we evaluate the likelihood of participation against nonparticipation (Caliendo and Kopeinig, 2008). In order to expand on the CIA, the matching approach's outcome variable(s) must be independent of treatment and conditional on propensity score. Therefore, in order to implement matching, a collection of variables X must be chosen that actually satisfies this criterion. Heckman et al. (1997a) and Dehejia and Wahba (1999) both demonstrate how leaving out critical factors can significantly increase bias in the estimates that are produced. Only factors that have an impact on both the decision to participate and the outcome variable should be considered (Sianesi, 2004; Smith and Todd, 2005). So, the first step in propensity score matching is to use a logit/probit model to estimate the propensity score. Given that the logit model is a very adaptable and user-friendly model from a mathematical standpoint, it was chosen for this study to estimate propensity scores.
$P_i = \frac{1}{1+e^{-z_i}} = \frac{e^{z_i}}{1+e^{z_i}}$………………………………………… ………………………(6)

Where; Pi is the probability that the *ith* farmer adopted the improved wheat varieties and that Pi is non-linearly related to Z_i (*i.e.,* X_i and βs). "e" represents the base of natural logarithms (2.718…), and Zi, is a function of n-explanatory variables, i.e., $Z_i=\beta_0+\beta_1 X_1+\cdots+\beta_n X_n$.

II. Defining Overlap and Common Support
According to Heckman et al. (1997a), a breach of the common support requirement is a significant cause of evaluation bias. In the analysis, only the comparison group's subset that is comparable to the treatment group should be used (Dehejia and Wahba, 1999). By contrasting the minima and maxima of the propensity score in the treatment and control groups, Caliendo and Kopeinig (2008) claim that it is possible to identify the region of shared support. The common support region is defined as the area that lies between the minimum and maximum propensity scores of the treated group (adopters of improved wheat technology) and comparison group (non-adopters), respectively. It will be defined by excluding observations with propensity scores that are less than the minimum of the treated group and more than the maximum of the comparison groups.

III. Choosing a Matching Algorithm
The most commonly used matching algorithms are:
Nearest Neighbor Matching (NN): The comparison group member with the closest propensity score is chosen to serve as a matching partner for a treatment person. In addition to NN matching without replacement, there are also NN matching variations with replacement. A healthy individual who has not received treatment can be matched more than once in the former situation, but only once in the later. Bias and variance must be balanced when using matching with replacement. Replacement will result in an improvement in average matching quality and a reduction in bias (Caliendo and Kopeinig, 2008).

Caliper Matching: If the closest neighbor is a great distance away, nearest neighbor matching may result in poor matches. Setting a tolerance limit on the maximum propensity score distance will prevent this (caliper). In order to impose a common support condition, caliper matching is one method. Bad matches are prevented when we utilize caliper matching, and the matching quality improves. When using caliper matching, a person from the comparison group is selected as a matching partner for a treated person who falls within the caliper (propensity range) and has the closest propensity score (Caliendo and Kopeinig, 2008). According to Smith and Todd (2005), one potential problem of caliper matching is that it can be challenging to determine the appropriate decision for the tolerance level in advance.

Radius Matching: an alternative to caliper matching known as radius matching. The fundamental concept behind this version is to use all of the comparison members within each caliper rather than just the nearest neighbor. This method has the advantage of only using as many comparison units as the caliper can hold, allowing for the use of additional (fewer) units when good matches are (are not) available. Thus, it shares the desirable aspect of oversampling while minimizing the chance of poor matches (Dehejia and Wahba 2002).

Kernel Matching: Kernel matching (KM); in order to create the counterfactual outcome, a nonparametric matching estimator that uses weighted averages of every member of the control group is used. Therefore, this approach's decreased variance, which is made possible by using more information, is one of its main advantages. These strategies have the potential flaw of using observations that may not match. Therefore, for kernel matching, it is crucial to apply the common support condition correctly (Caliendo and Kopeinig, 2008) For this study, the choice of matching algorithm is done by using criteria such as: the amount of matched sample lies on-support, Psedou-R2, and covariate balance after matching.

IV. Assessing the Matching Quality

At this point, it is determined whether the matching process can balance the distribution of the pertinent variables in both the control and treatment groups. This method involves comparing the circumstances before and after matching and determining whether any differences persist after conditioning on the propensity score. In the event of disparities, it is necessary to take corrective action, such as inserting interaction terms in the estimation of the propensity score, as matching on the score was not entirely successful. As stated by Rosenbaum and Rubin in 1983:

X Ц $D|P(D=1|X)$ ………………………………………………………. (7)

This means that after conditioning on P $(D = 1|X)$, additional conditioning on X should not provide new information about the treatment decision. Hence, if after conditioning on the propensity score there is still a dependence on X, this suggests either misspecification in the model used to estimate P $(D = 1|X)$ (Smith and Todd, 2005) or a fundamental lack of comparability between the two groups (Blundell *et al.*, 2005).

Standardized Bias

The standardized bias (SB) proposed by Rosenbaum and Rubin is an appropriate indicator to evaluate the distance in marginal distributions of the X variables (1985). The difference in sample averages between the treated and matched control subsamples, expressed as a percentage of the average sample variance for both groups, is the definition of each covariate X.

The SB before matching is given by:

SB before $=100\bar{X}1-\bar{X}0/\sqrt{0.5\cdot(V1(X)+V0(X))}$ ……………………………………………… (8a)

The SB after matching is given by:

SB after$=100\bar{X}1M-\bar{X}0M/\sqrt{0.5\cdot(V1M(X)+V0M(X))}$ …………………………………… (8b)

Where: X 1 (V 1) is the mean (variance) in the treatment group before matching and X 0 (V 0) the analogue for the control group. X 1M (V 1M) and X 0M (V 0M) are the corresponding values for the matched samples. Rosebaum and Rubin (1985) suggested that standardized bias less than 20% after matching indicates covariates are balanced; thereby there is no more mean difference exist between adopters and non-adopters.

T-Test

A similar strategy employs a two-sample t-test to determine whether there are significant variations in the covariate means for the two groups (Rosenbaum and Rubin, 1985). Differences are anticipated prior to matching, but after matching, the covariates should be balanced between the two groups and no significant differences should be observed. The *t*-test might be preferred if the evaluator is concerned with the statistical significance of the results.

Joint Significance and Pseudo-R2

Sianesi (2004) proposed using pseudo-R2s before and after matching to compare participants and matched nonparticipants. The pseudo-R2 shows how effectively the regressors X explain the likelihood of involvement. After matching, the distribution of variables across the two groups should not have any systematic differences, therefore the pseudo-R2 should be low.

A likelihood ratio test on the combined significance of all regressors in the probit or logit model was likewise advised to be rejected both before and after matching.

The Average Treatment Effect

The difference between the mean outcomes (grain yield and consumption expenditure) of matched adopters and non-adopters who have a common support, conditional on the propensity score, represents the average treatment effect on the treated (ATT). Thus, the following gives the mean impact of adopting superior wheat types technology.

$Ti=E(Y1|Di=1)-E(Y0|Di=0)$……………………………………………. (9)

Where: Ti, is a treatment effect, Y is the outcome (grain yield and consumption expenditure) and Di is a dummy whether household *i,* has the treatment or not. However, one should note that Y (Di = 1) and Y (Di = 0) cannot be observed for the same household at the same time. Due to this fact, estimating the individual treatment effect was not possible and one has to shift to estimating the average treatment effects of the population rather than the individual one. Therefore, following Takahashi and Barrett (2013), the average treatment effect on treated (ATT) can be defined as:

$ATT=E\{Y1-Y0|D=1\}=E(Y1|D=1)-E(Y0|D=1)$………………………. (10)

Where: Y1 = the outcome in the treated condition, Y0 = the outcome in the control condition; and D = Dummy, indicator variable denoting adoption of rust-resistant improved wheat varieties.

We can observe the outcome variable of adopters E ($Y1$| D = 1), but we cannot observe the outcome of those adopters had they not adopted E ($Y0$ |D = 1), and estimating the ATT using equation (10) may therefore lead to biased estimates (Takahashi and Barrett, 2013). Propensity score matching relies on an assumption of conditional independence where conditional on the probability of adoption, given observable covariates, an outcome of interest in the absence of treatment $Y1$ and adoption status, D are statistically independent (Takahashi and Barrett, 2013). Rosenbaum and Rubin (1983) define the propensity score or probability of receiving treatment as:

$p(X)=\text{pr}(D=1)\ |X$…………………….……..…….…….…………. (11)

Another important assumption of PSM is the common support condition, which requires substantial overlap in covariates between adopters and non-adopters, so that households being compared have a common probability of being both an adopter and a non-adopter, such that $0 < p(X) < 1$ (Takahashi and Barrett, 2013). If the two assumptions are met, then the PSM estimator for ATT can be specified as the mean difference outcomes of the adopters matched with non-adopters who are balanced on the propensity scores and fall within the region of common support, expressed as: $E[(Y1|D=1)-E(Y0|D=0)]=\tau ATT+E[(Y0|D=1)-E(Y0|D=0)]$

The difference between the left-hand side of the equation and τATT is the so-called 'selection bias'. The true parameter ATT is only identified if there is no selection bias:

$E[(Y0|D=1)-E(Y0|D=0)]=0$ thereby,

$ATT=E\ (Y1|D=1,\ p(X))-E(Y0|D=0,p(X))$………………..…………..… (12)

VI. Sensitivity Analysis

The selection on observables hypothesis provides the foundation for the estimation of treatment effects using matching estimators. Unobserved factors that influence both outcome variables (adopting superior wheat varieties that are resistant to rust) and assignment into treatment, however, could lead to a hidden bias (Rosenbaum, 2002). Sensitivity is the process of evaluating the degree to which an unmeasured variable affects the selection procedure in order to undercut the implications of matching analysis (Caliendo and Kopeinig, 2008).

To do so it is assumed that the participation probability $\boldsymbol{\pi i}$ is not only determined by observable factors (*xi*) but also by an unobservable component (*ui*):

$\pi i=\text{Pr}\quad (Di=1|xi)=F(\beta xi+\gamma ui)$ …………………………………………… (13)

γ is the effect of *ui* on the participation decision. If the study is free of hidden bias, *γ* will be zero and the participation probability is solely be determined by *xi*. However, if there is hidden bias, two individuals with the same observed covariates *x* have different chances of receiving treatment. Let us assume that we have a matched pair of individuals *i* and *j* and further assume that *F* is the logistic distribution. The odds that individuals receive treatment are then given by *Pi/* (1 - *Pi*) and *Pj/* (1 - *Pj*), and the odds ratio is given by:

$Pi1-PiPj1-Pj=Pi(1-Pj)\ Pj(1-Pi)=\exp(\beta xi+\gamma ui)\ \exp(\beta xj+\gamma uj)$ ……………………….(14)

If both units have identical observed covariates as implied by the matching procedure the *x* vector cancels out, implying that

$\exp(\beta xi+\gamma ui)\ \exp(\beta xj+\gamma uj)=\exp\{\gamma(ui-uj)\}$ ……………………………………….……. (15)

A factor involving the parameter and the distinction between their unobserved variables u causes both individuals' probability of receiving treatment to differ. The odds ratio is one, indicating that there is no hidden or unobserved selection bias, if unobserved factors are either the same (ui = uj) or have no effect on the chance of participation (= 0). Sensitivity analysis now examines how the values of and (ui -uj) affect conclusions regarding the program effect.

Assume, for the sake of simplicity, that the unobserved covariate is a dummy variable with ui 0, 1 in accordance with Aakvik (2001). According to Rosenbaum (2002), the following constraints on the odds ratio that one of the two matched persons will receive treatment are implied by (15):

$1e\gamma\leq Pi(1-Pj)\ Pj(1-Pi)\leq e\gamma$………………………………………………………………. (16)

Both matched individuals have the same probability of participating only if *eγ* = 1. Otherwise, if for example ***eγ*** = 2, individuals who appear to be similar (in terms of *x*) could differ in their odds of receiving the treatment by as much as a factor of 2. In this sense, *eγ is* a measure of the degree of departure from a study that is free of hidden bias (Rosenbaum, 2002). On the other hand, sensitive treatment effects can be obtained if a large value of ***eγ*** does not alter treatment effects (Aakvik, 2001). Therefore, to check the sensitivity of average treatment effect for deviation of conditional independence assumption this study applied the Rosenbaum bounding approach of sensitivity analysis for average treatment effect.

5. Results and Discussions

Factors that affect intensity of adoption of improved wheat production technology package

The variance inflation factors (VIF) of for continuous independent variables in the Tobit model is less than 10 and contingency test for discrete independent variables indicating that multicollinearity was not a problem with the finally implemented model. Hence, the relationship between the adoption index (dependent variable) and predictor variables were computed by employing Tobit model. The models also demonstrated a good fit at 1% level of significance which can be observed from F statistic.

The education level of household heads: This variable is a positive relationship with intensity of wheat technology adoption and significant at 1% probability level. Marginal effect is 0.022 from below. The marginal effect revealed that, being other things constant, if the year of schooling of education of household head increased by a year, the intensity of household being wheat technologies adopter increased by 2.2%. This finding coincides with the finding of Adunea (2017); Tariku, (2012), and Degefa (2019); that explained literacy of farmers positively and significantly affect adoption and intensity of use of wheat row planting technology.

Tropical livestock holding (TLU): This variable is significant at 1% level of significance in coefficient, robust and marginal effect' result. It has positive relationship with intensity of adoption of wheat production technology package. Marginal effect is 0.036 that means other things kept constant, if the number of livestock for householding increased by one TLU, intensity of adoption wheat production technology package increases by 3.6%. This finding matches with the finding of Gebremariam and Hagos (2018), and Degefa (2019); that showed TLU was found to have positive significant effect on the adoption and intensity of use of wheat technology package.

Access to extension services: It is positively related with intensity of adoption wheat technology package. This variable is significant at 1% probability level. Marginal effect is 0.082. This implies that if the accessibility of extension service for household increased by 1%, intensity of adoption of wheat production technologies increased by 8.2%. The finding is matched with Tariku (2012) and Degefa (2019).

Cultivated land size: This variable is positively related with wheat production technologies adoption intensity and significant at 5% probability level. Marginal effect is 0.04. This implies that as cultivated land size increased by one ha, intensity of adoption of wheat production technology package increased by 4%. This finding was in lined with the finding of Susie (2017) and Degefa (2019) which were found to be positively and significantly influencing the intensity of adoption with respect to different crops

Table 1: Estimation result of the Tobit model for factors of intensity of adoption improved

wheat technology package

Tobit			Regression	Number of obs =			216
			F(10, 206) =	44.29			
			Prob > F =	0.0000			
Log pseudolikelihood =30.554035				Pseudo R2 ==			0.5716
Variable	Coef.	Robust Std. Err.	T	P>t	dy/dx	[95% Conf.	Interval]
SEX	.0035326	.0332047	0.11	0.915	.0035326	-.061932	.0689971
AGE	-.0015744	.0017967	-0.88	0.382	-.0015744	-.0051167	.0019679
HFS	-.0011537	.0080593	-0.14	0.886	-.0011537	-.017043	.0147356
EDU***	.0219552	.0047032	4.67	0.000	.0219552	.0126826	.0312277
FE	.0013972	.0017821	0.78	0.434	.0013972	-.0021162	.0049106

CLS**	.0413946	.0185707	2.23	0.027	.0413946	.0047815	.0780077
AFL	.0112767	.0107357	1.05	0.295	.0112767	-.0098892	.0324426
AES***	.1937141	.0572356	3.38	0.001	.1937141	.0808714	.3065568
ACS	.0806136	.0619328	1.30	0.194	.0806136	-.0414899	.202717
TLU***	.0361487	.0135109	2.68	0.008	.0361487	.0095114	.0627861
_cons	.4082513	.0800752	5.10	0.000		.2503793	.5661233

*** & **Significant at 1% and 5% respectively; Source: survey result, 2022

Impact analysis of propensity score matching

The use of estimation of the propensity score is twofold: first, use to estimate the ATT and, second, use to obtain matched adopter and non-adopter observations. Thus, Propensity score methods allow the researcher to directly address the question of what can be earned from adopters and the loss of being non-adopters. According to (Grilli and Rampichini, 2011) the necessary steps when implementing propensity score matching is: Propensity Score estimation, choose matching algorithm, Check overlap/common support. To estimate the effect of treatment on wheat crop yield and consumption expenditure, PSM with different matching algorithms: nearest neighbor matching **(**NNM), caliper matching(CM) and kernel matching **(**KM) were most importantly used.

Matching of the treated and control households were mostly carried out to estimate the common support region. The main criterion for estimating the common support region is to delete all respondents or observations whose PSM is lower than the minimum PSM of treated or adopters and higher than the maximum in the control group or non-adopters (Caliendo and Kopeining, 2008). That is, deleting all respondents or observations out of the overlapping region.

Table 2: Predict propensity score common support region

Observations	Mean	Std. Dev.	Min.	Max.
Non-adopter	.0349201	.0900163	9.00e-09	.5729925
Adopter	.2957775	.192055	.0346429	.5077099
Total	.0472441	.110761	9.00e-09	.5729925

Source: own survey result, 2022

The summary statistics of propensity scores of farmers, the predicted propensity scores for adopters of wheat production technology package and non-adopters of wheat production technology package range from 0346429 to .5077099 with mean value of .2957775 and standard deviation .192055 for the adopter farmers, while it ranges from 9.00e-09 to .5729925 with mean value of .0349201 and standard deviation .0900163 for those non-adopter farmers. The common support region indicates that the propensity score for the overlap region ranges from.0346429 to .5729925. This is the region between the minimum propensity sco

re of the adopter and the maximum propensity score of non-adopter farmers in wheat production technology package. The table shows a summary of the propensity score for adopters, non- adopters, common support region and off-support regions from the two categories of small household farmers. Therefore, the production impact analysis considered both farmers involved in adopters and non-adopters of wheat technology package methods with propensity score of the overlap region i.e. propensity score ranging from .0346429 to .5729925. Accordingly, the common support region was satisfied in the range of .0346429 to .5729925 by dumping off 89 observations (observations from adopters).

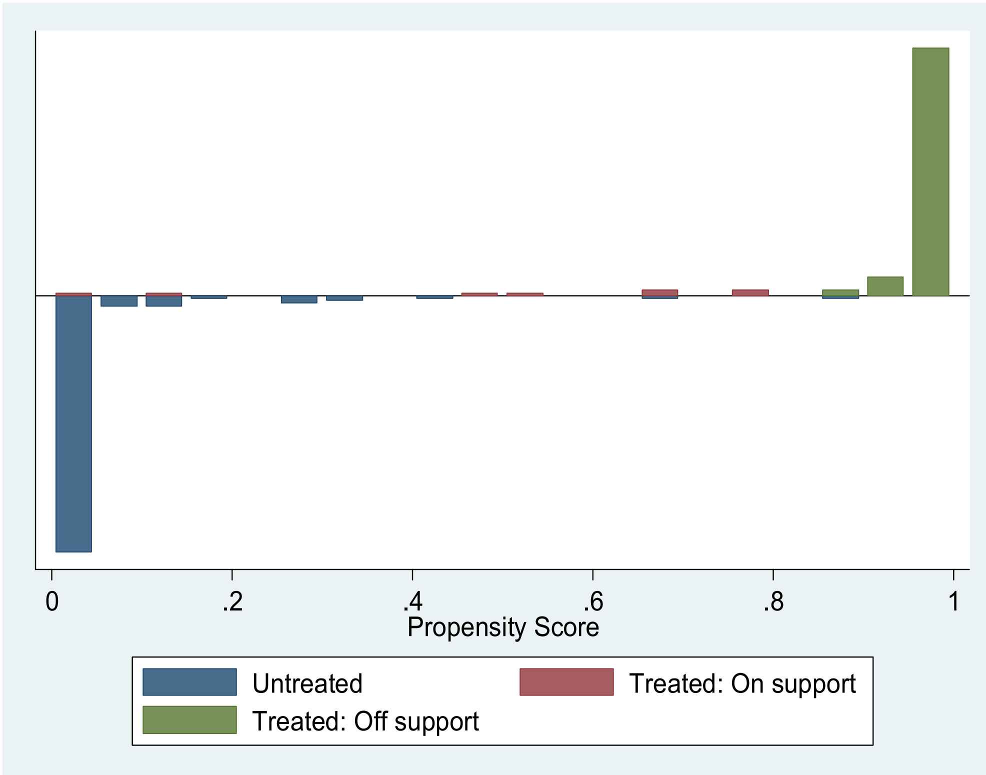


Figure 2 : Propensity Score Distribution of Sample Households before Matching

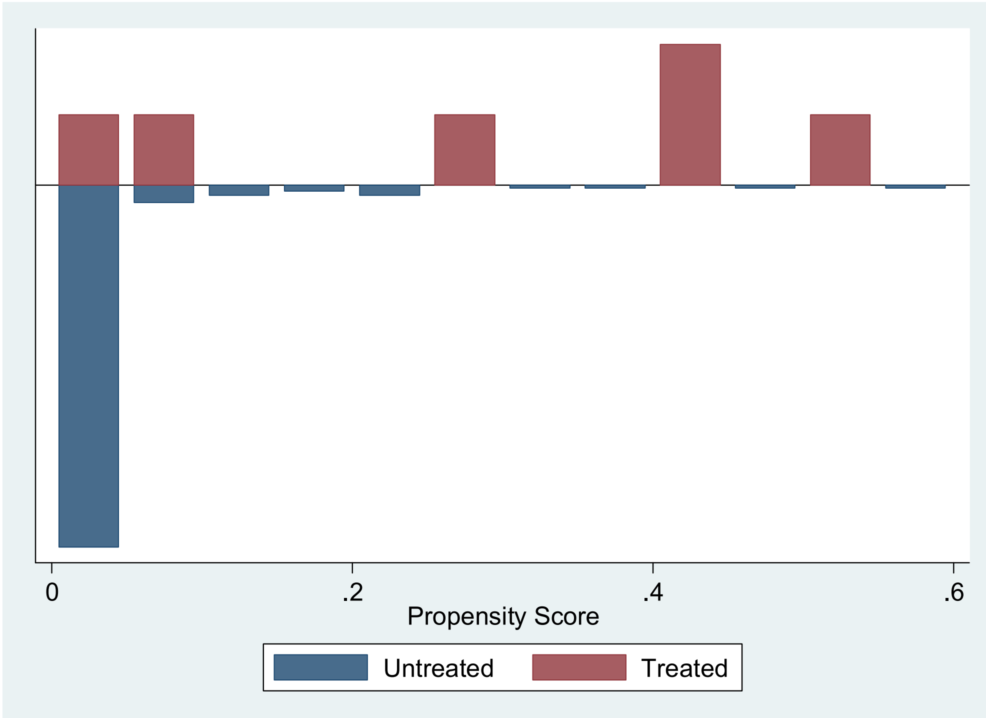


Figure 3: Propensity Score Distribution of Matched Sample Households

Source: Own computation,2022

Matching Algorithms of adopter and Non-adopter Households

It is known that choice of matching estimator is decided based on the balancing qualities of the estimators. According to Dehja & Wehba (1999), the final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test, pseudo-R2 and matched sample size. The balancing test is a test conducted to know whether there is a statistically significant difference in the mean value of per treatment characteristics of the two groups of the respondents and preferred when there is no significant difference. Accordingly, matching estimators were evaluated via matching the adopter and non-adopter households in common support region. Therefore, a matching estimator having balanced (insignificant mean differences in all explanatory variables) mean, bears a low pseudo R 2 value and the one that results in large matched sample size is preferred.

Table 3: Performance of Matching Estimators for Sample Households

		Performance Criteria				
Outcome	Matching algorithms	Balancing Test	Pseudo-R2	**Matched sample size**		
				Adopters	Non-adopters	**Total**
Wheat crop yield (WCY)	NNM (1)	8	1.000	6	121	**127**
	NNM (2)	9	1.000	6	121	**127**
	NNM (3)	9	0.442	6	121	**127**
	NNM (4)	10	0.264	6	121	**127**
	NNM (5)	9	0.175	6	121	**127**
	CM (0.1)	8	1.000	6	121	**127**
	CM (0.25)	8	1.000	6	121	**127**
	CM (0.5)	8	1.000	6	121	**127**
	KM (0.1)	8	0.469	6	121	**127**
	KM (0.25)	**9**	**0.231**	**6**	**121**	**127**
	KM (0.5)	**9**	**0.128**	**6**	**121**	**127**
Consumption expenditure Per capita (CEC)	NN(1)	8	1.000	6	121	**127**
	NNM (2)	9	1.000	6	121	**127**
	NNM (3)	9	0.442	6	121	**127**
	NNM (4)	10	0.264	6	121	**127**
	NNM (5)	9	0.175	6	121	**127**
	CM(0.1)	8	1.000	6	121	**127**
	CM (0.25)	8	1.000	6	121	**127**
	CM (0.5)	8	1.000	6	121	**127**
	KM (0.1)	8	0.469	6	121	**127**
	KM (0.25)	9	0.231	6	121	**127**
	KM (0.5)	**9**	**0.128**	**6**	**121**	**127**

Source: Own computation,2022

Estimation of Treatment Effect

Choice of the matching algorithm was carried out from the nearest neighbor, caliper, and kernel methods. The choice of the estimator based on three criteria; namely, balancing test, Pseudo R-square and matched sample size. The matching estimator which balances more independent variables has low pseudo- R2value and a result in large matched sample was chosen as being the best estimator of the data. Accordingly, Kernel matching (KM) (0.5) was found to be the best estimator of the data of household consumption expenditure per capita and wheat crop yield of adoption of improved wheat production technology package. As depicted in the table, relatively, this estimator resulted in the least pseudo- R2 value (0.128), a large number of matched sample size and having balanced (insignificant mean differences in all explanatory variables).

Table 4 : Average Treatment Effect on the Treated

Variable sample		Treated	Controls	Difference	S. E	T-stat
WCY	Unmatched	| 37.5	15.6528926	21.8471074	3.91653559	5.58
	ATT	37.5	15.6405427	21.8594573	5.21215535	4.19***
CEC	Unmatched	36660	16437.5207	20222.4793	1763.04841	11.47
	ATT	36660	16422.33	20237.67	2014.73832	10.04***

Source: Own computation, 2022

As showed, the Average Treatment effect on the Treated (ATT) was computed based on KM(0.5). Outcome variables are wheat crop yield which is measured in quintals and consumption expenditure per capita which is measured in Ethiopia Birr and in unit respectively. The KM(0.5) result revealed that the wheat crop yield of the rural households who were the adopter of wheat technology package was 21.86 quintals greater than non-adopter in given period. The estimated average treatment effect (ATT) was significant effect on wheat yield of adopter households with significant t - statistic (4.18) at 1 percent significance level ($p< 0.0005$). The impact of wheat technology package on rural household livelihood (by using household consumption expenditure) was based on a sample of matched treated and control groups, the estimated average treatment effect (ATT) significant effect on expenditure of adopter households with significant t - statistic (10.14) at 1 percent significance level ($p< 0.0005$). The average consumption expenditure of adopter households in wheat technology package was higher by 20237.67 birr per capita in given year when compared with the average consumption expenditure of non- adopter households.

It is clear that the average treatment effect on the treated (ATT) of wheat yield with t-value 4.19 and average consumption expenditure with t-value 10.14 which indicate the effective level of significance. So, it is concluded in this analysis that the adoption in wheat production technology package has positive wheat yield and consumption expenditure effect on the adopter households in the study area.
Therefore, adoption of wheat technology package has a positive impact on the life of the adopters indicating positive welfare effect or improving rural household livelihood on the side of adopters (Appendix VI). This finding coincides with finding of Hiwot (2018) that revealed households that use improved wheat varieties tend to have higher consumption expenditure at a household level than those who do not adopt. This finding also match with finding of Regasa (2018) that showed adoption of high yielding wheat varieties has significant impact on farm income of treated households as compared to the control groups.

Sensitivity Test for Average Treatment Effect on the Treated
Sensitivity analysis is a strong identifying assumption and must be justified. According to Grille & Raphine (2011), sensitivity analysis is the final diagnostic that must be performed to check the sensitivity of the estimated treatment effect to small changes in the specification of the propensity score. In Appendix-VII, the result was reported, based on this concept of the sensitivity analysis shows that the effect of treatment at gamma = 1; it has similar value in t-hat^{+} bound and t-hat^{-} bound (gamma = 1=no hidden bias) and so it is significant treatment. The treatment effect in t-hat^{+} is significant at 1% starting from (value 1 up to 1.35) and in t-hat^{-} is significant at 1 %(valu1 to 2). Moreover, the t-hat^{+} statistic adjusts statistic downward for the case of positive (unobserved) selection while t-hat^{-} statistic adjusts the statistic downward for the case of negative (unobserved) selection. This shows that average treatment effect on treated is insensitive to external change. Hence, there are no external variables which affect the result above calculated for ATT (both wheat crop yield and consumption expenditure per capita) in this range.We can, therefore, conclude that the results are insensitive to possible deviations emanating from the identified un confoundedness assumption and therefore it holds shown to have a positive significant impact on wheat crop yield and consumption expenditure per capita it should be promoted among rural households as a way of improving their livelihoods.

Conclusions

Poor adoption and Low use or lack of improved farm technologies is one of the major challenges facing wheat production in Ethiopia. Low utilization of farm inputs and adoption of improved farming techniques made yield of wheat low. The low yield, in turn, made the country unable to meet the high demand, and the country is net importer of wheat despite its high potential for wheat production. To feed the rapidly growing population and meet the high demand, smallholders need to increase wheat yield through adoption of improved agricultural technologies.

Improved Wheat technology package is one of agronomic practices believed to increase wheat yield in Ethiopia. The agricultural extension offices have been promoting and scaling up the improved wheat farm technique. As a result, improved wheat technology has been practiced in various wheat producing regions of the country. However, there is limited empirical knowledge on the determinant factors for adoption and intensity of the improved wheat farm technique and its impact on wheat yield and consumption expenditure.

To fill this gap, this study was carried out in major wheat producing zone of the country to identify the factors affecting the adoption and impact of improved wheat technology package. Cross-sectional data were collected from systematically random selected 216 farm households and logit model, Tobit model and propensity score matching methods were used to achieve the objective of the study. Binary logit model regression results indicated that sex, education level of household head, tropical livestock holding, access to credit service, availability of farm labor and extension services were positive and significantly influenced adoption whereas family size and farming experience were significant and negatively influence wheat technology package adoption.

Tobit model regression results revealed that education level of household head, tropical livestock holding, access to extension service and cultivated land size were significant and positively affect intensity of improved wheat technology package adoption. The propensity score matching showed adoption of wheat technology package has a robust and positive effect on farmers' wheat crop yield and consumption expenditure per capita. The average treatment effect on the treated (ATT) was 20,237.67 birr per capita in given year for consumption expenditure and about 21.86 quintals yield-per-hectare increase for adopters as compared to non-adopters which indicate that efforts to disseminate existing of wheat technology package highly contribute to increasing wheat yield among farm households.

Recommendations

Based on the findings of the study, the following recommendations were suggested.

1. Literacy campaigns and adult education strategies must be designed and implemented to improve the households' literacy level.
2. Appropriate livestock packages need to be introduced and promoted in the study area in order to make farmers accumulate capital as a cattle and design household assets building mechanisms. This may be, for instance, through improved veterinary service, feed and water development as deemed necessary.
3. Training and awareness creation programs through farmers training center (FTC) method as well as result demonstrations should be arranged before the implementation of the newly introduced technologies.
4. Concerned bodies should give due attention and assistance during a peak labor demanding seasons and technology introduction.
5. Decisions and measures need to be implemented in order to make the technology labor extensive since the study area is known by its dense population; it is difficult to increase household size as a response against the new technology. Thus, this could be done through designing appropriate agricultural tools that assist during planting or sowing season in order to facilitate the adoption of improved wheat technology
6. Encouraging extension services and facilitating access to credit in the study area.
7. Finally, further support of improved wheat production technology package adoption should be given due attention for its impact on wheat yield produced by smallholders

Future Research Directions

Only the cross-sectional data were used in the study. Furthermore, because this study only considered one woreda, it may not accurately reflect the effects of the adoption of wheat technology across all of Ethiopia's woredas. Therefore, in order to adequately assess the influence of adoption of technology on household livelihood, any researcher interested in investing relevant topics or comparable topics should employ panel data from multiple woredas, at least sufficient time series data in rural woreda. Last but not least, this study also fails to demonstrate a relationship between household livelihood and the adoption of wheat technological package, instead using consumption expenditures and wheat yield as proxies.

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