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Adoption and impact of improved wheat varieties on productivity and welfare among smallholder farmers in the Arsi Highland of Ethiopia

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ABSTRACT

This article evaluates the adoption and impact of improved wheat varieties on rural farm household welfare measured by consumption expenditure per adult equivalent and productivity per hectare in rural Ethiopia. The study utilises cross-sectional farm household-level data collected in 2017/2018 from a randomly selected sample of 323 farmers in Arsi Highland of Ethiopia. We estimate the adoption and causal impact of improved varieties by utilising endogenous switching regression complemented with a binary propensity score matching methodology. This helps us estimate the productivity and welfare effect of technological adoption by controlling for the role of selection bias problem stemming from both observed and unobserved heterogeneity. Our analysis reveals a consistent result across models indicating that adoption enhances wheat productivity per hectare by 0.63 tons/ha and household welfare by 31%. Even farm households that did not adopt would benefit significantly had they adopted. Education, wheat price, farm machineries, crop rotation, row planting, social capital (such as informal network, core trust, and institutional trust), training on varieties selection, and information on seed availability are found to be the main drivers behind the adoption of improved wheat varieties.

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Technology adoption; endogenous switching regression; propensity score matching; productivity; household welfare

1. Introduction

Ethiopia has been the leading producer of wheat in sub-Saharan Africa and third in the continent. Wheat is the fourth most important cereal crop by area in the country. In the 2019/20 main season, the total area under wheat production was about 1.9 million hectares of land while the total production was 5.8 million tons (CSA 2021). In Ethiopian wheat production systems, durum wheat and landraces used to be predominant, but bread wheat has now gained popularity and approximately 80% of the wheat area in Ethiopia is planted bread wheat (Shiferaw et al. 2014).

Because of its rich natural resource endowment, Ethiopia is a major producer of wheat in sub-Saharan Africa. However, in production per unit area, the country consistently lags behind average yields in sub-Saharan Africa with an average wheat yield of 2.37 tons/ha[1] compared to 2.76 tons/ha in Kenya and 3.61 tons/ha in South Africa (Brasesco et al. 2019). Furthermore, Ethiopia is experiencing a huge gap between production (4.5 million tons in 2016), and consumption level (5.4 million tons in 2016), which results in import dependence (FAO 2017). Hence, the country

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faces a greater risk of high and unstable wheat price and supply shortfalls, and therefore, at greater risk of food insecurity.

Despite the low yield, demand for wheat has been growing fast in Ethiopia as a result of the rapid urbanisation, increasing in population growth, rising incomes, and changes in dietary patterns (Shiferaw et al. 2014; Tadesse and Bishaw 2018). Hence, the country needs to improve the production and productivity of wheat through the development and dissemination of high yielding varieties.

In recent decades, the Government of Ethiopia has taken a series of measures to harness the untapped potential of wheat for the poor. The national agricultural research organisation of Ethiopia, and partner international research centres have developed and disseminated high yielding, semi-dwarf and widely adaptable improved wheat varieties with heat tolerance and resistance to major diseases and pests (Shiferaw et al. 2014; Tadesse and Bishaw 2018). However, despite the considerable efforts to develop and disseminate several improved wheat varieties, the empirical evidence on rates of adoption and impacts of these technologies on farm productivity and household welfare-related outcome indicators are scant.

Several previous research (see, for instance, Adegbola and Gardebroek 2007; Beltran et al. 2013; Katengeza, Holden, and Lunduka 2019; Kuntashula, Nhlane, and Chisola 2018; Mottaleb, Mohanty, and Nelson 2015; Tiruneh and Wassie 2020) on technological adoption have focused on the role of human and physical capital, and they have been silent on the role that social capital plays in technological adoption (Micheels and Nolan 2016). However, in recent years, economists have started to explore the role that social capital plays in the technological adoption decision (see, for instance, Grootaert and Bastelaer 2001; Krishna 2004; Lee, Jeong, and Chae 2011; Teilmann 2012). Unlike earlier social capital studies, instead of using one overall index for measuring social capital six factors are constructed of 19 indicators on the informal network, core trust, general trust, and institutional trust using principal component analysis. In addition, the number of different dimensions of social capital in the present analysis is higher than in previous adoption studies (Hunecke et al. 2017; Kaasa 2009; Micheels and Nolan 2016; Van Rijn, Bulte, and Adekunle 2012) analysing more than one dimension.

There is existing literature on the estimation of the impact of adoption of improved varieties on farm household productivity, smallholder welfare, poverty reduction, and household food security at country, region, and global scale (Asfaw et al. 2012; Dibba et al. 2012; Makate et al. 2017; Manda et al. 2017; B. Shiferaw et al. 2014; Solomon et al. 2012; Tiruneh and Wassie 2020; Wossen et al. 2017; Wu et al. 2010). However, rigorous analysis of the impact of improved wheat varieties technology on farm productivity and welfare under smallholder agriculture is scant in Africa, exceptions would be Shiferaw et al. (2014) and Tesfaye, Bedada, and Mesay (2016).

Moreover, most of the impact studies related to modern agricultural technologies were conducted largely for crops such as maize (Becerril and Abdulai 2010; Makate et al. 2017), sorghum (Musara and Musemwa 2020; Wubeneh and Sanders 2006), groundnut (Manda et al. 2017), rice (Dibba et al. 2012; Wu et al. 2010) and legume (Asfaw et al. 2012; Shiferaw, Kebede, and You 2008). To the best of our knowledge, this study is the first to quantitatively estimate the impact of improved wheat varieties adoption on household welfare measured by consumption expenditure per adult equivalent unit (AEU) in sub-Saharan Africa. Given the interest, this article aims to contribute to the hitherto small body of evidence on the rigorous impact evaluation of improved varieties adoption at the household level to design proper policy and programme interventions.

In particular, the study seeks to address the following relevant key policy questions; what are the socioeconomic, demographic, and institutional variables that affect farmers' adoption of improved varieties in Arsi highland? What is the impact of the adoption of improved varieties on farm household wheat productivity per hectare and welfare? In addition to its empirical relevance, this study contributes to the existing adoption literature by examining the farm household productivity per hectare and consumption expenditure per AEU outcomes using a rigorous approach that accounts for both observed and unobserved sources of heterogeneity between adopters and non-adopters.

Indeed, not distinguishing the causal effect of the adoption of improved varieties, the effect of unobserved heterogeneity could lead to biased impact estimates. As at the household level, many other factors may have changed with technology, which leads to misleading policy implication. Hence, to bridge this gap, we account for the endogeneity of the adoption decision by estimating the endogenous switch regression (ESR) model to compute the counterfactual and average improved varieties adoption effects. The results of the ESR model may be sensitive to its assumptions of exclusion restriction, the binary propensity score matching (PSM) approach was also used to check the robustness of estimated effects obtained from the ESR model. Considering the existing literature (Asfaw et al. 2012; Di Falco, Veronesi, and Yesuf 2011; Jaleta et al. 2016; B. Shiferaw et al. 2014; Wossen et al. 2017) on impact evaluation, this is one of the novel exercises to our best knowledge.

2. Data description

The data for this study comes from individual household surveys conducted in Arsi Zone, Oromia Regional State of Ethiopia, during the 2017/2018 crop season. The Region and Zone account for over 60% and 10% of the national bread wheat production, respectively. The primary survey was conducted in two stages. First, a reconnaissance survey was done by a team of experts to have a broader understanding of the production, multiplication, distribution, and marketing conditions of the seed in the study areas. During this exploratory survey, discussions were held with different stakeholders including farmers, private seed companies, seed multiplier farmer cooperatives, seed enterprises, and extension agents. The findings from this stage were used to refine the sampling methods and the survey instrument. The data were collected using a pre-tested structured questionnaire by skilled enumerators, who have a good understanding of the farming systems and speak the local language, namely "Afaan Oromoo".

A multi-stage sampling procedure was used to select districts, *kebele*s,[2] and farm households. In the first stage, eight districts namely Hetosa, Digalu Tijo, Lemu Bilbilo, Munesa, Lode Hetosa, Tiyo, Shirka, and Robe were purposively selected based on the intensity of bread wheat production. These districts represent the major wheat producing areas, and suitable agro-ecology for wheat production, out of the 25 districts in Arsi Zone. Second, based on random sampling, four districts were selected from the eight intensive wheat producing districts. Digalu Tijo, Lemu Bilbilo, Hetosa and Munesa districts have 26, 36, 25 and 44 administrative units respectively. Of which Digalu Tijo, Lemu Bilbilo, Hetosa and Munesa have 22, 33, 23, and 40 farmers' associations, respectively, and the remaining are urban administrative units. In the third stage, a random sample of two *kebeles* that grew bread wheat were selected from each district for the survey, giving rise to a total of eight *kebeles*. This was followed by probability proportional to size sampling (PPS)[3] of 78–83 farm households from each district. A total of 323 farm households in eight *kebeles* were surveyed using the standardised survey instrument. The number of sampled farm households and their adoption status by districts are reported in Table 1.

The survey covered a wider range of variables that influence improved varieties adoption, wheat productivity, and consumption expenditure. Key socioeconomic and institutional data collected at the household level, among other things, contained information on household characteristics, factor cost, access to factor input, wheat price, shocks, sustainable agricultural practice, social capital (such as informal network, core trust and institutional trust), information sources, location variable, farm productivity and consumption expenditures.

For collecting the structural and cognitive dimensions of social capital data, the Social Capital Assessment Tool (SOCAT) developed by Grootaert and Bastelaer (2002) was adopted. The social capital indicators were obtained using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The scales are chosen so that larger values reflect a larger stock of social capital. Two indicators used to measure informal network are whether farmers get well with people in their community, and whether farmers get along well with other farmers. Core trust is measured by two

Table 1. The number of sampled farm households surveyed and their adoption categories by districts.

	Districts				
Adoption status	Digalu Tijo	Lemu Bilbilo	Munessa	Hetosa	Total
Non-adopters	28	38	38	30	134
Adopters	50	45	42	52	189
Total	78	83	80	82	323

Source: own computation, 2017/18.

indicators: trust in family and friends, and trust in other farmers. Institutional trust is measured by four indicators: trust in the legal system, trust in the municipal government and their policies towards agriculture, trust in agricultural offices, and trust in research institutions. To reduce the multidimensionality of our social capital variables, we employed principal component analysis.

The consumption expenditure components include nine major categories including expenditure on food and foodstuff (such as grain, vegetables, livestock products and other food items like sugar, salt, spices, etc.), beverages (such as tea leaves, coffee), health (such as health insurance, medical expenditure, etc.), transport, clothing, energy (such as solar energy, electricity, kerosene), school, social activities (contribution to churches, wedding, gift, etc.) and entertainment over 12 months (2017/2018). We rely on consumption expenditure as a measure of household welfare because it is less prone to seasonal fluctuations and measurement error than household income. Hence, a more reliable welfare indicator than income (Deaton 2019). Besides, household income shows the ability of the farm household to purchase its basic needs of life while consumption expenditure reflects the effective consumption of farm households (Asfaw et al. 2012). The consumption expenditure was calculated and adjusted to adult equivalents.[4]

3. Econometric framework and estimation strategies

3.1 Modelling impact of improved varieties

Following Ali and Abdulai (2010) and Becerril and Abdulai (2010) improved varieties adoption decision can be modelled in a random utility framework. The difference between the utility from adoption (U_{Ai}) and non-adoption (U_{Ni}) of improved varieties may be denoted as A^*, such that a utility-maximising rational farm household, i, will decide to adopt if the utility gain from adopting of improved varieties is greater than the utility of not adopting ($A^* = U_{Ai} - U_{Ni} > 0$). Since these utilities are unobservable, they can be expressed as a function of observable elements in the following latent variable model:

$$A_i^* = Z_i\alpha + \varepsilon_i \text{ with } A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where A_i is a binary indicator variable that equals 1 if a farmer has adopted at least one improved varieties and 0 otherwise; α is a vector of parameters to be estimated; and ε is an error term normally and independently distributed with mean 0 and variance δ^2; Z represents variables that affect the expected benefits of adoption. To reduce the multidimensionality of structural and cognitive social capital indicators, we have used the principal component analysis, with varimax rotation. In this study, adoption of improved wheat varieties is defined if farm households used any of the improved varieties, either freshly purchased, and/or recycled improved varieties for not more than three years,[5] irrespective of the area planted because some households use both improved and traditional varieties. Recycling of seed is common among wheat-growing farmers in Ethiopia (Shiferaw et al. 2014), consequently, improved seed can be replanted usually up to three years without major drops in yield. In the study area, about 13% of the farmers replace seed every year; another 71% replace for two to three years; about 6% replace every four years, and 10% replace whenever new varieties are available.

Considering that the variable of interest here – productivity per hectare and/or consumption expenditure per adult equivalent (*AEU*) – is a linear function of observed variables along with a dummy variable of improved varieties use, the linear regression equation can be specified as

$$Y_i = X_i\beta + \gamma A_i + \mu_i \tag{2}$$

where Y_i represents outcome variables, representing productivity per hectare and/or consumption expenditure per *AEU*, A_i is an indicator variable for adoption as defined above, X_i are observable variables, β and γ are vectors of parameters to be estimated, and μ is an error term. If A_i is uncorrelated with the error μ_i and the remaining OLS assumptions are met, then OLS yields consistent estimates of model parameters β, including the treatment effects A_i (Powers 1993). The impact of adoption on the outcome variable is measured by the estimates of the parameter γ

A switch regression model that treats the adoption of improved wheat varieties as regime shifter is presented as follows:

$$Y_{1i} = X_i\beta_1 + \mu_{1i}, \quad \text{if } A_i = 1 \tag{3a}$$

$$Y_{2i} = X_i\beta_2 + \mu_{2i}, \quad \text{if } A_i = 0 \tag{3b}$$

However, if there is a correlation between the error terms outcome Equations (3a) and (3b) and adoption Equation (1), estimating (3a) and (3b) without accounting this leads to a bias estimate. Thus, for adopters and non-adopters of improved varieties, the outcome equation (in this case, productivity per hectare and/or consumption expenditure per AEU) corrected for endogenous adoption is given as

$$\text{Regime 1:} Y_{1i} = X_{1i}\beta_1 + \sigma_{1\varepsilon}\hat{\lambda}_{1i} + \eta_{1i}, \quad \text{if } A_i = 1, \tag{4a}$$

$$\text{Regime 2:} Y_{2i} = X_{2i}\beta_2 + \sigma_{2\varepsilon}\hat{\lambda}_{2i} + \eta_{2i}, \quad \text{if } A_i = 0 \tag{4b}$$

where $\hat{\lambda}_{1i} = \varphi(Z_i\hat{\alpha})/\Phi(Z_i\hat{\alpha})$ and $\hat{\lambda}_{2i} = \varphi(Z_i\hat{\alpha})/1 - \Phi(Z_i\hat{\alpha})$ are the inverse Mill's ratios (IMRs) computed from the selection equation (Equation (1)) to correct for selection bias in the selection-stage equation (outcome equations). β and σ are parameters to be estimated, and η is an independently and identically distributed error term with mean zero and constant variance. The standard error in Equations (4a) and (4b) are bootstrapped to account for the heteroskedasticity arising from the generated regressors ($\hat{\lambda}$).

Though the functional form (nonlinearity of the selection correction term, λ) may identify the systems of Equations (1), (4a), and (4b) (Lokshin and Glinskaya 2009), we use as selection instruments in the outcome variables related to the information sources (e.g., household access to improved varieties, contact with extension agent, information on varieties availability, distance to seed source (walking minute), and participation in seed training/variety selection). We establish the admissibility of the instrument if a variable is a valid selection instrument, it will affect the technology adoption decision, but it will not affect the outcomes equation (Di Falco, Veronesi, and Yesuf 2011; Jaleta et al. 2016).[6] Similarly, distance to seed market and variety information have been used as an instrument in other applications that address the impact of improved varieties adoption (Shiferaw et al. 2014). Di Falco, Veronesi, and Yesuf (2011) and Asfaw et al. (2012) also used different information and awareness related variables as an instrument in their analysis of the impact of the adoption of agricultural technology on food security in Africa.

Following (4a) and (4b), the actual and counterfactual expected productivity per hectare and/or consumption expenditure per AEU is given as follows:

$$\text{(a)}\ \ E[Y_{1i}|X, A_i = 1] = X_{1i}\beta_1 + \sigma_{1\varepsilon}\hat{\lambda}_{1i} \tag{5a}$$

$$\text{(b)}\ \ E[Y_{2i}|X,\ A_i = 0\,] = X_{2i}\beta_2 + \sigma_{2\varepsilon}\hat{\lambda}_{2i} \tag{5b}$$

$$\text{(c)}\ \ E[Y_{2i}\,|X,\ A_i = 1] = X_{1i}\beta_2 + \sigma_{2\varepsilon}\hat{\lambda}_{1i} \tag{5c}$$

$$\text{(d\ )}E[Y_{1i}|X,\ A_i = 0] = X_{2i}\beta_1 + \sigma_{1\varepsilon}\hat{\lambda}_{2i} \tag{5d}$$

Cases (5a) and (5b) along the diagonal of Table 2 represent the actual expectations observed in the sample. Equations (5c) and (5d) are the counterfactual expected outcomes. The counterfactual outcome is defined as the expected outcome of improved varieties adopters if their characteristics (X_{1i}) had the same return as non-adopter characteristics (β_2) and vice versa.

$A_i =$ 1 if farm households adopted improved wheat varieties; $A_i = 0$ if farm households did not adopt improved wheat varieties; $Y_{1i} =$ wheat productivity per hectare and consumption expenditure per AEU if households adopted; $Y_{2i} =$ wheat productivity per hectare and consumption expenditure per AEU if households did not adopt. $ATT =$ average treatment effect on treated; $ATU =$ average treatment effect on untreated.

$BH_1 =$ the effect of base heterogeneity for farm households that adopted $(a - d)$; $BH_2 =$ the effect of base heterogeneity for farm households that did not adopt $(c - b)$; $TH =$ transitional heterogeneity $(ATT - ATU)$.

Following Heckman, Tobias, and Vytlacil (2001) and Di Falco, Veronesi, and Yesuf (2011), we calculate the effect of treatment "to adopt" on the treated (ATT) as the difference between (a) and (c),

$$ATT = E\,[Y_{1i}\,|X,\ A_i = 1] - E[Y_{2i}|X,\ A_i = 1] = X_{1i}\,(\beta_1 - \beta_2) + \hat{\lambda}_1\,(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \tag{6}$$

which represents the effect of improved wheat varieties adoption on the outcome of the farm households that actually adopted the technology. Similarly, the effect of the treatment on the untreated (ATU) for farm households that actually did not adopt improved varieties as the difference between (d) and (b),

$$ATU = E[Y_{1i}|X,\ A_i = 0] - E[Y_{2i}|X,\ A_i = 0] = X_{2i}\,(\beta_1 - \beta_2) + \hat{\lambda}_2\,(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \tag{7}$$

We follow Carter and Milon (2005) and define as "the effect of base heterogeneity" for the group of farm households that decided to adopt improved varieties as the difference between (a) and (d),

$$BH_1 = E[Y_{1i}\,|X_{1i},\ A_i = 1] - E[Y_{1i}\,|X_{2i},\ A_i = 0] = \beta_{1i}(X_{1i} - X_{2i}) + \sigma_{1\varepsilon}(\hat{\lambda}_{1i} - \hat{\lambda}_{2i}) \tag{8}$$

Similarly for the group of farm households that decided not to adopt, "the effect of base heterogeneity" is the difference between (c) and (b),

$$BH_2 = E[Y_{2i}\,|X_1,\ A_i = 1] - E[Y_{2i}|X_{2i}\,A_i = 0\,] = \beta_{2i}\,(X_{1i} - X_{2i}) + \sigma_{2\varepsilon}(\hat{\lambda}_{1i} - \hat{\lambda}_{2i}) \tag{9}$$

The PSM approach is widely applied in the impact literature (Ali et al. 2018; Ali and Abdulai 2010; Mendola 2007) and we shall not present the methodology here. For a good overview of the specification, assumptions, and basic setup of binary matching methods, see Heckman, Ichimura, and Todd (1997) and Wooldridge (2002). Several matching methods have been developed to match adopters of improved varieties with non-adopters of the similar propensity score. Asymptotically, all matching methods should yield similar results. However, in practice, there are trade-offs in terms of bias and efficiency with each method (Caliendo and Kopeinig 2008). Hence, we use the nearest neighbour matching (NNM), caliper matching[7] and Kernel-based matching (KBM).[8]

Each of the three matching methods has some shortcomings. NNM faces the risk of bad matches if the closest neighbour is far away. This risk can be avoided by using caliper matching, which imposes a maximum tolerance level on the difference in propensity scores (caliper). Finally, Kernel

Table 2. Conditional expectations, treatment, and heterogeneity effects.

	Decisions stage		
Sub-samples	To adopt	Not to adopt	Treatment effects
Adopters	(a) $E[Y_{1i} \mid X_{1i}, A_i = 1]$	(c) $E[Y_{2i} \mid X_{1i}, A_i = 1]$	*ATT*
Non-adopters	(d) $E[Y_{1i} \mid X_{2i}, A_i = 0]$	(b) $E[Y_{2i} \mid X_{2i}, A_i = 0]$	*ATU*
Heterogeneity effects	BH_1	BH_2	*TH*

Notes: (a) and (b) represent observed expected wheat productivity per hectare/consumption expenditure per AEU; (c) and (d) represent counterfactual expected wheat productivity per hectare/consumption expenditure per AEU.
Source: Adapted from Di Falco, Veronesi, and Yesuf (2011) and Jaleta et al. (2016).

matching is a non-parametric matching estimation that uses weighted averages of all farm households in the control group to construct counterfactual. It has the advantage of minimising the potential risk of bad matches that would arise from the use of nearest neighbour matching methods (Caliendo and Kopeinig 2008).

Several balancing tests exist in the literature, the most widely used is the mean absolute standardised bias (MASB) between technology adopters and non-adopters suggested by Rosenbaum and Rubin (1985). They recommend that a standardised difference of greater than 20% should be considered too large and an indicator that the matching process has failed. Furthermore, Sianesi (2004) suggests a comparison of the pseudo R^2 before and after matching. The pseudo-R^2 is supposed to indicate how well the regressors explain the adoption probability. After matching, there should be no systematic differences in the distribution of covariates between the two groups and, therefore, the pseudo-R^2 should be fairly low. The test should not be rejected before but should be rejected after matching.

4. Results and discussions

4.1 Results of descriptive analyses

To reduce the multidimensionality of social capital and describe the underlying social capital data, the principal component analysis (Stata 2005) was implemented. Besides, the exact descriptions of the indicators result included in the analysis are presented in the Appendix (Table A1) because of space limitations. To determine the number of factors or components, the Kaiser (1960) criterion was followed in which one retains eigenvalue greater than 1 for principal components, or greater than 0 for common factors. This rule is also the default retention criterion for several commonly used statistical packages (e.g., SPSS, SAS, ad STATA). Variables corresponding to "large" components (loadings) are often subjected to interpretation as being important for describing the original data; variables corresponding to "small" loadings can be discarded (Gorst-Rasmussen 2012). Hence, for reasons of simplicity and clarity, the coefficients with absolute value less than 0.4 are suppressed.

The first and fourth factors can be interpreted as "institutional trust" as it covers all six indicators which consist of three macro and meso formal institutional environment trust and three agricultural institutional trusts. The statement that load on Factor 1 all seem to relate to trust in the formal institutional environment with emphasis on trusting the courts (Eigenvalue of 0.459), legal system (Eigenvalue of 0.414), and municipal government and their policies towards agriculture (Eigenvalue of 0.451). This institutional view posits that trusting the courts, legal system, and municipal government and their policies toward agriculture are the main determinants of the strength of community network (Grootaert and Bastelaer 2002). Factor 4 shows attitudes related to trust in the formal agricultural environment with emphasis on the agricultural research institution (Eigenvalue of 0.628), agricultural agents (Eigenvalue of 0.486), and agricultural offices (Eigenvalue of 0.419). This is referred to as the *structural-bringing social* capital – shows that respondents who have high scores in trusting agricultural institutions also tend to trust the agricultural research institutions.

The second factor can be interpreted as an "informal network" as it covers all four indicators which encompasses relationship within horizontal associations. This factor shows the strong positive correlation of getting along well with other farmers (Eigenvalue of 0.499), with friends (Eigenvalue of 0.487), and with people in my community (Eigenvalue of 0.474). Farmers who value informal networks find it highly important to get along well with other farmers within the farm community. The third set of variable highly relates towards core trust within the immediate environment, particularly trust of family and friends (Eigenvalue of 0.578), trust church and its people (Eigenvalue 0.568), and trust other farmers (Eigenvalue of 0.445). Grootaert and Bastelaer (2001) refers to this as a central element of cognitive social capital, named "Core Trust". The other statement that load highly on Factor 5 seems to relate to the respondents' own feelings of trustworthiness and feeling safe in the neighbourhood. This factor is also named as "Core Trust". This component shows a strong positive correlation of feeling trustworthy (0.634) and feeling safe in neighbourhood (0.648). What is interesting to note is that, we found that a question commonly used to investigate interpersonal trust – "Do you agree that most people could be trusted?" load highly on Factor 6. Putnam, Leonardi, and Nonetti (1993) refers to this as the *bonding element* of social capital.

Table 3 presents differences in the main socioeconomic and plot-level characteristics of adopters and non-adopters with their *t*-values for continuous variables and chi-square test for categorical variables. The data set contains 323 households, and of these, about 59% adopted improved varieties.

Adopter categories do seem to significantly differ in terms of the level of farm household head education and educational attainment. This suggests that education might be correlated with the decision to adopt. In particular, adopters generally own more cultivated own farmland than non-adopters, so that, adopters might have used their "success" to enlarge their operation land. Significant dissimilar is observable in access to off-farm activities between adopters and non-adopters, and the non-adopter households participating in off-farm work was comparatively higher.

Thus, adopters generally received higher wheat price than non-adopters, and spend less diammonium phosphate (DAP) fertiliser and chemical cost than non-adopters, suggesting greater benefits from this source. Quite interesting is the significant difference in farm machineries utilisation between adopters and non-adopters. These suggest that the utilisation of farm machineries might be correlated with the decision to adopt. Correspondingly, there are remarkable differences between adopters and non-adopters with respect to insects, and weed damage incidence. These suggest that adopter groups experience less incidence of insects, and weed damage as compared to non-adopters. The improved varieties adopters are also significantly distinguishable in terms of practicing crop rotation[9] and on-farm varieties selection. This suggests that practicing sustainable agricultural practice might be correlated with the decision to adopt. Furthermore, a significant difference was found in agronomic practices. For instance, row planting was significantly different between adopter and non-adopter groups.

Social capital[10] can be understood based on two distinct types, namely, structural and cognitive social capital (Uphoff 2000). Cognitive social capital is the intangible aspect of social capital, associated with shared norms, values, attitudes, trust, and beliefs. Structural social capital is associated with vertical or horizontal networks, in other words, intra-community ties (Woolcock and Narayan 2000). Two forms of such structural social capital exist: bonding and bringing (Putnam 1995). Bonding capital, typically occurs among those with strong ties while bringing social capital occurs mainly among those with weak ties (Teilmann 2012; Van Rijn, Bulte, and Adekunle 2012).

The study result depicts that adopter groups do seem to significantly differ in terms of the level of social capital as compared to non-adopter, i.e., adopters have higher peer-to-peer associations as compared to non-adopters. This factor is labelled as "Informal Network". Adopter categories are also distinguishable in terms of trust in agricultural institutions. This simple comparison suggests that trust in agricultural offices and research institutions can have an important influence on farmers' adoption of improved agricultural technology.

The average walking distance to seed source in a minute is significantly lower for adopters and they seem to have also more access to preferred improved varieties and extension services. However,

Table 3. Summary statistics for variables in regressions.

Variables	Full sample (N = 323) Mean	SD	Non-adopters (N = 134) Mean	SD	Adopters (N = 189) Mean	SD
Outcome variables						
Consumption expenditure per AEU (ETB[12])*	11088	6141	10472	6882	11524	5535
Log Consumption expenditure per AEU ***	9.18	0.51	9.09	0.58	9.25	0.45
Productivity per hectare per ton***	4.26	1.51	3.76	1.22	4.61	1.61
Household characteristics						
Gender of household head (1 = male)	0.9	0.31	0.91	0.29	0.88	0.32
Age of household head (years)	44.58	12.68	44.54	12.08	44.6	13.13
Education of household head (years) **	5.83	3.84	5.25	3.54	6.25	3.99
Family size (number)	5.81	2.48	5.72	2.57	5.87	2.41
Owned cultivated farm land (hectare) ***	1.63	1.22	1.37	1.01	1.81	1.33
Off-farm job participation (1 = yes) **	0.23	0.42	0.28	0.45	0.19	0.39
Rent in farm land (hectare)	0.55	0.7	0.49	0.54	0.59	0.8
Output and input price						
DAP fertiliser cost (ETB/kg) **	13.35	2.31	13.63	1.93	13.14	2.54
Urea fertiliser cost (ETB/kg)	8.2	6.14	8.28	6.51	8.14	5.89
Wheat price (ETB/kg) ***	7.31	1.26	7.05	0.73	7.49	1.26
Chemical cost per household (ETB)[13]	1556.81	1408.1	1398.6	1312.8	1669	1312.8
Rent tractor (1 = yes) ***	0.35	0.48	0.27	0.44	0.41	0.49
Rent combine harvester (1 = yes) ***	0.84	0.37	0.75	0.43	0.9	0.37
Face labour shortage (1 = yes)	0.37	0.48	0.37	0.49	0.36	0.48
Shocks						
Insect damage (1 = yes) *	0.37	0.48	0.43	0.45	0.33	0.47
Disease damage (1 = yes)	0.67	0.47	0.64	0.48	0.64	0.46
Weed damage (1 = yes)**	0.55	0.53	0.64	0.57	0.48	0.5
Sustainable agricultural practice						
Crop rotation (1 = yes)***	0.7	0.46	0.43	0.5	0.9	0.3
Practice seed selection (1 = yes)	0.67	0.47	0.63	0.49	0.7	0.46
Row planting (1 = yes) ***	0.32	0.47	0.17	0.38	0.42	0.5
Social capital						
Get well with community ***	4.23	0.68	4.04	0.72	4.37	0.72
Get well with farmers ***	4.25	0.68	3.97	0.6	4.44	0.66
Trust family & friends	4.23	0.71	4.24	0.74	4.22	0.69
Trust farmers	4.03	0.71	3.98	0.68	4.06	0.73
Trust legal system	3.51	1.07	3.56	101	3.48	1.12
Trust municipal government	3.66	.097	3.70	0.95	3.63	0.97
Trust agricultural office ***	3.59	0.89	3.33	0.84	3.77	0.88
Trust research institution ***	4.05	0.74	3.84	0.68	4.21	0.73
Information sources and location						
Distance to seed source (walking minute) ***	39.56	30.56	47.29	35.8	34.07	24.9
Extension contact (1 = yes)**	0.73	0.44	0.67	0.47	0.78	0.42
Training on variety selection (1 = yes) ***	0.62	0.49	0.46	0.5	0.72	0.45
Information on seed availability (1 = yes) ***	0.53	0.5	0.42	0.5	0.6	0.49
Access to preferred varieties (1 = yes) ***	0.24	0.43	0.13	0.34	0.32	0.47

Note: statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels.

non-adopters are more constrained by a lack of access to improved varieties and have less contact with the extension agents. The result also reveals that the adopter groups are distinguishable in terms of information on improved varieties availability and participation in seed training/variety selection.

This simple comparison of the two categories also suggests that adopter and non-adopter groups vary significantly in wheat productivity per hectare and welfare. The average wheat productivity from the survey data was 0.426 tons/ha. However, the average wheat productivity for adopters was 0.461 tons/ha, whereas the average wheat productivity for non-adopters was 0.376 tons/ha. The mean consumption expenditure per AEU for adopters is ETB 11524 per year, which is significantly higher than ETB 10472 per year by non-adopters. These unconditional statistics suggest that the adoption of improved varieties may have a role in improving household productivity per hectare and consumption expenditure per AEU.

However, given improved varieties adoption is endogenous, a simple comparison of productivity and welfare indicators among adopter and non-adopter groups have no causal interpretation. That is, the above difference in productivity and welfare may not be the result of improved varieties rather it might be due to other observed and unobserved factors. Hence, to test the effect of technological adoption on productivity and welfare accounting for all factors is reported in the subsequent section using endogenous switch regression analysis.

4.2 Estimation of the adoption model

Table 4 presents results from the first stage of ESR model. The dependent variable is binary improved wheat varieties adoption. The goodness-of-fit measures indicate that the selected covariates provide a good estimate of the conditional density of adoption. For instance, the Wald chi-square test statistics (161.02) indicate that the explanatory variables are jointly significant ($p < 0.01$).

Estimation results in Table 4 show that the probability of adoption of improved varieties is negatively associated with the gender of the household head. Female-headed households had a higher adoption rate compared to male-headed households. This could be due to the fact that some success has been achieved in targeting vulnerable rural female-headed households by NGOs and the Government of Ethiopia (Zeleke et al. 2021). Educated farm households are more likely to adopt because they are more informed, better receptive to improved varieties and manage such technologies successfully.

Off-farm participation has a negative effect on the improved varieties adoption. Our results indicate that economic incentives, like attractive wheat price, can have a significant positive effect on the adoption decision. This positive effect of wheat output price is consistent with Shiferaw et al. (2014) for improved varieties in Ethiopia. Renting a farm machine played a positive and significant role in affecting the likelihood of adoption of improved varieties, suggesting the positive effect of farm machineries in wheat cultivation and harvesting. However, the shortage of family labour is negatively associated with adoption. This reflects that improved varieties are more labour-intensive, because of the greater demands they impose on labour for weeding. This result is in agreement with Danso-abbeam et al. (2017). Similarly, incidence with weed shock has a negative effect on the adoption of improved varieties.

The role of sustainable agricultural practice also seems very important in determining the adoption decision. Farm households who practice crop rotation are more likely to adopt improved varieties. Furthermore, agronomic practice such as row planting has a significant and positive effect on the probability of adoption. Our results indicate that informal networks, for instance, getting well with other farmers, can have a significant role in the adoption decision. This could be due to enhanced information or better access to knowledge and resource mainly from the participation in the network. On the other hand, trust in families and friends are negatively associated with adoption decision. This finding could represent "a dark side" of social capital. Since, norms of core trust may result in inward-looking models of behaviour, promote conformity and reducing willingness to adopt improved varieties. However, this result does not imply that core trust is unimportant, it could serve other functions such as insurance to idiosyncratic shocks.

Trust in other farmers has a positive and significant impact on the probability of improved wheat varieties adoption. This postulates the critical role of social interaction among farmers in promoting technological adoption. Likewise, the result shows that the main components of social capital, such as trust in agricultural offices and research institutions influence adoption decision positively and significantly. This is expected, as this form of social capital captures agriculture-related links creating access to knowledge and resource through extension offices and research institutions. For instance, Van Rijn, Bulte, and Adekunle (2012) argue that strong intra-community trust and norms are associated with fewer innovation, and participation with "outsiders" is associated with enhanced adoption of innovations. Hence, we can argue that higher trust in the agricultural institution may lead to adoption decision.

Table 4. The decision to adopt improved wheat varieties: a probit model.

Explanatory variables	Coefficient	Std. err.	Marginal effect
Household characteristics			
Gender of household head	−0.545	0.369	−0.173*
Age of household head	0.006	0.011	0.002
Education of household head	0.067	0.032	0.024**
Family size	−0.006	0.049	−0.001
Owned cultivated farm land	0.178	0.108	0.064
Off-farm job participation	−0.656	0.285	−0.248**
Rent in farm land	0.142	0.156	0.054
Output and input price			
DAP fertiliser cost	−0.052	0.044	−0.019
Urea fertiliser cost	0.008	0.017	−0.003
Wheat price	0.195	0.104	0.07*
Chemical cost per household	−0.0001	0.0001	−0.0004
Rent tractor	0.665	0.276	0.225***
Rent combine harvester	0.651	0.313	0.249**
Face labour shortage	−0.588	0.253	−0.216**
Shocks			
Insect damage	0.211	0.306	0.075
Disease damage	0.146	0.307	0.053
Weed damage	−0.754	0.287	−0271***
Sustainable agricultural practice			
Crop rotation	1.727	0.232	0.609***
Practice seed selection	0.118	0.261	0.043
Row planting	0.755	0.222	0.249***
Social capital			
Get well with community	−0.056	0.19	−0.02
Get well with farmers	0.585	0.19	0.21***
Trust family & friends	−0.442	0.19	−0.16**
Trust farmers	0.463	0.184	0.166**
Trust legal system	−0.027	0.145	−0.01
Trust municipal government	−0.062	0.141	−0.22
Trust agricultural office	0.761	0.138	0.273***
Trust research institution	0.509	0.143	0.183***
Information sources and location			
Distance to seed source	−0.013	0.004	−0.005***
Extension contact	0.075	0.25	0.027
Training on varieties selection	0.368	0.217	0.136*
Information on seed availability	0.493	0.23	0.177**
Access to preferred varieties	0.374	0.313	0.128
Model diagnosis			
Wald chi2(33)	161.02		
Log pseudo-likelihood	−219.18		
Pseudo R2	0.544		
Number of observation	323		

Note: statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels.

Distance to seed source is negatively correlated with improved varieties adoption. Those farmers who reside near to seed source probably have better access to improved varieties and are more likely to adopt. This negative effect of distance to seed source is consistent with Asfaw et al. (2012) for improved varieties adoption in Tanzania and Ethiopia. Participation in seed training/variety selection has a positive and significant influence on the adoption of improved wheat varieties. The positive and significant effect of participation on varieties selection confirms the role of participation in raising awareness and promoting technology adoption. On the other hand, farm households with improved varieties information are more likely to adopt improved varieties, underscoring the relevance of the selected instrument. This may indicate that information availability on improved varieties may be the most crucial prerequisite for adoption. To adopt new improved variety farmers need to have information on seed availability. A similar result was found by Shiferaw et al. (2014) for improved wheat varieties in Ethiopia.

4.3 Welfare and productivity effects of technology adoption

This section discusses the results obtained from the two methods: ESR and binary PSM. Here we are interested in the question "How would the outcome of improved varieties adopters have changed, had adopters chosen not to adopt improved varieties." The results of PSM method are consistent with our main finding reported using an ESR approach.

4.3.1 Endogenous switching regression estimation results

Table 5 presents the expected outcome variables under actual and counterfactual condition obtained using the ESR treatment effects approach. The model accounted for both observable and unobservable sources of heterogeneity. The key outcome variables considered in the analysis are natural logarithms of consumption expenditure per AEU and productivity per hectare. The consumption expenditure per AEU is transformed into logarithms because it is very left-skewed.

Cells (a) and (b) denote the expected log consumption expenditure per AEU and productivity per hectare observed in the sample. The expected wheat productivity per hectare by farm households that adopted (4.61 tons) is higher than the group of households that did not adopt (3.76 tons). However, this simple comparison can be misleading and drive the researcher to conclude that on average the farm households that adopted improved varieties produce about 0.85 tons more than the households that did not adopt. Similarly, the expected log consumption expenditure per AEU by farm households that adopted improved varieties is higher than the group of households that did not adopt.

The last column of Table 5 presents the treatment effect of the adoption of improved wheat varieties. In the counterfactual case (c), current adopters would have produced 0.63 tons/ha less had they not adopted improved varieties, and instead relied on old unimproved varieties. The results further show that, without adoption, the consumption expenditure per AEU would have been lower by 30.4%. The average log consumption expenditure per AEU is not significant in the case when households that did not adopt adopted. However, the transitional heterogeneity effect for log consumption expenditure per AEU is positive; that is the effect is bigger for farm households that did adopt improved varieties with respect to the one that did not adopt.

In the counterfactual case (d) that farm households that did not adopt adopted, they would have produced about 1.33 tons more if they had adopted, implying that current non-adopters would have realised a higher level of productivity per hectare from switching to improved wheat varieties production. However, the transitional heterogeneity effect is negative (−0.7 tons), i.e., the productivity effect is greater for non-adopters. Taken together, the results clearly emphasise that the adoption of improved wheat varieties is associated with improved productivity per hectare and consumption expenditure per AEU. Hence, further dissemination efforts of improved varieties to non-adopters will be essential to maximise productivity and welfare benefits since 41% of farmer households are still non-adopters. The coefficient estimate of the second stage ESR is not discussed because

Table 5. Average treatment effects: Endogenous switching regression model.

	Decision stage		
Sub-samples	To adopt	Not to adopt	Treatment effects
Log consumption expenditure per adult AEU			
Adopters	(a) 9.25	(c) 8.95	ATT = 0.304(6.43)***
Non-adopters	(d) 9.12	(b) 9.09	ATU = 0.027(0.52)
	$BH_1 = 0.13$	$BH_2 = -0.14$	TH = 0.28
Productivity per hectare (in ton)			
Adopters	(a) 4.61	(c) 3.96	ATT = 0.64 (8.49)***
Non-adopters	(d) 5.08	(b) 3.76	ATU = 1.33 (16.59)***
	$BH_1 = -0.47$	$BH_2 = 0.20$	TH = −0.68

Note: statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. The number in brackets shows the absolute value of t-statistic.

of space limitations, but the estimated coefficients for productivity per hectare and log consumption expenditure per AEU are presented in the Appendix (Table A2).

4.3.2 Binary propensity score matching (PSM) estimation

As the results of the ESR model may be sensitive to its assumption, the PSM approach was used to check the robustness of the estimated effects obtained from the ESR models. We use a probit model to predict the probability to adopt the improved varieties because matching is based on the assumption of conditional independence, variables included in the model should satisfy the "balancing requirement". The matching variables used are the same as the explanatory variables presented in Table 2. Appendix (Figures A1 and A2) provides the histogram of the estimated distribution of the propensity scores as well as the region of common support for adopters and non-adopters. A visual inspection of the density distributions of the estimated propensity scores between adopters and non-adopters indicate that the common support condition is satisfied: there is a substantial overlap in the distribution of the propensity scores of the adopter and non-adopter groups. These reveal the significance of proper matching and the imposition of the common support condition to avoid bad matches.

A glance at Table 6 indicates results from covariate balancing tests before and after matching methods. The standardised mean difference (see Caliendo and Kopeinig 2008) for overall covariates used in the propensity score (around 235% before matching) is reduced to about 0.2% after matching. As indicated by the standard mean difference measure, the caliper approach has the best matching quality (about 0.2% after matching). The results reveal substantially reduced in total bias in the range of 97.1–99.9% through matching. The p-values of the likelihood ratio tests indicate that the joint significance of covariates was always rejected after matching; whereas it was never rejected at any significance level before matching.

As is evident in Table 6, the pseudo-R^2 also dropped significantly from 51% before matching to about 0% after matching. The low pseudo-R^2, low mean standardised bias, high total bias reduction, and the insignificant p-value of the likelihood ratio test after matching suggests that there is no systematic difference in the distribution of covariates between adopters and non-adopters after matching.

Different matching algorithms, NNM matching, caliper matching, and KBM, are used to estimate the effects of improved wheat varieties adoption on log consumption expenditure per AEU and wheat productivity per hectare. The different matching algorithms produced different quantitative results, but the qualitative findings are similar. The PSM results indicate that the adoption of

Table 6. Propensity score matching: quality test.

Matching algorithm	Pseudo R^2 before matching	Pseudo R^2 after matching	LR X^2(p-value) before matching	LR X^2 after matching	Mean standardised bias before matching	Mean[14] standardised bias after matching	Total% |bias| reduction
NNM[a]	0.513	0.000	225 ($p = 0.000$)	0.000 ($p = 0.988$)	235	0.2	99.9
NNM[b]	0.513	0.001	225 ($p = 0.000$)	0.39 ($p = 0.610$)	235	6.9	97.1
NNM[c]	0.513	0.000	225 ($p = 0.000$)	0.00 ($p = 0.988$)	235	0.2	99.9
NNM[d]	0.513	0.000	225 ($p = 0.000$)	0.00 ($p = 0.988$)	235	0.2	99.9
KBM[e]	0.513	0.000	225 ($p = 000$)	0.00 ($p = 0.971$)	235	0.5	99.8
KBM[f]	0.513	0.000	225 ($p = 0.000$)	0.00 ($p = 0.958$)	235	1.0	99.7

[a]NNM = single nearest neighbour matching with replacement and common support.
[b]NNM = five nearest neighbour matching with replacement and common support.
[c]NNM = single nearest neighbour matching with replacement, common support and caliper (0.1).
[d]NNM = five nearest neighbour matching with replacement, common support, and caliper (0.5).
[e]KBM = kernel based matching with bandwidth 0.03 common support.
[f]KBM = kernel based matching with band with 0.06 common support.

Table 7. Average treatment effects: propensity score matching.

Outcome variable	Matching algorithm	Mean of outcome variables based on matching observations		
		Adopters	Non-adopters	ATT
Log consumption expenditure per AEU	NNM[a]	9.198	9.135	0.063
	NNM[b]	9.198	9.12	0.078
	NNM[c]	9.198	9.135	0.063
	NNM[d]	9.198	9.135	0.063
	KBM[e]	9.185	9.127	0.058
	KBM[f]	9.198	9.108	0.09
Productivity per hectare	NNM[a]	4.816/4.835	3.634/4.023	0.811**
	NNM[b]	4.816/4.835	3.939/3.937	0.898**
	NNM[c]	4.816/4.835	3.634/4.023	0.811**
	NNM[d]	4.816/4.835	3.634/3.937	0.898***
	KBM[e]	4.884/4.919	3.795/3.788	1.132/1.132***
	KBM[f]	4.816/4.835	3.729/3.745	1.089/1.089***

[a]NNM = single nearest neighbour matching with replacement and common support.
[b]NNM = five nearest neighbour matching with replacement and common support.
[c]NNM = single nearest neighbour matching with replacement, common support and caliper (0.1).
[d]NNM = single nearest neighbour matching with replacement, common support and caliper (0.5).
[e]KBM = kernel based matching with bandwidth 0.03 common support.
[f]KBM = kernel based matching with bandwidth 0.06 common support.

improved varieties has a positive and significant effect on log consumption expenditure per AEU and wheat productivity per hectare.

The matching results from single and five NNM, caliper, and KBM with two different bandwidth approaches in Table 7 indicate that the adoption of improved varieties increase log consumption expenditure per AEU from 5.8% to 9%. This is the average difference in log consumption expenditure per AEU between similar pairs of households that belong to different technological status. Adoption of improved wheat varieties had raised the log consumption expenditure per AEU by about 6.3% for single NNM, and 9% for KBM (bandwidth = 0.06) on average compared to the non-adopters. Taking the caliper approach with a caliper of 0.1 and 0.5 as an example, the adoption of improved varieties had raised the log consumption expenditure per AEU by about 6.3%.

The matching result from NNM, caliper, and KBM approach in Table 7 generally indicate that the adoption of improved wheat varieties exerts a positive and significant effect on households' wheat productivity per hectare. Regarding productivity per hectare, matching results from single and five NNM, caliper and KBM (with the bandwidth of 0.03 and 0.06) approaches indicate that the adoption of improved varieties increase wheat productivity per hectare from 0.81 to 0.89 tons. The five NNM, caliper of 0.1, and KBM (bandwidth = 0.03) causal effects of adoption on productivity (measured in a ton, at 0.898, 0.811 and 1.132 tons per hectare, respectively) suggest that wheat yields of improved varieties adopters are higher by about 0.811 to 1.132 tons per hectare than non-adopters.

5. Conclusions and implications

This article evaluates the potential impact of the adoption of improved varieties on-farm productivity and household welfare in Arsi Highland of Ethiopia. The study utilises cross-sectional farm household-level data collected in 2017/18 from a randomly selected sample of 323 farm households in rural Ethiopia using the probability proportional to size sampling. We combine parametric with non-parametric techniques to mitigate selection biases that could stem from both observed and unobserved heterogeneity. The parametric estimation employs the ESR approach, while the non-parametric method involves the PSM method to estimate the impact of improved wheat varieties on wheat productivity per hectare and household welfare among households.

Our main results are summarised as follows: first, the group of farm households that did adopt have systematically different characteristics than the group of farm households that did not adopt. These differences represent sources of variation between the two groups that the estimation of an OLS model, including a dummy variable for adopting or not cannot take into account.

Second, even though the magnitude of estimated effects varies across estimation methods, consistent results were found across estimation methods. Indicating that improved wheat varieties adoption leads to a significant positive impact on productivity per hectare and household consumption expenditure per AEU. Interesting patterns emerge when we evaluate the ESR results for adopter and non-adopter groups. Farm households who actually adopted tend to be more productive per hectare than households that did not adopt in the counterfactual case that they did not adopt. Farm households who adopted have some characteristics (e.g., unobserved skills) that would make them more productive even without the adoption of improved varieties.

The study reveals that the impact of adoption on productivity per hectare is smaller for the farm households that actually did adopt than for households that did not adopt in the counterfactual case that they adopted. It seems, therefore, that while both adopter and non-adopter groups would benefit from the adoption of improved varieties, the farm households that did not adopt improved wheat varieties would benefit the most from adoption. This beneficial effect of the adoption of improved varieties is found to be large. Revealing that, if the farm households that did not adopt had adopted improved varieties, they would have produced more than the farm households that actually adopted.

These higher benefits to non-adopters indicate the existence of other limiting factors and barriers to the adoption of improved varieties. Besides, we found that adopters have significantly higher consumption expenditure per AEU than non-adopters of improved varieties even after controlling for all confounding factors. This confirms the potential direct benefit of improved varieties adoption on rural household productivity per hectare, as a higher gain of productivity per hectare from adoption also means higher consumption expenditure per AEU.

The question is if productivity per hectare and consumption expenditure per AEU effects of improved wheat varieties are so great, what explains the lack of adoption by about 59% of surveyed households? The adoption analysis result shows that gender of the household head, education of household head, wheat grain price, farm machine, crop rotation, row planting, social capital, distance to the seed source, training on varieties selection, and varieties information influence the adoption of improved wheat varieties. This implies the need for policy to strengthen, develop and leverage government information system, provide appropriate economic incentive via value chain development, schooling, training centres for participatory varieties selection, and rural institutions to promote an efficient and effective seed distribution system and create awareness about the existing improved wheat varieties. The result showed that some success has been achieved by the Ethiopian Government and non-government organisations in targeting vulnerable rural female-headed households.

Moreover, government and non-government organisations should also need to take the lead in the promotion and dissemination of improved varieties at the initial stages and in creating a supportive and enabling environment for effective participation of the private sector. In terms of agronomic practices, we find that adopters have reduced seeding rates and were more likely to try row planting than non-adopters even though row planting has an implicit cost of additional labour. There is also a need to promote the use of sustainable agricultural practices such as crop rotation and expand the use of agricultural mechanisation services on large extensions of land to increase wheat production and productivity of the smallholder farmers through enhancing the availability and affordability of farm machinery service as it will have a remarkable impact on farm productivity.

Even for adopters, high-yield gaps persist mainly due to the incidence of weed damage and low seed replacement rates of new varieties. Hence, development policies for agricultural transformation in developing countries need to remedy this problem by enabling farm households to replace old varieties with new superior varieties and aggressively increase access to, and use of improved varieties. This study indicates that such investments will have substantial impacts on improving farm productivity and consumption expenditure per AEU in rural Ethiopia specifically and developing nations in general.

The research findings provide strong support for the argument that social capital has a significant positive impact on the probability of improved varieties adoption, even if some dimensions have a negative influence. We "unbundle" social capital to different dimensions, and our result indicates that informal network, core trust, and institutional trust such as trust in agricultural offices and research institutions have a positive influence on adoption decision. The result support that when new varieties are introduced, not only do individual farm household and farm level characteristic affect the likelihood of adoption, but more importantly social capital also matters. Hence, to promote improved varieties adoption in Ethiopia in particular and sub-Saharan Africa in general agricultural policy and extension effort should prioritise and encourage community-level social capital (such as farmer-farmers networks, collective action, core trust, institutional trust, etc.) and the resources inherent in them to achieve agricultural transformation, as opposed to the conventional top-down approaches that neglect the existing social networks, information-sharing behaviour, core trust, institutional trust and community-based strategies in smallholder farming systems.

Notes

1. However, progressive farm households under optimum conditions in the study area could harvest up to 8 tons/ha indicating up to 338% yield gap.
2. This refers to the smallest administrative unit in the country.
3. Proportion to size sampling approach is specified as follows: $n = (z^2PQ/d^2)$ where n is the sample size, P is the proportion of farmers growing improved varieties in the study area which is stated based on adoption rates of 70% (Shiferaw et al. 2014), P is set at 0.70. The variable d is significant level at 5%, this also leads to a z-value of 1.96 and Q is the weighting variable and it is computed as $1-P$.
4. We employed the standard conversion factor based on the "OECD-modified adult equivalent scale" which is given by 1 + 0.5 (A-1) + 0.3C, where A and C represent the number of adult and children in a household, respectively.
5. The three years cut-off point was decided in consultation with wheat breeders and farmers.
6. The falsification test on the selection instruments variables shows that they are jointly statistically significant in the adoption decision (in selection equation: $chi^2 = 26.82$; p-value = 0.0001), but not in the consumption expenditure per AEU (in outcome equation: F-stat = 1.23; p-value = 0.2973) and productivity per hectare (in outcome equation: F-stat = 1.42; p-value = 0.2176).
7. Two caliper scales were used: 0.1 and 0.5.
8. The Epanechnikov kernel estimator with 0.03 and 0.06 bandwidth were used.
9. Farm households use different rotation practices such as legume-wheat, potato-wheat, maize-wheat or oil crops-wheat rotation systems.
10. The exact definition of social capital is subject of debate, even though according to Adler and Kwon (2002) it is the goodwill available to individuals or groups developed through social interaction.
11. Include the cost for pesticide and herbicide (such as Topik, Palase, 2, 4-D, Gran star), insecticide (such as Karate), and fungicide (such as Tilt®250 E.C).
12. 1 USD = ETB 27 during the survey period.
13. Include the cost for pesticide and herbicide (such as Topik, Palase, 2, 4-D, Gran star), insecticide (such as Karate), and fungicide (such as Tilt®250 E.C).
14. In most empirical studies a mean standardised bias below 3% or 5% after matching is seen as sufficient (Caliendo and Kopeinig 2008).

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Appendix

Table A1. Rotated component matrix results on social capital formation of the respondents.

	Factor					
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Statements	Formal Institutional Trust	Informal Network	Immediate environment Core Trust	Agricultural Institutional Trust	Own Felling Core Trust	General Trust
I get along well with people in my community		0.4735				
I get along well with other farmers		0.4993				
I get along well with family		0.4547				
I get along well with friends		0.4869				
I participate actively in community and volunteer for community work						0.4443
I trust family and friends			0.5784			
I trust church and its people			0.5683			
I trust other farmers			0.4451			
Do you agree that most people could be trusted						0.7368
I feel safe in my neighbourhood					0.6476	
I can safely say I am trustworthy					0.6338	
I trust municipal police						
I trust the legal system	0.4138					
I trust the municipal government and their policies towards agriculture	0.4506					
I trust the courts	0.4592					
I trust the parliament						
I trust the agricultural office				0.4191		
I trust the agricultural agent				0.4856		
I trust the research institution				0.6276		

Note: For reasons of simplicity and clarity, the coefficients with absolute value less than 0.4 are suppressed.

Table A2. Second stage endogenous switching regression estimates for the outcome variables.

	Productivity per hectare		Log consumption expenditure per AEU	
Variables	Adopters	Non-adopters	Adopters	Non-adopters
Household characteristics				
Gender of household head (1 = male)	0.228(0.364)	−0.125(0.436)	−0.094(0.082)	0.071(0.114)
Age of household head (years)	−0.034(0.014)	−0.03***(0.01)	0.004(0.003)	−0.002(0.004)
Education of household head (years)	−0.028(0.039)	0.021(0.043)	0.023***(0.007)	0.002(0.014)
Family size (number)	0.048(0.074)	0.051(0.053)	−0.122***(0.142)	−0.136(0.018)
Owned cultivated farm land (hectare)	0.059(0.119)	0.17(0.145)	0.081**(0.031)	0.186(0.045)
Off-farm job participation (1 = yes)	0.436(0.458)	−0.133(0.268)	−0.055(0.087)	0.071(0.1)
Rent in farm land (hectare)	0.03(0.184)	−0.184(0.206)	−0.001(0.048)	0.118(0.082)
Output and input price				
DAP fertiliser cost (ETB/kg)	0.029(0.066)	0.201(0.055)***	−0.009(0.010)	0.012(0.017)
Urea fertiliser cost (ETB/kg)	0.02(0.027)	−0.002(0.055)	0.004(0.005)	−0.000***(0.006)
Wheat price (ETB/kg)	0.265(0.107)**	−0.204(0.165)	0.057**(0.024)	0.117(0.067)
Chemical cost per household (ETB)[11]	0.000(0.000)	0.000(0.000)	0.000(0.000)	2.39e-06(0.0e-3)
Rent tractor (1 = yes)	−0.019(0.361)	0.362(0.317)	0.027(0.058)	0.344***(0.112)
Rent combine harvester (1 = yes)	−0.17(0.422)	−0.073(0.332)	−0.026(0.116)	−0.343(0.107)***
Face labour shortage (1 = yes)	−0.302(0.332)	−0.504(0.232)	0.105(0.638)	−0.083(0.09)
Shocks				
Insect damage (1 = yes)	0.389(0.350)	0.025(0.24)	−0.017(0.59)	−0.104(0.109)
Disease damage (1 = yes)	−0.192(0.362)	−0.244(0.322)	0.117*(0.626)	0.045(0.138)
Weeds damage (1 = yes)	−0.396(0.399)	−0.106(0.242)	−0.148(0.07)	−0.06(0.09)

(*Continued*)

Table A2. Continued.

	Productivity per hectare		Log consumption expenditure per AEU	
Variables	Adopters	Non-adopters	Adopters	Non-adopters
Sustainable agricultural practice				
Crop rotation (1 = yes)	−0.514(0.549)	−0.017(0.297)	0.023(0.1)	0.061(0.106)
Practice seed selection (1 = yes)	0.099(0.347)	−0.229(0.29)	−0.009(0.76)	−0.030(0.084)
Row planting (1 = yes)	0.219(0.269)	0.517(0.29)	−0.074(0.053)	−0.137(0.117)
Cognitive social capital				
Get well with community	0.357(0.275)	0.037(0.144)	0.059(0.048)	0.024(0.057)
Get well with farmers	−0.085(0.293)	−0.325*(0.182)	0.065(0.060)	0.045(0.079)
Trust family & friends	0.166(0.261)	−0.067(0.172)	−0.093**(0.047)	−0.06(0.076)
Trust farmers	−0.067(0.206)	−0.101(0.170)	0.335(0.041)	−0.083(0.057)
Trust legal system	0.174(0.160)	−0.262*(0.142)	−0.242(−0.024)	−0.002(0.422)
Trust municipal government	−0.016(0.189)	0.304(0.118)	0.004(0.041)	−0.041(0.039)
Trust agricultural office	−0.046(0.178)	−0.065(0.15)	−0.027(0.034)	0.005(0.039)
Trust research institution	−0.19(0.221)	−0.065(0.137)	−0.015(0.051)	0.06(0.045)
Inverse Mill's Ratio (IMR)	0.23(0.469)	-.164(0.302)	0.001(0.13)	0.179(0.106)
Constant	2.409(2.859)	5.704(2.093)	9.124(0.673)	9.125(0.64)
Model diagnosis				
F-stat	1.56	2.09	12.93	9.95
Prob > F	0.046	0.004	0.000	0.000
R-Squared	0.164	0.28	0.56	0.65
Number of observation	189	134	189	134

Note: ***, ** and * are significant at 1%, 5% and 10% level, respectively.

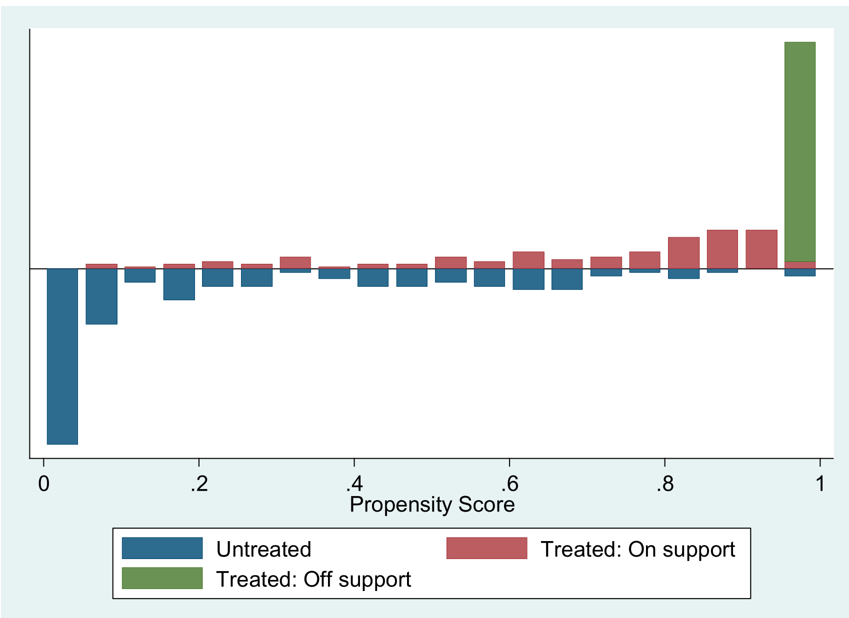

Figure A1. Effect on consumption expenditure per AEU.

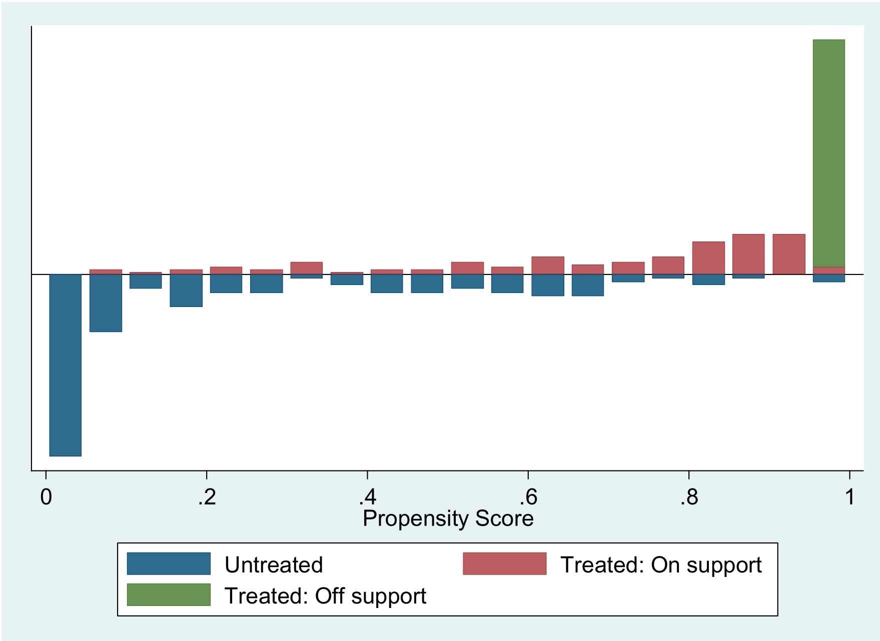

Figure A2. Effect on productivity per hectare.