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Adoption of improved wheat varieties and impacts on household food security in Ethiopia

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ABSTRACT

This article evaluates the impact of the adoption of improved wheat varieties on food security using a recent nationally-representative dataset of over 2000 farm households in Ethiopia. We adopted endogenous switching regression treatment effects complemented with a binary propensity score matching methodology to test robustness and reduced selection bias stemming from both observed and unobserved characteristics. We expand this further with the generalized propensity score (GPS) approach to evaluate the effects of continuous treatment on the response of the outcome variables. We find a consistent result across models indicating that adoption increases food security and farm households that did adopt would also have benefited significantly had they adopted new varieties. This study supports the need for vital investments in agricultural research for major food staples widely consumed by the poor, and efforts to improve access to modern varieties and services. Policies that enhance diffusion and adoption of modern wheat varieties should be central to food security strategies in Ethiopia.

Introduction

Wheat is among the most important staple food crops grown in Ethiopia. Given the low productivity of traditional varieties, Ethiopia imports significant quantities, especially in drought years when deficits are large. Some of the food import stems from food aid coming into the country under relief and recovery programs. One of the key strategies pursued by the government for ensuring food security in the country was to expand the availability of modern wheat varieties for farmers. In 2009/10 main season, the total area under wheat production was 1.68 million ha while the total production was about 3.07 million tons (CSA, 2011). Over the same time period, wheat accounted for about 16% of the total area of cereals in Ethiopia. There are about 4.6 million farm households (36% of cereal farm households) who are directly dependent on wheat farming in Ethiopia. The national average productivity of wheat is 1.83 tons/ha (CSA, 2011). Despite the low yields, demand for wheat has been growing fast in both rural and urban areas in the country. Changes in dietary patterns and a rapid growth in wheat consumption have been noted over the past few decades in several countries in sub-Saharan Africa (SSA) (Morris and Byerlee, 1993; Shiferaw et al., 2011). A recent analysis by Jayne et al. (2010) has also confirmed rapid growth in wheat consumption as a consequence of urbanization, rising incomes, and dietary diversification in Eastern and Southern Africa. While many countries in Africa are largely dependent on wheat imports to meet their growing demands, Ethiopia is one country where smallholder wheat production is prominent, allowing it to meet more than 70% of the demand from domestic production (Shiferaw et al., 2011). These statistics indicate the critical importance of improving the productivity and production of wheat through generation and development of improved wheat technologies in order to promote broad-based economic growth and poverty reduction in Ethiopia.

Both bread wheat and durum wheat are grown in Ethiopia and about 87% is grown during the main growing season (*meher*). While bread wheat is a recent introduction to Ethiopia, durum wheat is indigenous and mainly grown in the Central and Northern highlands. Durum wheat was the main wheat crop both in terms of area and production, but this has changed dramatically since the mid-1980s with the release and dissemination of semi-dwarf, high yielding and adaptable bread wheat varieties. In our sample, about 69% of sampled households have adopted bread wheat, while only 1% have adopted durum wheat varieties. Over the last several years, CIMMYT has been collaborating with the Ethiopian Institute of Agricultural Research (EIAR) in the development and dissemination of improved wheat varieties. Through this long-standing

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partnership, about 44 improved bread wheat and 30 durum wheat varieties have been released, with associated agronomic and crop protection practices.

Despite considerable efforts to develop and disseminate several modern wheat varieties, the adoption and livelihood impacts of these technologies have not been analyzed systematically. Although the literature on the adoption and impact studies of crop technologies is large, most studies have looked at the impact of other crops (maize, groundnuts, pigeonpeas, rice) on agricultural productivity and household welfare (e.g. Mendola, 2007; Minten and Barrett, 2008; Alene et al., 2009; Shiferaw et al., 2008; Asfaw et al., 2012; Becerril and Abdulai, 2010; Kijima et al., 2011; Kassie et al., 2011; Amare et al., 2012). Much less is known about the welfare impact of wheat technology at farm household level.

A recent study on the impact of improved groundnut varieties in rural Uganda found that adoption can significantly increase crop income and reduce poverty (Kassie et al., 2011). Some studies in West Africa using the economic surplus approach show that adoption of improved maize varieties is associated with improved household welfare (Alene et al., 2009). Kijima et al. (2008) found that the introduction of a new rice variety for Africa decreased poverty significantly without worsening income distribution. Minten and Barrett (2008) show that communes in Madagascar with higher rates of adoption of improved agricultural technologies, and consequently higher crop yields, enjoyed lower food prices, higher real wages for unskilled workers, and greater food security and lower poverty. Asfaw et al. (2012) found that the adoption of improved pigeonpea varieties in Tanzania increased household welfare as measured by per capita consumption expenditure.

The paper adds value to existing literature on impact assessment of agricultural technologies. First, our analysis uses a comprehensive and nationally representative household- and plot-level survey data from all major wheat growing areas of Ethiopia. This has allowed us to include several policy-relevant variables that were not included in previous studies. Second, to the best of our knowledge, this is the first rigorous paper on the link between food security and wheat technology adoption in Africa in general and in Ethiopia in particular. Rigorous impact assessment is important for informed and evidence-based policy making, for instance, to develop and implement appropriate support policy measures for improving targeting, access and use of modern varieties. Third, in addition to standard per capita food consumption measures of food security, we also consider farm households' self-reported subjective food security status. This allows us to check for consistency of measured indicators with farmers' assessment of their own food security status during the whole year, after taking seasonal shocks into account. The use of subjective measures, including self-reported poverty (see e.g. Deaton, 2010, who argues for wider use of self-reported measures from international monitoring surveys) and people's subjective perceptions of their own economic welfare (see e.g. Ravallion and Lokshin, 2002, who used subjective economic welfare measures in Russia) is a growing field, and our paper represents one of the first applications to evaluate technology impacts on food insecurity.

The next section describes the data and summary statistics for the variables selected for the empirical model. Section three presents the wheat adoption decision model and food security function with endogenous adoption and switching behavior to assess determinants of adoption and the resulting effects on household food security. We describe an endogenous switching regression (ESR) treatment effects approach to evaluate the responses of food security to variety adoption. Section four discusses the empirical results. Finally, the concluding section highlights the key findings and implications for policy to enhance adoption and impacts on food security.

Data and description of variables

The data used for this study is based on a farm-household survey in Ethiopia conducted during 2011 by the International Maize and Wheat Improvement Center (CIMMYT) in collaboration with the Ethiopian Institute of Agricultural Research (EIAR). The data was collected with a purpose of wheat technology adoption analysis and its impacts on smallholder producers. The sampling frame covered eight major wheat-growing agro-ecological zones that account for over 85% of the national wheat area and production distributed in four major administrative regions of Ethiopia. A total of 2017 farm households in eight agro-ecological zones, in 26 zones (provinces), 61 districts and 122 *kebeles* (local councils) were interviewed. The sample distribution by agro-ecology and region is shown in Table 1.

A multi-stage stratified sampling procedure was employed to select villages from each agro-ecology, and households from each village. First, agro-ecological zones that account for at least 3% of the national wheat area each were selected from all the major wheat growing Regional States of Ethiopia: Amhara, Oromia. Tigray, and Southern Nations Nationalities and Peoples (SNNP). Second, based on proportionate random sampling, up to 21 villages in each agro-ecology, and 15–18 farm households in each village were randomly selected.

The data was collected using a pre-tested structured questionnaire by trained and experienced enumerators who have good knowledge of the farming systems and speak the local language. The enumerators were trained and supervised by CIMMYT scientists in collaboration with EIAR senior researchers.

The survey covered a wide range of variables that influence technology adoption and food security at household, plot and village levels. Key socioeconomic data collected at the household level, among other things, contained information on consumption expenditures (home-produced consumed food, consumption of purchased food and non-food), respondents' perception of their own household food security status, marketed surplus, access to credit, asset ownership (crop land and livestock), age, gender and education level of the household head and members, family size, kinships (number of relatives in and outside the village that a respondent can rely on for critical support in times of need), social networks (number of traders respondents know in their vicinity), adoption of varieties and other technologies, sources of variety information, and marketing of own crop and livestock production. The consumption expenditure data was collected for the preceding year covering a period of 12 months. This was collected using carefully calibrated frequency of buying that varied across purchased food items and the amount spent during each period and then aggregated to the annual level. In order to enhance accuracy, this was discussed and provided jointly by both the husband (head of household) and the women (wife) in the family.

Data was collected on standard per capita food consumption and subjective food security indicators. The standard per capita food consumption indicator of food security is based on food expenditure (household's own consumption of home produced food + purchased food + aid or gift food), adjusted by adult equivalent. However, since food consumption is based on a single-round survey; consumption data may under- or over-report the true status of household food security. To minimize this problem, we estimate the models for both objective and subjective food security indicators. A recent study, Mallick and Rafi (2010), adopted subjective food security measures to overcome the shortcoming of the food consumption method pointed above. We use the perception of the respondents' own food security status to generate subjective measures of household food security in addition to the objective measures. Based on all food sources (own production + food

Table 1
Sampled *kebeles* (local units) and households by region.

AEZ[a]	Oromia		Amhara		SNNP		Tigray		Total		Sample households[b]
	No. of kebeles	*Sample*	No. of kebeles	*Sample*	No. of kebeles	*Sample*	No. of kebeles	*Sample*	No. of kebeles	*Sample*	
H2	542	17	0	0	47	1	0	0	589	18	307
H3	23	4	0	0	0	0	0	0	23	4	55
M1	86	2	139	3	0	0	0	0	225	5	68
M2	692	21	635	19	23	1	0	0	1350	40	681
SH1	103	3	10	0	73	2	0	0	186	5	85
SH2	283	10	19	1	281	10	0	0	583	21	361
SM2	195	6	445	14	6	0	191	6	837	27	437
SA2	79	2	0	0	0	0	0	0	79	2	23
Total kebeles	**2003**	**65**	**1248**	**37**	430	**13**	**191**	**6**	3872	**122**	**2017**
Sample households	**1059**		**621**		**240**		**97**		**2017**		

[a] Note: Tapid to cool humid mid-highlands (H2), Cold to very cold humid sub-AfroAlpine (H3), Hot to warm moist lowlands (M1), Tepid to cool moist mid-highlands (M2), Hot to warm sub-humid lowlands (SH1), Tepid to cool sub-humid mid highlands (SH2), Tepid to cool sub-moist mid highlands (SM2), Tepid to cool semi-arid mid highlands (SA2).
[b] Sample households were distributed across AEZs and Regions proportional to the number of Kebeles selected from each AEZ and Region.

purchase + safety nets and welfare programs + 'hidden harvest' from communal resources), the respondents assessed the food security status of their own households. The subjective food security status of the family captured for the preceding 12 months was grouped into the following four categories: food shortage throughout the year (chronic food insecurity), occasional food shortage (transitory food insecurity), no food shortage but no surplus (breakeven), and food surplus. Because some of the categories have few observations relative to others, we use binary food security as an additional outcome variable. In doing this, the four categories are combined into two: food secure (combining break-even and food surplus) and insecure (combining chronic and transitory food insecurity).

The survey also collected village level variables, such as distance to input and output markets, agro-ecological zones (proxy to rainfall and other agro-climatic variables), prices of crops, input costs, and administrative locations to capture spatial heterogeneity and unobserved policy variability.

Econometric framework and estimation strategy

The empirical challenge in impact assessment using observational studies is establishing a suitable counterfactual against which the impact can be measured because of self-selection problems. To accurately measure the impact of technology adoption on food security of farm households, the exposure to the technology should be randomly assigned so that the effect of observable and unobservable characteristics between the treatment and comparison groups is the same, and the effect is attributable entirely to the treatment. However, when the treatment groups are not randomly assigned, adoption decisions are likely to be influenced both by unobservable (e.g., managerial skills, motivation, and land quality) and observable heterogeneity that may be correlated to the outcome of interest.

Econometric approaches to deal with selection bias in cross-sectional data include propensity score matching (PSM), generalized propensity score (GPS) matching in a continuous treatment framework, and instrumental variable (IV) approaches. PSM only controls for observed heterogeneity while IV can also control for unobserved heterogeneity. The traditional IV treatment effect models with one selection and outcome equation assumes that the impact can be represented as a simple parallel shift with respect to the outcome variable. The endogenous switching regression (ESR) framework relaxes this assumption by estimating two separate equations (one for adopters and one for non-adopters) along with the selection equation (e.g. Kassie et al., 2008; Di Falco et al., 2011; Kabunga et al., 2012). In this paper, we adopt a binary ESR treatment effects approach to reduce the selection bias by controlling for both observed and unobserved heterogeneity despite its distributional (trivariate normal distribution) and exclusion restriction assumptions.[1] We check robustness of estimates from this model using a binary PSM and generalized propensity score (GPS) matching methods, although these methods do not control for unobserved heterogeneity. The GPS is an extension of the binary PSM methods for the case of continuous treatment impact assessment (for details see Hirano and Imbens, 2004). Unlike the ESR and PSM, the focus is on assessing the heterogeneity of treatment effects arising from different treatment levels, i.e., different intensities of adoption of improved wheat varieties. It uses the same assumptions as in the standard PSM methods, including selection into different intensities of adoption is based on a rich set of observed covariates.

Modeling impact of improved varieties on food security

The decision to adopt improved wheat varieties and its implication on food security can be modeled in a two-stage treatment framework. In the first stage of ESR, framers' choice of improved varieties is modeled and estimated using a probit model. In the second stage, the relationship between the outcome variables and technology adoption along with a set of explanatory variables is estimated using the ordinary least squares (OLS) model with selectivity correction.

The observed outcome of adoption of improved wheat varieties can be modeled following a random utility formulation. Consider the i^{th} farm household facing a decision on whether or not to adopt improved wheat varieties. Let U_0 represent the benefits to the farmer from the adoption of traditional/local varieties, and let U_k represent the benefit stream from the adoption of improved varieties. The farmer will adopt improved varieties if $I_i^* = U_k - U_0 > 0$. The net benefit (I_i^*) that the farmer derives from the adoption of improved varieties is a latent variable determined by observed characteristics (z_i) and the error term (ε_i):

[1] Though we tried to address the identification problem using the best methods possible using our rich cross-sectional dataset including varietal information, seed sources and agro-ecological variables (proxy for rainfall and other agro-climatic variables), we acknowledge that identification might still be a problem. While the consistency of the results across different methods supports evidence of impact, the results may need to be interpreted with caution.

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

where I_i is a binary indicator variable that equals 1 if a farmer adopts an improved variety and zero otherwise and α is a vector of parameters to be estimated. In this study, adoption is defined if farmers used any of the improved wheat varieties, either freshly purchased, and/or recycled improved varieties for not more than five years.[2] Recycling of seed is common among wheat farmers growing improved varieties. About 30% of the farmers recycle seed for 1–2 years; another 30% recycle for 3–5 years; about 20% recycle for 6–10 years, and 5% recycle for more than 10 years. This has implications for the food security status of households as the productivity of wheat declines with the number of years of recycling. The correlation between wheat productivity and the number of years of recycling is negative (-0.055^*) and significant ($p < 0.1$). Fig. 1 shows a similar trend where wheat productivity declines with the age of seed recycling for improved varieties.

The outcome functions, conditional on adoption, can be written as an endogenous switching regime model:

$$\text{Regime 1}: y_{1i} = x_{1i}\beta_1 + \eta_{1i,} \text{ if } I = 1 \tag{2a}$$

$$\text{Regime 2}: y_{2i} = x_{2i}\beta_2 + \eta_{2i,} \text{ if } I = 0 \tag{2b}$$

where y_1 *and* y_2 are outcome variables, representing per capita food consumption expenditure (hereafter consumption expenditure), binary food security status, chronic and transitory food insecurity, breakeven food security and food surplus for adopters and non-adopters, respectively; x represents a vector of covariates, and β is a vector of parameters to be estimated.

For the ESR model to be identified, it is important for the Z variables in the adoption model to contain a selection instrument in addition to those automatically generated by the non-linearity of the selection model of adoption. Distance to seed market and sources of variety information [government extension (1 = yes) and farmers cooperatives (1 = yes)] are the instrumental variables used for the identification of the impact of adoption on the food security outcome variables. The adoption behavior of farmers can be greatly influenced by access to certain sources of information as the diffusion process and content of information about the technology may differ by information sources (Adegbola and Gradebroek, 2007). Similarly, distance to the seed market affects the price and local availability of seed which in turn affects the incentive to adopt and the intensity of adoption (Shiferaw et al., 2008). We consider that these variables are likely to be correlated with the adoption of wheat varieties but are unlikely to influence the outcome variable directly or correlated with the unobserved errors of Eqs. (2a) and (2b). Distance to seed market has been used as an instrument in other applications that address hybrid maize adoption impact on household income in Africa (Heisey et al., 1998; Yorobe and Smale, 2012). Di Falco et al. (2011) used different information sources as instrument in their analysis of the impact of adaptation measures on food security in Ethiopia. A simple falsification test following Di Falco et al. (2011) was used to test the validity of the instruments.[3] Results show that the instruments considered are jointly statistically significant ($\chi^2 = 34.47 (p = 0.000)$ in the selection equation (1) but not in the outcome functions [$\chi^2 = 1.36$ ($p = 0.715$) and $\chi^2 = 6.11$ ($p = 0.106$) for non-adopters and adopters, respectively, when binary food security is used as an outcome variable] and [$\chi^2 = 1.73$ ($p = 0.630$) and $\chi^2 = 2.08$ ($p = 0.556$) for non-adopters and adopters, respectively, when per capita consumption expenditure is used as an outcome variable.[4]

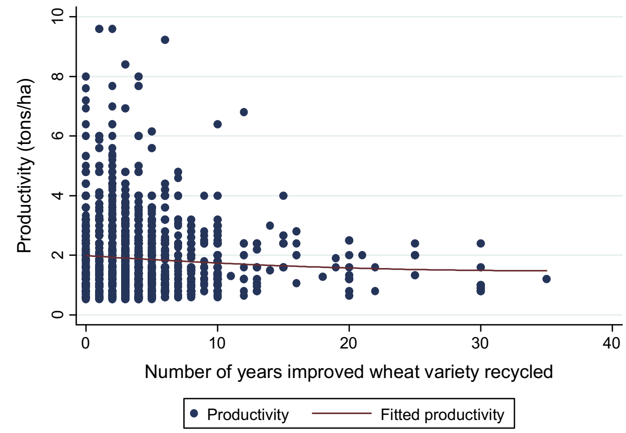

Fig. 1. Relationship between productivity and recycled age of improved wheat varieties. *Source*: Survey Data 2011

The estimation of β_1 and β_2 using ordinary least squares (OLS) might lead to biased estimates, because the expected values of the error terms (η_1 and η_2), conditional on the selection criterion, are non-zero. The error terms in Eqs. (1) and (2) are assumed to have a trivariate normal distribution with mean zero and covariance matrix specified as:

$$\operatorname{cov}(\varepsilon, \eta_1, \eta_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{1\varepsilon} & \sigma_1^2 & \cdot\, . \\ \sigma_{2\varepsilon} & \cdot & \sigma_2^2 \end{bmatrix}, \tag{3}$$

where $\sigma_\varepsilon^2 = \operatorname{var}(\varepsilon), \sigma_1^2 = \operatorname{var}(\eta_1), \sigma_2^2 = \operatorname{var}(\eta_2), \sigma_{\varepsilon 1} = cov(\varepsilon, \eta_1)$, and $\sigma_{\varepsilon 2} = \operatorname{cov}(\varepsilon, \eta)$. The variance of σ_ε^2 can be assumed to be equal to 1 since the β coefficients in the selection model are estimable up to a scale factor. The covariance between η_1 and η_2 is not defined since y_1 and y_2 are not observed simultaneously (Maddalla, 1983). The expected values of η_1 and η_2 conditional on the sample selection is non-zero because the error term in the selection Eq. (1) is correlated with the error terms of the food security functions (η_1 and η_2):

$$E(\eta_{i1}|I_i = 1) = \sigma_{1\varepsilon}\frac{\phi(z_i\alpha)}{\Phi(z_i\alpha)}$$
$$= \sigma_{1\varepsilon}\lambda_{i1} \text{ and}$$
$$E(\eta_{i2}|I_i = 0) = -\sigma_{2\varepsilon}\frac{\phi(z_i\alpha)}{1 - \Phi(z_i\alpha)}$$
$$= \sigma_{2\varepsilon}\lambda_{i2},$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ is the standard normal cumulative density function, $\lambda_{i1} = \frac{\phi(z_i\alpha)}{\Phi(z_i\alpha)}$ and $\lambda_{i2} = \frac{\phi(z_i\alpha)}{1-\Phi(z_i\alpha)}$. Where λ_{i1} and λ_{i2} are the Inverse Mills Ratios (IMR) computed from the selection equation and will be included in 2a and 2b to correct for selection bias in a two-step estimation procedure i.e., endogenous switching regression. The standard errors in (2a) and (2b) are bootstrapped to account for the heteroskedasticity arising from the generated regressors (λ).

[2] The five year cut-off point was decided in consultation with wheat breeders.

[3] As indicated earlier, the ESR model relies on a very strong exclusion restriction and the falsification test may not be sufficient to confirm identification. The seed sources may also be endogenous and partly correlated with the error terms. Similarly, distance to seed markets may be correlated with non-observables that affect food security outcomes. While variables that explain information sources are included in the second stage regression and distance to seed markets is not significantly correlated with output markets (correlation coefficient of 35%), the ESR model used here may not ensure identification.

[4] Similar results were found when chronic and transitory food insecurity and breakeven and food surplus food security outcome indicators were used.

Average treatment effects

The above framework can be used to estimate the average treatment effect on the treated (ATT) and untreated (ATU) by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios. Following Carter and Milon (2005), Di Falco et al. (2011) and the wage decomposition literature, we compute the ATT and ATU in the actual and counterfactual scenarios. The estimates from ESR allow for the computing of the expected values in the real and hypothetical scenarios presented in Table 2 and defined below:

Adopters with adoption (observed in the sample):

$$E(y_{i1}|I=1;x) = x_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{i1} \tag{4a}$$

Non-adopters without adoption (observed in the sample):

$$E(y_{i2}|I=0;x) = x_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{i2} \tag{4b}$$

Non-adopters had they decided to adopt (counterfactual):

$$E(y_{i1}|I=0;x) = x_{i2}\beta_1 + \sigma_{1\varepsilon}\lambda_{i2} \tag{4c}$$

Adopters had they decided not to adopt (counterfactual):

$$E(y_{i2}|I=1;x) = x_{i1}\beta_2 + \sigma_{2\varepsilon}\lambda_{i1} \tag{4d}$$

Eqs. (4a) and (4b) represent the actual expectations observed from the sample, while Eqs. (4c) and (4d) are the counterfactual expected outcomes. Using these conditional expectations the following mean food security outcome difference can be computed.

The expected change in adopter's food security, the effect of treatment on the treated (ATT) is computed as the difference between (4a) and (4d):

$$\begin{aligned} ATT &= E(y_{i1}|I=1,x) - E(y_{i2}|I=1,x) \\ &= x_{i1}(\beta_1 - \beta_2) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \tag{5}$$

Similarly, the expected change in non-adopter's food security, the effect of the treatment on the untreated (ATU) is given as the difference between (4c) and (4b):

$$\begin{aligned} ATU &= E(y_{i1}|I=0,x) - E(y_{i2}|I=0,x) \\ &= x_{i2}(\beta_1 - \beta_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \end{aligned} \tag{6}$$

The first term on the right hand side of Eq. (5) represents the expected change in adopter's mean outcome, if adopters' characteristics had the same return as non-adopters, or if adopters had similar characteristics as non-adopters. The second term (λ) is the selection term that captures all potential effects of difference in unobserved variables. Similarly, for the effect of treatment on the untreated, the first term in (6) can be interpreted as the expected change in the non-adopters mean outcome if non-adopters characteristics had the same return as adopters or if non-adopters had similar characteristics as adopters. The second term adjusts the ATU for the effect of unobservable factors.

The propensity score matching approach is widely applied in the literature and we shall not present the methodology here. For a good overview of the specification, assumptions, and basic setup of binary PSM and GPS matching methods, see Wooldridge (2002) and Hirano and Imbens (2004), respectively.

Table 2
Expected conditional and average treatment effects in the ESR framework.

Sample	Decision stage		Treatment effect
	To adopt	Not to adopt	
Adopters	(4a) $E(y_{i1}\|I=1,x)$	(4c) $E(y_{i2}\|I=1,x)$	ATT
Non-adopters	(4d) $E(y_{i1}\|I=0,x)$	(4b) $E(y_{i2}\|I=0,x)$	ATU

Table 3
Food security status and marketed surplus by area under improved wheat adoption.

Quartiles (based on area under improved varieties)	Per capita wheat consumption (kg)	Marketed surplus of wheat (kg)	Per capita food consumption (ETB)	Food security (1 = if household is food secure and 0 otherwise) (%)
1 (Lowest)	43.0	83.3	1386.8	53.9
2 (Lowest middle)	66.8	196.3	1533.2	63.2
3 (Upper middle)	91.2	701.4	1714.4	68.0
4 (Highest)	105.8	1078.0	1743.7	66.0

Empirical results

Results of descriptive analyses

Wheat remains the most important cereal in the study areas in terms of area share, total production, and its role in direct human consumption. About 88% of the sample farm households grew wheat and about 70% grew improved wheat varieties. The average area planted with improved wheat varieties was 2.63 *kert* which accounted for about 83% of the total wheat area.[5] Wheat production accounted for about 41% and 75% of the cereal cultivated area and production in the sample, respectively. The average per capita wheat consumption was 72 kg per annum and this accounted for about 38% of the total cereal consumption. Wheat accounted for 55% of the cereal marketed volume and 41% of the total marketed volume of crops for the sample households.

Considering the objective food security indicators, the average food consumption expenditure is about ETB1535 per year and the expenditure on food constitutes about 73% of the total consumption expenditure, including both purchased and own production. Home production consumption contributes 68% to the total food consumption, indicating that about 32% of the food consumption is purchased. This includes the buying of livestock products as well as staple foods by food-deficit households which do not produce all of what they need for their consumption.

Table 3 presents the association between the level of adoption and household food security and marketed surplus (quantity sold) of wheat, as adoption has differential impacts. The households were divided into quartiles based on cultivated area under improved wheat varieties. Without implying any causal relationship, Table 3 shows that the volume of wheat sold increases with the increasing intensity of the adoption of improved wheat varieties. The results in Table 3 further indicate that, household food security status (1 = food secure and 0 otherwise) and consumption expenditure increases with the area allocated to improved wheat varieties.

The unconditional summary statistics discussed above suggest that agricultural technology may have a role in improving household well-being. However, given that adoption is endogenous, a simple comparison of the welfare indicators has no causal interpretation. That is, the above differences may not be the result of improved wheat variety adoption, but instead might be due to other factors, such as differences in observed and unobserved characteristics. Therefore, we need to conduct robust multivariate analysis to test the impact of variety adoption on household welfare.

Several covariates were selected for the estimation of the conditional density of the treatment variable (I_i) and the outcome variable (food security). The summary statistics of the outcome, treatment and explanatory variables is given in Table 4. The selec-

[5] Kert (local land area unit) is approximately equivalent to 0.25 ha.

tion of covariates was based on previous adoption and impact studies, and theory of farm household decision-making under imperfect markets (de Janvry et al., 1991). When markets are imperfect, asset ownership (labor, capital, livestock, etc.), social capital (networks, education, etc.) and distance to service centers and input suppliers will determine household technology choices (Holden et al., 2001).

The descriptive summary shows that adopters have more farm size, received higher wheat and maize prices, and received more information on wheat varieties from extension workers compared

Table 4
Description of outcome, treatment and explanatory variables.

Variable	Description	Full sample		Adopters		Non-adopters	
		Mean	SD	Mean	SD	Mean	SD
Outcome variables							
Food security	Household food security status based on subjective response (1 = food secure; 0 = food insecure)	0.625		0.629		0.616	
Chronic food insecurity	Household suffers from chronic food insecurity (1 = yes; 0 = no)	0.022		0.020		0.027	
Transitory food insecurity	Household suffers from transitory food insecurity (1 = yes; 0 = no)	0.353		0.350		0.357	
Breakeven food security	Breakeven food security household (1 = yes; 0 = no)	0.469		0.480		0.441	
Food surplus	Food surplus household (1 = yes; 0 = no)	0.157		0.149		0.174	
Food consumption expenditure***	Per capita food consumption expenditure (in ETB - Ethiopian currency)	1535.84	849.12	1594.90	862.06	1395.03	800.71
Treatment variable							
Binary adoption	Household adopted improved wheat varieties (1 = yes)	0.705		0.705		0	0
Household characteristics							
Age	Age of household head (years)	43.545	12.655	43.405	12.342	43.881	13.377
Gender	Gender of the household head (male = 1)	0.935		0.937		0.930	
Illiterate	Household head has no schooling (1 = yes)	0.377		0.367		0.399	
Schooling to grades 2 and 6	Household head has schooling to grades 2 & 6 (1 = yes)	0.436		0.441		0.426	
Schooling above 6 grades	Household head has schooling above grade 6 (1 = yes)	0.187		0.192		0.174	
Family size	Household size	6.659	2.461	6.688	2.501	6.591	2.363
Farm size **	Farmland operated by household (kert)	2.185	1.659	2.233	1.626	2.072	1.732
Livestock ownership	Livestock ownership in TLU	3.571	3.385	3.574	3.276	3.563	3.633
Output and input price							
Wheat price***	Village level wheat price (ETB/kg)	4.982	0.855	5.025	0.850	4.881	0.861
Maize crop price	Village level maize price (ETB/kg)	4.729	0.494	4.725	0.529	4.737	0.400
Teff crop price	Village level teff price (ETB/kg)	5.040	1.444	5.027	1.224	5.072	1.867
Barley crop price***	Village level barley price (ETB/kg)	4.769	1.116	4.833	1.100	4.615	1.141
Fertilizer cost	Average village level fertilizer cost (ETB/kg)	7.032	1.076	7.036	1.246	7.021	0.470
Seed cost***	Average village level seed cost (ETB/kg)	14.293	13.221	13.001	12.429	17.375	14.494
Herbicide cost*	Average village level herbicide cost (ETB/liter)	83.768	15.441	83.348	15.622	84.769	14.967
Land quality and shocks							
Pest and disease**	Pests and diseases are key problems (1 = yes)	0.656		0.641		0.691	
Land quality	Proportion of farmland under fertile soil	0.873		0.875		0.870	
Social capital/network and information sources							
Relative	Number of relatives that the household has in & outside village	45.631	22.552	45.137	17.972	46.810	30.828
Trader	Number of traders that the farmer knows in and outside village	4.699	5.617	4.754	5.668	4.565	5.498
Variety information from extension***	Household accessed variety information from extension workers (1 = yes)	0.600		0.652		0.475	
Variety information from cooperatives	Household accessed variety information from cooperatives (1 = yes)	0.046		0.046		0.044	
Location characteristics							
Distance to output market***	Distance to nearest output market (walking minutes)	89.013	60.085	92.963	61.132	79.596	56.457
Distance to seed dealers		56.351	59.053	56.286	58.332	56.506	60.787
Humid mid-highlands (Cf.)	Household resides in Tepid to cool humid mid-highlands agro-ecology (1 = yes)	0.152		0.161		0.131	
Cold humid sub-Afro-Alpine	Household is located in cold to very cold humid sub-Afro-Alpine agro-ecology (1 = yes)	0.027		0.025		0.032	
Warm moist lowlands	Households is located in hot to warm moist lowlands agro-ecology (1 = yes)	0.034		0.037		0.025	
Moist mid-highlands	Households is located in tepid to cool moist mid-highlands agro-ecology (1 = yes)	0.338		0.292		0.446	
Sub-moist mid highlands	Households is located in tepid to cool sub-moist mid highlands agro-ecology (1 = yes)	0.217		0.247		0.144	
Warm sub-humid lowlands	Households is located in hot to warm sub-humid lowlands agro-ecology (1 = yes)	0.042		0.049		0.027	
Sub-humid mid highlands	Households is located in tepid to cool sub-humid mid highlands agro-ecology (1 = yes)	0.179		0.174		0.191	
Semi-arid mid highlands	Households is located in tepid to cool semi-arid mid highlands agro-ecology (1 = yes)	0.011		0.015		0.003	
Tigray Region (Cf.)	Household is from Tigary region (1 = yes)	0.048		0.051		0.003	
Amhara region	Household is from Amhara region (1 = yes)	0.308		0.321		0.277	
Oromia Region	Household is from Oromia region (1 = yes)	0.119		0.087		0.196	
Southern region	Household is from Southern region (1 = yes)	0.525		0.542		0.485	
Number of observations		2017	1421	596			

Note: *, ** and *** indicates adopters and non-adopters characteristics mean difference at 10%, 5% and 1% level of significance.

to non-adopters. Adopters are located far from output markets compared to non-adopters, indicating that the seed market is more important than output markets for initial adoption. Farmer coops provide grain marketing services to farmers to reduce marketing costs in distant areas. Mean per capita food consumption expenditure for adopters is ETB1595 per year, which is significantly higher than ETB1395 food expenditure by non-adopters. Although statistically insignificant, adopters compared to non-adopters are more food insecure considering the binary food security indicator.

Estimation of the adoption model

Table 5 presents results from the first stage of ESR. The dependent variable is binary wheat adoption. The various test of goodness-of-fit indicate that the selected covariates provide good estimate of the conditional density of adoption. For example, the Wald χ^2 test statistic (285.60) indicates that explanatory variables are jointly statistically significant ($P < 0.01$).

The probit results are only discussed briefly as our main objective is to evaluate the impacts on household food security. Table 5 shows that education, access to input and output markets, variety information source, agro-ecology, crop prices, crop land, input costs and location dummies are correlated with the probability of adoption. Our results indicate that economic incentives, such as attractive wheat prices, can have a significant effect on the adoption decision. The policy implication is that facilitation and dissemination of market information, including price and better market outlets, may facilitate investment in modern varieties. On the other hand, the price of competing crops (teff and maize) and input costs (seed and herbicide) were negatively associated with adoption. Distance to the output markets seems to be positively correlated with variety adoption, probably because farmer cooperatives first started expanding in distant villages with high agricultural potential, reducing transaction costs and making it possible for farmers to improve market access. However, the distance to seed dealers is negatively associated with adoption. Farmers who came to know improved varieties via extension agents are more likely to adopt compared to those who were informed by other dissemination pathways, probably because the predominant public extension system provides more reliable information on improved varieties and associated agronomic practices. Finally, some of the location dummy variables (agro-ecological and regional dummies) are correlated with adoption, likely reflecting unobservable spatial and ecological differences.

Table 5
The decision to adopt improved wheat varieties: a probit model.

Explanatory variables	Coef.	Std. Err.	P > z
Household characteristics			
Ln(household head age)	0.011	0.129	0.935
Household head has schooling to grades 2 and 6	0.087	0.074	0.235
Household head has schooling above 6 grades	0.240**	0.097	0.013
Ln(family size)	0.114	0.093	0.223
Gender	0.055	0.132	0.678
Livestock ownership	−0.015	0.010	0.148
Ln(farm size)	0.102*	0.051	0.045
Output price and input costs			
Wheat crop price	0.182***	0.050	0.000
Teff crop price	−0.071***	0.025	0.004
Maize crop price	−0.146*	0.077	0.057
Barely crop price	−0.029	0.030	0.342
Fertilizer cost	0.029	0.026	0.277
Seed cost	−0.011***	0.002	0.000
Herbicide cost	−0.006**	0.003	0.020
Social capital and access to information			
Relative	−0.002	0.002	0.231
Trader	0.003	0.006	0.641
Variety information from extension agents	0.361***	0.067	0.000
Variety information from cooperatives	0.132	0.156	0.400
Land quality and shocks			
Land quality	0.228	0.142	0.110
Pest and disease	−0.096	0.068	0.162
Location characteristics			
Ln(distance to output market)	0.105***	0.037	0.005
Distance to seed dealers	−0.001**	0.001	0.024
Humid sub-Afro Alpine	−0.690***	0.210	0.001
Warm moist lowlands	−0.136	0.211	0.518
Moist mid-highlands	−0.680***	0.111	0.000
Sub-moist mid highlands	−0.031	0.132	0.813
Warm sub-humid lowlands	0.293	0.192	0.127
Sub-humid mid highlands	0.140	0.133	0.293
Semi-arid mid highlands	0.505	0.391	0.197
Amhara region	0.589***	0.193	0.002
SNNRP region	−0.564**	0.223	0.012
Oromia Region	0.372*	0.200	0.063
Constant	0.217	0.748	0.772
Model diagnosis			
Wald chi2(32)	285.60***		
Log pseudo likelihood	−1087.770		
Pseudo R2	0.112		
Number of observations	2017		

Note: *, **, and *** denotes significance level at 10%, 5%, and 1%; robust standard errors reported.

Impacts on food security

This section discuss results obtained from the three methods: endogenous switching regression, binary propensity score and generalized propensity score matching.

Endogenous switching regression estimation results

Table 6 presents the expected food security under actual and counterfactual conditions obtained using the endogenous switching regression treatment effects approach. The key outcome variables considered in the analyses are: chronic food insecurity, transitory food insecurity, breakeven, food surplus and food security (=1 if households fall under breakeven and food surplus and 0 if households fall under chronic and transitory) and natural logarithms of per capita food consumption expenditure (hereafter consumption expenditure). The consumption expenditure is transformed into logarithms because it is very right-skewed. The coefficient estimates from the second stage of ESR are not discussed because of space limitations, but the estimated coefficients for consumption expenditure and binary food security are presented in the Appendix (Table A1). However, it is worth mentioning that the selection term is negative and significant in most cases, suggesting that farmers with lower than average per capita consumption expenditure and probability of food security are more likely to adopt improved wheat varieties.

As we see from the last column of Table 6, both adopters and non-adopters would benefit from adoption though in most cases households that did adopt would benefit the most from adoption. Adoption of improved wheat varieties increases the probability of food security, per capita food consumption, and the probability of attaining the food breakeven and food surplus status. On the other hand, it decreases the probability of chronic and transitory food insecurity. Households who actually adopted would have per capita food consumption expenditure of about ETB178 less had they not adopted.[6] This is the average treatment effect on the treated (ATT) which is statistically significant. The additional average food consumption expenditure for adopters at household level due to adoption is about ETB979 ($5.5 * 178$) where 5.5 is the average

[6] 1 USD = ETB 17 during the survey period.

Table 6
Average treatment effects: Endogenous switching regression model.

Outcome variables	Farm household type and treatment effect	Decision stage		
		To adopt	Not to adopt	Average treatment effect[a]
Per capita food expenditure	Farm households that did adopt (ATT)	1464.272	1286.684	177.588(15.353)***
	Farm households that did not adopt (ATU)	1417.425	1258.569	158.856(23.561)***
Binary food security	ATT	0.629	0.602	0.027(0.008)**
	ATU	0.661	0.616	0.045 (0.0118)***
Chronic food insecurity	ATT	0.0240	0.1225	−0.0985(0.0080)***
	ATU	0.0165	0.0330	−0.0164(0.004)***
Transitory food insecurity	ATT	0.3497	0.3698	−0.0201(0.0078)***
	ATU	0.3279	0.3439	−0.0160(0.0113)
Break even food security	ATT	0.4799	0.4169	0.0630(0.0051)***
	ATU	0.5024	0.4415	0.0609(0.0073)***
Food surplus	ATT	0.1484	0.1857	0.0373(0.0065)***
	ATU	0.1649	0.1747	0.0098(0.0101)

[a] Standard errors in parenthesis; ** and *** denotes significance level at 5% and 1%, respectively.

adult equivalent (AE) for the sample. Similarly, households that did not adopt, would have a per capita food consumption expenditure of about ETB159 (ETB875 at household level) more if they had adopted the technology, implying that current non-adopters would have realized higher levels of consumption from switching to improved wheat production under the given conditions.[7] This is the average treatment effects on the untreated (ATU) which is also statistically significant. We find similar qualitative results using binary food security status as an outcome variable, where the adoption of improved wheat varieties increases the probability of food security for adopters by about 2.7% points and by 4.5% points for non-adopters had they adopted improved varieties. The results for other outcome variables can be interpreted in a similar fashion.

Binary propensity score matching (PSM) estimation results

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 model. The matching variables used are the same as the variables presented in Table 5.[8] The matching methods passed different quality checking tests. We find that there is a considerable overlap in common support. Fig. 2 gives the histogram of the estimated propensity scores for adopter and non-adopters. A visual inspection of the density distributions of the estimated propensity scores for the two groups indicates that the common support condition is satisfied: there is substantial overlap in the distribution of the propensity scores of both adopter and non-adopter groups. The bottom half of the graph shows the propensity scores distribution for the non-adopters and the upper half refers to the adopters. The densities of the scores are on the *y*-axis. Table 7 presents results from covariate balancing tests before and after matching. The standardized mean difference (see Caliendo and Kopeinig, 2008) for overall covariates used in the propensity score (around 11% before matching) is reduced to about 3% after matching. The bias substantially reduced, in the range of 73–74% 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 before matching. The pseudo-R^2 also dropped significantly from 10% before matching to about 0.1% after matching. The low pseudo-R^2, low mean standardized bias, high total bias reduction, and the insignificant *p*-values of the likelihood ratio test after matching suggest that the proposed specification of the propensity score is fairly successful in terms of balancing the distribution of covariates between the two groups.

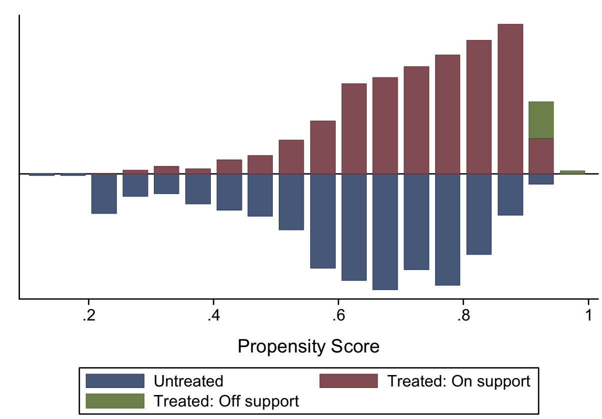

Fig. 2. Propensity score distribution and common support for propensity score estimation. *Note*: "Treated: on support" indicates the observations in the adoption group that have a suitable comparison. "Treated: off support" indicates the observations in the adoption group that do not have a suitable comparison.

Table 8 reports the estimates of the average adoption effects estimated by nearest neighbor matching (NNM), Kernel based matching (KBM) and Radius matching methods. The table reports results based on the single and five nearest neighbor method with replacement and the Epanechnikov kernel estimator with 0.03 and 0.06 bandwidth and bootstrapped standard errors with 100 replications reported.[9] We find numerically close results as in the ESR analysis, where adoption significantly increases average per capita consumption expenditure, probability of food security, and break-even food security and reduces the probability of chronic and transitory food insecurity. Adoption of improved wheat technologies increases average per capita consumption expenditure in the range of ETB209-260 (Table 8). Similarly, it increases the probability of food security in the range of 2.5–8.6%, and significantly reduces the probability of chronic (transitory) food insecurity in the range of 1.3–3.0% (1.3–5.9%), respectively. The reason for higher estimates of impact from the PSM method compared to estimates from the ESR results may be because of the effects of unobserved heterogeneity which is not accounted in the PSM approach. Assuming exogenous

[7] We checked the robustness of these results by transforming the per capita food consumption into a binary dummy variable using the 2010/11 food poverty line of ETB 1985 as threshold. The household is food secure if per capital food consumption is greater than or equal to this food poverty line and food insecure otherwise. We found that adoption significantly increases the average probability of food security by 6.8% (average adoption effect). On the other hand, the average treatment effect on the untreated (ATU) is 3.8%. These values are significant at less than 1% level and close to our findings using the PSM approach.

[8] The propensity score estimates are not reported, but can be made available on request.

[9] For nearest neighbor matching, the standard errors are not bootstrapped as the standard bootstrap is not valid (Abadie and Imbens, 2008).

Table 7
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 (*p-value*) *After matching*	Mean standardized bias before matching	Mean standardized bias after matching	Total% |*bias*| reduction
NNM[a]	0.099	0.010	247.45 ($P = 0.000$)	45.96 ($p = 0.110$)	10.621	3.949	62.8
NNM[b]	0.099	0.009	247.45 ($P = 0.000$)	31.92 ($p = 0.371$)	10.621	3.168	70.2
KBM[c]	0.099	0.007	247.45 ($P = 0.000$)	26.24 ($p = 0.663$)	10.621	2.715	74.4
KBM[d]	0.099	0.008	247.45 ($P = 0.000$)	28.52 ($p = 0.543$)	10.621	2.774	73.9

[a] NNM = single nearest neighbor matching with replacement, and common support.
[b] NNM = five nearest neighbor matching with replacement, and common support.
[c] KBM = with band width 0.06 and common support.
[d] KBM = with band width 0.03 and common support.

Table 8
Average treatment effects: propensity score matching.

Outcome variable	Matching algorithm	Mean of outcome variables based on matched observations		
		Adopters	Non-adopters	ATT
Per capita food consumption expenditure	NNM[a]	1609.514	1348.949	260.565 (57.908)***
	NNM[b]	1609.514	1374.796	234.718 (50.101)***
	KBM[c]	1609.514	1376.535	232. 979 (40.904)***
	KBM[d]	1609.514	1378.128	231.385 (39.790)***
	Radius matching	1609.514	1400.6487	208.865 (39.341)***
Binary food security	NNM[a]	0.6436	0.5575	0.0861 (0.0353)***
	NNM[b]	0.6436	0.5912	0.0524 (0.0294)*
	KBM[c]	0.6436	0.5824	0.0612 (0.0265)***
	KBM[d]	0.6436	0.5822	0.0613 (0.0315)***
	Radius matching	0.6436	0.6184	0.0252 (0.0145)*
Chronic food insecurity	NNM[a]	0.0152	0.0419	−0.0267 (0.0130)**
	NNM[b]	0.0152	0.0449	−0.0297 (0.0096)***
	KBM[c]	0.0152	0.0365	−0.0213 (0.0111)**
	KBM[d]	0.0152	0.0366	−0.0214 (0.0105)**
	Radius matching	0.0152	0.0274	−0.0121(0.0069)***
Transitory food insecurity	NNM[a]	0.3412	0.4001	−0.0594 (0.0348)*
	NNM[b]	0.3412	0.3639	−0.0227 (0.0289)
	KBM[c]	0.3412	0.3811	−0.0399 (0.0273)
	KBM[d]	0.3412	0.3812	−0.0400 (0.0285)
	Radius matching	0.3412	0.3543	−0.0131 (0.0215)
Breakeven	NNM[a]	0.4851	0.4120	0.0731 (0.0356)**
	NNM[b]	0.4851	0.4277	0.0574 (0.0303)*
	KBM[c]	0.4851	0.4180	0.0671 (0.0294)***
	KBM[d]	0.4851	0.4199	0.0652 (0.0306)***
	Radius matching	0.4851	0.4493	0.0359 (0.0200)*
Food surplus	NNM[a]	0.1584	0.1455	0.0129 (0.0274)
	NNM[b]	0.1584	0.1634	−0.0050 (0.0228)
	KBM[c]	0.1584	0.1643	−0.0059 (0.0175)
	KBM[d]	0.1584	0.1634	−0.0039 (0.0177)
	Radius matching	0.1584	0.1691	−0.0106 (0.0195)

Note: Standard errors in parenthesis (bootstrapped only for KBM and Radius matching); *,** and *** denotes significance level at 10%, 5% and 1%, respectively.
[a] NNM = single nearest neighbor matching with replacement and common support.
[b] NNM = five nearest neighbor matching with replacement and common support.
[c] KBM = with band width 0.06 and common support.
[d] KBM = with band width 0.03 and common support.

switching regression, and using per capita food consumption as an outcome variable, we find an ATT of ETB218.67 which is close to the results from the PSM model.

Continuous treatment effects estimation results

Both the endogenous switching regression and binary propensity score matching methods do not take into account the heterogeneity in the impacts of adoption. In order to evaluate the heterogeneous and incremental impacts of adoption on adopters, we employ a methodology of continuous treatment effects estimation following Hirano and Imbens (2004). In the first step, we estimate the conditional probability of receiving a particular level of treatment (intensity of adoption) given covariates (see Table 5) using maximum likelihood estimation (first stage regression). This provides the estimated GPS.[10] We then divided the treatment distribution by the treatment level into six groups (see Table A2). For each of the covariates used in the first stage of

[10] The results of the GPS estimates are not reported to save space, but are available from the authors upon request.

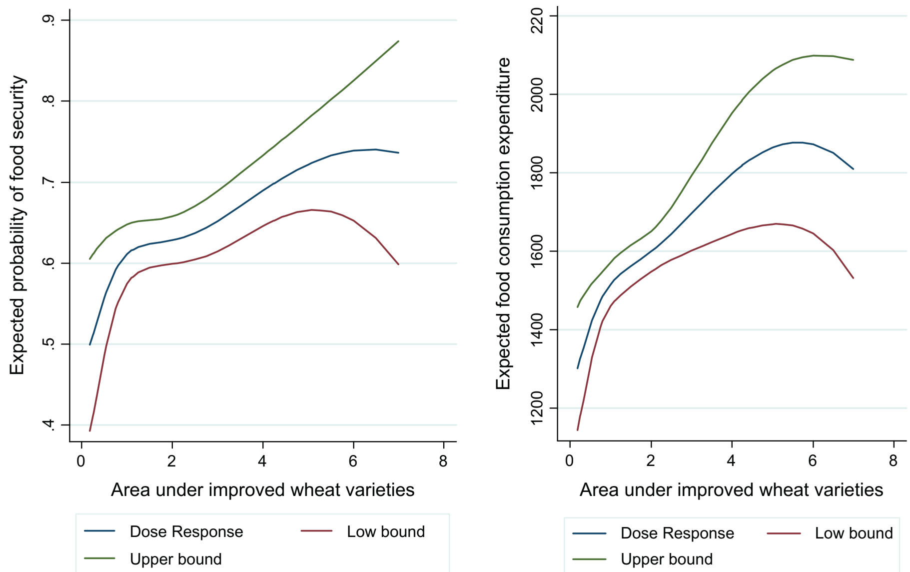

Fig. 3. Dose response (average treatment) function for probability of food security and per capita food consumption expenditure.

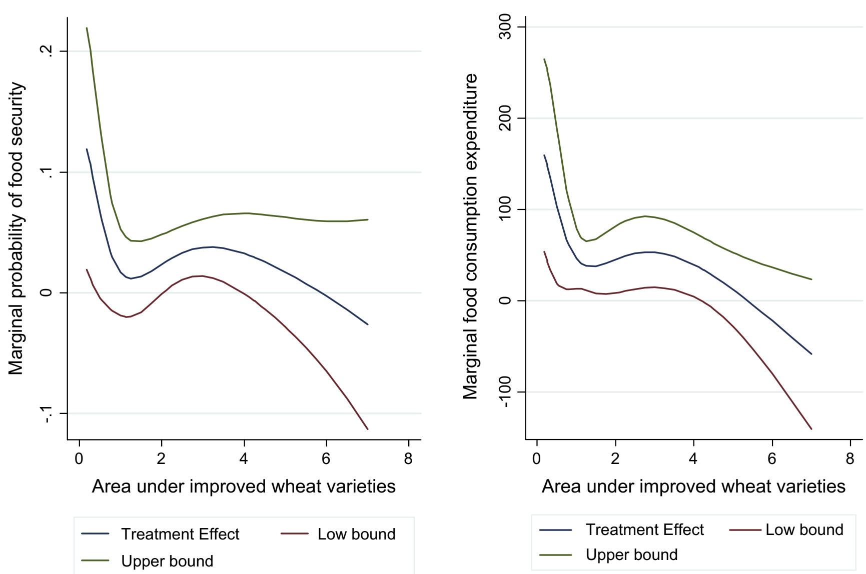

Fig. 4. Marginal treatment effects function for probability of food security and per capita food consumption expenditure.

regression, we then examine the balance by testing whether the mean in one of the six treatment groups is different from the mean in the other five groups combined. Comparing the first six columns (raw or unadjusted data) in Table 10 with the last six columns of the same table (adjusted data), results suggest that the covariate balance has clearly improved after GPS adjustment. For instance, the first interval has 14 variables that have a t-statistics greater than two, in absolute value, without conditioning on the GPS; whereas, after adjusting with the GPS, this is reduced to three variables. In general, the covariate imbalance reduced by 60% after adjustment.

After balancing the covariates across the treatment intervals, we estimate the second stage regression where the conditional expectation of the outcome variables is regressed as a function of level of treatment and its square and estimated GPS. It is estimated by different regression models depending on the nature of our outcome variables.[11] In the last step, the second stage regression outcome is averaged over the GPS at each level of the treatment we are interested in and this provides the average dose response function.[12] The standard errors and confidence intervals of the dose–response function were estimated via bootstrapping using 100 replications to take into account estimation of the GPS and second stage regression parameters. Based on average response function, the treatment effect function which is the derivative of dose–response function is computed. The treatment effect function shows the marginal effects of changing the treatment variable by a given unit on the outcome variable along the selected values of the treatment variable.

The results reveal that the average food consumption expenditure and the probability of food security increase as the area devoted to improved wheat increases (Fig. 3). However, the food

[11] In our case, we used OLS and probit to estimate food consumption expenditure and binary food security status, respectively.

[12] According to Hirano and Imbens (2004), the estimated coefficients from the second stage regression do not have a causal interpretation, except that testing whether the joint significance of all coefficients associated with GPS are equal to zero can be used to assess whether the covariates introduce bias.

consumption expenditure and the probability of food security reach diminishing return at 6 kert (1.5 ha) and 7 kert (1.75 ha), respectively. The probability of food security increases from 51% at about 0.25 kert under improved varieties to 74% at the 7 kert adoption level. Similarly, the per capita food consumption increases from ETB1327 at 0.25 kert to ETB1810 at 7 kert. The marginal treatment effects results also tell a similar story, although the effects quickly decline and reach a diminishing return at 3.5 kert and 4.5 kert for food consumption expenditure and probability of food security, respectively (Fig. 4). These results show that a one unit (1 kert) increase in the area under improved wheat varieties will on average increase the probability of food security by 2.9% and the per capita food consumption by 45.0% (ETB246 per household).

Conclusion

We have analyzed the effects of modern wheat technology adoption on food security among smallholder farmers in Ethiopia. We use a recent nation-wide and rich farm household survey to estimate these effects. A combination of parametric and non-parametric econometric techniques is used to mitigate biases stemming from both observed and unobserved heterogeneity and to test robustness of results. The parametric estimation employs endogenous switching regression treatment effects approach while the non-parametric method involves application of a binary propensity score matching estimator complemented with generalized propensity score estimator to measure incremental effects under heterogeneous continuous treatment (adoption levels).

Results are consistent across estimation methods and indicate that wheat technology adoption has generated a significant positive impact on food security. While the magnitude of estimated effects varies across estimation methods, the impacts of adoption are not trivial. Farm households that did adopt would benefit the most from adoption. At the household level, the ATT, which is the actual effect that adopters experience through adoption, are ETB976 and 2.7% points for food consumption expenditure and binary food security outcome variables, respectively. Similarly, the ATU at the household level is also significant at about ETB861 and 4.5% for food consumption expenditure and binary food security outcome variables, respectively. Numerically these results are similar to the binary propensity score matching estimator which corrects for selection bias stemming from observed heterogeneity.

The adoption analysis results show that prices of wheat, the price of competing crops, sources of variety information, input costs, agro-ecology and geographical location influence the adoption of improved wheat varieties. These results provide strong evidence for the positive impact of adoption of modern agricultural technologies for a major food staple on alleviating food insecurity in rural Ethiopia. However, exploiting the full benefits of the technology in improving food and nutritional security will require increased investments and policy support for improving wheat productivity through greater access to variety information, improved seeds, complementary inputs, such as fertilizer and herbicides, better producer prices and value chain development for reducing transaction costs related to input and output markets. About 30% of the wheat growers are not currently benefiting from modern varieties. The higher benefits to non-adopters, had they adopted the technology, indicate the existence of other limiting factors and barriers to adoption. These are often related to information and access to seeds and capital to invest in new seeds. Even for adopters, high-yield gaps persist mainly due to poor agronomy, lack of fertilizer use, repeated recycling of seed and failure to replace out-dated varieties with modern cultivars. Development policies for agricultural transformation in Ethiopia would need to remedy this situation and aggressively increase access to, and use of, modern wheat varieties. This study indicates that such investments will have substantial impacts in improving household food security and reducing hunger and poverty in rural Ethiopia.

Appendix A

See Tables A1 and A2.

Table A1
Endogenous switching regression estimates for selected outcome indicators.

Variables	Per capita food consumption expenditure						Probability of food security					
	Adopters			Non-adopters			Adopters			Non-adopters		
	Coef.	Std. Err.	P > t	Coef.	Std. Err.	P > t	Coef.	Std. Err.	P > z	Coef.	Std. Err.	P > z
Household characteristics												
Ln(household head age)	-0.018	0.054	0.744	-0.074	0.078	0.339	0.007	0.160	0.967	-0.246	0.227	0.280
Schooling to grades 2 and 6	-0.005	0.028	0.859	0.013	0.048	0.784	-0.169*	0.087	0.053	-0.090	0.138	0.515
Schooling above grade 6	0.011	0.038	0.761	0.038	0.069	0.581	-0.272**	0.125	0.029	0.136	0.207	0.511
Ln(Family size)	-0.640***	0.037	0.000	-0.612***	0.062	0.000	-0.545***	0.119	0.000	-0.598***	0.186	0.001
Gender	0.126***	0.045	0.006	0.036	0.081	0.655	-0.010	0.152	0.948	0.108	0.231	0.640
Livestock ownership	0.039***	0.005	0.000	0.039***	0.006	0.000	0.177***	0.019	0.000	0.135***	0.024	0.000
Ln(farm size)	0.006	0.007	0.427	0.005	0.014	0.729	0.004	0.027	0.869	0.012	0.042	0.772
IMR	-0.708***	0.125	0.000	-0.385***	0.150	0.010	-1.415***	0.399	0.000	-0.353	0.440	0.422
Output and input prices												
Wheat price	−0.063***	0.020	0.002	−0.081***	0.039	0.041	−0.303***	0.065	0.000	−0.259**	0.116	0.025
Teff price	−0.002	0.012	0.839	0.015	0.014	0.291	0.112***	0.039	0.004	0.025	0.040	0.541
Maize price	0.051*	0.025	0.042	0.078	0.075	0.300	0.138*	0.083	0.095	0.492**	0.234	0.036
Barely price	0.007	0.011	0.500	0.021	0.026	0.425	0.017	0.038	0.656	0.142*	0.076	0.063
Fertilizer cost	0.034***	0.007	0.000	−0.002	0.047	0.970	0.222***	0.080	0.006	0.313**	0.134	0.019
Seed cost	0.004***	0.001	0.000	0.002	0.002	0.268	0.011***	0.004	0.007	−0.001	0.007	0.839
Herbicide cost	0.002	0.001	0.112	−0.002	0.002	0.391	0.003	0.003	0.465	−0.006	0.006	0.279
Land quality and shocks												
Land quality	0.165***	0.053	0.002	0.101	0.091	0.265	0.229	0.178	0.198	0.007	0.260	0.977

Pest and disease	−0.044	0.025	0.073	−0.029	0.045	0.522	−0.418***	0.084	0.000	−0.244*	0.133	0.066
Social capital and network												
Relative	0.000	0.001	0.755	0.000	0.001	0.773	−0.005**	0.002	0.027	0.002	0.002	0.324
Trader	0.002	0.002	0.203	0.006	0.004	0.101	0.012	0.009	0.182	0.021*	0.012	0.071
Location characteristics												
Ln(distance to output main market)	−0.046***	0.015	0.002	−0.046*	0.025	0.070	−0.121***	0.043	0.005	−0.062	0.075	0.406
Humid sub-Afro-Alpine	0.193**	0.090	0.033	0.078	0.169	0.646	0.221	0.278	0.426	−0.917*	0.501	0.067
Warm moist lowlands	0.049	0.056	0.378	−0.175	0.155	0.260	0.517**	0.238	0.030	−0.194	0.452	0.668
Moist mid-highlands	0.243***	0.056	0.000	0.107	0.110	0.333	0.664***	0.184	0.000	−0.202	0.324	0.533
Sub-moist mid highlands	0.045	0.043	0.297	−0.256**	0.115	0.027	−0.024	0.147	0.871	−0.968***	0.327	0.003
Warm sub-humid lowlands	−0.180***	0.069	0.009	−0.087	0.154	0.573	−0.313	0.206	0.129	−0.009	0.517	0.986
Sub-humid mid highlands	0.019	0.043	0.664	−0.025	0.097	0.795	−0.080	0.153	0.603	−0.609**	0.285	0.033
Semi-arid mid highlands	−0.275**	0.107	0.011	−0.382	0.348	0.273	−1.156***	0.404	0.004	(omitted due to collinearity)		
Amhara region	−0.262***	0.071	0.000	−0.579***	0.137	0.000	0.238	0.240	0.321	0.397	0.394	0.314
Southern region	0.181*	0.093	0.052	−0.289*	0.175	0.100	2.045***	0.315	0.000	1.280**	0.518	0.013
Oromia Region	−0.049	0.068	0.475	−0.442***	0.146	0.003	0.342	0.246	0.165	0.285	0.418	0.496
Constant	8.220***	0.274	0.000	8.408***	0.707	0.000	−0.036	1.072	0.973	−1.966	2.106	0.351
Model diagnosis												
F/LR/Wald Chi2	18.86***			6.46***			214.08***			121.1***		
R-squared/Pseudo R2	0.289			0.255			0.152			0.153		
Log likelihood	NA			NA			−795.02			−335.47		
Number of observations	1421			596			1421			594		

Note: *, **, and *** denotes significance level at 10%, 5%, and 1%; robust standard errors reported.

Table A2
Covariate balancing for generalized propensity score matching.

Covariate/group of households	Data before adjustment by GPS						Data adjusted by GPS					
	[0.18, 5]	[0.54, 1]	[1.1, 2]	[2.1, 3]	[3.25, 6]	[6.5, 10]	[0.18, 5]	[0.54, 1]	[1.1, 2]	[2.1, 3]	[3.25, 6]	[6.5, 10]
Ln(household head age)	−1.3	**2.5**	0.7	0.0	**−2.2**	−0.5	−1.3	**2.5**	0.5	0.8	−1.0	0.1
Schooling to grades 2 and 6	1.6	1.3	−0.6	−1.6	−1.1	1.7	1.2	0.8	−0.7	−1.3	−0.5	1.7
Schooling above 6 grades	−0.5	−0.8	1.9	0.2	−0.2	−2.2	0.0	−0.6	2.1	0.4	−0.6	−2.3
Ln (family size)	**2.5**	**3.7**	1.4	**−3.3**	**−3.8**	−1.2	1.0	1.4	1.4	−1.8	−1.0	0.0
Gender	**2.2**	0.2	**2.4**	**−2.1**	**−2.2**	−1.3	0.2	−0.8	2.1	−1.2	−1.0	−0.9
Wheat price	**4.3**	0.1	0.9	−0.8	**−2.9**	−2.0	1.8	−1.3	0.6	−1.1	−2.2	−1.1
Teff price	0.2	**−5.0**	−0.2	**3.3**	2.0	0.5	1.6	**−3.3**	−0.2	1.6	1.0	0.8
Maize price	0.6	1.2	0.0	−0.7	−0.9	−0.3	0.0	0.4	−0.1	−0.6	0.7	−0.2
Barley price	**3.1**	−1.2	0.4	1.8	**−3.0**	−0.6	1.4	−2.3	0.5	2.4	−1.9	−0.3
Farm size	**4.1**	1.7	1.0	−0.2	**−5.2**	−2.1	1.5	−1.5	1.4	1.6	−2.6	−0.2
Livestock ownership	**4.3**	**4.9**	1.5	−4.3	**−5.4**	−2.4	1.0	2.2	1.4	−1.9	−2.9	−1.5
Land quality	0.6	1.2	−1.0	0.8	−1.4	0.2	0.8	0.8	−0.8	1.4	−0.6	0.2
Ln(distance to output market)	**2.4**	1.2	**−2.3**	−0.1	−0.5	−0.1	1.9	−0.1	−2.2	0.4	1.4	−0.1
Relative	0.2	1.5	0.9	0.8	−3.3	−0.4	−0.2	1.0	0.8	1.9	−1.3	−0.2
Trader	1.3	0.5	0.4	−1.3	−0.5	−1.0	0.9	0.2	0.4	−1.1	−0.3	−1.4
Pest and disease	**−2.9**	0.0	**2.1**	−0.4	0.3	0.1	−1.5	1.4	2.1	−1.7	−0.9	−0.7
Fertilizer cost	−0.3	−1.2	−1.8	1.2	2.0	1.1	−0.1	−0.3	−1.6	0.4	0.2	0.9
Ln(seed cost)	1.3	1.4	0.1	−1.1	−1.2	−1.0	−2.4	0.5	0.4	−1.0	−2.2	−1.3
Herbicide cost	−1.6	**3.3**	−0.1	−1.1	−1.0	0.0	0.1	2.3	0.4	0.1	−0.1	−0.3
Humid sub−Afro−Alpine	1.1	1.6	0.3	−1.9	−1.4	0.8	0.0	0.5	0.7	−0.8	−0.3	0.7
Warm moist lowlands	**−2.8**	0.1	**2.9**	1.4	−2.0	−1.3	−0.7	−0.1	**2.8**	1.1	1.1	−2.7
Moist mid−highlands	−0.1	−2.7	0.2	0.2	2.2	0.6	−0.4	−1.1	−0.5	−1.0	0.8	0.6
Sub−moist mid highlands	**−2.8**	−0.2	−0.8	1.3	2.0	0.1	−0.9	1.4	−0.9	0.6	1.6	0.8
Warm sub−humid lowlands	**2.6**	0.3	−1.4	−1.0	0.3	−0.7	1.5	−0.5	−1.5	−1.3	0.0	−2.3
Sub−humid mid highlands	−0.5	−0.6	−0.4	1.2	−0.3	1.8	0.4	−0.8	0.1	1.0	−0.8	1.6
Semi−arid mid highlands	1.6	1.8	−0.4	−1.8	−1.1	0.6	1.1	1.1	−0.6	−0.7	−0.3	0.9
Amhara region	**−5.6**	−4.2	−0.4	4.5	4.3	1.9	**−2.8**	0.7	−1.4	1.1	0.4	0.6
Southern region	**−4.3**	−0.6	1.3	1.3	1.1	0.9	−1.7	1.2	1.1	−0.3	−1.3	0.1
Oromia Region	**9.3**	6.0	−0.4	−6.2	−6.2	−2.8	3.9	−1.3	1.0	−2.0	−0.6	−1.1

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