Impacts of Adoption of Improved Wheat Technologies on Households' Food Consumption in Southeastern Ethiopia

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Abstract

This study aims at shedding light on the potential impact of agricultural technology adoption on household food consumption status. The analysis is based on the data collected from randomly selected 200 farm households in Southeast Ethiopia. Since the process of technology adoption usually involves non-random placement of adopters, we employed a propensity score matching method to avoid bias arising from possible self-selection. The results show that adoption of improved wheat technologies has a robust and positive effect on farmers' food consumption per adult equivalent per day. The Average Treatment Effect on the Treated (ATT), based on three estimation algorithms, ranges from 377.37 calories per day to 603.16 calories per day which indicates that efforts to disseminate existing wheat technologies will highly contribute to food security among farm households.

Keywords: Impact, adoption, food consumption, propensity score matching, Ethiopia.

1. Introduction

Studying how individuals are able to escape poverty is a central issue of economic development theory. Of the poor people worldwide (those who consume less than a 1 dollar-a-day), 75 per cent work and live in rural areas and projections suggest that over 60 per cent will continue to do so up to 2025 (Mendola, 2007). These are good reasons to emphasize research on rural poverty reduction, and to redirect attention and expenditure towards agricultural development.

Food insecurity is a manifestation of poverty confronting many developing countries, especially those found in Sub-Saharan Africa and South Asia. For instance, about one third of the people in SSA are food insecure (Graaff, et al 2011). Agricultural growth is seen as a best-bet strategy for achieving food security because of the fact that agriculture is central to the livelihood of more than half of the world's population. Growth in agricultural production can reduce food insecurity by increasing the amount food available for consumption. This is particularly important for rural consumers whose food entitlement is mainly based on own production (Adekambi, *et al*, 2009).

Agricultural production can be increased through extensification (i.e. through expansion of farm lands) or intensification (i.e. by using more inputs and technologies per unit of land). However, extensification is not a viable strategy to increase agricultural production in most of the food insecure countries where high population pressure is a critical bottleneck. Where land is scarce, intensification, which entails investments in modern inputs and technologies, is a better option to increase agricultural production and reduce food insecurity. This option was effectively implemented by several Asian countries in 1970s and was dubbed the "green revolution".

New agricultural technologies and improved practices play a key role in increasing agricultural production (and hence improving national food security) in developing countries. Where successful, adoption of improved agricultural technologies could stimulate overall economic growth through inter sectoral linkages while conserving natural resources (Abdulai, 2006, Sanchez, et al 2009). Given the close link between food insecurity, farming and environmental degradation the impact of cultivation practices has received significant attention in the last two decades. New cultivation techniques have been introduced in many countries to enhance productivity in the agriculture sector.

Ethiopia is an agrarian country where more than 80% of the total population depends directly or indirectly on agriculture. Agriculture contributes for about half of the GDP and for more than 90% of foreign exchange earnings (EEA report, 2011). Cereals (mainly tef, wheat, maize, and sorghum) are dominant in different parts of the country satisfying about 70% of the average Ethiopian's calorie intake (Howard, et al 1995; Abebe 2000). While agricultural productions are still taking place using traditional methods, efforts have been made by the Ethiopian governments to improve situations through dissemination of improved agricultural technologies to farmers.

Wheat is among a few crops which has received special attention from the Ethiopian government and NGOs operating in the country. In this regard, the government has paid attention to research and extension of wheat technologies. Studies to develop improved wheat technologies have been conducted since the 1950s with the assistance of international research centers and foreign donors resulting in several improved wheat varieties and management practices. The role of the International Maize and Wheat Improvement Center (CIMMYT) is immense in the process of development of improved wheat varieties. The improved wheat varieties (together with improved agronomic practices) have been introduced and disseminated to wheat farming communities in different parts of the country through the extension system operated by the government.

Lode Hetosa district is one of wheat producing districts which has benefited from researches on wheat and subsequent transfers of improved wheat varieties and agronomic practices. While success stories can be anticipated regarding the extension of wheat technologies in Lode Hetosa, no published study discussing the impact of the disseminated technologies on households' food security has been found (to the best of the authors knowledge). A few studies conducted so far in similar agroecologies (but different districts) could identify factors affecting the adoption of improved what technologies (e.g. Bekele, et al 2000; Tesfaye, et al 2001; Hailu, 2008) but didn't go further to assess the impacts of the technologies. Therefore, this study has been designed to fill this research gap. Specifically, the study deals with the analysis of the impact of growing improved wheat varieties on food security given that the varieties are planted using the recommended planting method (i.e. row planting).

2. Adoption and Impact of Improved Agricultural Technologies

The adoption of an innovation within a social system takes place through its adoption by individuals or groups. According to Feder *et al*. (1985), adoption may be defined as the integration of an innovation into farmers' normal farming activities over an extended period of time. It is also noted that adoption, however, is not a permanent behavior. This implies that an individual may decide to discontinue the use of an innovation for a variety of personal, institutional, and social reasons one of which might be the availability of another practice that is better in satisfying farmers' needs.

Adoption is a mental process through which an individual passes from hearing about an innovation to its adoption that follows awareness, interest, evaluation, trial, and adoption stages (Bahadur and Siegfried, 2004). It can be considered a variable representing behavioral changes that farmers undergo in accepting new ideas and innovations in agriculture anticipating some positive impacts of those ideas and innovations.

Dixon et al (2006) posits that adoption of improved varieties can have impacts at different levels. First, improved wheat varieties can generate significant field-level impact on yield and stability. Second, intensification of food crops often leads to the release of land, water and labor resources for on-farm diversification. Third, higher and more stable wheat yields produce people-level impacts on household food security and household income. Fourth, the combination of intensification and diversification creates further household level impacts on wider dimensions of household livelihoods and poverty reduction, including the off-farm effects on the local economy and in more distant cities.

Several studies in Africa show that adoptions of improved agricultural technologies, though variably and incompletely, had positive impacts on income, food security and poverty reduction (e.g. Wanyama, et al 2010; Solomon et al 2010**,** Adekambi, *et al 2009, Kassie, et al 2010).* Using the number of months that grains stay in store as a proxy to food security, Wanyama et al (2005) showed that soil management technologies had a positive impact on the food security of the farming community within the soil management project area and its neighborhood in Kenya.

Setotaw et al (2003) found that adoption of improved agricultural technologies (improved varieties and agronomic practices) have positively and significantly affected household's food security in Ethiopia. Solomon et al (2010) examined the impacts adoption of chickpea varieties on the level of commercialization of smallholder farmers in Ethiopia. They found that adoption of improved chickpea varieties has a positive and robust effect on marketed surplus which reduces food insecurity in adopter households. A study by Adekambi et al, (2009) on the impact of agricultural technology adoption on poverty in Benin indicates the increase in productivity of rice farmers, following the adoption of NERICA varieties. These results suggest that the promotion of NERICA cultivation can contribute to improving expenditure/income of farmers and consequently to poverty reduction. Similarly, Kassie, et al (2010) found that improved ground technologies had a significant positive impact on crop income and poverty reduction in Uganda.

Studies conducted in Asia also reveal similar results. Using a propensity score matching method, Mendola (2007) examined the impacts of agricultural technology adoption on poverty reduction in rural Bangladesh. Findings show a robust and positive impact of agricultural technology adoption on farm households' well-being. Similarly, Wu et al (2010) conducted an impact study rural China and found that adoption of agricultural technologies had a positive impact on farmers' well-being thereby improving household income.

Methodology

The study area

The study was conducted in Lode Hetosa district (*woreda*) of Southeast Ethiopia. Administratively Lode Hetosa woreda[1] is under Oromia Regional State. It is divided into 22 kebeles[2] of which 19 are rural kebeles and the remaining ones are urban-based. According to the population census report of CSA (2007a), a total of 107,688 people live in the woreda out of

[1] Woreda is the third level in Ethiopian formal administrative structure next to Federal and Regional level governments.
[2] A kebele is the lowest level in Ethiopian formal administrative structure which is next to woreda.

which more than 85% live in rural areas. The administrative and commercial town of the district, Huruta, is located at 164 km from Addis Ababa (towards the East) and 39 km from zonal capital, Asela to Eastern direction on Iteya-Arsi Robe main road.

The weather condition of the woreda is suitable for wheat production. The temperature varies between 10^0C-25^0C. The annual rainfall ranges from 800mm to 1400mm and the average rainy days are about 120 days in the year. The rainfall pattern is bi-modal: a short rainy season (Belg) from February to March) and a long rainy season (Meher) from June to September. Wheat is the major crop produced in the area. For instance, it covered about 33% of the total cultivated land in in 2007 in Arsi Zone (where the study area is located) (CSA 2007b). In addition to what, various types of crops, such as barley, tef, maize, horse beans, field peas, and various types of oil seeds, are cultivated in the area. Moreover, livestock such as cattle, sheep, goats, pack animals, and poultry, are important sources of livelihoods in the area.

Data Collection

Both primary and secondary data were used in the study. However, the study relies dominantly on primary data whereas secondary data are used to supplement the primary data. Primary data were collected through a household survey. A two- stage sampling technique was employed to identify the sample units i.e. farm households. First, five major wheat producer kebeles were selected purposively with the help of agricultural experts in the area. Second, 40 households were randomly selected from the member list each kebele summing up to 200 households. The sample size was fixed taking into account the resources we had to conduct the survey. A structured questionnaire was developed and used to collect the data which was administered by trained enumerators. Data were collected on several issues including total food consumption during a week before the survey, households' demographic characteristics, asset endowments, access to market, access to credit, membership in different rural institutions, and income sources. Interviews were also conducted with district level agricultural experts and selected farmers to generate supplementary (qualitative) data.

Analytical Approach

The objective of this study is to assess the impact of improved wheat technologies (improved wheat varieties and row planting method) on households' food consumption level. If the technologies were randomly assigned to farmers, we could assess the impact of their adoption on households' food consumption by comparing the average consumption of adopters and non-adopters. In such a case, the average treatment effect (ATE) can be computed as follows:

$$\text{ATE} = E\,(Y_1 \mid D = 1) - E\,(Y_0 \mid D = 1)$$

This is based on the assumption that the output levels of the adopters before their adoption ($E(Y_0|D=1)$ can reasonably be approximated by the output level of non-adopters during data collection ($E(Y_0|D=0)$. Otherwise, estimation of ATE using the above equation is not possible since we do not observe $E(Y_0|D=1)$ though we do observe $E(Y_1|D=1)$ and ($E(Y_0|D=0)$. However, technologies are rarely randomly assigned. Instead, technology adoption usually occurs through self-selection of farmers or, sometimes, through program placement. In the presence of self-selection or program placement, the above procedure may result in a biased estimation of the impacts of improved technologies since the treated group (i.e. the adopters) are less likely to be statistically equivalent to the comparison group (i.e. the non-adopters) in a nonrandomized setting.

The propensity score matching (PSM) method, which was developed by Rosenbaum and Rubin (1983), has been extensively used in economics since 1990s to solve the above problem. Rosenbaum and Rubin(1983) defined 'propensity score' as the conditional probability of receiving a treatment given pre-treatment characteristics:

$$P(X) \equiv \Pr\{D = 1|X\} = E\{D|X\}$$

where $D = \{0, 1\}$ is the indicator of exposure to treatment and X is the multidimensional vector of pre-treatment characteristics.

The PSM method is a systematic procedure of estimating counterfactuals for the unobserved values ($E(Y_1|D=0)$ and $E(Y_0|D=1)$ to estimate impact estimates with no (or negligible) bias. The validity of the outputs of the PSM method depends on the satisfaction of two basic assumptions namely: the Conditional Independence Assumption (CIA) and the Common Support Condition (CSC) (Becker and Ichino, 2002). CIA (also known as Unconfoundedness Assumption) states that the potential outcomes are independent of the treatment status, *given X*. Or, in other words, after controlling for *X*, the treatment assignment is "as good as random". The CIA is crucial for correctly identifying the impact of the program, since it ensures that, although treated and untreated groups differ, these differences may be accounted for in order to reduce the selection bias. This allows the untreated units to be used to construct a counterfactual for the treatment group. The common support condition entails the existence of sufficient overlap in the characteristics of the treated and untreated units to find adequate matches (or a *common support*). When these two assumptions are satisfied, the treatment assignment is said to be strongly ignorable.

Estimating Propensity Scores and Assessing Match Quality

We used the probit model to estimate propensity scores. More than a dozen of selected variables were included in the model. Because the matching procedure conditions on the propensity score but does not condition on individual covariates, one must check that the distribution of variables are 'balanced' across the adopter and non-adopter groups. Rosenbaum and Rubin (1985) recommend that standardized bias (SB) and *t*-test for differences be used to check matching quality. If the covariates *X* are randomly distributed across adopter and non-adopter groups, the value of the associated pseudo-R^2 should be fairly low and likelihood ratio should also be insignificant. A bootstrapping method was used to compute the standard error for the estimate of the technology impact.

Choosing a Matching Algorithm

Three commonly used matching algorithms, namely nearest neighbor matching, radius matching, and kernel-based matching, were employed to assess the impact of improved wheat technologies on households' food consumption. The nearest neighbor matching (NNM) method matches each farmer from the adopter group with the farmer from the non-adopter group having the closest propensity score. The matching can be done with or without replacement of observations. NNM faces the risk of bad matches if the closest neighbor is far away. This risk can be reduced by using a radius matching (RM) method, which imposes a maximum tolerance on the difference in propensity scores. However, some treated units may not be matched if the dimension of the neighborhood (i.e. the radius) is too small to contain control units. The kernel-based matching (KM) method uses a weighted average of all farmers in the adopter group to construct a counterfactual. The major advantage of the KM method is that it produces ATT estimates with lower variance since it utilizes greater information; its limitation is that some of the observations used may be poor matches.

Results and Discussion

Descriptive Statistics

The average family size was 5.2 persons per household. But there was a wide variation in family members among households. The heads of the sample households were, on average, 43 years old and were engaged in farming for about 23 years. The majority (78%) of the sample households was male-headed which is expected in Ethiopian context. About 46% of the respondents were literates; this figure is greater than the national figure for adult literacy (36%)[3] indicating that the area is better off in terms of education.

The landholding of the sample households ranges from 0.5 ha to 9 ha with an average figure of 2.2 hectares. The average livestock (including cattle, sheep, goats, pack animals, and poultry) was 6 TLU with the minimum and the maximum holdings of 0.04 TLU and 18.6 TLU respectively. The average labor force available was 3 man equivalents. While all of the sample

[3] http://www.unicef.org/infobycountry/ethiopia_statistics.html

households generated cash income by selling crops (such as wheat, barley, tef and vegetable crops), about 54% could do also from off-farm activities. About 72% had access to institutional credit to purchase farm inputs. The average distance from the nearest market place was 3.8km with the minimum and maximum figures equal to 2 km and 7 km, respectively.

The adoption process of agricultural technologies depends primarily on access to information and on the willingness and ability of farmers to use information channels available to them. The role of information in decision-making process is to reduce risks and uncertainties to enable farm households to make the right decision on adoption of improved agricultural technologies. In Access to information on agricultural technologies, in our case, was represented by three variables, namely: access to extension services, participation in field demonstration of agricultural technologies, and connections to towns. The results show that more than 70% of the total sample respondents had access to extension services and also participated in technology demonstration events (Table 2). Similarly, more than 70% visited nearby towns which could have improved their access to information.

Adopters are significantly different from non-adopters with respect to many of the variables considered (Tables 1 and Table 2). Farm size (or land holding) and livestock holding (TLU) are highly important continuous variables to differentiate the two groups. Among the dummy variables considered in our analysis, participation in off-farm activities, access to institutional credit, and education were important. Adopters were superior to their counterparts in terms of all of the aforementioned variables.

Table 1: Characteristics of adopters and non-adopters (summary statistics for continuous variables)

Variable	Adopters		Non-adopters		Total		t-value
	Mean	SD	Mean	SD	Mean	SD	
age	42.3	9.1	43.4	10.7	42.8	9.8	0.69
family size	5.3	2.8	5.2	2.3	5.2	2.5	0.14
farm exp.	21.9	9.5	24.7	11.0	23.3	10.3	1.87*
Farm size(ha)	2.44	1.26	1.95	0.83	2.19	1.09	3.26***
Livestock(TLU)	7.05	3.41	5.51	3.19	6.28	3.39	3.28***
Labor (ME)	2.96	1.39	3.07	1.56	3.02	1.48	0.51
Market access	3.38	1.94	3.90	1.90	3.87	1.92	0.25

**Note: * , **, *****show significance at 10%, 5%, and 1% levels, respectively

Table 2: Characteristics of adopters and non-adopters (summary statistics for dummy variables)

Variable		Adopters		Non-adopters		Total		χ2-value
	category	No.	%	No.	%	No.	%	
Education	literate	54	58.7	38	41.3	92	46	5.15**
	illiterate	46	42.6	62	57.4	108	54	

Sex	male	78	50	78	50	156	78	0.000
	female	22	50	22	50	44	22	
Off-farm activity	Yes	75	69.4	33	30.6	108	54	35.51***
	No	25	27.2	67	72.8	92	46	
Access to credit	Yes	81	56.6	62	43.4	143	71.5	8.86***
	No	19	33.3	38	66.7	57	28.5	
Extension contact	yes	83	58	60	42	143	71.5	12.98***
	no	17	29.8	40	70.2	57	28.5	
Visit towns	yes	76	53.9	65	46.1	141	70.1	2.91
	no	24	40.7	35	59.3	59	29.5	
Participation in field days/ demonstrations	Yes	77	51.7	72	48.3	149	74.5	0.66
	no	23	45.1	28	54.9	51	25.5	

Note: *,**,*** show significance at 10%, 5%, and 1% levels, respectively

Estimation Results of Propensity Scores

The importance of estimation of the propensity score is twofold: first, to estimate the ATT and, second, to obtain matched treated and non-treated observations. The results of the probit model are reported in Table 3. They indicate that age, education, farm experience, participation in off-farm activities, access to credit, extension contact, and livestock holding are important variables that determine farmers' propensity to adoption of wheat technologies.

Table 3 Results of the probit regression model

Variables	Coefficients	t-value
Age of household head	0.114***	3.91

Sex of household head	0.176	0.66
Education of household head	0.739***	2.83
Family size	0.031	0.37
Off-farm activity	1.499***	5.73
Farm experience	-0.118***	-4.11
Market access	-0.177**	-2.28
Land holding	0.242	1.42
Labor availability	-0.208	-1.58
Livestock ownership	0.151***	3.29
Credit access	0.826***	3.10
Extension contact	0.734***	2.94
Visit towns	0.146	0.65
Participation in Field days/technology demonstration	0.423	1.54
constant	-5.22***	-5.26
Sample size	200	

Note: **, *** show significance at 5% and 1% levels, respectively

Among adopters, the predicted propensity scores range from 0.0466782 to 0.9991589, with a mean of 0.719. Among non-adopters, they range from 0.0046937 to 0.9447411, with a mean score of 0.281. Thus, the common support assumption is satisfied in the region [0.04667817 to 0.99915887], enforcing the exclusion of 19 non-adopters from the analysis.

Before computing the ATT, the similarity of the subsample of control cases that are directly compared with the treated cases should be tested using the so-called “pstest”. This test helps to balance information for propensity scores and for each covariate before and after matching. The standardized bias difference between treatment and control samples was used as a convenient way to quantify the bias between treatment and control samples. In almost all cases, it is evident that sample differences in the raw data (unmatched data) significantly exceed those in the samples of matched cases. The process of matching thus creates a high degree of covariate balance between the treatment and control samples that are used in the estimation procedure.

The imbalances between the treatment and control samples in terms of the propensity score amounts to more than 100% before matching. This bias was significantly reduced well below 1% after matching. Table 4 shows the values of Pseudo R^2 and LR chi-square before and after matching which can be used as indices for the fulfillment of the balancing requirement. The low value of pseudo-R^2 and the insignificant LR Chi-square reported in columns 3-5 support the hypothesis that both groups have the same distribution in covariates after matching. These results clearly show that the matching procedure is able to balance the characteristics in the treated and the control groups. We therefore used these results to evaluate the effect of adoption of improved wheat technologies among groups of households having similar observed characteristics.

Table 4: Balance Indicators before and after Matching

	Before matching	**After matching**		
		NNM	RM(0.01)	KM
Pseudo R^2	0.38	0.04	0.07	0.06
LR $\chi2$ (p − value)	105.13***	9.19	11.38	12.89

Note: *** significant at less than 1% probability level.

Estimation of Treatment Effect: Matching Algorithms

The Average Treatment effect on the Treated (ATT) was computed based on the three alternative matching methods. Table 5 shows the estimates of ATT from the three matching algorithms. The outcome variable is food consumption per adult equivalent per day measured in kilocalories. The t-statistics were based on bootstrapped standard errors with 500 replications which were used to verify whether the observed effect was significant or not.

The results show that adoption of improved wheat varieties planted in spacing positively and significantly affect food consumption level of households. The increase in food consumption per adult equivalent per day ranges from 265 (11 %) kilocalories in the case of caliper 0.01 to 509(23%) in the case of kernel-based matching. A comparative analysis shows that adopters are better than non-adopters by 21% in terms of the level of food consumption using the NNM with replacement and this gain was statistically significant at 1%probability level. In this case, the mean food consumption of the adopters was 2694 kcal and that of the non-adopters was 2217 kcal.

A similar finding was estimated using Kernel-based matching which was done using two levels of bandwidth (i.e. 0.06 and 0.01). Using a 0.06 bandwidth, adopters, on average, could consume about 2694 kcal per adult equivalent per day; this amount is greater than the corresponding figure of non-adopters by about 23%. The difference is statistically significant ($P< 0.000$). A similar result was obtained by using a 0.01bandwidth KM method.

The results of the caliper matching algorithm also confirm the difference between the adopters and the non-adopters in terms of food consumption per adult equivalent per day. Using a caliper of 0.1, the mean food consumption was about 2694 kcal for adopters while the corresponding figure for the non-adopters was 2294 kcal which shows that adopters were better than non-adopters by about 17% in terms of food consumption. The difference is significant at 1% level. Using a caliper of 0.5 matching method, the estimated average food consumption per adult for adopter was about 2694 Kcal which was greater than that of the non-adopters by about 16%. The difference is also statistically significant at 1%. Similarly, using a caliper of 0.01 the mean calorie consumption of the treated group was about 2613Kcal which is greater than that of the non-adopters by about 16%. Based on a caliper of 0.05, the difference between the two groups was still significant at 1% level; but the mean gain from adoption was only 11% in this case.

Table 5: ATT under different matching algorithm

Type of matching	Treated	Control	ATT	% gain	BSE	T-value
NNM with replacement	2694	2217	477	22	114.93	4.15***
Caliper 0.1	2694	2294	400	17	102.55	3.90***
Caliper 0.5	2694	2324	369	16	89.50	4.13***
Caliper 0.05	2653	2289	363	16	97.02	3.74***
Caliper 0.01	2613	2348	265	11	131.34	2.02***
KM bwidth 0.06	2694	2194	500	23	102.79	4.87***
KM bwidth 0.01	2694	2185	509	23	119.91	4.25***

Note: BSE = Bootstrapped standard errors with 500 replications; *** significant at less than 1% level

Conclusion

New agricultural technologies play a key role in increasing agricultural productivity. Since rural households are basically entitled to food through own production, higher agricultural productivity can easily translate to a better food security condition among these households which could be manifested by higher consumptions. Though adoptions of agricultural technologies may enhance food security among the adopters, impact figures actually vary across different agroecologies, socioeconomic contexts, and features of the improved technologies signifying the role of empirical studies.

In this study, we assessed the impact of improved wheat technologies on households' food consumption. A propensity score matching approach was used to compare adopter households with non-adopters in terms of their food consumption levels as measured in calorie intake per adult equivalent per day. The results show that wheat technologies (proxied by improved wheat varieties grown based a recommend planting space) had a robust and positive impact on farmers' food consumption levels. In the mean time we could identify factors affecting adoption of improved wheat technologies; age, education, farm experience, participation in off-farm activities, access to credit, extension contact, and livestock holding were found to be important variables to determine farmers' propensity to adopt. Overall, our results are in agreement with the findings of other researchers on the impacts of technology adoption (Wu, et al, 2010; Kassie, et al, 2010; Mendole, 2007).

The implication of the findings is straight forward; though the adoption of improved wheat technologies is quite low in Ethiopia, those households who could use the technologies could improve their food consumption levels. Hence, scaling up the best practices of the adopters to other farmers can be considered as one option to enhance food security in the area while introducing new practices and technologies is another option.

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