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The Effect of Improved Storage Innovations on Food Security and Welfare in Ethiopia

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Abstract

Postharvest loss exacerbates the food insecurity and welfare loss of farming households in developing countries. This paper analyses the effect of improved storage, a climate-smart crop management technology, on household food and nutrition security, market participation and welfare using nationally representative data from Ethiopia. Endogenous switching regression models are employed to control for selection bias and unobserved heterogeneity. The results show that improved storage use is mainly associated with climatic factors, access to extension service, liquidity constraints, infrastructure and market access. Improved storage significantly increases the dietary diversity, reduces child malnutrition and negative changes in diet. In addition, use of improved storage technologies increases farmers' participation in output markets as sellers, the proportion of harvest sold and their marketing flexibility by altering the choice of market outlets. Further, the paper provides evidence that households that did not use improved storage would have benefited significantly had they decided to adopt. Overall, the study suggests that improved storage technologies are effective tools for risk coping and enhancing food security and would play a key role in the current debate of feeding a growing population in the face of climate change.

Keywords: storage economics; postharvest loss; food security; climate-smart technology; endogenous switching regression; Ethiopia.

JEL Classification: Q12, Q16, Q18, O33, D13

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1. Introduction

Postharvest loss presents a significant challenge for food security and agricultural production efficiencies in developing countries. In developed economies, postharvest loss is characterised as a consumer behavior while in developing countries it is an infrastructural factor largely due to financial, managerial and technical deficiencies (Conteh *et al.*, 2015; FAO, 2011; Premanandh, 2011). Consequently, in developing countries, food loss is concentrated at stages 'close to the farm' such as production, handling, and storage (Lipinski *et al.*, 2013; Parfitt *et al.*, 2010; Premanandh, 2011). The problem is more acute in Sub-Saharan Africa where a significant portion of the production is lost because of poor storage, lack of structured markets, limited processing capacity and weather related factors (Affognon *et al.*, 2015; Shiferaw *et al.*, 2011; Tefera, 2012; Tefera *et al.*, 2011). Globally, estimates show that roughly one-third of the food produced for human consumption is lost or wasted, which translates into 1.3 billion tones each year, worth nearly one trillion US dollars (FAO, 2011). A quarter of the food lost annually is thought to be enough to feed the world's hungry (FAO, 2012). In Sub-Saharan Africa, postharvest loss is estimated to be about 37% which is equivalent to an annual percapita food loss in the range of 120 - 170 kgs (FAO, 2011; Sheahan & Barrett, 2016). However, estimates vary widely (e.g. Parfitt *et al.*, 2010; Lipinski *et al.*, 2013; Rosegrant *et al.*, 2015; Affognon *et al.*, 2015; Rutten, 2013) by region and crop type (Lipinski *et al.*, 2013). The value of post-harvest cereal grain losses alone in Sub-Saharan Africa (SSA) could total $4 billion a year (World Bank *et al.*, 2011). This estimate of annual loss (i) exceeds the total value of cereal food aid SSA received over the last decade; (ii) equates to the average annual value of cereal imports of SSA over the 2000–2007 period, and (iii) is enough to feed nearly 48 million people at 2,500 kcal per person per day (Juma *et al.*, 2013; Stathers *et al.*, 2013; World Bank *et al.*, 2011). In Eastern and Southern Africa alone, food losses are valued at $1.6 billion per year which is nearly 13.5% of the total value of grain production (Abass *et al.*, 2014). Producing extra food to compensate losses also represents a waste of resources (Lipinski *et al.*, 2013; Stathers *et al.*, 2013).

Postharvest loss impacts food security, nutrition and household welfare through various channels. One of the direct mechanisms through which postharvest loss undermines food security and nutrition is through reducing food availability. Food loss also tightens food markets and contribute to high food prices by removing part of the food supply from the market (Tefera *et al.*, 2011) which in turn lowers farmers' income and discourages investment in productivity-enhancing technologies. Besides its negative economic impacts, postharvest loss also has substantial environmental repercussions manifested through the unsustainable use of scarce natural resources (e.g. land, water), production inputs (fertiliser, pesticides) and energy to produce and process food that is lost (Lipinski *et al*., 2013; Kummu *et al*., 2012). This would not only result in long-term food insecurity and diminished welfare but also jeopardise future generations' food production capacity. Postharvest food loss and food waste each year account for 3.3. bn tones of CO_2 emissions, contributing nearly 14% to the global emission (Juma *et al*., 2013). In sum, postharvest loss entails opportunity costs or resource misallocation. Hence, tackling postharvest loss across the entire food chain would significantly help in improving food security and reducing the environmental footprints of food systems (Sheahan & Barrett, 2016).

Improving postharvest storage efficiency would not only help mitigate potential postharvest losses (World Bank *et al*., 2011), but it would potentially complement the sustainable intensification paradigm (Tscharntke *et al*., 2012; Juma *et al*., 2013). However, for many years, significant resources have been devoted to increasing agricultural production in developing countries, without making an equal push for reducing postharvest losses (Affognon *et al*., 2015). This provides evidence that there has been a policy bias towards production and pre-harvest research. Due to the renewed interest in agriculture in the aftermath of the recent food, climate and financial crises (Dethier & Effenberger, 2012), postharvest loss mitigation interventions are now seen as important elements of reducing food insecurity in Sub-Saharan Africa (Sheahan & Barrett, 2016). Improved storage technologies could be useful strategies for tackling post-harvest losses, coping with increasing food demand, improving the efficiency of the agricultural sector, enhancing agricultural productivity and sustainability (Basu & Wong, 2015; Lybbert & Sumner, 2012; Lipinski *et al*., 2013). They could also be potential interventions for promoting market participation and help smallholder farmers break out of the semi-subsistence poverty traps (Barrett, 2008). A number of improved storage technologies (e.g. metal silo, airtight drums, improved granaries, hermetic bags, etc) (Kaminski & Christiaensen, 2014; Lipinski *et al*., 2013) have been promoted in Sub-Saharan Africa (Hodges *et al*., 2011; Tefera *et al*., 2011). However, few studies assessed farm households' decisions to use such technologies and their impact on household welfare. In general, the literature on the welfare impacts of agricultural innovations is highly skewed to pre-harvest or production techniques and the evidence base on the impacts of postharvest technologies is thin.

Recent systematic reviews on postharvest loss mitigation interventions and their impact underscore the lack of rigorous studies which establish an empirical link between interventions (e.g. postharvest storage innovations) and household welfare (Affognon *et al*., 2015; Sheahan & Barrett, 2016). Among the few exceptions is a study by Gitonga *et al*. (2013) who used propensity score matching and found that metal silos almost completely reduce postharvest storage losses, help farmers increase months of storage by between 1.8 - 2.4 months, reduce expenditure on storage chemicals, ensure sale of surplus at higher prices and reduce the period of inadequate food provision. However, their evaluation approach did not control for possible bias from unobserved endogeneity. Cunguara and Darnhofer (2011) used doubly robust estimator, sub-classification regression and matching methods and found that improved granaries had no significant impact on household income in rural Mozambique. Mutenje *et al.* (2016), using a multinomial endogenous switching regression model, found that joint adoption of improved storage and improved maize varieties provides the highest maize yield in Malawi, compared with other combination of technologies. Kaminski and Christiaensen (2014) analysed the extent of post-harvest loss in Malawi, Tanzania, and Uganda using a Tobit model, and their findings point to the importance of improved storage technologies in reducing post-harvest loss. However, their study did not demonstrate causality. Bokusheva *et al.* (2012) used a double hurdle and Tobit models to identify factors affecting adoption of metal silos in four Central American Countries: El Salvador, Guatemala, Honduras, and Nicaragua. They found that the adoption of metal silos improved the food security and well-being of adopters.

The overarching objective of this study was to estimate the food security, household welfare and marketing performance effects of postharvest food storage technologies using a diverse set of identification and estimation strategies that address selection and endogeneity problems. The study focuses on Ethiopia, a Sub-Saharan African country where the challenges of climate change, postharvest loss, food insecurity and undernutrition are ubiquitous. The paper contributes to the literature on the impacts of climate-smart agricultural innovations, the nascent postharvest research and storage economics in the following ways. First, this study uses nationally representative household level data which allows inclusion of policy-relevant variables and deriving national level estimates. Second, unlike previous studies which used a single measure for welfare, this study uses various objective and subjective measures to capture the different dimensions of food security. Third, this paper bridges the nutrition and agricultural innovations literature by comprehensively estimating the impact of improved food storage technologies on child nutritional status. To the best of our knowledge, there are few rigorous empirical studies that estimated child nutrition effects of agricultural innovations. Slavchevska (2015) reported a positive link between agricultural production and child nutrition in Tanzania. Manda *et al.* (2016) found improved varieties to reduce under-5 stunting in eastern Zambia. Fourth, the study employed recent methodological developments which are appropriate for impact evaluation in a cross-sectional setting.

The rest of the paper is organised as follows. The next section describes the empirical estimation strategies, data, and the variables. Section three discusses the empirical results. The concluding section highlights the key findings and policy implications of the study.

2. Methodology

2.1. Conceptual framework

Farm households are assumed to be heterogeneous agents and their decision to use improved storage is constrained by resources, information and the availability of the technology (Foster & Rosenzweig, 2010). Investment on improved storage will, therefore, only be attractive to households if the perceived benefits substantially offset the costs since technical superiority is insufficient. Hence, households' decision to use the innovation could be viewed through the lens of constrained optimisation where the household chooses the technology if it is available, affordable and its use is expected to be beneficial (de Janvry *et al.*, 2010). The expected benefit the i^{th} household derives from the use of the technology in time t is determined by a set of variables that are observable to the researcher (Z_{it}), those that are not observable(η_{it}), and independently and identically distributed (*i.i.d.*) error term (u_{it}). Denoting S_{it} as a binary indicator of improved crop storage technology use and $E(U^*)$ as the expected utility to be derived from the innovation, a household's decision whether to adopt improved storage technology depends on the net gains that might result from its use. A household uses the innovation if and only if she/he expects a higher utility from use *i.e.* if $E(U^*) > 0$.

The outcome variable Y_{it} is also a function of observed variables including household characteristics, system level factors, climatic factors and agroecology (X_{it}), technology use status (S_{it}), unobserved variables such as innate abilities and managerial capacity (V_{it}), and an *iid* error term (ϵ_{it}). The adoption and outcome equations are represented as follows.

$$\boldsymbol{S_{it} = S_{it}(Z_{it}, \eta_{it}, u_{it})} \tag{1}$$

$$\boldsymbol{Y_{it} = Y_{it}[X_{it}, S_{it}(Z_{it}, \eta_{it}, u_{it}), V_{it,} \epsilon_{it}]} \tag{2}$$

The observed variables in the adoption (selection) and outcome equations (X and Z), and the unobserved variables (η and V) can share elements. Hence, there is a need to investigate the interdependence between the improved storage technology adoption equation and outcome equations.

2.2. Estimation strategy

The interest here is to estimate the average effect that use of improved storage technology has on food security, welfare and marketing performance for user households - the average treatment effect on the treated (ATT). When households are not randomly exposed to improved storage technologies, they either self-select into adoption or the technologies might be provided to targeted households (Alene & Manyong, 2007). Hence, the adoption of improved storage innovations is considered potentially endogenous. Failure to account for selectivity bias and endogeneity would obscure the true impact of the technology. Recent developments in the econometrics literature make estimation of causal effects using non-experimental techniques possible even when randomisation is ruled out.

We address the selection and endogeneity problems by utilising the endogenous switching regression methods (Lokshin & Sajaia, 2011; Malikov & Kumbhakar, 2014). Endogenous switching regression (ESR) designs account for endogeneity by estimating a simultaneous equations model with endogenous switching by full information maximum likelihood (Lokshin & Sajaia, 2004). Although it relies on normality assumptions like the instrumental variable methods, the approach is more efficient than instrumental variables techniques. Through modeling both selection and outcome equations, ESR has the advantage of controlling for factors which affect the treatment itself and disentangling the factors influencing the outcomes among treated and control groups (Besley & Case, 2000). Besides accounting for selection bias arising from unobserved factors that potentially affect both improved storage use and the outcomes, endogenous switching regression model controls for structural differences between improved storage users and non-users regarding the outcome functions (Alene & Manyong, 2007; Seng, 2016). Previous empirical studies have employed the framework to study impact of modern technologies on food security and welfare (e.g. Asfaw *et al.*, 2012; Khonje *et al.*, 2015; Shiferaw *et al.*, 2014; Coromaldi *et al.*, 2015) and impact of climate change adaptation on food security (e.g. Di Falco *et al.*, 2011).

2.2.1. Endogenous switching regression

Consider a farm household i that faces a decision on whether or not to use improved storage. Let the indicator variable be S_i taking a value of 1 for households who decided to use improved storage and 0 otherwise. This leads to two possible states of the world: a decision to use ($S = 1$) and not to use ($S = 0$), and two population units: users and non-users. Let's denote the benefits to the household of not using improved storage by U_0 and the benefit stream from the use of improved storage innovations by U_1. Under a random utility framework, a rational farm household will choose to use improved storage innovations if the net benefit of adoption is positive i.e. $U_1 > U_0$ or $U_1 - U_0 > 0$. The net benefit ($U^* = U_1 - U_0$) is represented by a latent variable which is itself a function of observed characteristics (Z_i) and error term (u_i).

Conditional on households' decision to use improved storage denoted by a *selection* function, S_i, there are two potential outcomes to the two population units: the outcome without treatment (Y_0) and the outcome with treatment (Y_1). This can be put in a 'potential outcome framework' as:

$$\boldsymbol{Y_i = (1 - S_i)Y_{0i} + S_iY_{1i}} \tag{3}$$

$$\boldsymbol{Y_i} = \begin{cases} \boldsymbol{Y_{1i}} \ \ if\ \boldsymbol{S_i = 1} \\ \boldsymbol{Y_{0i}} \ \ if\ \boldsymbol{S_i = 0} \end{cases} \tag{4}$$

The gain from treatment (treatment effects or impact) is provided as $Y_1 - Y_0$. Nonetheless, the challenge here is that either of the outcomes is observed for a random sample of household causing a '*missing data*' problem (Heckman *et al.*, 1997). Hence, taking a simple difference and averaging cannot give the effect of the treatment.

In the endogenous switching model, the behavior of a farm household is described with two outcome equations and a selection function that determines which regime the household faces. Households' improved storage technology use decision is represented by the following latent variable framework (Lokshin & Sajaia, 2004, 2011).

$$\boldsymbol{S_i^* = \tau Z_i + u_i} \tag{5}$$

With

$$\boldsymbol{S_i} = \begin{cases} \boldsymbol{1} \ \ if\ \ \boldsymbol{S_i^*} > 1 \\ \boldsymbol{0} \ \ if\ \ \boldsymbol{S_i^* \leq 0} \end{cases} \tag{6}$$

Conditional on selection, the outcomes are represented by a switching regime as follows:

$$\boldsymbol{Regime\ 1}\text{:}\ \boldsymbol{y_{i1} = \beta_1 X_{1i} + \epsilon_{1i}} \qquad \boldsymbol{if\ \ S_i = 1} \tag{7}$$

$$\boldsymbol{Regime\ 2}\text{:}\ \boldsymbol{y_{i0} = \beta_0 X_{0i} + \epsilon_{0i}} \qquad \boldsymbol{if\ \ S_i = 0} \tag{8}$$

Z represents a vector of observable variables that determine the decision to use such as household (head's) characteristics, system level variables, and climatic factors. In the continuous equations, y_{ij} are the outcome variables; X_{1i} and X_{0i} are vectors of explanatory variables assumed to be weakly exogenous; and β_1, β_0 and τ are vectors of parameters to be estimated. The error terms of the continuous (ϵ_{1i} and ϵ_{0i}) and selection equations (u_i) are assumed to follow a trivariate normal distribution with zero mean vector and covariance matrix defined as: [3]

$$\boldsymbol{\Omega} = \begin{bmatrix} \boldsymbol{\sigma_u^2} & \boldsymbol{\sigma_{1u}} & \boldsymbol{\sigma_{0u}} \\ \boldsymbol{\sigma_{1u}} & \boldsymbol{\sigma_1^2} & . \\ \boldsymbol{\sigma_{0u}} & . & \boldsymbol{\sigma_0^2} \end{bmatrix} \tag{9}$$

Since the error terms in the selection equation are correlated with those in the outcome equations, the means (expected values) of the error terms in the outcome equations conditional on the sample selection are non-zero (Di Falco *et al.*, 2011). If the estimated covariances turn to be significant, improved storage use and outcome are correlated proving evidence of endogenous switching.

We estimated the endogenous switching regression models using the full information maximum likelihood estimation (Clougherty & Duso, 2015; Lee & Trost, 1978; Lokshin & Sajaia, 2004). After estimating the model's parameters, the conditional expectations or expected outcomes are computed as follows.

For improved storage users who actually adopted:

$$\boldsymbol{E(y_{1i}|S_i = 1,\ x_{1i}) = x_{1i}\beta_1 + \sigma_1\rho_1 f(\tau Z_i)/F(\tau Z_i)} \tag{10}$$

For improved storage non-users had they decided to use improved storage (counterfactual):

$$\boldsymbol{E(y_{1i}|S_i = 0,\ x_{1i}) = x_{1i}\beta_1 - \sigma_1\rho_1 f(\tau Z_i)/(1 - F(\tau Z_i))} \tag{11}$$

For improved storage users had they decided not to use improved storage (counterfactual):

$$\boldsymbol{E(y_{0i}|S_i = 1,\ x_{0i}) = x_{0i}\beta_1 + \sigma_0\rho_0 f(\tau Z_i)/F(\tau Z_i)} \tag{12}$$

For improved storage non-users who actually did not adopt:

$$\boldsymbol{E(y_{0i}|S_i = 0,\ x_{0i}) = x_{0i}\beta_1 - \sigma_0\rho_0 f(\tau Z_i)/(1 - F(\tau Z_i))} \tag{13}$$

[3] σ_u^2 is the variance of the error term in the selection equation and σ_1^2 and σ_0^2 are variances of the error terms in the continuous equations. The covariances are given as non-diagonal values. The variance of the error term in the selection equation can be assumed to be 1 (τ is estimable only up to a scalar factor). In the covariance matrix, the dot (.) indicates that the two outcomes cannot be observed simultaneously for a particular household (Lokshin and Sajaia, 2011).

Following Heckman *et al.* (2001) and Di Falco *et al.* (2011), the treatment effect on the treated (TT) is computed as the difference between expected outcome for farm households that adopted improved storage (eq. 10) and the counterfactual hypothetical cases that they did not use (eq. 12). The treatment effect on the untreated (TU) is computed as the difference between the outcome they would have obtained in the counterfactual scenario that they decided to use (eq. 13) and the expected outcome for farm households who did not use improved storage (eq. 11). The conditional expectation equations are also used to calculate heterogeneous effects (Di Falco *et al.*, 2011; Carter & Milon, 2005). Households that use improved storage innovations may have better food security or other outcomes than the households that did not use regardless of the fact that they decided to use, but because of unobservable characteristics such as skills and knowledge *i.e.* the effect of base heterogeneity (Carter & Milon, 2005). The computation of the effect of base heterogeneity for households that decided to use (BH_1) and for the household who did not use improved storage (BH_0) is indicated in Table 1. Another important statistic is transitional heterogeneity (TH) which measures whether the effect of the improved storage technologies use is larger or smaller for households that adopted or for households that did not, in the counterfactual case that they did use (Di Falco *et al.*, 2011).

Table 1. *Conditional expectations, treatment, and heterogeneous effect*

Subsamples	**Decision stage**		**Treatment effects**
	To use	**Not to use**	
User households	(a) $E(y_{1i} \mid S_i = 1)$	(b) $E(y_{0i} \mid S_i = 1)$	TT
Non-user households	(c) $E(y_{1i} \mid S_i = 0)$	(d) $E(y_{0i} \mid S_i = 0)$	TU
Heterogeneous effects	BH_1	BH_0	TH

Note:

(a) TT: the effect of the treatment (use of improved storage) on the treated (user households)

(b) TU: the effect of the treatment on the untreated (non-user households)

(c) BH_i = the effect of base heterogeneity for households that used (S=1) and did not use (S=0)

(d) TH = TT – TU is the transitional heterogeneity

2.2.2. Endogenous switching probit model

We are also interested in estimating the impact of improved storage innovations on various binary outcome measures of food security and marketing performance. Unlike for continuous outcome variables, accounting for sample selection and endogenous switching for binary outcomes where the data is fit using non-linear models is challenging (Heckman, 1978, 1986;

Miranda & Rabe-Hesketh, 2006). Hence, estimations using two-stage procedures (such as Heckman's sample selection model) would lead to wrong conclusions and produce inconsistent results. Consequently, we utilise the endogenous switching probit framework which is analogous to the endogenous switching regression for the continuous outcomes (Lokshin & Glinskaya, 2009; Lokshin & Sajaia, 2011; Miranda & Rabe-Hesketh, 2006).

Let the decision to use improved storage be represented by the following latent response model:

$$\boldsymbol{S_i^*} = \boldsymbol{Z_i\alpha} + \boldsymbol{\mu_i} \tag{14}$$

$$\boldsymbol{S_i} = \begin{cases} \mathbf{1}, & if\ \boldsymbol{S_i^*} > 0 \\ \mathbf{0}, & otherwise \end{cases} \tag{15}$$

Where S_i^* represent a continuous latent variable, α is a parameter to be estimated and μ_i is an error term. The binary response y_i is also defined as follows:

$$\boldsymbol{y_i^*} = \boldsymbol{x_i\beta} + \boldsymbol{\tau S_i} + \boldsymbol{u_i} \tag{16}$$

$$\boldsymbol{y_i} = \begin{cases} \mathbf{1}, & if\ \boldsymbol{y_i^*} > 0 \\ \mathbf{0}, & otherwise \end{cases} \tag{17}$$

Where y_i is the main outcome variable and y_i^* represents a continuous latent variable, β represents a vector of parameters to be estimated, τ is the coefficient of the endogenous treatment dummy, and u_i is a residual term.

The endogenous switching problem, in this case, is that the response y_i for the i^{th} household is not always observed. Besides, y_i is assumed to depend on the endogenous dummy S_i and a vector of explanatory variables, x_i. The endogenous dummy S_i also depends on a vector of explanatory variables, Z_i. There is a possibility that vectors x_i and Z_i share elements. A direct estimation of equation 16 and interpreting τ as the casual effect would result in biased estimates due to unobserved endogeneity. Endogenous switching probit regression would correct for this bias by simultaneously estimating the selection and outcome equations with proper instrumentation of the improved storage use decision (Aakvik *et al.*, 2000; Lokshin & Sajaia, 2011). The endogenous switching probit framework models the decision to use improved storage innovation and its effect on various binary outcomes in a two-stage treatment framework. In the first stage, farm households' decision to use improved storage is modeled and estimated using a probit model. In the second stage, the relationship between the binary outcomes and improved storage use along with a set of explanatory variables is determined using probit model with selectivity correction.

Following Lokshin and Sajaia (2011), the binary outcomes conditional on improved storage use are specified as an endogenous switching regime model:

$$\boldsymbol{Regime\ 1}: \boldsymbol{y^*_{1i} = \beta_1 X_{1i} + \varepsilon_{1i}} \qquad \boldsymbol{y_{1i} = I(y^*_{1i}} > 0) \tag{18}$$

$$\boldsymbol{Regime\ 2}: \boldsymbol{y^*_{0i} = \beta_0 X_{0i} + \varepsilon_{0i}} \qquad \boldsymbol{y_{0i} = I(y^*_{0i}} > 0) \tag{19}$$

observed y_i is a dichotomous realisation of the latent variables and it is defined as:

$$\boldsymbol{y_i} = \begin{cases} \boldsymbol{y_{1i}}, & if\ \boldsymbol{S_i = 1} \\ \boldsymbol{y_{0i}}, & if\ \boldsymbol{S_i = 0} \end{cases} \tag{20}$$

where y^*_{1i} and y^*_{0i} are the latent variables that determine the observed binary outcomes y_1 and y_0 for improved storage users and non-users, respectively. X_1 and X_0 are vectors of weakly exogenous variables; Z_i is a vector of variables which determine a switch between the regimes; β_1 and β_0 are vectors of parameters to be estimated, and ε_{1i} and ε_{0i} are the error terms in the outcome equations. We estimated a full information maximum likelihood (FIML) endogenous switching probit model to estimate the parameters of interest (see Lokshin & Glinskaya, 2009; Lokshin & Sajaia, 2011).

The effects of improved storage technology on households outcomes are estimated based on the methodological framework developed by Aakvik *et al.* (2000) and Lokshin and Sajaia (2011). Like the endogenous switching regression model, the switching probit model also allows for the estimation of the treatment effect on the treated (TT) and the treatment effect on the untreated (TU). The model also estimates the effect of improved storage technology for a household randomly selected from the population of households with characteristics *x* (treatment effect, TE). The effect of improved storage technology on the outcome of interest can vary not only by the observed household characteristics (*x*) but also by unobserved characteristics (μ). The effects of unobserved heterogeneity are accounted for using the framework developed by Heckman and Vytlacil (2005) and used by Lokshin and Glinskaya (2009). This is captured by estimating marginal treatment effects (MTE) to identify the effect of improved storage technology on households induced to change the outcomes because of the improved storage technology.

2.2.3. Exclusion restriction

An exclusion restriction is used for better identification of both the endogenous switching regression and endogenous switching probit models. Selection of the exclusion restriction is guided by economic theory and empirical studies. Studies by Di Falco *et al.* (2011), Shiferaw *et al.* (2014) and Khonje *et al.* (2015) used information sources such as government extension, farmer-to-farmer extension, radio information, market and climate information and distance to inputs as exclusion restrictions. This paper uses the presence of an agricultural development or extension agent in the village as an exclusion restriction based on two reasons. First, extension service is the primary source of knowledge and information about new and improved technologies for farmers especially when the cost of information and knowledge is prohibitive (e.g. Genius *et al.*, 2014; Krishnan & Patnam, 2014). In addition to its role in developing skills and knowledge of farmers to adopt new and improved technologies, extension could play a vital role in the facilitation of linkages with other institutional support services such as input supply, output marketing and credit. Second, development or extension agents are usually assigned at the administrative level and their assignment is less likely to be influenced by households' behavior. Besides, the presence of extension agent in the village or community is determined outside farmer's improved storage technology use decision (Kadjo *et al.,* 2013).

A falsification test for admissibility of the exclusion restriction following Di Falco *et al.* (2011) confirms that it is a possible selection instrument since the variable is significantly correlated with improved storage use at less than 1% level, but not correlated with the outcomes for non-user households. We did additional tests for the exclusion instrument (Appendix, Table A.5.). The Durbin and Wu–Hausman (DWH) tests for exogeniety of the selection instrument are found to be highly insignificant. Wooldridge's (1995) score test of exogeneity which can tolerate heteroskedastic errors also fails to reject the null hypothesis of exogeneity. We computed the Anderson canonical correlation statistic (Baum *et al.*, 2007) to test for identification of the model. The test rejects the null hypothesis of underidentification of the model at less than 1% and justifies that the excluded instrument is relevant. We further checked robustness of the results by estimating the Cragg-Donald chi-square statistic which also rejects the null of weak identification at less than 1% level of significance. Furthermore, we assessed the weak instrument robust inference using the Anderson–Rubin's test (Baum *et al.*, 2007), which also confirmed the validity of the selection instrument.

2.2.4. Matching and Inverse probability weighting Methods

We compared the endogenous switching regression model results with results from the matching and inverse probability weighting estimates. Kernel-based matching is used for this paper. Kernel matching is a non-parametric matching estimation that uses weighted averages of all individuals in the control group to construct counterfactual outcome of a treated observation (Heckman *et al.*, 1998). It has the advantage of minimising the potential risk of bad matches that would arise from the use of nearest neighbor matching methods (Caliendo & Kopeinig, 2008). Inverse probability weighting (IPW) estimation is another method for adjusting for confounding when using observational data (Curtis *et al.*, 2007; Donald *et al.*, 2014). Unlike matching techniques, IPW assigns greater weights to control (comparison) groups with higher estimated probabilities of selection into the treatment (Handouyahia *et al.*, 2013). Another attractive feature of IPW is its efficiency (minimum variance) within the class of semi-parametric estimators and matching techniques including kernel and nearest neighbor matching (Hirano *et al.,* 2003).

Various diagnostics were undertaken to check the quality of the matching. A visual inspection of the density distribution of the propensity scores and the overlap in the distribution of the propensity scores (figure A.1) indicates that the common support condition is satisfied. Diagnostic tests also show a fairly low pseudo R^2, high total bias reduction and insignificant p-values of the LR test after matching (Appendix, Table A.6), which provides evidence that the proposed specification is successful in terms of balancing the distribution of the covariates between the treatment and control groups. Estimates from the propensity score matching are sensitive to hidden bias or unobserved factors. The thresholds at which the estimates are sensitive to such bias are computed using the Rosenbaum bounds (*rbounds)* for continuous outcomes and MH bounds (*mhbounds)* for binary outcomes (see Becker and Caliendo, 2007). The results are summarised in the Appendix, Table A.7.

2.3. Data

The study used data from Ethiopian Socioeconomic Survey (ESS), a nationally representative cross-sectional survey of rural households of Ethiopia in the 2013/14 year. The data is collected under the Living Standards Measurement Study-Integrated Surveys on Agriculture Initiative (LSMS-ISA) in collaboration with Central Statistical Authority (CSA). The data were collected in three rounds of visits to the households. The first round was carried out in September and October 2013 and collected information on post-planting agriculture activities. The second round was conducted in November-December 2013 to complete the livestock questionnaire. Information on post-harvest agriculture and household characteristics were collected during the third round that took place from February-April 2014. The survey collected detail information on demographics, health (including anthropometric measurement for children), food and non-food consumption expenditure, food security, and shocks, safety nets, among others. It also captured information on both post-planting and post-harvest activities, land holding, crop harvest, storage, and utilisation. In addition to the household data, the survey solicited community level information on access to services such as weekly markets, cooperatives, financial institutions, irrigation scheme and presence of agricultural development or extension agent. The household location is geo-referenced which enables linking the household data with geographic data sets including climatic variables (rainfall and temperature) and geographic characteristics such as distance to main markets, nearest road, and population centers. After excluding observations with no information on crop storage and storage methods, the analysis here is based on a sample of 2514 rural households.

2.4. Variables

2.4.1. Outcome variables

This paper utilises both objective and subjective measures of food security. This addresses limitations of previous studies which used a single measure without aligning different measures of food security with the food security dimensions (Coates, 2013; Maxwell *et al.*, 2014). The measures of food security and nutrition used include whether the household worries that there would be no enough food for the household and the coping strategies employed to secure sufficient food, the diversity of household diets, percapita food consumption expenditure and anthropometric measurements of child nutritional status (Anderman *et al.*, 2014). We used real percapita consumption expenditure as an indicator of welfare (Deaton, 2003; Moratti & Natali, 2012). Other studies have also used the same indicator for welfare (e.g. Asfaw et al., 2012; Khonje et al., 2015; Mmbando *et al.*, 2015).

The household dietary diversity (HDD) score is an attractive proxy indicator for food security and the socioeconomic ability of a household as it is highly correlated with caloric, protein and nutrient adequacy, household income and child nutritional status (Hoddinott & Yohannes, 2002; Swindale & Bilinsky, 2006; Webb *et al.*, 2006). The household food insecurity and access scale (HFIAS) and coping strategies are other indicators used in this study to capture household behaviors regarding anxiety and uncertainty over household insecure access or food supply (Coates, 2013; Cordeiro *et al.*, 2012; Maxwell *et al.*, 2014; Swindale & Bilinsky, 2006). Closely following the existing literature (Coates et al., 2006; Maxwell et al., 2008), we combine the individual coping strategies to construct two indicators of food security: negative change in diet and reduced food intake. Negative changes in diet include strategies where the household have to rely on less preferred food or limit the variety of foods eaten which corresponds to dietary change. Dietary changes are easily reversible without jeopardising long-term prospects of the households. Reduced food intake is very similar to food rationing and constructed from strategies such as limiting the number of meals taken per day as well as the portion size, restricting consumption of adults so that children can eat, borrowing food or relying on external help from others, and have no food or any kind, or going an entire day and night without eating anything.

The nutritional status of under-5 children is measured using anthropometric measures. We used stunting and wasting as indicators of child malnutrition. Stunting is preferred as it is the most important long term indicator of child nutritional status and wasting is a short term indicator of acute malnutrition (WHO, 1995; Manda *et al.*, 2016; Slavchevska, 2015). Two indices, height-for-age (HAZ) and weight-for-height (WHZ) were constructed and recorded as a z-score, which describes the number of standard deviations by which the child's anthropometric measurement deviates from the median in the 2006 WHO child growth standard. The z-score cut-off point between -3 and -2 classify low height-for-age and low weight-for-height as moderate stunting and wasting suggesting moderate undernutrition, and a z-score of less than -3 defines severe stunting or wasting which shows severe undernutrition (WHO, 1997).

The study also looks at households' market participation, the proportion of harvest sold to market and choice of market outlet. Integrating smallholders to markets is touted to be one of the mechanisms through which agriculture plays an enormous role in reducing rural households' vulnerability to food insecurity and market shocks (Barrett, 2008; Baiphethi & Jacobs, 2009). At the micro level, it also has a positive impact on food security (Seng, 2016), household welfare and livelihoods (Asfaw *et al.*, 2012; Olwande et al., 2015). While household commonly stores crops for consumption, improved storage might enable households to store crops for markets. Hence, analysing the relationship between improved storage innovations and households' market participation would be of policy relevance. Market participation is defined as a binary outcome taking the value of 1 if the household sales any of its harvest and 0 otherwise. The proportion of harvest sold indicates the level of market participation. Choice of market outlet is an indicator for marketing flexibility which measures whether the household sells any of its harvest in local (village) markets or main markets. Food storage as a physical capital would affect farm households' market participation along with other factors such as market and production shocks, market imperfections (Rao & Qaim, 2011), access to irrigation, infrastructure and proximity to urban centers (Seng, 2016; Stephens & Barrett, 2011).

2.4.2. Choice of explanatory variables

Variables that would affect the decision to use improved storage technologies and the outcomes were selected based on economic theory, empirical studies on technology adoption and policy documents. The key variables of interest are mainly drawn from the literature on adoption and impact of agricultural innovations (e.g. Asfaw *et al*, 2012; Bezu *et al.*, 2014; Coromaldi *et al.*, 2015; Manda *et al.*, 2016; Di Falco *et al.*, 2011; Khonje *et al.*, 2015; Mutenje *et al.*, 2016; Shiferaw *et al.*, 2014; Cunguara & Darnhofer, 2011) and postharvest economics (Affognon *et al.*, 2015; Bokusheva *et al.*, 2012; Gitonga *et al.*, 2013; Kaminski & Christiaensen, 2014; Stathers *et al.*, 2013; Barrett, 2008; Seng, 2016). Accordingly, factors that commonly influence adoption of agricultural innovations, food security, welfare, and market participation are the household characteristics (gender of the household head, age and education of the household head, household size), household wealth indicators (livestock ownership, farm size, and asset ownership). Other factors include access to credit or finance, information and off-or non-farm income opportunities. Social safety nets, access to markets and infrastructure are also included. The average annual rainfall and temperature patterns, as well as those during the wettest quarter of the survey years, are introduced to account for the effect of pre and post-harvest rainfall and temperature patterns (Kaminski & Christiaensen, 2014). We also controlled for the effect of child characteristics (gender and age), access to improved water sources and sanitation on child nutritional status (Manda *et al.*, 2016). We used the same set of variables in the endogenous switching regressions and the propensity score matching and inverse probability weighting estimations. Description of the main explanatory variables and the descriptive statistics is provided in the Appendix, Table A.1.

3. Results

Results of the econometric models are presented in the succeeding sections. We first discuss the results of the first stage (probit) results of the endogenous switching regression which estimates the determinants of household's decision to use improved storage (Appendix, Table A.2).

3.1.1. Determinants of improved storage use

The statistical significance and sign of the estimated coefficients of the determinants of improved storage use are broadly consistent with the literature (e.g. Affognon *et al.*, 2015). The probability of using improved crop storage technologies increases with age, a proxy for experience. This is consistent with the finding of Kaminski and Christiaensen (2014) who report postharvest loss rates to fall with the age of the household head, and this could probably be due to the mediating effect of age for improved storage innovations use. Experienced farmers are also more likely to be knowledgeable about solutions for storage losses, hence proactive for adopting improved storage technologies (Kaminski & Christiaensen, 2014). Wealth indicators are found to have no significant association with the adoption of improved storage technologies. The positive coefficient for distance to nearest market shows that the probability of using improved storage increases with distance from the main market. This suggests that farm households use improved storage so that they would be less dependent on markets for food. The probability to use improved storage also falls with the presence of large weekly market in the community. This also justifies the role of improved storage as a substitute for local markets. The explanation for the positive coefficient of distance to administration could also be the possibility that remote households would use improved storage so as to reduce dependence on other external support for food. Distance to the major road is negatively correlated with improved storage use decision. This could be due to two possible reasons. One, households with poor access to roads are also constrained to get access to information about postharvest loss mitigation alternatives. Second, farming households with poor access to infrastructure such as roads might have less incentive to produce and store for markets. Hence, they would rather rely on traditional and poor storage techniques to store food for consumption.

Access to extension service is positively correlated with improved storage use. Households in villages with agricultural development extension agents are more likely to use improved storage technologies. Adegbola *et al.* (2011) also found households' decision to use improved storage technologies to increase with contact with an extension agent. Access to finance and non-farm business ownership are also positively correlated with improved storage use. This is predictable since non-farm income opportunities and access to finance relax capital or income constraints which are the major factors that might deter improved storage use (Gitonga *et al.*, 2013). However, social transfers have a negative correlation, possibly since transfer programs are often a supplement to food availability and would discourage investment in improved storage (Gitonga *et al.*, 2013; Sheahan & Barrett, 2016). The presence of an irrigation scheme in the village is positively correlated with improved storage use decision. Irrigation access has production increasing effect, and postharvest loss increases with production (Kaminski & Christiaensen, 2014; World Bank *et al.*, 2011). Hence, this might induce farmers to use improved storage.

The effect of climatic factors on improved storage use decisions brings interesting results. While the effect of mean annual temperature on the probability to use improved storage is positive and significant, there is a negative correlation between the mean temperature of the wettest quarter and improved storage use. This is predictable since higher temperatures have the tendency to reduce humidity and accelerate drying (hence postharvest loss) which reduces demand for improved storage (Kaminski & Christiaensen, 2014). A possible explanation for the negative correlation is the possibility that the mean temperature of the wettest quarter would negatively affect production (Kaminski & Christiaensen, 2014), hence reduces demand for improved storage. There is positive and statistically significant correlation between yearly rainfall and improved storage use decision. This is not surprising since production would increase with annual rainfall and this would induce demand for improved storage. In sum, the results of this study corroborate previous evidence.

3.1.2. Endogenous switching regression: Treatment Effects

The full information maximum likelihood estimates of the endogenous switching regression model are presented in Tables 2 and A.3 (Appendix). The Wald tests confirm the joint significance of the error correlation coefficients in the selection and outcome equations (Table A.3). The significant correlation coefficients of the selection equation and the outcome equations for improved storage users indicate the presence of self-selection in the use of improved storage technologies. This also suggests that improved storage use had a significant impact on the corresponding outcomes among users, and users would have gained greater benefits from improved storage use than non-users had non-users chose to use (Alene & Manyong, 2007). Insignificant correlation coefficients of improved storage use equation and outcome equations for non-users imply that users and non-users have the same value of the outcomes given their observed characteristics. However, the differential effects of improved storage on the two groups is possibly due to initial differences in unobserved factors (Alene & Manyong, 2007). Interesting economic interpretations are also derived from the signs of the error correlation coefficients in the selection and outcome equations. The correlation coefficients between the error terms of improved storage adoption equation and food security outcome equations have similar signs. This provides evidence of hierarchal sorting (Alene & Manyong, 2007; Fuglie & Bosch, 1995) where improved storage users have above average returns irrespective of adoption, but they are better off adopting. On the other hand, non-users have below average returns regardless of adoption but they are better off without adopting improved storage (Alene & Manyong, 2007). In the welfare and proportion of harvest sold equations, the error correlation coefficients alternate in signs indicating adoption of improved storage is guided by comparative advantage (Alene & Manyong, 2007; Fuglie & Bosch, 1995) which suggests that improved storage user households have above average values of the outcomes than non-use, and non-users also have above average outcomes from non-use. Table 2 presents the expected values of the various outcomes under the actual and counterfactual conditions and the resulting treatment effects.

Table 2. *Endogenous switching regression based treatment effects*

Outcome variables	*Household type and treatment effects*	*Decision stage*		*ATEs*
		To use	*Not to use*	
Household dietary diversity score	User households (ATT)	5.92	5.67	0.25 (0.05) ***
	Nonuser households (ATU)	7.66	5.65	2.01 (0.05) ***
	Heterogeneous effects	-1.74	0.02	-1.76
Percapita food consumption (*ln*)	User households (ATT)	5.44	5.45	-0.01 (0.02)
	Nonuser households (ATU)	5.45	5.44	0.01 (0.02)
	Heterogeneous effects	-0.01	0.01	-0.02
Total real percapita consumption (*ln*)	User households (ATT)	5.93	5.91	0.02 (0.02)
	Nonuser households (ATU)	6.08	5.94	0.14 (0.02) ***
	Heterogeneous effects	-0.15	-0.03	-0.12
Proportion of harvest sold (%)	User households (ATT)	18.85	18.15	0.70 (0.28) **
	Nonuser households (ATU)	25.32	21.37	3.95 (0.34) ***
	Heterogeneous effects	-6.47	-3.22	-3.25

Note: Ethiopian Socioeconomic Survey (ESS) (2013-14); ATT – Average Treatment Effect on the Treated, ATU – Average Treatment Effect on the Untreated, ATE – Average Treatment Effects; Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

The results from the endogenous switching regression based treatment effects show that improved storage has a positive and significant impact on dietary diversity score. The expected dietary diversity score for the households that used improved storage technologies is 5.92 while it is 5.65 for those who did not use. In the counterfactual case, households who used the technology would have obtained a dietary diversity score of 5.67 had they decided not to use. Hence, improved storage use had increased the dietary diversity score by 0.25 points for users. In the counterfactual case, households that did not adopt improved crop storage technologies would have increased the dietary diversity score by about 2.0 had they adopted. The positive effect on dietary diversity is expected since improved storage technologies would help households increase their food crops storage through relaxing risk-aversion to postharvest loss and encouraging farmer's production of diverse crops (Oluwatoba *et al.,* 2016). The results are in agreement with other studies that report positive link between improved storage and food security (Gitonga *et al.*, 2013; Snapp & Fisher, 2015). Improved storage is not found to have a significant effect on percapita food consumption expenditure and real percapita consumption expenditure for users. However, non-users would have had higher percapita consumption expenditure (14%) had they decided to use improved storage. Our study finds no significant impact of improved storage on household welfare. Cunguara and Darnhofer (2011) also reported insignificant impact of improved granaries on household income in Mozambique. Improved storage is found to increase the proportion of harvest sold to markets by 0.70 than the counterfactual scenario of not using improved storage. Non-user households would have increased the proportion of harvest sold by 3.95 had they decided to use improved storage.

The negative base heterogeneity effect for almost all outcomes implies that improved storage user households have lower food security, welfare and market performance not possibly due to their decision to use improved storage, but possibly due to unobservables. Adjusting for the potential heterogeneity in the sample, there is evidence that households who decided to use improved crop storage technologies tend to have benefits lower than the average irrespective of adoption, but they are better off adopting than not adopting (Di Falco *et al.*, 2011). The negative transitional heterogeneity effect also indicates that the effect is higher for improved storage non-user households had they decided to use.

Coefficients of the key explanatory variables in the endogenous switching regression model return important information (Table A.3). The difference in the coefficients of the explanatory variables in the outcome equations of improved storage user and non-user households illustrates the presence of heterogeneity in the sample (Di Falco *et al.*, 2011). Overall, the observed household demographic characteristics are important determinants of the outcomes for both improved storage user and non-user households. Some of these explanatory variables have a heterogeneous effect on the outcomes for the improved storage user and non-user households. For improved storage non-user households, dietary diversity score increases when the head is male but decreases with the age of the head. However, gender and age of the household head are not correlated to food security status of improved storage user households. Consistent with the theory, household heads with less than primary education record lower dietary diversity and welfare. While enjoying a primary education is positively correlated with dietary diversity score for improved storage user households, it deemed inadequate to positively affect dietary diversity score for non-user households. Livestock holding and mobile ownership are found to increase food security regardless of improved storage use. However, farm size and asset holding are positively correlated with dietary diversity score for non-user households.

Interestingly, the presence of a large weekly market in the community has a positive correlation with food security for households not using improved storages. This is not surprising since households who lack access to improved storage technologies will rely on local markets for food. While dietary diversity score decreases with distance to the nearest market for non-user households, the correlation is insignificant for user households. Hence, this provides evidence that due to poor market access, improved storage technologies can substitute food markets through enhancing the consumption of own production (Carletto *et al.*, 2015; Basu & Wong, 2015). Food security falls with distance to major road for user households. Climatic factors and shocks also have differential effects on the food security of improved storage user and non-user households. Dietary diversity score diminishes with an increase in mean annual temperature for non-users. However, it increases when there is an increase in the mean temperature of the wettest quarter for same households. This could be due to postharvest loss mitigating effect of temperature in the wettest quarter (Kaminski and Christiaensen, 2014). Mean annual rainfall is positively correlated with household diversity for non-user households, whereas the amount in the wettest quarter is negatively correlated with dietary diversity score. Rainfall patterns pre-harvest would increase production that would mediate the positive effect on dietary diversity score. A possible explanation for the negative effect is that higher rainfall during and after the harvest would lead to increase in postharvest losses through creating a favorable environment for pest infestation. Exposure to production shocks is found to reduce the food security of improved storage user households, whereas, market shocks reduce dietary diversity score for non-user households. This is expected and could explain the reason those households decide to use improved storage as a coping mechanism (Stathers *et al.*, 2013).

3.1.3. Endogenous Switching Probit model results

Results of the full information maximum likelihood endogenous switching probit model which estimated the effect of improved storage technology use on selected food security and market participation outcomes is provided in Tables 3 and A.4. (Appendix).

Table 3. *Treatment effects: Endogenous switching probit estimates*

Outcomes	*Treatment Effects*			
	ATT	*ATU*	*ATE*	*MTE*
Food security				
Minimum acceptable diet	0.069 ***	0.064 ***	0.062 ***	0.047 ***
Household food insecurity access scale	-0.203 ***	-0.055 ***	-0.093 ***	-0.034 ***
Negative change in diet	-0.893 ***	-0.098 ***	-0.265 ***	0.049 ***
Reduced food intake	0.126 ***	-0.089 ***	-0.036 ***	-0.043 ***
Child nutritional status				
Stunting	-0.333 ***	-0.049 ***	-0.109 ***	-0.084 ***
Wasting	0.000	-0.007 ***	-0.005***	0.000 ***
Marketing performance				
Market participation	0.346 ***	-0.649 ***	-0.396 ***	-0.844 ***
Sale in local markets	0.187 ***	0.552 ***	0.459 ***	0.546 ***
Sale in main markets	-0.164 ***	-0.291 ***	-0.257 ***	-0.281 ***

Note: Ethiopian Socioeconomic Survey (ESS) (2013-14); ATT – Average Treatment Effect on the Treated, ATU – Average Treatment Effect on the Untreated, ATE – Average Treatment Effect, and MTE – Marginal Treatment Effect; Bootstrapped standard errors; * p<0.10, ** p<0.05, *** p<0.01

Improved storage adoption has increased the probability of consuming minimum acceptable diet i.e. a household dietary diversity score of 4 or more (Labadarios *et al.*, 2011) by about 7 percentage points for user households than in the counterfactual scenario of non-use. Non-user households would have increased the probability of meeting a minimum acceptable diet by about 6 percentage points had they adopted improved storage. Household using improved storage have 20.3 percentage points lower probability of food insecurity as measured by the household food insecurity and access scale. These results corroborate the findings of Bokusheva *et al.* (2012) and Gitonga *et al.* (2013). While improved storage reduced the likelihood of negative change in diet by 89.3 percentage points, it also increased reduced food intake (food rationing) by 12.6 percentage points for improved storage user households. This might be since food rationing is not related only to food availability but also household size and intrahousehold allocation of food. The result also suggests that improved storage is not a sufficient instrument to cope with food insecurity. The study further estimated the impact of improved storage on child nutritional status using prevalence of stunting and wasting. Interestingly, improved storage reduces the prevalence of under-5 stunting by about 33.3 percentage points compared to the counterfactual scenario of not using improved storage technologies. The negative effect on children stunting is realised as improved storage could increase the consumption of food from own production particularly during market failures (Slavchevska, 2015). This provides evidence that improved storage reduces the prevalence of malnutrition through ensuring food availability and increased access to food during leans seasons when stocks are depleted and food prices are high (Vaitla *et al.*, 2009). This is consistent with the finding of Manda *et al.* (2016) who found improved maize varieties to reduce the probability of stunting in Zambia, and Slavchevska (2015) who reported a positive link between agricultural production and child nutritional status in Tanzania. Improved storage does not have a significant impact on children wasting for user households. However, it would have reduced children wasting by 7 percentage points for non-user households had they decided to use improved storage.

Turning into the marketing performance impacts, improved storage adopters have about 35 percentage points higher probability of participation in markets as sellers compared with the counterfactual scenario of households who do not use improved storage technologies. The positive impact of improved storage on market participation as seller of crops and proportion of harvest sold is consistent with our theoretical predictions. The positive impact on market participation in general shows that improved storage encourages sale of crop through reducing storage loss. Hence, users of improved storage would sale crops to meet their cash requirements whenever prices are attractive (Park, 2006; Stephens & Barrett, 2011). The other channel through which improved storage increase marketing performance is through its complementary with yield enhancing technologies such as improved crop varieties (Mutenje *et al.,* 2016; Ricker-Gilbert and Jones, 2015). Further analysis of the estimates of the impact on market flexibility revealed that improved storage use increases the probability to sell their crops in local markets by about 19 percentage points. However, it reduces the sale of crops in primary markets by about 16 percentage points. This could explain the role of improved storage in reducing households' dependence on intermediaries and sale of crops in bulk in main markets. This is consistent with existing studies which argue that improved storage users are more likely to participate in local or village markets where they would get better prices and become less dependent on intermediaries who are common in main markets (Xhoxhi *et al.*, 2014; Bokusheva *et al.*, 2012). Hence, improved storage enable marketing flexibility through altering the location of sale which would enable households to take advantage of seasonal and temporal price fluctuations (Bokusheva *et al.*, 2012; Florkowski & Xi-ling, 1990).

3.2. Comparing results across various estimation methods

Estimates from the endogenous switching regression models are compared with estimates obtained using kernel-based matching and inverse probability weighting methods. Table 4 summarises the average treatment effects from the various techniques.

Table 4. *Comparing results from alternative specifications: Average treatment effects (ATT)*

Outcome	*Endogenous switching Regression*	*Kernel matching*	*Inverse probability weighted (IPW)*
Food security, nutrition, and welfare			
Household dietary diversity score	0.25***	0.22 **	0.24 **
Minimum acceptable diet	0.069***	0.04 **	0.04 **
Percapita food consumption exp. (*ln*)	-0.01	0.10 **	0.10 **
Real percapita total consumption exp. (*ln*)	0.02	0.09 **	0.09 **
Household food insecurity and access scale	-0.203***	-0.01	-0.01
Negative change in diet	-0.893***	0.00	0.00
Reduced food intake	0.126***	0.04	0.04 *
Stunting	-0.333***	-0.07 *	-0.06
Wasting	0.000	-0.02	-0.02
Marketing performance			
Market participation	0.346***	0.11 ***	0.10 ***
Proportion of harvest sold (%)	0.70**	2.12 **	2.00 **
Sale in local markets	0.187***	0.04	0.04
Sale in main markets	-0.164***	-0.08 ***	-0.08 **

Note: Ethiopian Socioeconomic Survey (ESS) (2013-14); * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Overall, the results of the propensity score matching and inverse probability weighting are fairly consistent. The results indicate that improved storage adoption has a positive effect on food security, welfare and marketing performance. The results of the endogenous switching regression and the alternatives specifications coincide in the direction of the effect for most of the outcome indicators. However, comparing the magnitude of the impacts, one can note that propensity score matching and inverse probability weighting provides estimates which are fairly lower for most of the indicators than the endogenous switching regression models. Two conclusions could be made comparing the results from the endogenous switching regressions and the alternative estimations. First, methods that only account for selection on observables would understate the magnitude of the effects leading to a downward bias than methods which also account for unobserved heterogeneity. Second, the discrepancies in the magnitudes of the effects would mean that the endogenous switching regression model is not as biased as the matching techniques.

4. Conclusion

Improved storage innovations could be part of climate smart technologies which help in sustainable food production through tackling postharvest food loss and mitigating agriculture's contribution to climate change. The study takes advantage of nationally representative data from Ethiopia to provide national level estimates. Food security and household welfare are assessed using objective and subjective measures including dietary diversity, per capita food and total consumption expenditure, household food insecurity and access scale, food related coping strategies and child nutritional status. The paper also estimated the market participation impact of improved storage technology adoption using households' participation in output market as a seller, the proportion of harvest sold and marketing flexibility in terms of choice of market outlets. Full information maximum likelihood endogenous switching regression models are used to account for endogeneity and sample selection. The analysis is complemented with propensity score matching and inverse probability weighting methods.

Results of the study lead to the following main conclusions. First, households' decision to use improved storage is mainly determined by institutional factors such as access to the market, road, and proximity to town, access to finance, extension service, and irrigation. Climatic factors also play a role in affecting the decision to use improved storage. However, household characteristics play fewer roles. Interestingly, households choose to use improved storage on the basis of comparative advantage when the objective is market participation. However, when the objective is food security, they make the decision based on hierarchal sorting. Second, improved storage innovations positively affect food security through increasing dietary diversity score, reducing self-reported food insecurity, and reducing child malnutrition. The positive effect of improved storage on household dietary diversity score and the negative effect on under-5 child stunting suggest that such innovations are not only climate-smart; they are also nutrition-smart. Third, improved storage technologies positively affect the marketing performance of households by increasing their participation in output markets as sellers, increasing the proportion of harvest sold, and enabling market flexibility through influencing choice of market outlets. Fourth, differences in household characteristics, institutional and climatic factors have heterogeneous effects on food security, welfare and market participation among improved storage users and non-users. From a policy intervention perspective, policy makers need to acknowledge the role of various factors that hinder or favor the adoption of improved storage technologies and the translation of benefits from technological change into food security and nutrition outcomes.

While promoting improved storage adoption provides a path for sustainable economic and social development, the policy challenge would be how to make such innovations accessible and work for the resource poor, food insecure and vulnerable.

Further research is recommended for investigating the local market economy, climate change mitigation, and resource use efficiency effects of improved storage technologies. Examining the complementarity or substitutability between household level storage technologies and larger scale storage facilities would also be of policy relevance. Future research could also examine the synergetic impacts of storage technologies and other production risk management practices such as crop diversification on household level development outcomes.

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6. Appendix

Table A.1. *Description and summary statistics of main explanatory variables*

Variables	*Description*	*Non users*		*Users*		
		Mean	*Std Dev*	*Mean*	*Std Dev*	*t*
Household characteristics						
Male headed	1 if the head is male; 0 if female	81.0		81.6		-0.33
Age of head	Age of the household head in years	46.00	14.69	47.60	14.81	-2.30 **
Household size	Number of household members	5.29	2.24	5.42	2.21	-1.26
Adult equivalent	Adult equivalent scale for the household	4.26	1.84	4.42	1.83	-1.46
No education (head)	1 if the head has no education; 0 otherwise	69.25		61.65		3.46 ***
Primary education	1 if the head has primary education; 0 otherwise	27.4		33.6		-2.82 ***
Secondary education	1 if the head has secondary education; 0 otherwise	1.4		2.4		-1.43
Postsecondary education	1 if the head has post-secondary education; 0 otherwise	1.0		0.9		0.15
Livestock holding (TLU)	In tropical livestock units	3.49	4.09	3.37	3.09	0.72
Farm size (ha)	Cultivated land in hectare	1.73	1.12	1.68	1.18	0.75
Asset index[4]	Asset index	-0.11	1.65	-0.05	1.56	-0.86
Mobile owned	1 if the head/household own a mobile; 0 otherwise	36.7		37.8		-0.51
Finance access	1 if has access to finance; 0 otherwise	23.8		24.7		-0.43
Non-farm enterprise	1 if owns a non-farm enterprise; 0 otherwise	7.4		5.7		1.46
Public transfers	1 if the household received; 0 otherwise	3.72		14.0		-6.89 ***
Private food transfer	1 if the household received; 0 otherwise	3.88		3.59		0.33
Private cash transfer	1 if the household received; 0 otherwise	8.78		8.95		-0.12
Distance to the main road	Distance to major road in Kms	16.26	17.54	13.28	13.10	4.46 ***
Distance to nearest market	Distance to nearest market in Kms	63.82	49.60	73.13	43.05	-4.43 ***
Distance to admin. center	Distance to administration center Kms	157.23	112.57	166.90	95.18	-2.07 ***
Shocks and climatic factors						
Production shocks	1 if hh reports; 0 otherwise	4.68		4.73		-0.05
Market shocks	1 if hh faces price hikes; 0 otherwise	12.2		10.1		1.41
Mean annual temperature	12 month average in ^{0}C	19.59	3.33	17.51	2.65	15.69 ***
Mean temp the wettest quarter	Mean temperature of the wettest quarter in ^{0}C	19.29	3.36	16.94	2.77	17.14***
Mean annual rainfall	Average 12 months total RF in mm (in 00's)	9.167	2.588	10.076	2.214	-8.38 ***
Rainfall of wettest quarter	Rainfall amount of the wettest quarter in mm (in 00's)	5.0489	1.336	5.1805	0.974	-2.62 **
Community level variables						
Weekly market	1 if exist ; 0 otherwise	48.0		44.4		1.54
Cooperative	1 if exist in the community; 0 otherwise	16.5		19.1		-1.42
Agriextension expert	1 if exist ; 0 otherwise	94.5		97.4		-3.48 ***
Irrigation scheme	1 if exist ; 0 otherwise	71.9		70.3		0.75
Observations		592		1922		

Note: Ethiopian Socioeconomic Survey (ESS) (2013-14); * p<0.10, ** p<0.05, *** p<0.01

[4] Asset index is computed as the score along the first principal component of a principal component analysis applied to households' assets (including farm implements, furniture, electronics, personal items and other assets).

Table A.2. *Endogenous switching regression estimates of determinants of improved storage technologies use*

Variables	*Coeff (Std Err)*
Household (head) characteristics	
Male headed	0.024 (0.093)
Age of the household head	0.009 (0.003) ***
Household size	0.018 (0.017)
Less than primary education (head)	-0.102 (0.083)
Secondary education or above (head)	-0.048 (0.194)
Farm size (ha)	-0.050 (0.032)
Asset index	0.006 (0.025)
Livestock ownership (TLU)	-0.010 (0.013)
Nonfarm enterprise	0.193 (0.076) **
Institutional factors	
Distance to main road	-0.005 (0.002) **
Distance to admin. center	0.001 (0.000) ***
Distance to nearest market	0.005 (0.001) ***
Mobile ownership	0.008 (0.080)
Access to finance or credit	0.253 (0.080) ***
Social transfers	-0.433 (0.154) ***
Private cash transfers	0.016 (0.130)
Private food transfers	0.025 (0.197)
Weekly market	-0.318 (0.069) ***
Irrigation scheme	0.185 (0.085) **
Cooperatives	0.082 (0.093)
Agricultural extension expert	0.537 (0.194) ***
Shocks and climate factors	
Production shocks	-0.093 (0.124)
Market shocks	0.163 (0.113)
Annual mean temperature (^{0}C)	0.123 (0.061) **
Mean temperature of wettest quarter	-0.254 (0.059) ***
Annual mean rainfall (mm)	0.007 (0.002) ***
Annual mean rainfall of wettest quarter	-0.005 (0.005)
Constant	-0.249 (0.369)
Observations (N)	2136

Note: Ethiopian Socioeconomic Survey (ESS) (2013-14); Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table A.3. *Endogenous Switching Regression estimation for continuous outcomes*

Variables	*Household dietary diversity score*		*Per capita food consumption expenditure (ln)*		*Real per capita consumption expenditure (ln)*		*Proportion of harvest sold*	
	Nonusers	*Users*	*Nonusers*	*Users*	*Nonusers*	*Users*	*Nonusers*	*Users*
Male headed	0.216**	0.019	0.086*	-0.155**	0.063	-0.130*	2.839**	0.982
	(0.102)	(0.184)	(0.048)	(0.076)	(0.042)	(0.069)	(1.176)	(1.954)
Age of the head	-0.006**	-0.010	0.003**	0.001	0.000	-0.001	-0.026	0.016
	(0.003)	(0.010)	(0.001)	(0.002)	(0.001)	(0.002)	(0.032)	(0.055)
Household size	0.041**	0.005	-0.102***	-0.117***	-0.092***	-0.115***	-0.350	0.814*
	(0.020)	(0.040)	(0.009)	(0.017)	(0.008)	(0.015)	(0.216)	(0.426)
Below primary educ (head)	-0.943***		-0.048		-0.138*		2.275	-0.245
	(0.292)		(0.090)		(0.077)		(2.537)	(3.868)
Primary education (head)	-0.588**	0.267	0.105	0.061	-0.001	0.075	0.870	-0.241
	(0.292)	(0.204)	(0.089)	(0.075)	(0.076)	(0.066)	(2.538)	(3.777)
Secondary or above (head)		0.968**		0.332*		0.360**		
		(0.380)		(0.188)		(0.164)		
Livestock owned (TLU)	0.052***	0.111***	0.020***	0.053***	0.019***	0.053***	-0.314***	-0.417
	(0.013)	(0.028)	(0.006)	(0.012)	(0.005)	(0.011)	(0.099)	(0.265)
Farm size (ha)	0.100**	-0.000	0.059***	-0.000	0.042***	-0.009	3.016***	0.903
	(0.039)	(0.073)	(0.017)	(0.029)	(0.015)	(0.026)	(0.449)	(0.681)
Asset index	0.251***	0.124	0.038***	0.067***	0.051***	0.086***	-0.015	-0.239
	(0.038)	(0.078)	(0.012)	(0.025)	(0.011)	(0.022)	(0.358)	(0.655)
Non-farm enterprise	0.161*	0.009	0.057	-0.035	0.054	-0.073	-1.236	0.539
	(0.093)	(0.190)	(0.042)	(0.064)	(0.037)	(0.056)	(1.015)	(1.571)
Mobile own	0.328***	0.583***	0.150***	0.033	0.166***	0.051	0.514	3.420**
	(0.097)	(0.182)	(0.042)	(0.072)	(0.037)	(0.062)	(1.022)	(1.727)
Distance to major road	0.002	-0.013*	0.003*	-0.003	0.003**	-0.003	0.015	-0.035
	(0.003)	(0.007)	(0.001)	(0.003)	(0.001)	(0.002)	(0.032)	(0.060)
Weekly market	0.245***	0.063	-0.037	0.150**	-0.017	0.133**	-1.494*	1.360
	(0.086)	(0.286)	(0.036)	(0.069)	(0.031)	(0.061)	(0.885)	(1.496)
Distance to market	-0.002**	0.001	-0.003***	-0.001	-0.002***	-0.001	-0.019*	0.053**
	(0.001)	(0.004)	(0.000)	(0.001)	(0.000)	(0.001)	(0.010)	(0.021)
Distance to zone capital	-0.000	-0.001	-0.000*	0.001	-0.000	0.000	-0.006	-0.006
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.008)
Production shock	-0.144	-0.702***	0.030	-0.133	0.036	-0.098	-0.639	-3.864*
	(0.121)	(0.237)	(0.052)	(0.107)	(0.044)	(0.091)	(1.355)	(2.159)
Market shock	-0.270**	0.128	0.057	0.076	0.021	-0.006	0.240	-1.583
	(0.130)	(0.272)	(0.052)	(0.106)	(0.045)	(0.091)	(1.358)	(2.041)

Annual mean T^0	-0.151**	-0.263	0.030	-0.050	0.047*	-0.014	0.939	1.567
	(0.071)	(0.168)	(0.030)	(0.058)	(0.027)	(0.051)	(0.809)	(1.276)
Mean T^0 of wettest Qrt	0.172**	0.372	-0.001	0.048	-0.028	0.020	-0.633	-0.179
	(0.068)	(0.236)	(0.030)	(0.056)	(0.026)	(0.049)	(0.740)	(1.277)
Mean annual RF	0.019***	0.013	0.001	0.002	0.001	0.001	0.054*	0.005
	(0.003)	(0.008)	(0.001)	(0.002)	(0.001)	(0.002)	(0.031)	(0.043)
Total RF of wettest Qrt	-0.032***	-0.045***	-0.014***	-0.022***	-0.011***	-0.020***	-0.199***	-0.313***
	(0.005)	(0.011)	(0.002)	(0.005)	(0.002)	(0.004)	(0.057)	(0.100)
Irrigation scheme	0.127	0.347	0.056	0.182**	0.026	0.163**	2.137**	-0.573
	(0.097)	(0.286)	(0.044)	(0.072)	(0.039)	(0.064)	(1.033)	(1.719)
Cooperatives	0.080	-0.055	-0.029	0.001	0.011	-0.007	0.785	-0.872
	(0.113)	(0.205)	(0.044)	(0.078)	(0.037)	(0.068)	(1.250)	(2.030)
Finance access	-0.276**	-0.513*	0.063	-0.135**	0.079*	-0.185***	-1.050	-1.477
	(0.115)	(0.264)	(0.046)	(0.066)	(0.041)	(0.060)	(1.146)	(1.544)
Social transfers	-0.109	-0.707	-0.077	-0.421***	-0.129***	-0.331**	-5.159***	-1.577
	(0.126)	(0.524)	(0.054)	(0.144)	(0.048)	(0.143)	(1.395)	(2.858)
Private cash transfer	0.349**	0.470*	0.073	-0.058	0.115**	-0.029	-3.139**	0.468
	(0.143)	(0.271)	(0.062)	(0.136)	(0.053)	(0.117)	(1.463)	(2.439)
Private food transfer	0.142	-0.310	-0.098	0.017	-0.134**	0.057	-0.817	-9.037***
	(0.243)	(0.361)	(0.079)	(0.161)	(0.067)	(0.150)	(2.233)	(3.087)
Constant	5.378***	6.302***	5.803***	6.909***	6.495***	7.422***	15.138***	5.383
	(0.494)	(1.172)	(0.185)	(0.374)	(0.160)	(0.347)	(4.582)	(8.863)
Model diagnosis								
Wald $\chi 2$	443.78***		374.54***		380.64***		133.43***	
$\boldsymbol{\sigma_i}$	1.57 ***	1.66 ***	0.68 ***	0.63 ***	0.60 ***	0.56 ***	17.38 ***	14.61 ***
	(0.03)	(0.48)	(0.02)	(0.03)	(0.01)	(0.02)	(0.40)	(0.52)
ρ_i	-0.11	-0.60	0.09	0.02	0.10	-0.12	0.14 ***	-0.21 ***
	(0.17)	(0.48)	(0.11)	(0.11)	(0.14)	(0.32)	(0.06)	(0.07)
Observations	2136		2136		2136		2135	

Note: Ethiopian Socioeconomic Survey (ESS) (2013-14); Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.4. *Endogenous switching probit model estimates for selected outcomes*

Variables	*Household food insecurity access scale*		*Market participation*	
	Users	*Non-users*	*Users*	*Non-users*
Male headed	-0.221	-0.477***	-0.016	0.252**
	(0.232)	(0.132)	(0.153)	(0.120)
Age of the head	0.020***	0.006	0.011***	-0.003
	(0.007)	(0.004)	(0.004)	(0.004)
Household size	0.181***	0.084***	0.048*	0.022
	(0.050)	(0.026)	(0.028)	(0.024)
Less than primary education		0.663*		0.253
		(0.372)		(0.275)
Primary education (head)	0.614***	0.688*	0.235*	0.096
	(0.231)	(0.366)	(0.131)	(0.277)
Secondary or above (head)	-0.554		-0.432	
	(0.664)		(0.341)	
Livestock owned (TLU)	-0.226***	-0.042*	-0.009	-0.041***
	(0.053)	(0.023)	(0.024)	(0.012)
Farm size (ha)	-0.247**	-0.311***	0.133*	0.313***
	(0.120)	(0.090)	(0.073)	(0.056)
Asset index	-0.053	-0.121	-0.002	-0.068**
	(0.086)	(0.106)	(0.053)	(0.032)
Non-farm enterprise	0.457**	0.084	0.045	-0.302***
	(0.206)	(0.144)	(0.128)	(0.109)
Mobile own	0.102	0.095	0.117	-0.020
	(0.232)	(0.134)	(0.133)	(0.100)
Distance to road	-0.000	-0.010**	-0.013***	-0.002
	(0.009)	(0.004)	(0.005)	(0.004)
Weekly market	0.375	0.105	-0.182	-0.060
	(0.254)	(0.159)	(0.119)	(0.123)
Distance to market	0.011***	0.005***	0.006***	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)
Distance to zone capital	0.001	0.001	0.000	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
Production shock	0.720**	0.417***	0.046	-0.201
	(0.300)	(0.154)	(0.188)	(0.136)
Market shock	0.492*	0.571***	-0.081	0.149
	(0.279)	(0.176)	(0.206)	(0.151)
Annual mean T^0	0.227	0.380***	0.471***	0.096
	(0.166)	(0.100)	(0.170)	(0.082)
Mean T^0 of wet Qrt	-0.359**	-0.385***	-0.462***	-0.038
	(0.160)	(0.085)	(0.133)	(0.093)
Mean annual RF	-0.004	0.002	0.004	0.002
	(0.008)	(0.005)	(0.004)	(0.005)
RF of wettest Qrt	0.044***	0.004	-0.012	-0.013*
	(0.017)	(0.008)	(0.008)	(0.007)
Irrigation scheme	-0.039	0.027	0.199	-0.059
	(0.233)	(0.143)	(0.139)	(0.137)
Cooperatives	0.022	-0.685***	-0.016	-0.312***
	(0.272)	(0.193)	(0.148)	(0.119)
Finance access	0.395	0.409***	-0.088	0.023
	(0.241)	(0.132)	(0.148)	(0.137)
Social transfer	-0.560	0.114	-0.190	-0.071
	(0.499)	(0.180)	(0.251)	(0.158)
Cash transfer	0.667**	-0.092	0.411	-0.172
	(0.320)	(0.194)	(0.300)	(0.152)
Food transfer	0.650*	0.513*	-0.734	-0.160
	(0.385)	(0.266)	(0.457)	(0.230)
Constant	-4.182***	-2.436**	-1.973***	-0.039
	(1.053)	(0.967)	(0.747)	(0.549)
Wald $\chi 2$	201.98***		202.47***	

ρ_i	0.41 (0.47)	0.51 (0.49)	0.97 (0.05) ***	-0.45 (0.49)
Observations	2136		2135	

Notes: Ethiopian Socioeconomic Survey (ESS) (2013-14); Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table A.5. *Additional tests for the exclusion restriction*

Test	*Null hypothesis/Test type*	*Test results*
Durbin test	Exclusion instrument is exogenous	F=0.003, p = 0.9618
Wu–Hausman test	Exclusion instrument is exogenous	F =0.002, p = 0.9620
Wooldridge's score test	Exclusion instrument is exogenous	$\chi 2$=0.003, p=0.9596
Anderson canonical correlation statistic	Underidentification	LR=8.32, $\chi 2$ p= 0.0039
Cragg-Donald statistic	Underidentification	$\chi 2$ =8.16, p=0.0043
Anderson–Rubin's	Weak instrument robust test	$\chi 2$= 0.01, p=0.9139

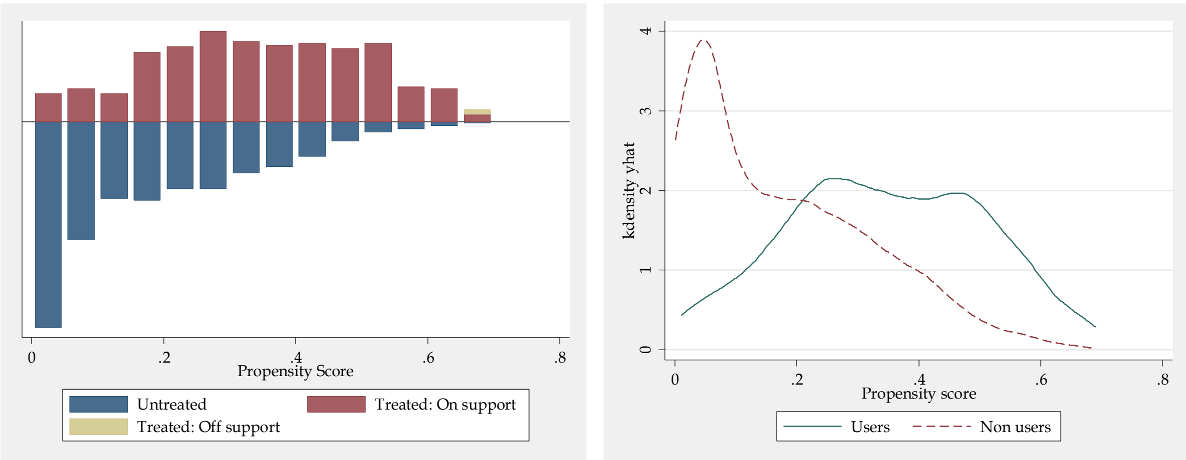

Figure A.1. *Common support condition and distribution of propensity scores*

Table A.6. *Matching quality test*

Sample	*Pseudo R²*	*LR* $\chi 2$	*P* > $\chi 2$	*Mean standardized bias*	*Total bias reduction (%)*
Before matching	0.169	373.0	0.000	19.2	89.6%
After matching	0.004	5.1	1.000	2.0	

Table A.7. *Sensitivity analysis: Rosenbaum bounds (rbounds) and Mantel-Haenszel (MH) bounds*

Outcomes	*rbounds*		*mhbounds*	
	sig^{+}	sig^{-}	$p_{mh}+$	$p_{mh}-$
Household dietary diversity score	1.10	>3.00		
Minimum acceptable diet			1.5-2.0 & >3	>3.00
Per capita food consumption expenditure	1.20	>3.00		
Real per capita consumption expenditure	1.15	>3.00		
Child stunting			1 & > 3	1 & >3.00
Market participation			1.6	>3.00
Proportion of harvest sold	1.00	1-1.02 & >3		
Sale in main markets			>3.00	>3.00

Note: Gamma: Odds of differential assignment due to unobserved factors

sig^{+} upper bound significance level

sig^{-} lower bound significance level

$p_{mh}+$ Significance level (assumption: overestimation of treatment effect)

$p_{mh}-$ Significance level (assumption: underestimation of treatment effect)

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