Can metal silo technology offer solution to grain storage and food security problem in developing countries? An Impact evaluation from Kenya

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Abstract

Maize is the most important food staple in developing countries with a stable demand throughout the year and seasonal production which is sometimes occasioned by crop failure. Farmers store maize for food security and protection against price fluctuation. However, traditional methods of storage do not provide protection against theft and insect damage resulting in huge postharvest losses. Metal silo offer solution to this problem but its impact has not been studied at farm level. This study used propensity score matching approach to evaluate the impact of metal silo technology on postharvest loss abatement, cost of storage, length of maize storage and household food security. This study used cross sectional representative data of major maize growing zones in Kenya collected from 1468 households. The results reveal that households that do not adopt metal silo sell much of their grain within the first month after harvest at low prices. Metal silo adopters however, store and sell most of their maize five months after harvest when prices are attractive. Metal silo adopters on average saved US$134 worth of grain and US$18 on cost of storage pesticides compared to non-adopters. Adopters of metal silo store their maize longer for two months and are food secure for at least a month longer than non-adopters. Metal silos are effective in reducing grain losses due to maize weevil and larger grain borer and therefore needs to be promoted to small scale farmers in Africa.

Key words: propensity score matching, metal silo, food security, storage cost, loss abatement

1. Introduction

Maize is one the three globally most important cereals providing calories to over 4.5 billion people in 94 developing countries (von Braun et al., 2010). It ranks third as the world's most traded cereal with half of it being grown in developing countries (Abbassian, 2006; UNDP, 2010) but ranks first in productivity (Basappa et al., 2007). The area under maize in the developing world is estimated at 100 million hectares with an average daily per capita consumption of 0.5kg to 1.0kg.

Maize is the principal crop in sub Saharan Africa with 35 million tons produced on about 25 million ha yearly. Although maize is primarily grown for livestock and industrial use (distillation) in the developed world, 95% of the crop in Africa is grown as food staple for human consumption and provides food and income to more than 300 million smallholder farmers (Tefera et al., 2011a). In Kenya, it is the most important food staple crop for over 80% of population contributing 65% of total staple food caloric intake and an annual per capital consumption of 88 kg of maize products (Ariga et al., 2010; Munyua et al., 2010).

Despite its importance in food security, farmers in developing countries have continued to experience postharvest losses either due to reduced quality or quantity. The main causes of postharvest losses are the storage insect pests and improper drying. Surveys in Kenya have shown that 10-20% of postharvest losses are due to insect pests but this varies with agro-ecological zones. Poor storage accounts for about 5-10% loss and 5%loss is attributed to diseases (Bett and Nguyo, 2007). The main storage pests of maize in East Africa are the maize weevil and the larger grain borer (Abebe et al., 2009; Bett and Nguyo, 2007; Kimenju and De Groote, 2010; Tefera et al., 2011b).

Production of most cereals is seasonal resulting in fluctuating supplies that do not match the stable demand throughout the year. Grain storage serves an important role in stabilizing prices by taking the produce off market during peak season and releasing it back when the grain is in short supply (Proctor, 1994). Improved storage therefore becomes an important aspect of household food security and rural livelihoods since it ensures continuous stable supply of food and better farm incomes(Thamaga-Chitja et al., 2004). Although the primary purpose why farmers store grain is for household food security, some store for market speculation purposes and others use it as seed in the following season (Proctor, 1994). However, most farmers still sell a large proportion of their produce immediately after harvest at low prices only to buy later in the market at high prices (Kimenju and De Groote, 2010). The desire to have strategic food reserves and stabilize prices could explain state intervention in storage. However, reducing losses before and after harvest at the farm level have not received much attention from the state(Tefera et al., 2011b).

Most smallholder farmers in developing countries still rely on old storage technologies but the traditional way of storing unshelled maize in traditional stores has proved difficult with the advent of the LGB. This forces most smallholder farmers sell off their grains immediately after harvest to avoid the damage by storage pests and consequently receive low prices (Tefera et al., 2011b). The LGB is an invasive storage pest accidentally introduced in Africa from Central America and now recognized as the most destructive pest of maize. The most common traditional maize storage facilities used by smallholder farmers in Africa include traditional crib or granary, baskets (Adita) and large pots. In response to challenges posed by maize weevil and LGB, improved storage technologies have been developed including actellic super (a mixture of pirimiphos-methyl and permethrin), super grain bag (IRRI super bag), polypropylene bags and the metal silo (Kimenju and De Groote, 2010). Metal silo prevents grain from damage by pests and allows for longer storage periods and hence an important storage technology in the fight against hunger and food insecurity in developing countries. Metal silo with a capacity of 990 kg can conserve enough grain to feed a household of five members for one year (FAO, 2008).

Six-month on-station trials conducted in Kenya's maize agro-ecological zones on the effectiveness of the various modern storage technologies have shown that grains stored in metal silo were not damaged by weevil and larger grain borer. Storage losses of maize stored using other technologies increased with time (Kimenju and De Groote, 2010). Through its effective grain storage project, CIMMYT has disseminated the metal silo technology to farmers in Kenya and Malawi since 2008. Though metal silos have been proved to be technically effective against the main grain storage pests, their distribution and adoption by smallholder farmers are limited and their impact have not yet been evaluated using empirical data. This study therefore evaluated the impact of metal silos on maize storage at household level. Specifically, we determined the impact of metal silos on cost of storage, loss abatement, length of storage and food security. This study for the first time reports on the impact of metal silos in Africa using propensity score matching.

2. Methodology

2.1 Conceptual framework

The decision of whether or not to adopt new storage technology such as metal silo depends on the utility the farmer expects to derive from the innovation. Farmers only adopt technologies if the expected utility of adopting (U_{MSa}) is greater than non adoption (U_{Msn}) i.e. $U_{MS}= U_{Msa}- U_{Msn}>0$ (Ali and Abdulai, 2010; Kassie et al., 2011).

Random utility models presume that the utility U_{MS} derived by individual household from using the metal silo technology is composed of a deterministic component v_{Msi}, which can be calculated based on observed characteristics and a stochastic error component ε_{Msi}, which is unobserved, so that

$$U*_{MSi} = \beta V_{MSi} + \varepsilon_{MSi} \qquad U_{MSi} = 1[U*_{MSi} > 0] \tag{1}$$

where $U*_{MS}$ is a binary indicator variable that takes a value of 1 if a household adopts metal silo and 0 otherwise, β is a vector of parameters to be estimated, V is a vector of explanatory variable and ε is the error term. The error component ε_i is never observed hence we do not have enough information to make prediction on individual's choice but we can predict patterns of households' adoption of metal silo from among other alternative storage technologies.
The conditional probability of metal silo adoption by a household based on the observable characteristics can then be estimated using either binary probit or logit:

$$\Pr(U_{MSi} = 1) = \mathrm{pr}(U*_{MSi} > 0) = 1 - F(-\beta V_i) \tag{3}$$

Where F is the cumulative distribution function for $\varepsilon_{i,}$ which is assumed to be normally distributed

2.2 Theoretical model for impact evaluation

Assessing the impact of an intervention or program on the beneficiaries involves measuring the performance of program against an explicit counterfactual, such as the situation in the absence of the program. Impact evaluation based on experimental research designs offers unbiased estimates. This is because the treatment is randomly assigned to beneficiaries and, thus, independent of pretreatment observable characteristics as well as the potential outcomes. Randomized experiments allows for direct estimation of the casual effect of treatment on outcome variable without selection bias (Imbens and Jeffrey, 2009). The limitation of randomized experiments lies in its inability to ensure balancing of covariates.

In non-experimental studies, individuals who adopt may be different from non-adopters because of observable and unobserbale characteristics. This is referred to as a self-selection problem in the literature of adoption and impact studies. We cannot estimate the causal effect, unless we solve the selection problem to overcome this shortcoming.

Researchers have proposed various methods for analysis of observational data which include the Heckman correction, instrumental variable method, difference in difference, panel and matching method (Nichols, 2007). The Heckman correction and instrumental variable approaches require that researchers find a valid instrument that determine the treatment status but not the outcome variable, which is a challenge in many empirical studies. However, the non-linearity of the inverse Mill's ratio in the Hekcman correction approach can serve as an exclusion restriction (or an identification) variable. Although we do not have valid instrument in our dataset, it worthwhile to mention that correcting the selection problem is a necessary but may not always sufficient for estimating the causal effect. The common support between adopters (treatment) and non-adopters (control group) is also a problem in impact studies. Difference-in-deference is suitable for impact analysis of longitudinal data to control for time invariant characteristics of households when comparing the treatment and counterfactual groups. The key assumption of difference-in-difference is that the change in the observed outcome variable is due to the interventions after controlling for the observable and unobservable characteristics (de Janvry et al., 2011). In the current study, the nature of data is cross sectional data and hence we could not use this approach. All the parametric methods mentioned above are characterized by functional form assumptions and lack of common support and assumes selection on unobservables.

2.2 Propensity score matching (PSM)

This study uses the propensity score matching method to evaluate the impact of metal silo grain storage technology on the length of postharvest maize storage, losses, food security and cost of storage. This method does not require distributional form assumption. It also does not require exogeneity of covariates to identify the causal effect of interest (Diagne and Demont., 2007; Heckman and Vytlacil, 2007). Unlike the parametric methods described above, the PSM assumes that conditioning on observable variables eliminates sample selection bias. PSM constructs a statistical comparison group by matching every individual observation of adopters with an observation with similar characteristics from the group of non-adopters. In essence, matching models create the conditions of an experiment in which adopters and non-adopters are randomly assigned, allowing for the identification of a causal link between technology choice and outcome variables. Although there are a number of technology adoption impact studies using PSM (Ali and Abdulai, 2010; Kassie et al., 2011; Kiiza et al., 2010), it does not address selection problem due to unobserved heterogeneity. However, the assumption of selection of observables is no more restrictive than assuming away problems of weak instruments when the Heckman correction or the IV approach is employed in cross-sectional data analysis (Jalan and Ravallion, 2003).

Estimation of the causal effect of metal silo on our variables of interest was executed in two stages. In the first stage, the propensity scores were estimated using the logit model.
In the second stage, three propensity score matching algorithms were used: the nearest neighbor matching, kernel matching and radius matching. In kernel based matching, each person in the treatment group is matched to a weighted averages of individuals who have similar propensity scores with greatest weight being given to people with closer scores. Nearest neighbor matches a subject from control group to a subject in the treatment group-based on the closest propensity score. Radius matching use a tolerance level on the maximum propensity score distance between a subject in the treatment group and all individuals in the control group who are within that distance (Chen and Zeiser, 2008).

The main purpose of propensity score matching is to balance the distribution of observed covariates (Lee, 2008).Therefore, we employ different covariates balancing tests (Rosenbaum and Rubin, 1985; Sianesi, 2004). Equality of means of observed characteristics in the treated and control groups were examined using a two sample *t*-test, pseudo-R^2 , p-values of the likelihood ratio test and propensity score graph (psgraph). After matching, there should be no systematic differences in the distribution and overlap of covariates between the two groups. As a result, the pseudo-R^2 should be lower and the joint significance of covariates should be rejected (or the p-values of the likelihood ratio should be insignificant). The propensity score graph (psgraph) was used to check the common support condition for metal silo storage technology adopters and non-adopters.

Additionally, the balancing property is checked using mean absolute standardized bias (MASB) between adopters and non-adopters suggested by Rosenbaum and Rubin (1985), in which they recommend that a standardized difference of greater than 20 percent should be considered too large and an indicator that the matching process has failed.

The observable covariates considered in this study based on previous adoption and impact studies include individual, household and environmental factors. Individual factor likely to influence adoption of metal silo include age, gender, education, maize farming experience and literacy of the household head. Literate and more experienced farmers are more likely to be knowledgeable on solutions to storage problem and proactive in adopting them.

Household characteristics considered in this study include size, land size and hosting social events. Households with more land are likely to produce more maize compared to those that have lesser parcels and therefore need for storage facilities. Households with many members are more likely to deplete their stored maize sooner. Big social events like burial or wedding in African setting usually involve hosting many people and consumption of a lot of food. Households that host such events are likely to exhaust their stored grain reserves sooner.

Agro-ecological zones were included in the analysis to control for geo-climatic conditions. Access to financial services is also important in adoption of metal silo. This was assessed by asking if any member of the household owned a bank savings account or a mobile phone virtual (M-Pesa) account.

2.3. Sampling and data collection

The survey was conducted from October, 2010 to March, 2011 covering all maize growing zones of Kenya, with the household as the sampling unit. It was conducted in two phases with the first phase targeting households that did not own metal silo (control group) and the second phase households that adopted metal silo for grain storage. Same questionnaire was administered to the two groups. All the study areas were grouped into six agro-ecological zones to allow for comparison between the treatment and control.

2.2.1 Sampling and data collection

An optimization model was used to determine the number of sub-locations and households to be covered using a stratified two-stage sampling procedure. First a list of sub-locations (Census 2009) was obtained from Kenya National Bureau of Statistics (KNBS) and grouped them into one of the six maize production zones (Table 1.). 18 sub-locations were selected from each of the dry transitional (DT) and dry medium altitude (DMA), 20 sub-locations each from the moist mid altitude (MMA), and high tropics (HT) and finally 30 sub-locations from the moist transitional (MT) resulting in a sample size of 1344 households. Random sampling procedure was used to select 12 households in each of the zones except for coastal lowlands where 6 households were selected per sub-location due to budgetary constraints.

Table 1: Sampling design for baseline and metal silo adoption survey

AEZ	Baseline survey (2010-2011)		Metal silo adoption survey (2011)		
	Non-adopters	Adopters	Adopters (for maize)	Adopters (for other grains)	Disadopters
Low tropics	90	0	0	0	0
Dry mid altitude	215	2	2	0	0
Dry transitional	203	0	0	0	0
Moist transitional	354	0	49	10	6
High tropics	240	0	0	0	0
Moist mid altitude	238	2	54	3	0
Total	1,340	4	105	13	6

The household survey of the metal silo storage technology was conducted in 18 districts, distributed in three agro-ecological zones namely moist transitional, moist mid transitional and dry mid altitude. The survey targeted all the farmers who had acquired metal silos either through the project implementation partners or through the artisans in Nyanza and Eastern provinces. A sampling list of 94 households distributed in 12 districts was obtained for the Nyanza region from which 73 households were interviewed. A list containing 51 metal silo owners distributed in 6 districts was obtained from Embu and were all interviewed. This formed treatment group of 124 households which was compared to the randomly selected control group.

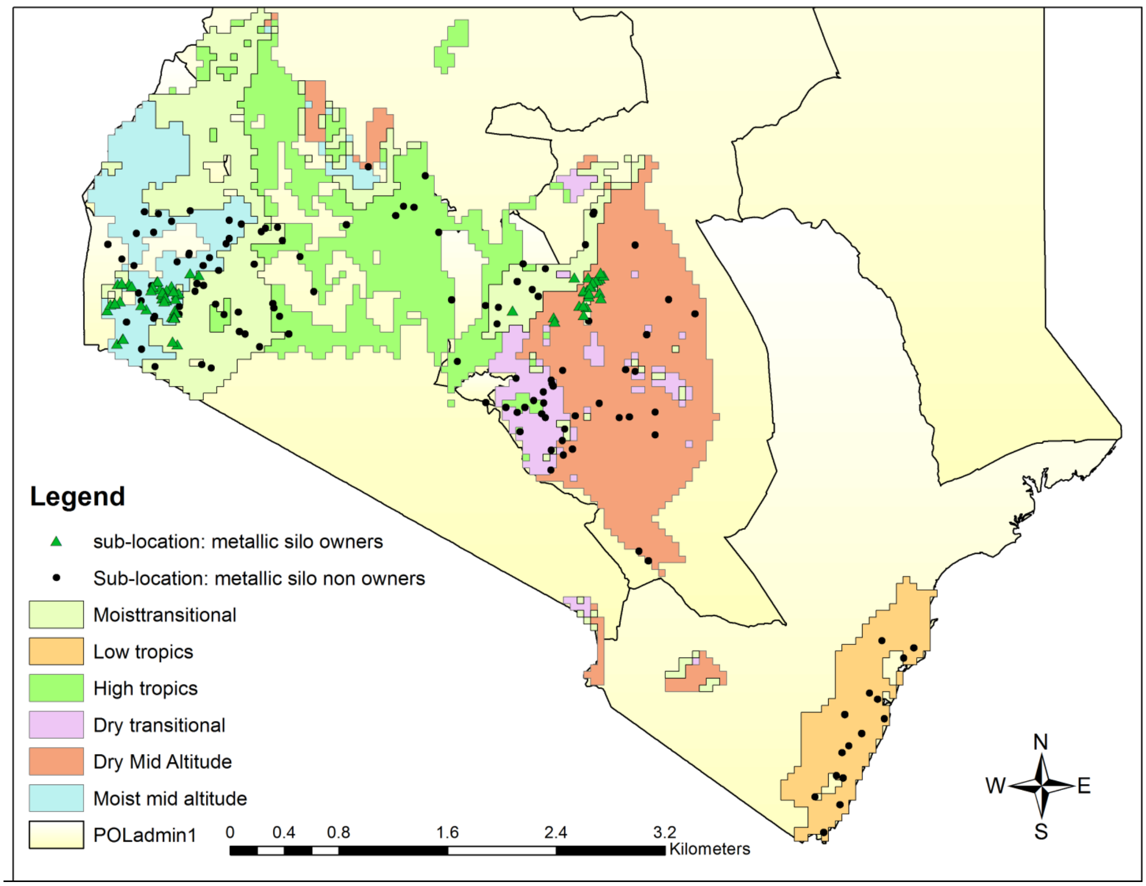

Figure 1: Map with selected sub-locations for the adopters and non adopters of metal silo

Data were collection by three teams, each comprising of a supervisor, six enumerators and a driver. The questionnaire was pretested and revised before data collection. Each team was provided with a car, 2 GPS machines, and laminated slides clearly showing various storage facilities and main grain storage insect pests.

3. Results

3.1. Household social and demographic characterization

Most household heads are males with an average age of 53 years for both the adopters and non adopters of metal silo (Table2). Literacy and years of formal education of the household head were significantly higher for adopters than non-adopters. Adopters and non adopters of metal silo differed in many household characteristics. Metal silo adopters had larger families (7 members) when compared to their counterparts who, on average, had six members. Adopters also had higher access to financial services than non-adopters with 97% owning mobile phone-based accounts (M-PESA) and 78% bank savings accounts. About 74% of non-adopters owned a mobile phone account and 46% had bank savings account. Mobile banking can reduce transaction cost in the purchase of metal silos. The distance from the nearest passable road was negatively related to adoption of metal silo. Distance from the passable road can influence the ease of accessing home and consequently household's decision to own a metal silo. Metal silos are heavy and bulky depending on the capacity and in most cases require a pickup for transportation. Non adopters had more experience in maize farming (28 years) but cultivated less land (5 acres) than adopters who had 24years experience and cultivated 8.3 acres. Adopters were on average 1.5 km away from the nearest passable road and the others were 3.1 km off the road. The differences in the means of the observable characteristics between the adopters and non-adopters indicated a potential source of bias, hence the need for matching and selection bias test.

Table 2. Demographic and social economic characteristics

	Variable	non adopters N=1340 Mean	non adopters N=1340 Std. Error Mean	Adopters N=128 Mean	Adopters N=128 Std. Error Mean	t-test for Equality of Means: Mean Difference	t-test for Equality of Means: Sig. (2-tailed)
Individual	Age of the household head	53.4	0.42	53.3	1.06	0.1	0.933
	Gender of the household head	1.2	0.01	1.1	0.03	0	0.194
	Literacy of the household head	0.8	0.01	1	0.02	-0.1	0
	household head education (Years)	7.1	0.12	10.3	0.38	-3.2	0
	Farming experience	27.7	0.43	24.6	1.24	3.2	0.03
Household	Household size	6	0.07	6.9	0.26	-0.9	0
	Hosting big social events	0.2	0.01	0.3	0.05	-0.1	0.174
	Savings /bank account	0.5	0.01	0.8	0.04	-0.3	0
	Virtual mobile M-Pesa account	0.7	0.01	1	0.02	-0.2	0
	Distance to a passable road	3.1	0.17	1.5	0.36	1.6	0.004
	Land owned (acre)	4.4	0.18	9.1	1.72	-4.7	0
	Total land cultivated LRS)	4.7	0.15	8.2	0.72	-3.6	0
Outcome	Maize storage	5.2	0.08	6.6	0.25	-1.4	0
	Loss due to storage pests (Kg)	74.9	6.8	3.4	1.65	71.5	0
	lossvalue (US$)	42.1	3.82	1.9	0.93	40.2	0
	Cost of storage chemicals (US$)	6.7	1.04	4.6	0.69	2	0.471

3.2. Maize storage behavior among adopters and non-adopters

Adopters and non-adopters differed substantially in their maize storage behavior. The length of maize storage was six months for the non-adopters control and seven months for the adopters (Table 2). Households that adopted metal silo were more food secure because they were able to store their grains for longer period than households in the control group. Non-adopters of metal silo went without enough food for two months during the year before the survey, as compared to slightly less than a month for the adopters. The average household expenditure on storage chemicals was US$ 7 for non adopters and US$ 5 for metal silo adopters. The average storage loss of maize is 75 kg for households that use other storage facilities and 3.5 kg for metal silo adopters.

Adopters and non-adopters of metal silos also differed in their sales behavior. Both groups sold maize within the first month after harvest (Figure 2). Non-adopters of metal silos, however, sold most of their maize within the first month after storage. Likely, they were trying to avoid damage by storage pests as well as meeting some immediate cash needs. Each household on average sold 180 kg within the first month after harvest at low prices. The average sales declined sharply to 25 kg by the third month and then rose to 47 kg by the fifth month before steadily declining to 17 kg by the eighth month.

Adopters of metal silos, on the other hand, sold little grain in the first month after storage and increased steadily to a peak of 150 kg five months after storage to take advantage of improved prices. The sales declined in sixth month but rose sharply in the eighth month to give room for the next crop.

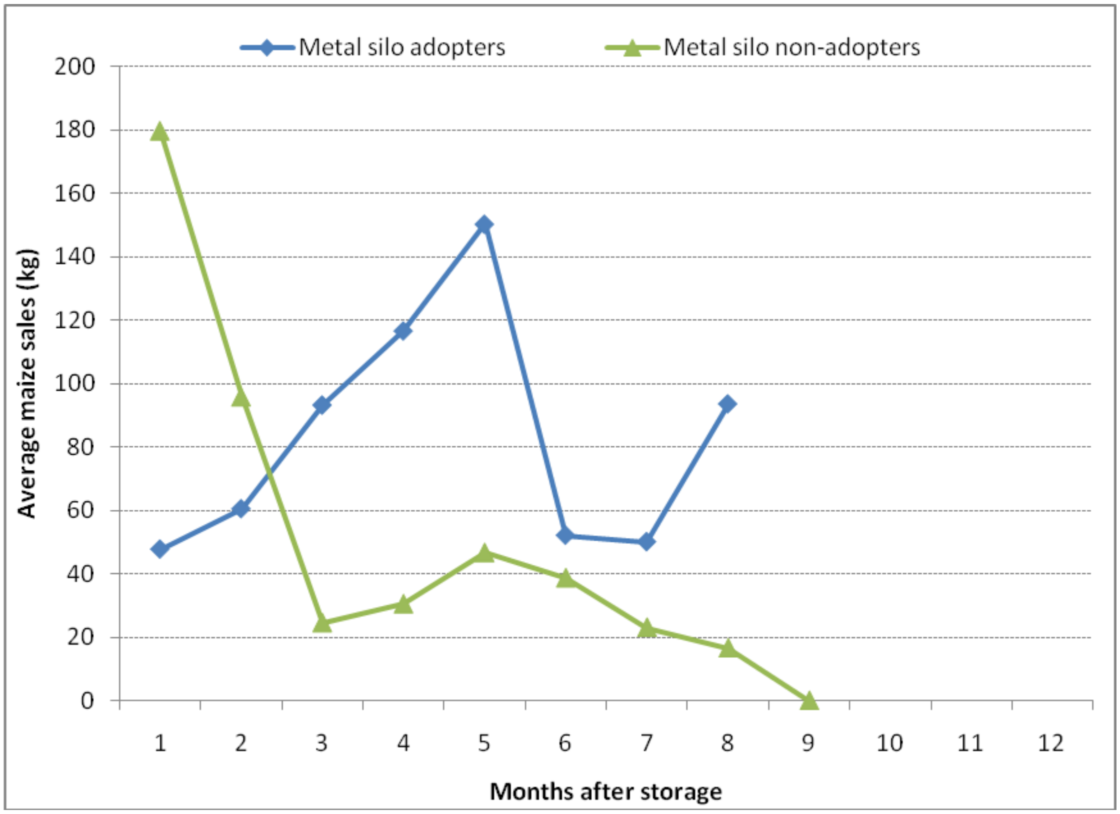

Figure 2. Maize sales in the months after harvest (kg sold/hh)

3.3 Propensity score Matching

Adopters and non adopters of metal silo were matched on the observable characteristics to estimate the conditional probability of the i^{th} household adopting the technology. The estimation of the logit regression identified several factors that affected the likelihood of adopting metal silos by households (Table 3.). Only farmers in moist transitional and moist mid altitude were found to have adopted metal silos. Higher literacy level, owning a mobile phone M-PESA account and a bank savings account also increased the likelihood of adoption. An increase in years of farming experience in maize farming, on the other hand, was associated with a decline in the probability of adoption.

Table 3. Propensity score matching of adopters and non adopters

Silownership	Coef.	Std. Err.	P>z
Mtransitional	2.63	0.78	0.00
MMAlt	3.24	0.79	0.00
Pdfemale	-0.41	0.27	0.13
PdMale	0.33	0.42	0.43
PdFemale	-0.90	0.78	0.25
HHsize	0.05	0.04	0.24
HHGender	0.37	0.38	0.33
HHAge	0.02	0.01	0.20
HHLiteracy	1.08	0.53	0.04
M_PesaAcc	1.33	0.56	0.02
SavingsAcc	0.79	0.27	0.00
Experience	-0.02	0.01	0.09
Socialeven~5	0.21	0.24	0.39
Distrde7	-0.07	0.03	0.03
Landown	0.05	0.02	0.01
Lnshell	0.09	0.09	0.32
Totalcult	0.04	0.02	0.08
_cons	-8.64	1.32	0.00
Number of obs	892		
LR chi2(17)	178.01		
Prob > chi2	0.000		
Pseudo R2	0.2475		
Log likelihood	-270.6193		

3.4. Testing the validity of the propensity score matching

After matching, three tests were conducted to control for selection bias. The first was the propensity score test *(pstest),* which showed a significant reduction in bias after matching (Table 4.). The pseudo R^2 which explains how well the covariates explain the probability of adopting metal silo was low after matching. The p-values of the likelihood ratio test were all insignificant after matching, indicating nonexistence of systematic differences in the distribution of covariates between the adopters and non adopters of metal silo (Table A1). The joint significance of the covariates could not be rejected at any significance level before matching but was rejected after matching in all the three matching techniques. This was an indication of insignificant difference of the means of covariates after matching. This further showed that the estimated propensity scores balanced well the matched adopters and non adopters of metal silo.

The second test was the Heckman two-step correction for selection bias, performed to check the robustness of PSM results. The inverse Mills ratio or Lambda was not significant suggesting that the error terms in the selection and primary equations are not correlated, hence the unobserved factors do not significantly influence the odds of adopting metal silo (Table A2).

Thirdly, the distributions of propensity scores for the metal silo adopters and non-adopters greatly overlap indicating that most of them have a positive probability of technology adoption (Figure 3.). Other outcome variables like length of maize storage and food security indicators have similar distribution. Metal silo adopters who had positive propensity scores with appropriate matches from among the non-adopters are shown on the graph as ‘treated on support’. The treated off support are adopters who did not find suitable match from among the non adopters and were very few.

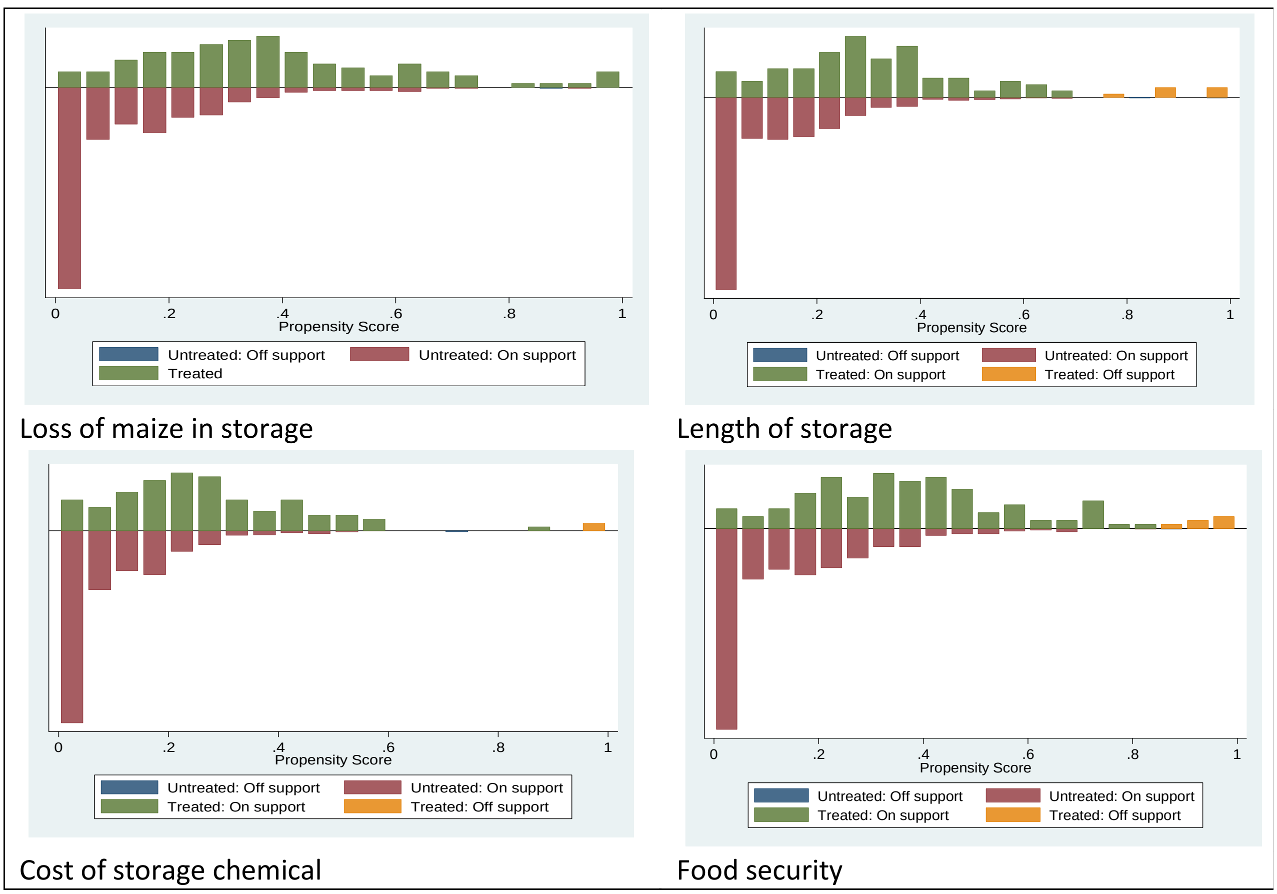

Figure 3 Propensity score distribution and common support

3.5. Impact of metal silo technology on maize storage

Results of the three matching algorithms show that loss suffered due to insect damage, cost of storage chemicals, length of postharvest maize storage, and food security indicators are all significantly different between the adopters and non adopters of metal silo, after matching.

The impact of metal silo on the value of maize loss abatement was found to be positive and significant, for all matching algorithms (Figure 4). Metal silo adopters lost an average of US$ 2 worth of grain due to storage pest compared to US$ 135 suffered by non adopters. The net effect of metal silo adoption was a 99 percent reduction in maize storage losses due to insect pests. The average treatment effects on the treated (ATT) estimates, which measure the impact of the technology on adopters, varied slightly depending on the matching technique. Kernel matching had the lowest estimate of the ATT at US$95 followed by radius matching (US$120).

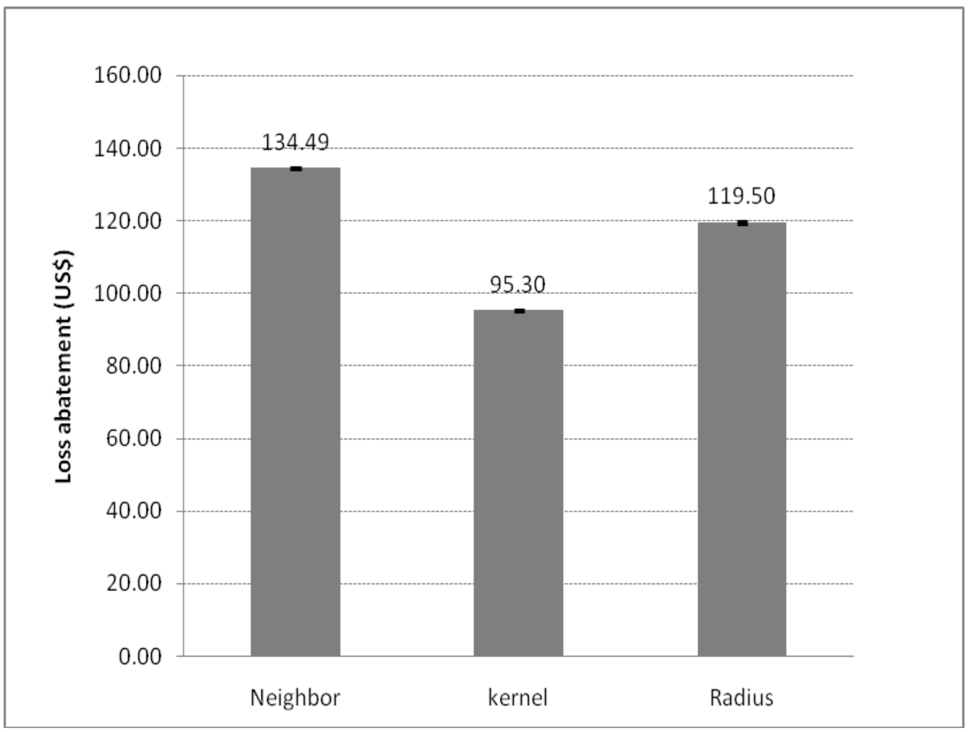

Figure 4. Impact of metal silo on value of storage loss abatement

The mean effect of the metal silos on the cost of storage was also found to be significant for all matching techniques (Figure 5). Metal silo adoption reduced storage cost by between 52% (radius matching) and 67% (neighbor matching). The average treatments effect on the treated

(ATT) shows that metal silo adopters saved about US$18 per season. Some metal silo adopters still used storage pesticides because they were so instructed during the installation by the artisans. Some also kept maize aside in bags for consumption to avoid opening the silo so often.

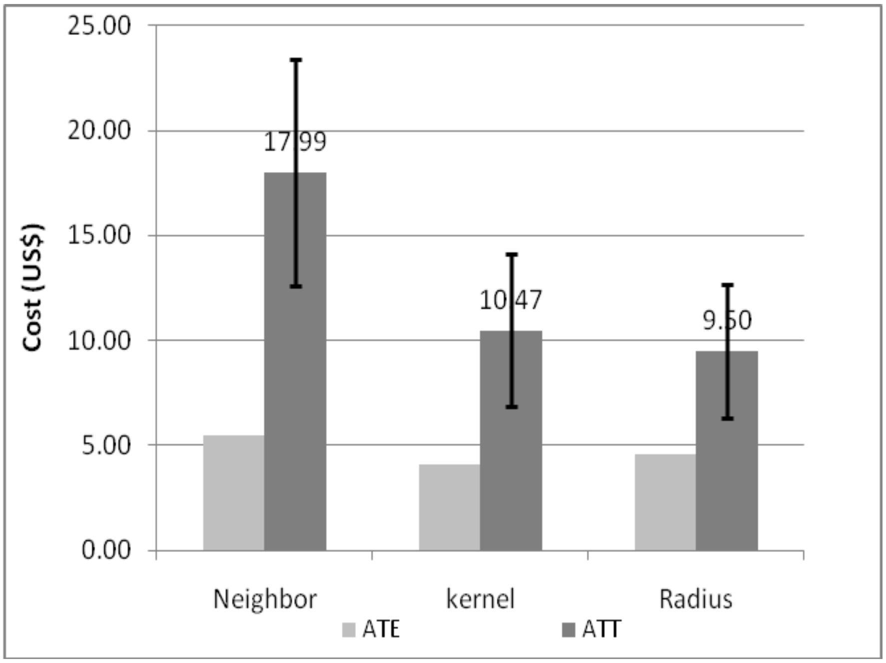

Figure 5. Impact of metal silo on cost of storage chemicals

The results of the impact analysis show that metal silos have a positive and significant impact on the length of storage and food security (Figure 6). The results are similar for both indicators and for the three matching methods. The average impact of metal silo on the length of maize storage is between 1.8 months and 2 months. The estimation of the average effect of metal silos using neighbor is slightly higher than when kernel and radius matching techniques are used. Similarly, adoption of metal silo for maize storage increased the period during which the household was food secure by more than one month. This implies that households that have adopted metal silo for grain storage are on average able to store their maize for at least six weeks longer than non-adopters.

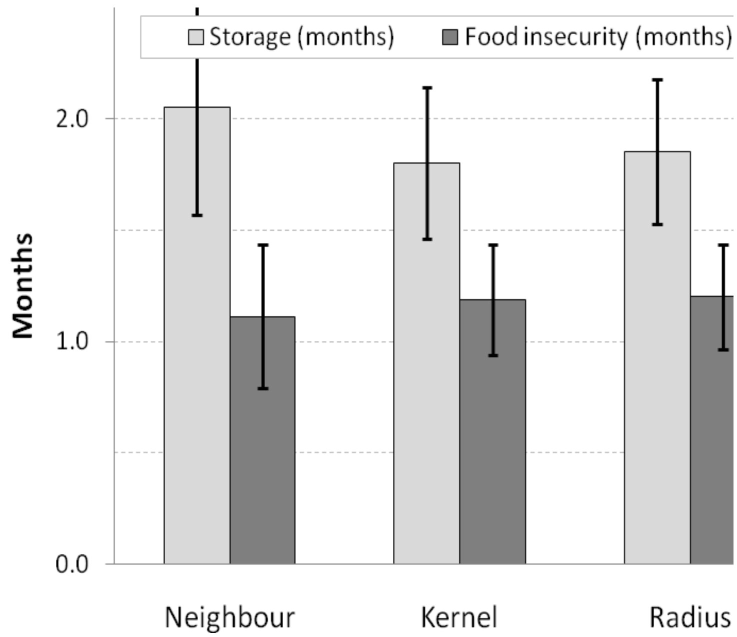

Figure 6. Impact of metal silo on length of storage and food security

4. Conclusion

This study used propensity score matching approach to evaluate the impact of metal silo technology on postharvest loss abatement, cost of storage, length of maize storage and household food security. The results show that literacy, access to financial services and access to the road positively influence the adoption of metal silo technology, while experience has a negative effect.

Results reveal that households that did not adopt metal silos sold most of their grain within the first month after harvest at low prices, while adopters only sold small portion of the maize in the first month. Most adopters sold much of their grains five months after harvest to benefit from better prices.

Metal silo adopters saved an average of US$ 134 worth of grain from damage by insect pests. They also spent less on storage chemicals by 67% compared to non adopters. The cost incurred by the adopters can be attributed to the advise they received from the artisans to treat the maize before storage. However, another study had shown that damage by storage insects to maize stored in metal silo is negligible with or without pesticides (Kimenju and De Groote, 2010). The impact of metal silo on storage costs could be larger had the households been trained on how to effectively use the metal silo for grain storage.

These findings imply that adoption of metal silo storage technology could significantly improve food security situation through reduced losses due to storage insect pests and delayed selling of harvested maize and other grains. This would also help smallholder farmers obtain better prices for their produce, improve their income, and help to stabilize food prices. The relatively high cost of the metal silo, however, constitutes an impediment to its widespread adoption. Economic analysis is therefore needed to provide guidelines to the circumstances under which the technology is economical. To help small scale farmers access the technology, credit facilities should be considered.

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Appendix

Table A 1. Test for absolute bias

Variable	Sample	Mean		%bias	% reduct|bias|	t-test	
		Treated	Control			t	p>|t|
Mtransitional	Unmatched	0.50	0.50	1.4		0.14	0.891
	Matched	0.50	0.48	5.8	-322	0.44	0.660
MMAlt	Unmatched	0.48	0.21	59.5		6.35	0.000
	Matched	0.48	0.49	-1.7	97.2	-0.11	0.909
Pdfemale	Unmatched	0.28	0.35	-14.2		-1.39	0.165
	Matched	0.27	0.33	-13	8.4	-1	0.320
PdMale	Unmatched	0.15	0.08	21.7		2.37	0.018
	Matched	0.14	0.10	12.6	42.1	0.93	0.352
PdFemale	Unmatched	0.02	0.05	-12.5		-1.14	0.256
	Matched	0.03	0.02	0.9	92.5	0.09	0.932
HHsize	Unmatched	6.83	6.02	29.2		3.08	0.002
	Matched	6.83	6.76	2.7	90.8	0.2	0.844
HHsize	Unmatched	6.83	6.02	29.2		3.08	0.002
	Matched	6.83	6.76	2.7	90.8	0.2	0.844
HHGender	Unmatched	1.14	1.19	-12.7		-1.22	0.224
	Matched	1.15	1.16	-3.7	70.4	-0.29	0.772
HHAge	Unmatched	53.52	53.10	3.1		0.29	0.774
	Matched	53.14	52.36	5.7	-85.3	0.46	0.646
HHLiteracy	Unmatched	0.96	0.83	43.9		3.74	0.000
	Matched	0.96	0.95	2.8	93.6	0.3	0.764
M_PesaAcc	Unmatched	0.97	0.76	62.1		5.14	0.000
	Matched	0.97	0.96	1	98.5	0.13	0.900
SavingsAcc	Unmatched	0.79	0.49	66.6		6.23	0.000
	Matched	0.78	0.79	-1.2	98.2	-0.1	0.921
Experience	Unmatched	24.87	27.64	-19.1		-1.85	0.064
	Matched	24.60	23.85	5.2	72.9	0.42	0.672
Socialeven~5	Unmatched	0.31	0.26	10.0		1.05	0.293
	Matched	0.30	0.30	1.6	83.6	0.12	0.903
Distrde7	Unmatched	1.57	3.19	-33.2		-3.04	0.002
	Matched	1.64	1.97	-7.0	79	-0.64	0.524
landown	Unmatched	9.34	4.10	36.0		5.31	0.000
	Matched	6.30	6.66	-2.5	93.1	-0.4	0.691
lnshell	Unmatched	1.84	1.32	32.7		3.26	0.001
	Matched	1.73	1.67	3.8	88.4	0.31	0.756
Totalcult	Unmatched	8.34	4.74	55.7		6.94	0.000
	Matched	7.18	7.95	-11.9	78.6	-1.02	0.307

Table A2: Heckman two-step correction model

Variable	dy/dx	Std. Err.	Z	P>|z|	X
Mtrans~l*	0.63	0.33	1.92	0.06	0.44
MMAlt*	0.86	0.26	3.30	0.00	0.33
Pdmale*	0.12	0.09	1.34	0.18	0.50
Pdfemale*	0.03	0.06	0.52	0.60	0.36
PdMale*	0.51	0.34	1.50	0.13	0.09
HHsize	0.01	0.01	1.64	0.10	6.16
HHGender	0.10	0.06	1.70	0.09	1.19
HHAge	0.00	0.00	1.57	0.12	52.88
Saving~c*	0.05	0.04	1.50	0.13	0.49
M_Pesa~c*	0.15	0.07	2.26	0.02	0.75
Distrde7	-0.01	0.01	-1.82	0.07	2.74
Landown	0.01	0.01	1.89	0.06	4.64
Experi~e	0.00	0.00	-1.58	0.12	27.00
HHEDU	0.02	0.01	1.89	0.06	7.43
Lnincome	0.10	0.05	1.93	0.05	11.24
Lnshell	0.01	0.01	0.80	0.43	1.23
Lambda	0.25	0.21	1.24	0.22	2.03
Number of obs		891			
LR chi2(17)		223.39			
Prob > chi2		0.000			
Pseudo R2		0.3076			
Log likelihood		-251.406			
y = Pr(Silownership) (predict)		0.071206			

Table A3: Impact of metal silo adoption on cost of storage, loss abatement, length of storage and food security

Outcome variable	Matching algorithm	Treated	Controls	ATT	ATE	S.E.	T-stat	n=treated	n=controls	Total
	Kernel matching	2.05	97.34	-95.30	-47.77	10.69	-8.91			
loss abatement (US$)	Radius	1.99	121.49	-119.50	-53.06	11.07	-10.79	112	559	671
	Neighbor	1.99	136.48	-134.49	-53.70	25.10	-5.36			
	Neighbor	4.42	22.41	-17.99	-5.48	5.39	-3.34			
Cost of storage (US$)	Radius	4.42	13.92	-9.50	-4.60	3.19	-2.98	121	539	660
	Kernel	4.44	14.91	-10.47	-4.12	3.62	-2.90			
	Kernel	6.65	5.21	1.44	1.80	0.50	2.90			
Length of storage (months)	Radius	7.03	5.70	1.33	1.85	0.33	4.08	124	768	892
	neighbor	7.03	5.83	1.20	2.05	0.49	2.47			
	Kernel	1.00	1.83	-0.83	-1.22	0.36	-2.30			
Food insecurity (months)	Radius	0.97	1.81	-0.84	-1.10	0.36	-2.34	124	765	889
	neighbor	0.97	1.92	-0.95	-1.38	0.41	-2.33			