Impact of Post-harvest Loss Interventions on Post-Harvest Losses of Maize among Small Holder Farmers in Tanzania: A Difference in Difference (DID) [1]Analysis

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Abstract: We conducted a randomised controlled trial to test the impact of three simple and cost effective post-harvest loss prevention innovations suitable for smallholder farmers in low income economies. The interventions include, use of tarpaulins, use of hermetic bags and use of simple mechanised maize shellers. We use propensity score matching (PSM) and difference in difference (DID) method to empirically evaluate impact. Results show thatcombined use of the three innovations by smallholder households contribute to a reduction in postharvest losses amounting to about 273.6 Kilos of maize per household (About 3 bags per household). We conclude that simple cost effective postharvest loss mitigation innovations could go along a way in combatting food security and increase household incomes.

Key words: Randomised control trial, Difference in Difference, post-harvest loss

Introduction

The UNDESA (2015) estimates that the world population would hit the range of 9.7 billion people by 2050. The implication on food requirement is obvious. "In order to feed this larger, …population, food production (net of food used for biofuels) must increase by 70 percent" FAO (2016 p.2).Developing countries are expected to have the most increase in population and so far the policy response has focussed on yields and productivity increase through adoption of high yielding varieties and input use. Whereas food availability and accessibility would increase through increments in production, Berners-Lee et al (2018), emphasize that a production led strategy would pose certain challenges. They argue that feeding the growing population "will not necessarily be solved by increases in production because there is a limit to the potential for efficiency gains, and many of these come with greater environmental costs, while increasing agricultural area by land use change almost invariably leads to losses of biodiversity" Berners-Lee (2018 P.1). Further, massive yields increments may not be feasible everywhere in the context of climate change, land and resource constraints. Besides increased production, sustainable food sufficiency can be improved through improved food distribution systems and reducing losses. Thus, post-harvest loss reduction is not only critical in improving food sufficiency, but also translates in to real increments in farm produce and therefore incomes for farmers. The Wold Bank estimates that 1% reduction in post-harvest loss, would increase economic gains by up to $40 million annually, the bulk of the benefits would accrue to smallholder farmers.

The UNFAO (2017) estimates the absolute number of food insecure persons globally to have risen to 821 million up from 804 million in 2016. Africa bears the biggest burden of undernourished people. About 23% of its population was undernourished by 2017 up from 21% in 2016. Despite the dire need of food and nutrition security, it is further estimated that about 1.3 billion tons of food are globally wasted and Africa bears the brunt of the calamity (Regmi and Aulakn, 2013). Postharvest losses in Africa reduce small holder farmers' incomes by up to 15% (Regmi and Aulakn 2013). The UNFAO estimates that one third of food produced is either lost or wasted,

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[1] This paper utilises data from an AGRA study that focussed on their post-harvest interventions work in Tanzania. The study was funded by the Rockefeller foundation.

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translating to US$ 2.6 trillion every year, a figure that includes about US$ 700 billion in environmental costs and US$ 900 billion in social costs. For Sub-Saharan Africa, post-harvest losses in grain have been estimated at US$4 billion annually, a figure that is more than the total value of food aid in the last decade. There is therefore a justification for low cost simple but effective post-harvest loss reduction innovations suitable for low income countries.

Kalita and Kumar 2017 hold that "More than one-third of food is lost or wasted in postharvest operations. Reducing the postharvest losses, especially in developing countries, could be a sustainable solution to increase food availability, reduce pressure on natural resources, eliminate hunger and improve farmers' livelihoods". (Kalita and Kumar 2017 P. 1) Similarly AGRA[3] observes that "About 30 per cent of the grains produced on the continent is lost due to inadequate post-harvest management, lack of structured markets, inadequate storage, and limited processing capacity" AGRA[4].

The Kenya National Bureau of Statistics (2018) estimates post-harvest losses in Kenya to the tune of 1.5b USD and mainly occur in the course of storage and transportation to markets. Tanzania produced over half a billion metric tons of maize in 2015; with small holder farmers contributing about 85% of the produce. However post-harvest losses are high and in some rural areas they range between 30-40% of produce (Kalita and Kumar 2017). Post-harvest losses not only decrease the amount of food available for human consumption but they also impact on agricultural inputs. "For every $1 spent to improve yields, $0.19 are lost due to inadequate postharvest practices"[5] APHLIS 2019.

The implication of post-harvest losses on the 70% of agricultural dependent African households is dire, and hence; "finding sustainable solutions to this problem holds tremendous promise for enhancing inclusive economic growth, food security, and nutrition" (Agra 2016). A reduction in post-harvest losses would not only improve food security but would go a long way to address issues of waste management, wastage of productive resources and greenhouse gas emissions. It is estimated that food loss account for "about 4.4 giga tonnes of greenhouse gas emissions each year; these include on-farm agricultural emissions and the energy used to produce, transport and store food that is ultimately lost or wasted……. If food loss and waste were its own country, it would be the world's third-largest emitter—surpassed only by China and the United States" APHLIS 2019[6]. Innovations for Post-harvest loss mitigation will therefore bear global relevance in the critical issues of food security, climate and general household livelihoods.

Post-harvest losses are a global concern spanning beyond just food security, but also with implications on incomes, climate change and health. Effective policies to combat post-harvest losses will not only impact livelihoods though increased incomes, but will go a long way to save the environment and reduce health concerns through the reduction of greenhouse gas emissions. We analyse the impact of three simple postharvest loss reduction innovations for maize harvests in 14 districts across Tanzania. The interventions comprised: use of tarpaulins for drying maize, use of simple mechanised shellers, and use of hermetic bags for maize storage. A tarpaulin is a canvas that is used for drying maize (other than drying by spreading on the bare ground). A tarpaulin can also be used beneath maize shellers to ease collection of spilled maize. A simple mechanised sheller provides an alternative to manual shelling of maize, which may involve beating bulk maize with sticks. Hermetic bags are airtight and can preserve maize for a long time after harvest as long as the bag remains closed.

[4]https://agra.org/news/thousands-of-african-farmers-to-benefit-from-reduced-post-harvest-losses/
[5] African Post Harvest Loss Information Systems (APHLIS): https://www.aphlis.net/en/news/29#/
[6]https://www.aphlis.net/en/news/29#/

Conceptualizing impact of post-harvest innovations

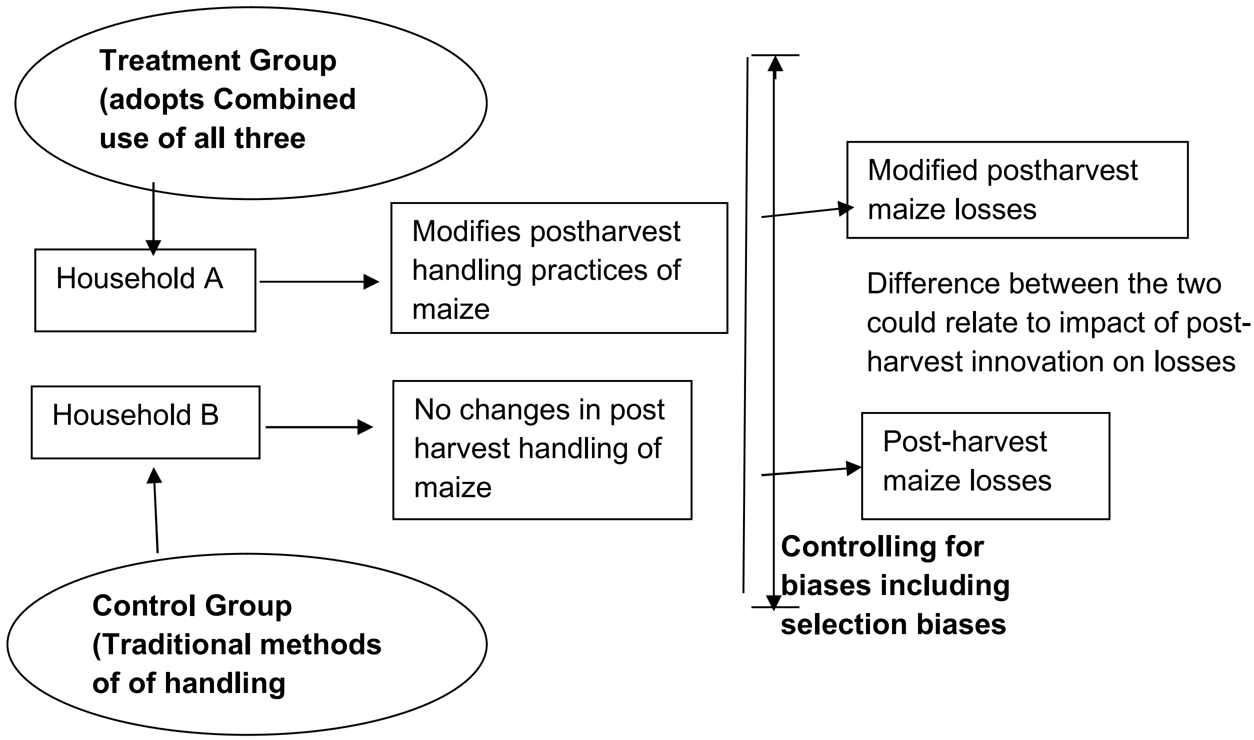

Figure 1: Conceptualization of the impact of post-harvest innovations on maize post-harvest losses. Adapted with modification from Kiiru (2008)

Our conceptualization is highly simplified as an illustration of how impact is transmitted through the impact chain. Managing postharvest losses depends on various factors besides adoption of different postharvest management innovations. Farmer and household attributes both observable and unobservable may matter for post-harvest loss reduction. For example, a farmer may possess very good equipment to manage post-harvest losses, suppose they are ignorant of the proper use of the equipment, the overall impact of the equipment in reducing post-harvest losses would be compromised. Proper knowledge on how to operate an equipment also depends on other factors, like experience, education level, age of user among others. There are also other unobservable factors that may affect the management of post-harvest losses, for example exposing harvests to wet conditions may accelerate rot and spoilage, yet with weather variability it takes a discerning farmer to know if there is likely to be rains in the next couple of days in the absence of formal weather forecasts. Some of the factors that affect postharvest losses are difficulty to measure and capture in an empirical model, yet proper attribution demands that all these factors be controlled for empirically.

Data and Project Design

This paper draws from a study to evaluate the impact of three interventions to curb post-harvest losses in Tanzania. We use two waves of panel data collected at baseline and midline. Randomization was not done at the household level rather it was done at higher clusters (cooperative and at the farmer group)[7]. At baseline (2014) a sample of 1,648 smallholder farming households (both control and treatment) was used. By the time of the midline survey there had been at least two full seasons from planting to harvesting and storage. Though the overall study was not complete at the time, data collected at midline is what informs our analysis. In 2016 the same households

[7] This paper utilises data based on the placement of a development intervention. There was need to preserve farmer groups for ease of service delivery. All households within a randomised group were part of the sample.

were interviewed but with a sample attrition of 5% for both treatment and control groups. Data collected include household socioeconomic data, maize production and post-harvest losses at the various stages from harvest to transport and storage.

Sampling Strategy

The study used a multistage sampling strategy. Study samples were selected using a randomization process at every stage. The first randomization was at farmer organization level. A farmer organization constitutes several farmers' groups. The selected samples of farmer organizations after the randomisation process were broken down to their constituent farmer groups. Another randomization was done at the farmer group level and a sample of farmer groups selected. All households in the sampled farmer groups were involved in the study. The same sample selection process was used to sample households in the treatment and control groups. Treatment and control groups were located in similar ecosystems supportive of maize production, but in different villages. Households in both the treatment and control groups were maize producers. The treatment group constitutes households that received and used post-harvest interventions (Tarpaulins, mechanised maize shellers, and hermetic bags). Control group households did not use such interventions at the time of the study, rather they continued with their traditional practices of maize handling. In the traditional method, other than use tarpaulin maize is dried on the bare ground, other than use a mechanised Sheller, a heap of maize is manually shelled by beating with sticks. Finally, in the traditional method, maize is stored in an open granary or in a normal sisal bag. The treatment group also benefited from training on proper use of post-harvest loss management innovations as well other agronomic practices including inputs use.

Methodology: Randomised but Potentially Biased Sample

Farmer groupings are likely to suffer selection bias. Farmers don't randomly select in to groups, rather every group has a joining criterion that ensures that only farmers of particular characteristics join. The implication is that there is a possibility that our treatment and control groups at baseline lack common support. In order to address the problem, we settled on a methodology that combines both propensity Score Matching (PSM) and Difference in difference analysis (DID) to measure impact. We use PSM at baseline data to select a sample of both treatment and control group with common support, then use the same sample at midline for the difference in difference analysis. A study by Heckman et al. (1997) was the first to show that combining both PSM and DID estimator removes observable and unobservable selection biases. Smith and Todd (2005) also used PSM-DID estimators in their study that evaluated the impact of a labour markets training program and concluded that the PSM-DID estimator was the most robust. Blundell and Dias (2000) demonstrated that both PSM and DID could be used in bias ridden repeated cross-sectional data.

PSM-DID estimator has been used to evaluate policy impacts. Aerts and Schmidt (2008) combined both PSM and DID to evaluate the impact of subsidised public research and development on private research and development in two countries; Flandres and Germany. First they used propensity score matching to construct a counterfactual. They then followed the PSM analysis with a DID approach. The approach ensured that the temporal difference between firms is accounted for in a bid to estimate treatment effect. Binci et al 2018 used a combination of both PSM and DID to measure the impact of an education intervention program (EQUIP-T) on quality of primary education and learning outcomes.

There is therefore a case for combining both PSM and DID in potentially biased samples at baselines or in cases were only cross sectional data is available. In the cases where only cross sectionals of data sets are available PSM is used to create a counterfactual.

Model Estimation

Propensity Score Matching (PSM)

In the context of selection biases, mere comparison of impact indicators between the two dis similar control and treatment groups would be invalid as a measure to determine the impact of an intervention. The use of PSM ensures that a valid counterfactual is constructed by creating a control and treatment group that are similar across observable characteristics. Sample attrition is expected with using propensity score matching, in that control and treatment households that have no good matches in terms of propensity scores are discarded.

The propensity score is a summary of the observable characteristics that drive treatment, or rather the probability that an individual household falls in to the treatment group, on the basis of individual household characteristics. Only two steps are involved when using PSM for the purpose of constructing a valid counterfactual (Binci et al 2018). Baseline data is used in the first stage of the PSM to construct a propensity score for each household in both

treatment and control groups. A probit or logit model is used in the first stage to estimate the probability of a household being treated whether in the control or treatment group. The second stage of constructing a propensity score involves the matching, where treatment and control groups with similar propensity scores are matched. The PSM is ideal at baseline data to ensure that the samples of treated and untreated households have common support.
The logit specification of the form:

$$\Pr(T = \langle 1 | X_i \rangle) = \frac{e^{f(x_i)}}{1 + e^{f(x_i)}} \quad \text{.........(1)}$$

$\Pr(T = \langle 1 | X_i \rangle)$ is the probability of a household being treated conditional on covariates X_i for unit i. Taking logs on this equation we obtain a linear equation of the form:

$$F(Y) = (X\beta) \quad \text{.........(2)}$$

Where Y is dummy variable that takes the value of 1 for the treated and 0 otherwise. X is a matrix of household characteristics and β is a coefficient to be estimated using maximum likelihood. Estimating the equation yields the propensity scores for each individual household. Each treated household is matched with untreated household using the propensity scores to obtain a sample that has common support. To test for balanced samples we used a t test to assess the differences across the control and treatment groups. For balanced samples we expect that differences are insignificant.
Out of a sample of an initial sample of 1648 only 848 households had good matches and were used for the impact evaluation using the difference in difference method.

Difference in Difference (DID) Methodology

The DID method accounts for time-invariant unobserved characteristics that correlate with post-harvest losses. However the method may not eliminate time-variant differences. In that case we can only asses the validity of a trend assumption that post-harvest losses continued in tandem after the introduction of the simple post-harvest management innovations. We use a household panel data collected at two time periods: at baseline and at midline. The panel comprised of a matched sample at baseline. The treatment group comprises farmers that received the post-harvestmanagement innovations (Tarpaulins, mechanised shellers and hermetic bags). The control group did not use these post-harvest management innovations at the time of the survey.

The Formal DID Model

We observe individuals in two time periods, t = 0, 1; where 0 indicates a time period before the treatment group receives the treatment (at baseline) and 1 indicates a time period after the treatment group receives treatment (midline). Every observation is indexed by the letter i = 1, ..., N ; individuals will typically have two observations each, one pre-treatment and one post-treatment. For the sake of notation let $\overline{Y}_0^T$ and $\overline{Y}_1^T$ be the sample averages of the outcome for the treatment group before and after treatment, respectively, and let $\overline{Y}_0^C$ and $\overline{Y}_1^C$ be the corresponding sample averages of the outcome for the control group. Let the subscripts correspond to time period while superscripts correspond the treatment status.

The outcome variable (Y_i) (post-harvest losses) is modelled as follows

$$Y_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i . t_i) + \varepsilon_i \quad \text{.........3}$$

Where the coefficients given by the greek letters α, β, γ, δ , are all unknown parameters and εi is a random, unobserved "error" term which contains all determinants of Y_i which our model omits. We interpret the coefficients as follows: α is the constant term β is treatment group specific effect. It accounts for average permanent differences between treatment and control, γ is time trend common to control and treatment groups, δ true effect of treatment group

As already stated our estimation involves using propensity scores for matched control and treatment households at the baseline. We then use the DID estimator to estimate the treatment effects across treated and matched comparison households that already have common support. Khandker, Koolwal, & Samad (2009) argue that can only internal validity as opposed to external validity can be ensured. Hence only the average treatment-on-the-treated (ATT) effect can be estimated reliably. “In addition, validity of the ATT estimates is based on weaker assumptions of conditional independence assumption and common support” Barasa 2019 p10.

We adapt Khandker, Koolwal, & Samad (2009) and Villa (2016) approach and use a panel data with two time periods (baseline and midline) so that $t = (1,2)$. The DID estimator is calculated as:

$$ATT_{PSM}^{DID} = \frac{1}{N_T}\left[\sum(\bar{Y}_{i2}^{T} - \bar{Y}_{i1}^{T}) - \sum w(i,j)_{KM}(\bar{Y}_{j2}^{c} - \bar{Y}_{j1}^{c}) \right. \text{……………………….4}$$

$\omega(i,j)_{KM}$ is the kernel matching weights assigned to the jth control households that is matched to treatment household i.

Results

Descriptive Results

Two-thirds of respondents both at baseline and midline were male smallholder farmers aged 35 -55 years old. This result is interesting from a gender perspective. Studies show that women play a critical role in smallholder agriculture providing on average 43% of all agricultural labor globally. In Sub-Saharan Africa women provide 50% of Agricultural labor; in Eastern Africa Women contribute slightly over 50% of agricultural labor (FAO 2011). If women were that critical in the smallholder farming systems in Eastern Africa, why would they be underrepresented in a survey like this one?? One answer to this question relates to the issue of the unit of analysis for the study. The study was designed as a household survey collecting data from head of household. Men are over represented as heads of households in Eastern Africa and the same scenario mirrors in terms of the survey respondents. There are serious logical queries with household based sampling strategy especially in the smallholder agriculture sector in sub-Saharan Africa. For example, if women drive productivity in the smallholder agriculture sector, how is it tenable to sample at the household level where the head of household is mainly male. Is it not more logical to sample individual famers? If sampling was to be at the individual farmer level and more so focusing on those that labor in the sector, responses would be more accurate and hence better data for policy. We argue that any practical attempt to improve the small holder agriculture sector must recognize the role of women and recognize women’s agency in the sector. Recognizing the role of women and working closely with them to intervene in the smallholder agriculture sector is beyond “mere women empowerment” rather it’s about improving critical socioeconomic outcomes for the society as a whole.

Results also show that the treatment group recorded higher yields than control group at midline. The treatment group increased yields by 1.89 MT/H while yields by the control group remained significantly unchanged over the period. The main explanation pertains the extra service that the project delivered to farmers; Farmers in the treatment group were trained on agronomic practices including inputs use. Indeed compared to the control group, there was increased use of agricultural inputs by the treatment group between baseline and midline period of the study. Good weather and good rainfall was also a key agricultural enabler within the period.

Besides training on agronomic practices, treatment farmers also benefited from training on bulk handling of maize produce. As a result, there was increased use of self-propelled maize shellers by treatment farmers. Smallholder farmers did not own these machinery rather they hired from other farmers or farming societies. Those that could not hire mechanized shellers they would use the traditional method that involve use of threshing sticks.
By midline survey at least 50% of farmers in the treatment groups adopted the practice of extra drying of maize harvest while the control group continued with the old practice where maize is left to dry on stalks, threshed and stored immediately after harvest. The treatment group adopted the use of tarpaulins to dry maize some more in the hot sun before storage. There was no mechanized drying equipment.

Maize brokers are very active among the smallholder agriculture sector. About 18% of farmers in the survey sold their maize immediately after harvest at the farm gate; hence not much to store. Sales at the farm gate also fetch much lower prices. Another 41% of farmers sell their maize shortly after harvest and from their homes, still at lower prices, though with lower storage costs. At midline the treatment group recorded lower incidence of direct maize sales at the farm gate or shortly after harvest. The change in attitude by treatment group could be explained by the training they received on post-harvest loss reduction through better storage. Farmers that sold their maize much later after harvest stood to gain from better prices. Treatment farmers also benefited from training on maize aggregation. Aggregation is supposed to enable individual smallholder farmers to access more lucrative markets that demand bulk sales. Accessing such markets enables farmers to avoid the "exploiting" brokers. This paper however did not do an indepth analysis on the actual effects of maize aggregation on market access.

More than 70% of smallholder farmers did not add any value to their maize before selling. Only 20% cleaned their maize before selling as a matter of value addition. Only 10% of farmers sold some of their maize as flour. Though small holder farmers would normally produce enough maize for their food requirements, "premature" sales implied that some households were still exposed to hunger and malnutrition. About 16% of households ended up running out of maize supplies annually. Such households would purchase maize at much higher prices than they sold their own produce.

Table 1 here

Results from the Difference in Difference analysis

Results show that at baseline, post-harvest loss differences were statistically insignificant for both control and treatment groups; an indicator that the sampling frame for apportioning households to both control and treatment groups was well randomised. Midline results showed significant differences in post-harvest losses between the control and treatment groups. Overall post-harvest loss mitigation innovations contributed to a reduction in postharvest losses amounting to about 273.6 Kilos of maize per household (About 3 bags per household). We conclude that simple cost effective postharvest loss mitigation innovations could go along a way in combatting food security and household incomes.

Results show insignificant loss differences between control and treatment groups at baseline. From the results above there could have been other factors driving post harvest losses for all farmers due to the fact that both control and treatment groups recorded increased post-harvest losses. The treatment group recorded increased losses of up to 462Kilos per household while the control group recorded losses of up to 746.6 kilos per household. Post-harvest loss interventions for the treated therefore reduced post-harvest losses by 273.6 Kilos per household.
The increased postharvest losses could be partly attributed to a policy change at the time that saw a temporary ban on maize exports. The local market was over supplied, maize prices in the local market dropped by about 50%. The study at midline established that farmers could not sell all the maize they hoped to sell citing issues of low prices (36%) and low demand (67%).

Significance of Results

The importance of this study is twofold; first, we attempt to measure self-reported household post-harvest losses as a way to generate evidence and magnitude of post-harvest losses. Whereas the estimation of post-harvest loss is not new there are criticisms that the earlier estimates that are widely used could be exaggerated (Christiaensen 2018). Secondly the study derives its significance from the fact that we are able to show that simple and affordable innovations could go along way in reducing post-harvest losses, thus increasing household incomes and improving food security.

Conclusion and policy implications

Post-harvest losses are still a major challenge to farmers in sub-Saharan Africa. Causes of post-harvest losses could be weather related, poor storage and poor handling of crop at various stages of the post-harvest process. The effects of post-harvest losses can be devastating to household incomes and food security. Hunger and lost incomes could have gendered impacts if women and children are disproportionately affected.

Immediate crop sales after harvest have been used as a strategy by farmers to reduce postharvest loses during storage. A strategy that reduces farmer incomes due to depressed prices that characterise harvest periods. Early sales may also be occasioned by household financial demands to settle school and health related issues/emergencies. The downside of early sales is the fact that farmers purchase the same food in local stores when their supplies run out but at higher prices, creating a vicious cycle of low incomes.

This study has found that combined use of simple and affordable post-harvest loss innovations like hermetic bags, tarpaulins and mechanised shellers can have significant impacts on reducing postharvest losses. Farmer training and awareness on postharvest handling while providing access to credit at favourable terms asa market regulation mechanism may address the problem of losses and farm incomes by minimizing the effects of early sales of produce.

This study also brings to the fore the issue of development interventions that are in harmony with the policy arena. For example, while development agents in our case were working hard to improve yields while managing post-harvest losses as a strategy to increase household incomes, a national trade policy banning the usual exports of maize to the neighbouring countries undermined such efforts. The depressed maize prices that followed coupled with oversupplied markets and more produce than anticipated increased overall losses for both the treatment and control households. The most important lesson here is about creating awareness on development initiatives by development partners while advising the policy maker on how policies could be supportive to the initiatives.

Further studies in this area could disaggregate farmers by gender either female or male farmers other than by female and male headed households for effective mainstreaming of gender issues in agriculture. This is pertinent especially for developing countries, where more women than men are employed in the smallholder agriculture sector.

Appendices

Appendix 1

DIFFERENCE-IN-DIFFERENCES ESTIMATION RESULTS

Number of observations in the DIFF-IN-DIFF: 848

	Before	After	
Control:	160	105	265
Treated:	219	364	583
	379	469	

Outcome var.	Overa~s	S. Err.	|t|	P>|t|
Before				
Control	194.741			
Treated	184.023			
Diff (T-C)	-10.718	94.488	-0.11	0.910
After				
Control	746.648			
Treated	462.326			
Diff (T-C)	-284.323	96.574	2.94	0.003***
Diff-in-Diff	-273.605	135.109	2.03	0.043**

R-square: 0.04

* Means and Standard Errors are estimated by linear regression

**Inference: *** p<0.01; ** p<0.05; * p<0.1

Appendix 2: Sample Balance

```
TWO-SAMPLE T TEST

Number of observations (baseline): 399
          Before        After
   Control: 180          -          180
   Treated: 219          -          219
            399          -

t-test at period = 0:
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Weighted Variable(s)	Mean Control	Mean Treated	Diff.	|t|	Pr(|T|>|t|)
Overall_loss	194.741	184.023	-10.718	0.25	0.8001
Size1	4.836	4.826	-0.010	0.06	0.9499
Educ1	2.210	2.210	-0.000	0.01	0.9955
lnharvest	7.981	8.032	0.051	0.39	0.6970
Overall_loss	194.741	184.023	-10.718	0.25	0.8001
employ	0.860	0.836	-0.025	0.66	0.5083

```
*** p<0.01; ** p<0.05; * p<0.1
Attention: option kernel weighs variables in cov(varlist)
Means and t-test are estimated by linear regression
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