

MWAPATA CAPACITY BUILDING SEMINAR: USING RCTs IN AGRICULTURAL DEVELOPMENT ECONOMICS

FEATURED STUDY:

Incentive Mechanisms for Smallholder Farmers to Exploit Price Arbitrage Opportunities for Grain Legumes: Experimental Evidence from Malawi.

By Tabitha C. Nindi March 18th, 2021



Office of Foreign Disaster Assistance



Acknowledgements

- Co-authors on the paper featured in today's presentation:
 - Dr. Jacob Ricker-Gilbert
 - Dr. Jonathan Bauchet

About me !!!

- **Research Background :** Research Fellow at the Centre for Innovation and Industrial Research (CIIR) under MUST.
- Extensive experience in econometric methods using observational data, running large RCTs, experimental auctions, and developing math programming models.
- **Research interests**: Poverty and rural development, agricultural technology and innovations, agricultural marketing, food security and food safety.
 - Today's paper- Smallholder farmers' post-harvest grain management decisions → Group storage as a grain storage commitment device.

Key discussion objectives

- 1. Introduction to RCTs basics
- 2. Use the featured paper to show how to navigate through administering RCTs in practice
- 3. Exposure to common issues and challenges of administering RCTs

Outline

- 1. Introduction to RCTs
 - Why RCTs
 - Clustered RCTs
 - When to use RCTs
- 2. Featured Study Motivations
 - Agricultural commodity price seasonality
 - Smallholders' "sell low and buy high" behavior
- 3. Literature and contributions
- 4. Research objectives
- 5. Methods
 - Study setting, sampling and randomization
 - Experimental design
 - Power calculations in practice
 - Data collection
 - Treatment effects estimation
- 6. Main Results of featured paper
- 7. Conclusions and Policy Implications

Why Randomized Control Trials?

The field of development economics has just been added to the list of Nobel prizes in 2019.

□Any guesses which research methods are accredited for these Nobel prizes???

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Randomized Control Trials

□ 3 Nobel prizes : Duflo ; Banerjee and Kremer for their use of RCTs in development economics

□YES! RCTs are currently big deal in development economics

Why Randomized Control Trials?

- RCTs involves comparison of intervention group(s) to control group
- □ at least 2 groups:-Featured paper had three intervention groups and a control group.
- Reliable way of estimating causal impact of interventions
- □Useful for project impact evaluations. ✓ Pilot project with plans for scale-up





Why Randomized Control Trials?

Given the set of RCT is **random assignment** of subjects to groups

□This helps to eliminate confounding factors by ensuring study groups are equalized.

Level of randomization could be at individual level or cluster level.

- ✓ Study setting
 - High likelihood of contamination
 - Inclusiveness for ethical reasons
- ✓ Data availability
 - Limited sampling frame at individual level
- ✓ Budget limitations



Clustered Randomized Control Trials

Featured paper in this seminar used a clustered RCT with 3 interventions.

✓ Random assignment was at farmer club

Clustered RCTs have their own complexities in terms of design and analysis

- 1. Requires more participants for a given statistical power
- 2. Need to factor intra-cluster correlation (ICC) in power calculations typically based on estimates from baseline study or literature.
- 3. Analysis requires clustering of std. errors as well since outcomes for subjects in same cluster may be correlated.



When are RCTs appropriate?

When we have SMART impacts i. e. Specific, Measurable, Achievable, Realistic, Timely.

✓Not appropriate for outcomes are hard to measure

- ✓Not suitable when quick answers are required
 - Exceptions depending on type of interventions and outcomes e. g. Food safety information RCT vs. WTP

□ Requires strategic planning as cannot be undertaken retrospectively

✓ Monitor control group for contamination

Require large samples-not suitable when have very low units of analysis limits achievement of randomization

Agricultural Commodity Price Seasonality in SSA

In SSA agricultural commodities, such as soybeans and groundnuts, often exhibit large seasonal price fluctuations that offer smallholders an opportunity to maximize their agricultural returns.

See Gilbert, Kaminski & Christiaensen, 2017; Burke et al. 2019; Kaminski, Christiaensen & Gilbert, 2014.

However, majority of smallholders in SSA are unable to capitalize on these price arbitrage opportunities.

In fact, smallholder farmers are often involved in what is considered "the selling low and buying high phenomenon" (Burke et al., 2019; Stephens and Barrett, 2011; Gabriel and Hundie, 2006).

Agricultural commodity price seasonality in SSA



- Average legume price changes after the onset of Harvest (April).
- Substantial increase in prices.

"Sell low and buy high" phenomenon



Source: MoAFS/FAO Data 2010-2017 and Malawi PICS Data

- Average legume price changes after the onset of Harvest (April).
- Substantial increase in prices.
- At baseline close to 62 % of respondents had their largest legume sales at harvest season (April-July).

"Sell low and buy high" phenomenon



Source: MoAFS/FAO Data 2010-2017 and Malawi PICS Data

- Average legume price changes after the onset of Harvest (April).
- Substantial increase in prices.
- At baseline close to 62 % of respondents had their largest legume sales at harvest season (April-July).
- About 72 % of respondents had the most purchases in lean season (December-March).

▶46% sell low-and buy-high





Research Question and Objective

What is the GAP?

Objectives:

- Estimate the impacts of an improved storage technology along with two storage commitment devices on smallholders' <u>legume</u> storage behavior.
- Estimate and compare impact of the two storage commitment devices on smallholders' legume storage behavior.

Impact evaluation for possible scale up

SMART Outcomes include quantity stored at harvest, weeks stored before largest sell, total sales, inventories, net sales (kgs), & net sales value(MK).

A clustered RCT with three storage interventions was implemented.

- \blacktriangleright Treatment 1 \rightarrow Storage technology
- > Treatment 2 \rightarrow Storage technology & storage commitment device at village level
- > Treatment $3 \rightarrow$ Storage technology & storage commitment device at community level

Study Setting, Sampling and Randomization

Target the central region of Malawi.

- Mchinji and Lilongwe districts.
- Predominately the major agricultural region in the country.

□Key producers of legumes e. g. soybeans, groundnuts.



Study setting, sampling and randomization

NASFAM STRUCTURE There is an active network of farmer organizations in • Up to 6 Assoc/ district Malawi. Association • 21 GACs /Assoc. on average • We worked with the • At community level **Group Action** National Smallholder Center (GAC) • 15 clubs/ GAC on average Farmers' Association of Malawi (NASFAM). • At village level Club • 10 farmers /Club on average □ It is the largest smallholder organization with over 43 associations across the At household level Farmer country.







Study setting, sampling and randomization

□All farmers were informed about the research surveys through NASFAM lead farmers in their villages.

During survey, 5 farmers per club were randomly selected regardless of club size or number of farmers in that club that showed up.

✓ Analysis uses sampling probability weights, and these are based on the inverse proportionality to probability of being sampled (Cameroon and Trivedi, 2005).

Treatment assignment at club level i. e. clubs randomly assigned to treatment or control groups.

Clustered RCT where study setting & budget played a role Inclusiveness , contamination, and ignoring already existing cluster would require stratification or making implausible assumptions about ICC



Experimental design: Interventions

1. Treatment 1 [PICS Only]

- a. Farmers received 2 PICS bags (100 kg each).
 - ✓ Trained how to use the bags.
 - ✓ Stored **at home**



2. Treatment 2 [PICS + Village group store]

- a. Farmers also received 2 PICS bags & training.
- b. Farmers stored in groups with their club within their village.
- c. Grain deposit and withdraw conditions agreed at club level.

- 3. Treatment 3 [PICS + Warehouse group store]
 - Farmers also received 2
 PICS bags & training.
 - b. Farmers stored in groups at centralized NASFAM warehouse in their community further way from home.
- More than 1 club stored at each warehouse and deposit & withdraw conditions were stricter and agreed upon at warehouse level.

Methods Experimental design: Interventions

Evaluate treatment effects (ITT) of our storage interventions.

□Outcomes: quantity stored at harvest, weeks stored before largest sell, total sales, inventories, net sales (kgs), & net sales value(MK).

Recruited 377 clubs based on minimum power calculation requirement of 75 clusters per group and 5 farmers per cluster for ICC of 0.1 and MDE of 0.33.



Sample size: power calculations in practice (Ex-ante)

The power of the design is the probability to reject the hypothesis of zero effect for

a given effect size and statistical significance level (Duflo et al ,2008).

 \rightarrow Ability to pick up or detect the impact of an intervention when its actually there

Power Formula (MDE):



Sample size: power calculations in practice (Ex-ante)

□What matters in common language:

- 1. Effect size/ MDE/ Cohen d
 - Need more power to be able to pick up a small effect/change
- 2. Sample size

Need more observation to be able to pick up a small effect/change

3. Variance

> Noisy outcomes require more power and more observations to be able to pick up a given effect

4. Proportion of sample in T vs. C

Unequal proportions require more power and more observations while equal proportions help to increase efficiency as they give equivalent distributions

5. Significance level

Sample size: Power calculations for clustered RCT (Ex-ante)

□For a given N we have less power when we randomize by cluster

(unless ICC is zero).

FICC is the proportion of total variation explained by the within cluster level variance

 \succ High ICC \rightarrow low **m** (observation per cluster) and large **M** (number of clusters per group)

□Number of cluster key determinant of power for clustered RCTs

	Effect Size Po	Significance Level ower	Variance
Power with clustering:	$\frac{EffectSize}{\sqrt{1+\rho(m-1)}} =$	$(t_{(1-\kappa)}+t_{\alpha})*\sqrt{\frac{P(1-\kappa)}{P(1-\kappa)}}$	$\frac{1}{(-P)} * \sqrt{\frac{\sigma^2}{N}}$
	ICC Average Cluster S	Proportion in Treatment	Sample Size

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Sample size: What you need for power calculations in practice (Ex-ante)

Example of clustered RCT as used in the featured paper

- a) Decide on number of treatments
- b) Get parameters required to calculate sample size:
 - 1. Set power (1-β), typically 0.8 or 0.9;
 - 2. Set Significance level or α typically α =0.05;
 - 3. Set allocation ratio or Proportion of Sample in T vs. C typically P=0.5;
 - 4. Set delta or effect size for T vs C based on at baseline or literature or national data
 - 5. Estimated mean of the outcome(s) at baseline or literature or national data
 - 6. Estimated std. Dev. of outcome(s) at baseline or literature or national data
 - 7. Estimated ICC or ρ at baseline or literature or national data
- c) Calculate sample size , resulting budget and adjust parameters accordingly

Power Calculations for the Group storage experiment (RCT1)

Parameter sources for the key outcomes

LSMS data 2016 for Mean and Variance of Outcomes			Module detail	Delta			
Legumes	Mean	Std dev.	ICC(village)	Source	Channa et al 2020	Burke et al 2019	Aggarwal et al 2018
Stored at Harvest(kg)	261	158	0.1	Ag Module I: I40 +I35	29% more	X	29 to 55
Storage length (Weeks)	11	8	0.0005	Ag module I: I24	Х	Х	4 weeks
Total Sale Revenue(MK)	159,600	78,530	0.1	Ag module I: I03	K30, 000 - K38, 000	K3,800-K13,500	10-15 %
Inventory	180	355	0.006	Ag Module I: I40	30% increase (223)	25% more inventory	Х
Net Sales (kg)	363	569	0.03	Ag Module I: I02	128-135	24 – 46 kg more	Х
Net Sales Value (MK)	125,150	94,150	0.04	Ag Module I: I02	50% (233)	Х	Х

Set parameter for calculations

Means and ICC at village (club) level from the World Bank agricultural household survey 2016

Key Outcomes	Mean	SE	ICC	SE (4 ICC)	Delta
Storage at harvest (kg)	261	158	0.12	0.028	25
Storage length (Weeks)	11	8	0.08	0.055	1
Sales revenues (MK)	159,600	78,530	0.0001	0.002	10,000

Methods Using Stata for power calculations 2 - Stata/SE 16.1 File Edit Data Graphics Statistics User Window Help 📑 🖹 🚔 📳 👁 • 🖬 • 💕 Variables Hist... **T 4** Time series . Bower, precision, and sample-size analysis power twomeans, cluster - Power analysis for a two-sample means test in a CRD 2 Multivariate time series . Kilter variabl Methods organized by: /__ 1 Filter methods here Main Table Graph Iteration 1985-2019 StataCorn LLC 1 1 1 Spatial autoregressive models Name -Correlations Statistics Compute * Accepts numlist (Examples 0 Hazard rates Longitudinal/panel data . • Test comparing two independent means ay Drive Effect size and experimental-group mean ANOVA (multiple means) # Command ation, Texas 77845 USA Special Multilevel mixed-effects models One sample Error probabilities PC https://www.stata.com There are no Survival analysis . Test comparing two independent means in a cluster randomized design 0.05 * Significance level 0.8 stata@stata.com Power ~ 00 items to show. -Odds ratio 01 (fax) Epidemiology and related Proportions R-squared Clusters Endogenous covariates ▶ 11 May 2021 Regression slope Specify the number of clusters Specify cluster sizes/sample sizes: Stata licens Standard deviations • CI for a two-means difference Serial numbe Survival rates Variances Group clusters Group cluster sizes Sample-selection models . Licensed t Outcome Hypothesis test Treatment effects 75 * Control * Control Confidence interval 75 * Experimental * Experimenta SEM (structural equation modeling) 1 Notes: Allow fractional numbers of clusters and sample size LCA (latent class analysis) [No Title 1 Uni advice. ,000; see help set_maxvar. Effect size 2. Max FMM (finite mixture models) Means Standard deviation and intraclass correlation IRT (item response theory) 276 * Control Common standard deviation Multivariate analysis 152 * Common value O Group standard deviations Survey data analysis . Lasso Meta-analysis 0.100 rho = 0.1 * Intraclass correlation Multiple imputation Estimated power Nonparametric analysis Specify varying cluster sizes Exact statistics . nower - 1 9999 Resampling . Power, precision, and sample size Sides Properties Two-sided test Bayesian analysis • \triangle < > Command Treat number lists in starred(*) options as paralle Postestimation ▲ Variables OK Cancel Submit Other . ? C 🖻 C:\Users\Tabitha\Documents

□Statistics → Power, precision and sample size → Means→ Two independent samples → Test for two independent means in a clustered randomized design

Using Stata for power calculations

	eration		
Compute:			* Accepts numlist (Example
Power		\sim	
Group-specific numbers of Control-group number of c Experimental-group numbe Group-specific cluster sizes Control-group cluster size Experimental-group cluster Power	clusters lusters er of clusters size	Specify cluster s Group cluster si	izes/sample sizes: Zes
Trect size and experimenta	al-group mean		
/5	Lontrol	5	* Control
75 * [Experimental	5	* Experimental
Effect size Means 276 20	* Control * Experimental ~	Standard devia Common s 152 Group stan	ation and intraclass correlation tandard deviation * Common value dard deviations * Control * Experimental
		0.1	* Intraclass correlation
Specify varying cluster * (sizes Coefficient of variation 1	for cluster sizes	* Intraclass correlation
Specify varying cluster Sides: Two-sided test Treat number lists in star	sizes Coefficient of variation 1 red(*) options as paralle	for cluster sizes	* Intraclass correlation

Getting MDE power twomeans 276, diff(20) sd(152) k1(75) k2(75) m1(5) m2(5) rho(0.1) ビ 🗄 🌒 🚪 👁 • 🖬 • 🖻 • 🖬 🛍 🔲 🔍 • 😣 Hist... **T 4 ×** Varia power twomeans 276, diff(20) sd(152) k1(75) k2(75) m1(5) m2(5) rho(0.1) 2 2 Filter command: Estimated power for a two-sample means test 1 Cluster randomized design, z test assuming sd1 = sd2 = sd 0 Ho: m2 = m1 versus Ha: m2 != m1 # Command Study parameters: 1 power t... alpha = 0.0500 delta = 20.0000 m1 = 276.0000 m2 = 296.0000 diff = 20.0000 sd = 152.0000 Cluster design: K1 = 75 K2 = 75 M1 = 5 M2 = 5 N1 = 375 N2 = 375 rho = 0.1000 Estimated power: power = 0.3312 ommand Prop MDE of 0.2 is small, 0.5 is Medium and 0.8 is large, Duflo et al 2007

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Using Stata for power calculations

<pre>Num</pre>	power twomeans, cluster - Power analysis for a two-	sample means test in a CRD - 🗆 🗙	Getting Delta	
<pre>"Accepts winks: of duties: George-specific number of duties: George-s</pre>	Main Table Graph Iteration			
Lobards point Automates of Custers Control spont mutuation of Custers Specify duster sizes Specify duster sizes Specify wing cluster sizes Specify wing cluste	Compute: Group-specific numbers of clusters	* Accepts numlist (Examples)	power twomeans 276, sd(150) k1(75) k2(75) m1(5) m2(5) rho(0.	1) power(0.8)
Understand Specify duster sizes	Group-specific numbers of clusters Control-group number of clusters Experimental-group number of clusters	0.8 * Power ~		
Interface Effect size Since Effect size Since Estimated experimental-group mean for a two-sample means test Curster assuming sizes Estimated experimental-group mean for a two-sample means test Estimated experimental-group mean for a two-sample means test Curster assuming size Estimated experimental-group mean for a two-sample means test Curster assuming size Estimated experimental-group mean for a two-sample means test Curster assuming size Standard deviation and intractass correlation Social deviations Social deviations Specify varying duster sizes Side: '' Control test sizes Specify varying duster sizes Side: '' control test sizes '' control test	Control-group cluster size Experimental-group cluster size Power	Specify cluster sizes/sample sizes:	Performing iteration	
Study fractional numbers of clusters and sample sizes Effect size Means 25 * Experimental 0 0 0 * Control 1 * Control 1 * Control 1 * Control * Con	Effect size and experimental-group mean	Group cluster sizes V	Estimated experimental-group mean for a two-sample means test Cluster randomized design, z test assuming sd1 = sd2 = sd Ho: m2 = m1 versus Ha: m2 != m1; m2 > m1	
Effect size Weans 276 • Control 1 • Common standard deviation 1 • Common standard deviation 1 • Common standard deviation 1 • Control • Experimental • Control • Experimental • Control • Experimental • Control • Control • Control<	Allow fractional numbers of clusters and sample size	5 * Experimental	Study parameters:	
Treat number lists in starred(*) options as parallel	Effect size Means 276 * Control 25 * Experimental ~ Specify varying cluster sizes * Coefficient of variation for cluster Sides: Two-sided test ~	Standard deviation and intraclass correlation Common standard deviation Common standard deviations Control * Control * Experimental 0.1 * Intraclass correlation uster sizes	<pre>alpha = 0.0500 power = 0.8000 m1 = 276.0000 sd = 150.0000 Cluster design:</pre>	
	Treat number lists in starred(*) options as parallel			
OK Cancel Submit		OK Cancel Submit	Command 4	24

Data collection and follow-ups

Baseline study was conducted April-May of 2018 using a structured & pre-tested questionnaire.

≻Our sample has 1736 legume farmers.

This was followed by implementation of the storage interventions.

□Follow-up data collected after every 4 months → collecting data on outcome variables in August 2018; December 2018.

Following estimation framework by Burke et al. (2019), evaluate variations in treatment effects across quarters.

►Increase statistical power.

Data collection and follow-ups

Baseline Balance : Did randomization work?

□No difference in observable at baseline across groups

□Joint orthogonality test using multinomial probit suggests variables are balanced across groups at baseline (F=125; p=0.1258).

Treatment effects

□Intention to Treat effects (ITT) –effect of treatment **assignment** i. e. for everyone regardless of compliance status

□Average Treatment effect (ATE) – effect of treatment for everyone

□Local Average Treatment effect – for compliers only

Treatment effects estimation

□We use ANCOVA to estimate intention to treat (ITT) effects on outcomes of interest. Aggregate Effects:

 $y_{ij} = \alpha + \beta PICS_j + \lambda Villagestore_j + \rho Warehousestore_j + \gamma A_j + \partial Q_{ij} + \delta y o_{ij} + \varepsilon_{ij}$ (1) Quarterly Effects:

$$y_{ijt} = \alpha + \sum_{d=2}^{d=3} \beta_d Q_{djt} * PICS_{jt} + \sum_{d=2}^{d=3} \lambda_d Q_{djt} * Villagestore_{jt} + \sum_{d=2}^{d=3} \rho_d Q_{dijt} * Warehousestore_{jt} + \sum_{d=2}^{d=3} \partial_d Q_{dijt} + \gamma A_{jt} + \delta y o_{ij(t-1)} + \varepsilon_{ijt}$$

$$(2)$$

 $> y_{ij}$ is observed outcome; *PICS_j*, *Villagestore_j* and *Warehousestore_j* are binary variables =1 if household received Treatment 1, 2 & 3 respectively for *i*=1,2,..., *n* farmers in club *j*.

 $> yo_{ij(t-1)}$ is the baseline (lagged) outcome value for ANCOVA analysis, $A_{jt} \& Q_{d_{ijt}}$ are a set of association & period dummy variables respectively and our standard errors clustered at club level.

Treatment effects estimation : Common Issues of concern for RCTs

1. Compliance Rate

- □Not all treated households complied with treatment interventions.
- Example of credit intervention RCT with zero take up rate

2. Multiple Hypothesis Testing

- Deal with p-hacking or familywise error rate if you have multiple hypothesis
- Our results are robust even after adjusting for multiple hypothesis testing using Andersons' sharpened q-values.



Take-up Rate by Treatment Group

Treatment effects estimation : Issues of concern for RCTs

3. Attrition

 \Box Attrition at 7% & 14% for 1st and 2nd follow-up surveys, respectively.

Results suggest attrition is not random & we account for it in our analysis.

Variables	Overall rate	Control	PICS Only	Village	Warehouse	p-values
				program	program	
Follow-up 1 Attrition	7% (127 households)	2.5%	1%	2%	1.5%	0.0057
Follow-up 2 Attrition	14% (236 households)	6%	2%	3%	3%	0.4111

Treatment effects estimation : Issues of concern for RCTs

4. Contamination

Contamination	Percent of sample in control group	
Number that Purchase PICS bags	2% (12 households)	
Number that used PICS to store legumes	0.18% (1 household)	
Number that stored legumes in groups	0	
Number that stored legumes in warehouse	0	

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Storage at harvest(kg)		Weeks stor	Weeks stored largest sale		(MK)
=1 for PICS only (T1)	32*	34*	1.7*	1.5*	20,919*	23,161**
	(19)	(19)	(0.9)	(0.9)	(11,806)	(11,528)
=1 for PICS+ Village group store (T2)	73***	74***	2.5***	2.4***	28,442**	30,073***
	(20)	(19)	(0.9)	(0.9)	(11,671)	(11,440)
=1 for PICS+ Warehouse group store (T3)	42**	42**	1.8*	1.8*	23,849*	23,763*
	(18)	(18)	(1.0)	(1.0)	(13,632)	(13,280)
Constant	78	62	10.0***	10.4***	107,218***	120,080***
	(51)	(56)	(1.9)	(1.9)	(15,872)	(17,016)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	1,358	1,358	1,358	1,358	1,358	1,358
R-squared	0.01	0.01	0.10	0.13	0.06	0.06
F-Test	P-value	P-value	P-value	P-value	P-value	P-value
Treatment 1=Treatment 2	0.0412	0.0425	0.3912	0.3505	0.5268	0.5537
Treatment 1=Treatment 3	0.5932	0.6386	0.9667	0.8812	0.8270	0.9636
Treatment 2=Treatment 3	0.0930	0.0908	0.4344	0.4572	0.7444	0.6404

Note: Standard errors clustered at club level in parentheses ; *** p<0.01, ** p<0.05, * p<0.1 & US\$1=MK750

Main Results

Table 1.2: Quarterly Treatment Effects on Key Outcomes(ITT)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Legume invo	entories at end	Net legum	Net legume sales(kg) Net value of sales (N		
	of qua	rter (kg)				
Panel A: Four months after harvest season	, August 2018 (Quarter 2)				
PICS only (T1)	0.3	2.1	26.8***	27.7***	7,854***	7,847***
	(18.9)	(18.5)	(3.6)	(3.7)	(1,125)	(1,186)
PICS+ Group store at village (T2)	45.5**	47.4**	42.0***	42.7***	12,395***	12,422***
	(21.4)	(21.0)	(1.8)	(1.9)	(583)	(641)
PICS+ Group store at warehouse (T3)	42.6*	45.3*	32.2***	33.1***	9,677***	9,801***
	(23.7)	(23.7)	(2.6)	(2.8)	(907)	(928)
Constant	60.7***	31.2*	5.5*	-1.3	838	-1,490
	(15.5)	(16.9)	(2.8)	(4.9)	(853)	(1,562)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	3,114	3,114	3,114	3,114	3,114	3,114
R-squared	0.01	0.01	0.10	0.11	0.09	0.09
Treatment 1=Treatment 2	0.0177	0.0191	<0.001	0.0001	0.8304	0.8237
Treatment 1=Treatment 3	0.0476	0.0437	0.2000	0.2067	0.7537	0.7202
Treatment 2=Treatment 3	0.9203	0.9557	0.0001	0.0001	0.9349	0.9112

Note: Standard errors clustered at club level in parentheses ; *** p<0.01, ** p<0.05, * p<0.1 & US\$1-MK750

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	(1)	(2)	(3)	(4)	(5)	(6)		
VARIABLES	Legume inventories at end of quarter (kg)		Net legume	Net legume sales(kg)		Net value of sales (MK)		
Panel B: Eight months after harvest s	eason, Decem	ber 2018 (Qua	arter 3)					
PICS only (T1)	17.5	19.1	18.7	19.6	7,138*	7,087*		
	(14.7)	(14.5)	(12.9)	(12.8)	(4,150)	(4,116)		
ICS+ Group store at village (T2)	25.6*	26.9**	27.0*	27.7*	9,214**	9,164*		
	(13.2)	(13.0)	(14.9)	(15.0)	(4,684)	(4,712)		
ICS+ Group store at warehouse (T3)	0.3	2.5	5.3	6.1	4,301	4,351		
	(10.3)	(10.1)	(12.3)	(12.2)	(4,279)	(4,297)		
onstant	60.6***	31.2*	5.5*	-1.3	838	-1,490		
	(15.5)	(16.9)	(2.8)	(4.8)	(853)	(1,562)		
aseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes		
ssociation controls	No	Yes	No	Yes	No	Yes		
bservations	3,114	3,114	3,114	3,114	3,114	3,114		
-squared	0.01	0.01	0.10	0.11	0.09	0.09		
reatment 1=Treatment 2	0.5464	0.6290	0.4140	0.4167	0.3276	0.3294		
reatment 1=Treatment 3	0.2565	0.2355	0.1643	0.1606	0.7928	0.8025		
reatment 2=Treatment 3	0.0402	0.0506	0.0461	0.0464	0.2279	0.2358		

		(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Storage at	harvest(kg)	Weeks store	ed before largest sale	Sales revenue	e(MK)
=1 for participation in T1		36*	37*	1.9*	1.7*	23,156*	25,250**
		(21)	(20)	(1.0)	(1.0)	(12,870)	(12,461)
=1 for participation in T2		105***	105***	3.5***	3.4**	40,594**	42,690***
		(27)	(27)	(1.3)	(1.3)	(16,520)	(16,058)
=1 participation in T3		67**	67**	2.9*	2.9*	38,114*	37,925*
		(28)	(28)	(1.5)	(1.5)	(21,732)	(21,199)
Constant		116**	101**	11.3***	11.8***	123,146***	137,094***
		(47)	(50)	(1.7)	(1.7)	(12,690)	(14,721)
Baseline outcome control		Yes	Yes	Yes	Yes	Yes	Yes
Association controls		No	Yes	No	Yes	No	Yes
Observations		1,358	1,358	1,358	1,358	1,358	1,358
R-squared		0.06	0.07	0.01	0.01	0.01	0.01
F-Test		P-value	P-value	P-value	P-value	P-value	P-value
Treatment 1=Treatment 2	\bigcap	0.0067	0.0066	0.1809	0.1602	0.2442	0.2334
Treatment 1=Treatment 3		0.2042	0.2120	0.5346	0.4737	0.4535	0.5205
Treatment 2=Treatment 3	l	0.1642	0.1686	0.5908	0.6216	0.9123	0.8221

Note: Standard errors clustered at club level in parentheses ; *** p<0.01, ** p<0.05, * p<0.1 & US\$1=MK750

Conclusions and Policy Implications

□All three storage interventions significantly helped treated farmers to:

✓ Store more legumes at harvest (34 to 74 kgs),

- \checkmark Store longer (1 to 2 weeks) as well as
- ✓ Make more revenue from legume sales (MK22,000 to MK29,000; US\$1=MK750) compared to control households.

Out of the two storage commitment devices, the village storage program was relatively more effective at incentivizing farmers to store more at harvest compared to warehouse storage program.

□LATE estimates suggest that this is influenced by the low take-up rate in the warehouse storage program due to

□Transportation costs

Limited desire to store with a larger group outside the farmers' village.

Conclusions and Policy Implications

□ This essay estimates the impacts of storage and commitment constraints and findings provide empirical evidence on the effectiveness of the three storage interventions implemented in this study.

➢ Guide for policy, development agencies and NGO interested in helping farmers exploit intertemporal price arbitrage opportunities.

□Findings also help provide empirical estimates of the impacts and effectiveness of warehouse programs such as WRS and village grain banks for smallholders in developing countries.

Provides insights on viability of warehouse programs suggesting that incentivizing farmers to store together locally within villages may be more effective than centralized warehouse programs. □We acknowledge funding support from the United States Office of Foreign Disaster Assistance under agreement AID-OFDA-G-17-00250

□ The project title was "Increasing Smallholder Malawian Farmers' Access to Improved Storage Technology and Credit"





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