The effects of improved on-farm storage on food price in local markets - Experimental evidence from Tanzania

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Abstract

Seasonal food price gaps, which are the differences between the highest and lowest prices in a harvest cycle, have important welfare consequences in Sub-Saharan Africa. In a region where income from agricultural production and expenditure for food both have considerable shares in household's budgets, poverty and food security are closely linked to food prices and their seasonal changes. The extent of seasonal price gaps in the region suggest that intertemporal arbitrage is constrained. This paper argues that high post-harvest losses during storage limit farmer's intertemporal arbitrage, and thereby contribute to seasonal price gaps. The argument is tested by randomly allocating an improved on-farm storage technology to smallholder farmers groups in two districts of Tanzania. The technology, hermetic storage bags, can minimize storage losses even under extended periods of storage. Local market prices are tracked on a weekly frequency over the course of two harvest cycles. The results document significant effects of improved on-farm storage on local market prices in both harvest cycles, with most pronounced effects in the lean season, the time shortly before a new harvest is brought in. The results further show a significant reduction of seasonal food price gaps in the first harvest cycle by 16%, as well as in the second harvest cycle (albeit not significantly so in the second cycle). The results suggest that the absence of suitable storage technologies is an important limiting factor for smallholder farmers to make use of intertemporal arbitrage opportunities. The results thus highlight the need to consider improved on-farm storage as policy and development option to counter seasonal food price gaps and their adverse effects on poverty and food security.

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1 Introduction

Seasonal fluctuations of food prices have been shown to have adverse effects on poverty and food security in Sub-Saharan Africa, particularly in rural areas (e.g. Bellemare, Barrett, & Just, 2013; Dercon & Krishnan, 2000; Kaminski et al., 2016). Income from agricultural production constitutes about two thirds of the total income of the average rural household in the region (Davis, Di Giuseppe, & Zezza, 2017). Yet, rural households also spend an estimated two-thirds of their total income on food purchases (Mulangu, Chauvin, & Porto, 2012), as self-produced food crops do not cover the food needs of most households throughout a harvest year (Frelat et al., 2015). The implication is that rural households' income and the ability to access food on the markets are intrinsically linked to food prices and their seasonal changes.

As production is cyclical in the mostly rain-fed agriculture in the region, food prices fluctuate with harvest seasonality. The associated seasonal price gaps, which are the differences between the highest and lowest prices for a given market in a harvest cycle, are substantial (e.g., Gilbert, Christiaensen, & Kaminski, 2017). Among staple crops, seasonal price gaps are most pronounced for maize at 33% on average, as reported in a comparison of seven African countries, which is more than two and a half percent larger than in international reference markets (Gilbert et al., 2017). The extent of price seasonality in Sub-Saharan Africa for a storable crop like maize suggests that market participants have limited prospects to exploit intertemporal arbitrage opportunities.

The literature has attributed these arbitrage constraints and the resulting price seasonality to the selling and buying behaviour of rural households (e.g. Kadjo, Ricker-Gilbert, Abdoulaye, Shively, & Baco, 2018; Burke, Bergquist, & Miguel, 2019; Fink, Kelsey, & Felix, 2018; Dillon, 2017; Stephens & Barrett, 2011; Basu & Wong, 2015). Households tend to sell the majority of their produce soon after harvest and only keep a small amount in own stock. When their stocks are used up later in the season, they buy back food for household consumption. The resulting excess supply at harvest time leads to price reductions, and higher demand in the lean season increases prices, thus explaining high seasonal price gaps. Several studies have aimed at linking such behaviour to credit and liquidity constraints at harvest time. The empirical evidence suggests that credit and liquidity constraints are indeed conducive to early sales after harvest as farmers seek to cater for immediate cash need, such as payments for school fees (e.g. Kadjo et al., 2018; Dillon, 2017, among others).

However, the only experimental study testing whether these effects actually lead to market prices changes finds mixed results (Burke et al., 2019). Their results show that providing smallholder farmers in Kenya with credit at harvest time reduces early sales at low prices and likewise decreases purchases at high prices in the lean season. While the study shows statistically significant market price increases at harvest time, the results neither show significant price effects as the season progress, nor for the lean season. Likewise, an increase of storage levels is only observed early in the season, and not for the lean season.

This paper argues that high post-harvest losses during storage explain why farmers intertemporal arbitrage is constrained. Even in the absence of liquidity and credit constraints, farmers have little incentive to store for extended periods of time if they expect substantial storage losses. In the case of maize, for example, these post-harvest losses are estimated at 25.6% on average in Sub-Saharan Africa (Affognon, Mutungi, Sanginga, & Borgemeister, 2015). Without suitable storage options, incurred storage losses represent storage costs for farmers, which progressively increase with storage duration. It is hence argued here that post-harvest losses during storage are a constraint for smallholder farmer's intertemporal arbitrage and thereby contribute to seasonal food price gaps.

The argument is tested by randomly allocating a simple improved storage technology to smallholder farmers in Tanzania, clustered in 62 farmers groups, and by measuring their local market prices for maize with a weekly frequency, during one full harvest cycle. The technology, hermetic storage bags, limits atmospheric oxygen, which leads to desiccation of insects and pests that otherwise cause losses in stored grains (Murdock, Margam, Baoua, Balfe, & Shade, 2012). Hermetic storage bags are capable of substantially reducing post-harvest losses in extended periods of storage (e.g. Abass et al., 2018; Murdock et al., 2012; Groote et al., 2013; Baoua, Amadou, & Murdock, 2013; Chigoverah & Mvumi, 2016; Likhayo, Bruce, Mutambuki, Tefera, & Mueke, 2016). The hypothesis is that the improved storage technology results in additional demand for food stocks in times of decreasing prices, which buffers price dumps, and additional supply through the release of food stocks in times of increasing prices, which buffers price spikes. Taken together, the improved storage technology is expected to reduce the seasonal gap in food prices. The experiment is implemented in two districts of Tanzania, which diverge in the extent of market integration, and more pronounced effects are expected in the district with lesser market integration.

2 Storage, Post-Harvest Losses and Arbitrage in Local Food Markets

The conceptual framework for the argument in this paper builds on the model of competitive storage, first proposed by Gustafson (1958), formalized by Samuelson (1971) and Newbery and Stiglitz (1981), and empirically tested by Deaton and Laroque (1992, 1996; c.f. also Cafiero, E. S.A Bobenrieth H., J. R.A. Bobenrieth H., & Wright, 2011). The model proposes a simple logic, in that additional demand for stocks in times of decreasing prices reduces price dumps, and the release of supply stocks when prices are increasing, reduces price spikes. In developing country markets with ample seasonal price fluctuations, the benefits from intertemporal arbitrage through storage, would, in principle, be substantial. Yet, farmers do not appear to take advantage of it (e.g. Stephens & Barrett, 2011).

Post-harvest losses during storage limit farmers' possibilities for keeping stocks over an extended period of time in rural areas of developing countries. As many smallholder farmers rely on traditional storage methods, mainly polypropylene bags, which are highly prone to insect attacks, large losses occur (for a meta-analysis, see Affognon et al., 2015). For example, in Kenya, experimental evidence shows that maize stored in common polypropylene bags without chemical protectants, is around 2.6-2.8% after 3 months of storage, 10-15% after 6 months of storage, and 30% after 9 months of storage (Likhayo et al., 2016). In the study population, post-harvest losses are similarly high, estimated at around 30% of the harvest on an average, per year, based on farmer self-assessments (c.f. Brander, Bernauer, & Huss, 2019).

Considering this scenario, it is not rational for farmers to store for 9 months until the lean season, unless they expect maize prices to increase by more than 45% plus direct storage, capital and opportunity costs. It is hence argued here that high post-harvest losses impose substantial costs on storage, and limit farmer's ability to arbitrage price fluctuations.

What would be the expected effects of reduced storage losses for falling or decreasing markets? Consider the stylized example of two markets, one with a storage technology that limits storage losses, and one with a technology where high losses occur. Higher losses lead to a relative increase of storage costs, all else equal. When market prices are falling, all market participants are expected to increase their stocks, yet a higher increase is anticipated in the market with improved storage technology due to lower storage costs. The higher stock demand is expected to lead to a relative increase of prices in the market with improved storage, as compared to the market with high storage losses. When prices increase, market participants release their stocks again to arbitrage on the price change. As stocks are higher in the market with improved storage, so is the additional market supply, which is expected to lead to lower prices as compared to prices in the market without improved storage.

Taken together, in falling markets, an improved storage technology is expected to result in higher prices, whereas in increasing markets, it is expected to result in lower prices, relative to the control condition. These effects are anticipated to reduce the seasonal price gap, i.e. the difference between the highest and lowest prices for a given market in a harvest cycle. Moreover, more elastic supply and demand should also have implications for food price volatility; a reduction of price volatility is anticipated.

3 Methods

The effects of improved on-farm storage on local market prices are tested in a matched-pair cluster-randomized control trial, implemented in two districts of Tanzania with 1'023 participating households, clustered in 62 farmers groups, matched in 31 pairs.

3.1 Experimental Setting

In Tanzania, production and consumption are dispersed over widespread markets, and distance and limited transport infrastructure leads to high transaction costs for trade between markets, which also applies to many other developing countries (Mitra & Boussard, 2012, p. 3). Such markets are termed here "segmented markets" as high transaction costs lead to a more independent development of supply and demand, and corresponding prices, compared to well-integrated markets. Due to their limited scope, segmented, local markets provide an avenue to experimentally test the effect of an intervention for improved on-farm storage on local prices.

Two districts with segmented markets in Tanzania are selected for the experiment, both of which are characterized by similar seasonal patterns of production and consumption, and maize is the staple crop in each district. While one of the two study districts, Kilosa, has higher agricultural productivity and is better integrated in domestic and international markets due to its proximity to the main ports and trading hubs, such as Dar es Salaam, the second district, Kondoa, has less productivity and is less integrated in domestic and international markets due to transport constraints and distances. Due to the scope of the experimental intervention, it is expected that the treatment effects are more pronounced in the district with more limited market integration, Kondoa. Figure SI-1 shows a map of the study areas.

3.2 Intervention

In recent years, hermetic storage bags were developed, which effectively reduce post-harvest losses, even under extended periods of storage in developing country field settings (e.g. Abass et al., 2018; Murdock et al., 2012; Groote et al., 2013; Baoua et al., 2013; Chigoverah & Mvumi, 2016; Likhayo et al., 2016). Hermetic storage bags limit atmospheric oxygen, which leads to desiccation of insects and pests that otherwise cause losses in stored grains (Murdock et al., 2012). Currently, the uptake of hermetic storage remains low in many developing countries, including Tanzania, as was confirmed in discussions with various actors in these markets.

The experimental design randomly allocated this improved on-farm storage technology to smallholder farmers, clustered in farmers groups. The hermetic storage bags used are of the brand Purdue Improved Crop Storage ("PICS"). The control farmers groups did not receive an intervention. Members of treatment farmers groups were allocated five hermetic storage bags per person with the capacity to store 500kg of maize in total, as well as a standardized training in their use. The experimental intervention was implemented from July to October 2017 by the NGO Helvetas Swiss Intercooperation.

3.3 Experimental Design

A matched-pair, cluster-randomized design is implemented to assess the effect of improved on-farm storage on market prices, following Imai, King and Nall (2009b). Pair-wise matching increases statistical efficiency, reduces potential bias, and yields more robust results (Imai et al., 2009b).

Random allocation was conducted at farmers group level, which form the clusters of this study. Based on a list of 70 farmers groups, established by Helvetas, 67 of these groups were successfully visited and recruited for the study by Sustainable Agriculture Tanzania, which is an NGO independent of Helvetas. All members of these farmers groups were eligible to participate. The three groups that were not met after two attempts, were located in Kondoa district. Furthermore, two groups were excluded as they had members participating in more than one of the selected farmers groups.

Pairs-wise matching was done using baseline variables for average distance to market, soil type, and a district dummy, as these variables were expected to correlate with future outcomes (c.f. Bruhn & McKenzie, 2009). Soil type and district dummy were necessary matches, whereas the average distance to market was matched through an "optimal greedy" algorithm using the R package "blockTools" (Moore & Schnakenberg). Subsequently, random allocation of clusters within each pair to treatment and control, respectively, was done through an automated random allocation, based on a random number seed.

3.4 Data collection

All data was collected through SMS-based mobile phone surveys to retrieve local market prices at weekly frequency. Participant's mobile phone numbers were registered during recruitment of study farmers groups.

The main outcome variable, local maize price, was measured through weekly surveys among the full sample of study participants. Every Wednesday at 1pm, study participants received an SMS survey asking about current market prices in their community. The survey was closed on each following Saturday at 23:59, local time.

Upon completion of a short survey, respondents received an airtime transfer (prepaid top-up) of 500 Tanzanian Shilling (approximately 0.2 USD to 0.25 USD, depending on the exchange rate during the observation period) to incentivize participation. Treatment and control group participants received equal pay-outs. In the observation period for this paper, the survey was implemented for 42 weeks, with an average of 428 households participating per week, yielding 18'007 price observations.

The question on local market prices was asked in Swahili, translated from the English version: "Currently, how much does it cost to buy 1 debe of local maize in your community? Reply with the price of 1 debe of local maize in Shillings" (Kwa sasa, debe moja la mahindi linauzwa kwa shilingi ngapi kwenye jamii yako? jibu bei ya debe moja la mahindi). A "debe" (plastic tin) is a local volume measure for maize, approximately 18 to 20kg (Coulter & Golob, 1992). Debe is the most common unit for retail purchases of maize on local markets and thereby reflects a consumer/retail price. For easier interpretation, the measure in debe is converted to units of 100kg of maize (size of bags), for most of the analysis in this paper, assuming an average weight of 19kg per debe.

Household storage levels were measured through quarterly surveys. The surveys on storage levels were open for completion for 7 days among the full sample of study participants, ensuring time-wise comparable measures between geographically dispersed farmers groups. The respective question posed to study participant was: "What is the exact number of debe of your own maize harvest that you have in storage? Reply with the number of debe." (Taja kiasi kamili cha debe za mahindi uliyovuna mwenyewe yaliyopo katika hifadhi yako kwa sasa? Jibu idadi/jumla ya debe).

Due to the nature of the data collection via SMS survey, measurement errors need to be considered, which is done by excluding price observations that are more than two standard deviations different from the mean submission of their cluster in a given week. Storage outliers are removed, if measurements deviated more than one and a half times from the interquartile distance in a given quarterly survey.

3.5 Measurement

The observation period covers one full harvest cycle from mid-September 2017 until mid-July 2018. The beginning of the observation period is determined by the end of the harvest season in 2017, which was delayed due to adverse climatic conditions. The harvest in 2018 was brought in at a usual time and started in July.

Following the standard approach in the literature, the seasonal price gap is calculated as the difference between the highest and lowest monthly price for a given market in a harvest cycle (e.g., Gilbert et al., 2017),

$$Seasonal\ Price\ Gap = max\left(p_{s,m}\right) - min(p_{s,m}), \tag{1}$$

where $\mathrm{p}_{\mathrm{s,m}}$ denotes the natural logarithm of prices in season s and month m. To make the results comparable to the literature, monthly prices are used, calculated as the average of weekly prices per calendar month. Results based on weekly prices are presented for comparison.

Price volatility is estimated from the standard deviation of weekly returns, denoted by r_t, where returns are calculated as the difference between the natural logarithm of two consecutive prices. Furthermore, price volatility estimates, based on the standard deviation of monthly returns, is shown again for comparison with the literature (e.g. Minot, 2014). Specifically, volatility is calculated as

$$Price\ Volatility = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \bar{r})^2}\ , \tag{2}$$

$$\text{where } r_t = \ln(p_t) - \ln(p_{t-1}),$$

$$\text{and } \bar{r} = \frac{1}{T}\sum_{t=1}^{T} r_t\ .$$

The harvest cycle is divided into three periods of 14 weeks each for intraseasonal analysis. For the remainder of this paper, the first period is termed the “harvest season”, the second period is referred to as the “post-harvest season”, and the last period before the subsequent harvest is brought in, is termed the “lean season”.

3.6 Estimation

The intent-to-treat (ITT) effect is estimated for all outcome variables, which is the total effect of the treatment on outcomes of interest, irrespective of experimental compliance (Gerber & Green, 2012). In this regard, it is a conservative estimate of the treatment effect.

Following Imai, King and Nall (2009b), the ITT effect is estimated as the average of within-pair mean differences between treatment and control clusters. Their equal weighting approach, which gives each pair the same weight in the estimation, is used. As suggested by Hill and Scott (2009), these within-pair mean differences are estimated through a mixed-effects model, with random intercepts for each pair. This empirical set-up provides more flexibility in the estimation, but yields equal estimators, if clusters have equal weight, as compared to the original approach of Imai, King and Nall (c.f. the discussion in Imai, King, & Nall, 2009a).

The following specifications are considered. The mixed-effects model specification for observation i in cluster j, and pair k, is

$$Y_{ijk} = \tau T_{jk} + \alpha_k + \epsilon_{ijk}, \tag{3}$$

where τ, is the estimated treatment effect (ITT), T_{jk} is a cluster-level treatment dummy variable, and α_k are random intercepts, where $\alpha_k \sim \mathrm{N}(\alpha_0, \sigma_\alpha^2)$.

To estimate the ITT conditional on harvest year, an interaction between T_{jk} and $HarvestYear$ is included in the model specification in Equation 3, where $HarvestYear$ is a categorical variable indicating the number of harvest years since project start,

$$Y_{ijk} = \tau_1 T_{jk} + \gamma HarvestYear_t + \tau_2 (T_{jk} * HarvestYear_t) + \alpha_k + \epsilon_{ijk}, \tag{4}$$

where $\alpha_k \sim \mathrm{N}(\alpha_0, \sigma_\alpha^2)$.

To estimate effects on prices in intraseasonal time periods, an interaction between T_{jk} and a categorical variable $season$ is included in the model specification in Equation 3:

$$Y_{ijk} = \tau_1 T_{jk} + \gamma season + \tau_2 (T_{jk} * season) + \alpha_k + \epsilon_{ijk}, \tag{5}$$

and where $\alpha_k \sim \mathrm{N}(\alpha_0, \sigma_\alpha^2)$.

When the outcome variable is aggregated at cluster-level, i.e. price seasonality and price volatility, as well as for robustness checks, the mixed-effects model specification for cluster-level observation j, and pair k, is

$$Y_{jk} = \tau T_{jk} + \alpha_k + \epsilon_{jk}, \tag{6}$$

where τ, is the estimated treatment effect (ITT), T_{jk} is a cluster-level treatment dummy variable, and varying random intercepts α_k, where $\alpha_k \sim \mathrm{N}(\alpha_0, \sigma_\alpha^2)$.

For robustness checks for harvest year effects based on cluster-level mean prices, the interaction between T_{jk} and $HarvestYear$ is added to the model specification in Equation 6:

$$Y_{jk} = \tau_1 T_{jk} + \gamma HarvestYear_t + \tau_2 (T_{jk} * HarvestYear_t) + \alpha_k + \epsilon_{jk}, \tag{7}$$

where $\alpha_k \sim \mathrm{N}(\alpha_0, \sigma_\alpha^2)$.

For robustness checks for intraseasonal price effects based on cluster-level mean prices, the interaction between T_{jk} and $season$ is added to the model specification in Equation 6:

$$Y_{jk} = \tau_1 T_{jk} + \gamma season_t + \tau_2 (T_{jk} * season_t) + \alpha_k + \epsilon_{jk}, \qquad (6)$$

where $\alpha_k \sim \mathrm{N}(\alpha_0, \sigma_\alpha^2)$.

The mixed-effects models are estimated with the R-package “lme4” (Bates, Mächler, Bolker, & Walker, 2015).

4 Results

4.1 Price Trend in Observation Period

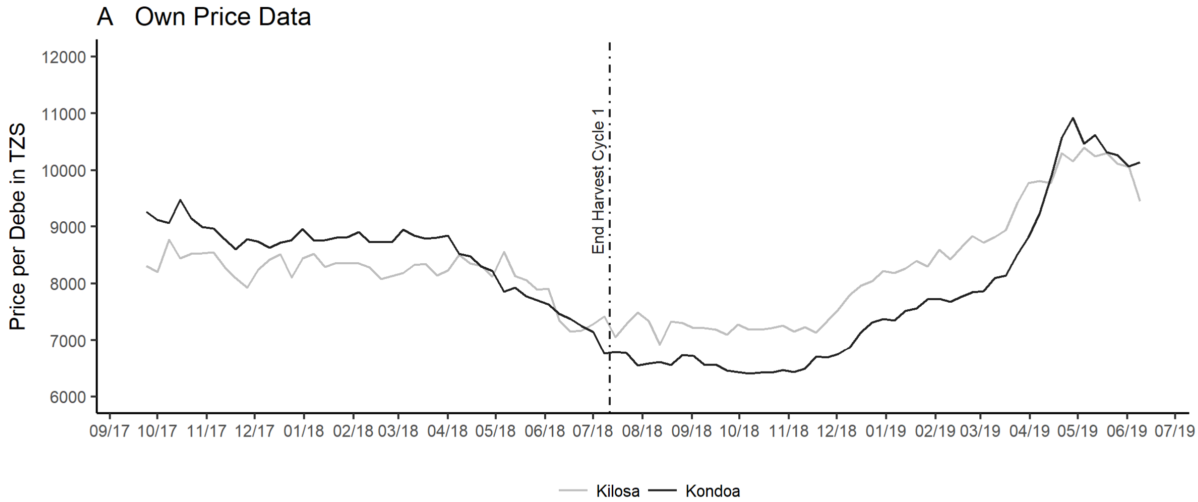
Figure 1 illustrates the price development in the two study districts during the observation period. In both districts, prices show similar trends.

In the harvest cycle of year one, market prices are higher at the beginning of the harvest cycle and then decrease sharply before levelling out again as the subsequent harvest is brought in (see Figure 1 where the end of the first year harvest cycle is represented by the vertical dashed line). Specifically, market prices have slightly decreased after the harvest until the end of the year, and substantially decreased from the second week of April until the next harvest – a time that represents the lean season. The price decrease is more pronounced in Kondoa, the less integrated markets, as compared to the more integrated markets in Kilosa. Decreasing price patterns are observed in the study regions in one out of four years, as anecdotal evidence, and price data from the World Food Programme suggests.[1] One plausible explanation for the decreasing price trend in first harvest cycle, are national trade policy interventions in Tanzania. From June 2017 until November 2017, the Tanzanian government had enacted an export ban for maize to counter high maize prices. While only small changes in prices are visible for the time when the ban was lifted in November, it is plausible that sales from accumulated private and national maize stocks in the months before the next harvest in July 2018, led to an outward shift of the supply curve, which could explain the sharp decrease of maize prices towards the end of the harvest cycle.

In contrast, prices in the second harvest cycle show an increasing trend after the harvest is brought in. Prices remain relatively stable in the months after harvest until December 2018, and then begin to increase strongly increase until the end of the observation period. The increase is more pronounced in the district of Kondoa as compared to Kilosa. **Data collection for this second harvest cycle is on-going, and this paper presents data collected until 9 June 2019.** The pattern of increasing prices after harvest is the more typical case, occurring in about three out of four years in the study regions. The price increase possibly reflects the expectation of a below-average 2019 harvest in Tanzania.

[1] See for example price data from World Food Programme (2019)

Figure 1: Market prices in the two study districts based on own weekly data



Notes: Maize prices per debe (approx. 19kg) in Tanzanian Shilling (TZS) for the two study districts based on own data, collected via SMS-based mobile phone surveys amongst study participants from the control groups (see Chapter 3.4). The grey lines show data for the Kilosa district. The black lines represent price data for the Kondoa district. Dashed vertical line shows the end of the first harvest cycle in the observation period. The second harvest cycle is not yet completed.

4.2 Effects of Treatment on Market Prices

For decreasing market prices, which corresponds to the first harvest cycle observed in this study, the expectation is that improved on-farm storage results in additional market demand, which leads to higher prices. In contrast, for a pattern of increasing market prices as observed in the second harvest cycle, the expectation is that the improved on-farm storage results in additional market supply through the release of stocks, leading to lower prices.

Figure 2 illustrates prices in treatment and control markets in the observation period, and Figure 3 shows differences between treatment and control prices. In the first harvest cycle from September 2017[2] until July 2018, prices are similar after harvest before prices in treatment markets increase relative to control a few months thereafter, particularly in the lean season of year one (grey shaded area). In the time of decreasing prices, treatment prices are higher than control prices, consistent with our hypothesis. As the second year's harvest is brought in (July 2018), prices stabilize again for a few months and then sharply increase in the post-harvest and lean seasons of year two. Again consistent with our hypothesis, for the second harvest cycle, the expected differences between treatment and control markets are observed. In this case, as prices overall increase, prices in the treatment markets decrease relative to control.

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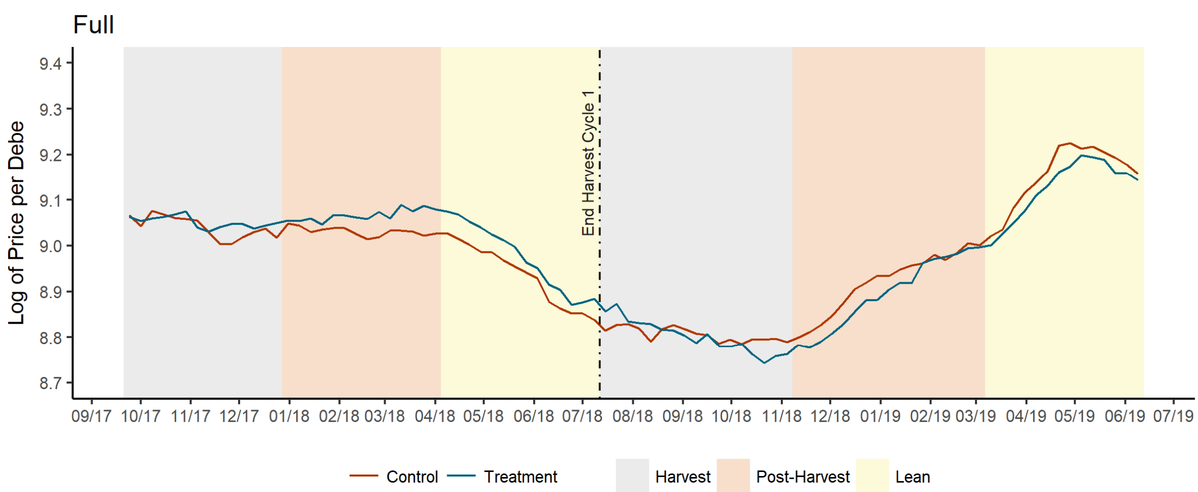
[2] The harvest season in year one was delayed due to adverse climatic conditions, while the harvest in year two was brought in at a usual time. In both districts, prices in markets treated with improved on-farm storage and control markets

These observations from visual inspections are mirrored in Table 1, which presents the results estimated based on Equation 4, outlined in Chapter 3.6. Column 1 shows the base model for the full observation period. In column 2, the positive coefficient for the variable Treat shows that in the first harvest year, prices in treatment markets were higher than in control markets. Prices in treatment markets were 2.9% higher than control market prices in the first harvest cycle, on average.[3] The interaction of the variable Treat with HarvestYear2, a dummy variable indicating observations in the second harvest cycle, shows a negative coefficient, i.e. lower prices in treatment as compared to control groups in the second harvest cycle. Prices in treatment markets in the second harvest cycle were 4.7% lower than control market prices. These effects are statistically significant at the 5% level. The treatment effects are robust to an alternative model specification where the dependent variable are cluster-level mean local maize prices per week (see Table SI-1).

One immediate implication of these results is that the markets in our study areas are indeed highly segmented as a limited intervention has market price effects. On-site visits have reinforced this impression as the communities in which study farmers groups are located are quite small and remote (around 50-100 households per community is a reasonable estimation).

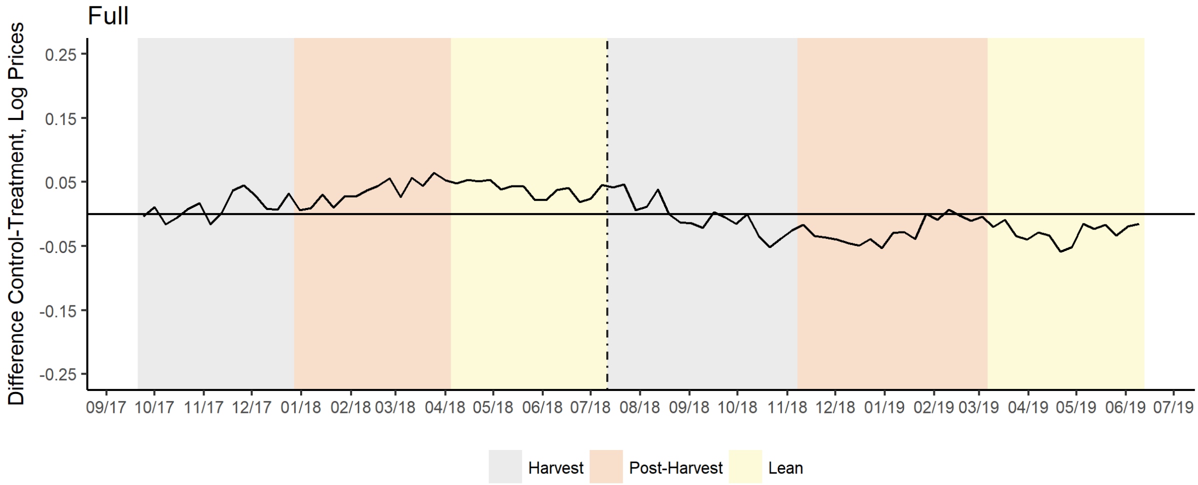
Figure 2: Development of market prices in experimental groups



Notes: Average of log local maize prices by treatment (blue line) and control (red line) groups. Calculations based on weighted observations, such that each cluster has equal weight. Colour background illustrates time periods where grey denotes harvest periods, red denotes post-harvest period, and yellow shows lean period. Black dotted line shows end of the first harvest cycle.

[3] Calculation example: ((exp(0.0287)-1)*100)

Figure 3: Difference of Market Prices between Experimental Groups



Notes: Difference of log local maize prices between treatment and control groups. Calculations based on weighted observations, such that each cluster has equal weight. Colour background illustrates time periods where grey denotes harvest periods, red denotes post-harvest period, and yellow shows lean period. Black dotted line shows end of the first harvest cycle.

Table 1: **Effects of treatment on market prices.** The dependent variable is the natural logarithm of local maize prices, measured weekly for the full observation period (Sept 2017-June 2019), through SMS-based mobile phone surveys amongst study participants. Treat is a cluster-level indicator for treatment assignment showing the intent-to-treat (ITT) effect. HarvestYear is a dummy variable indicating the second harvest year (from July 2018). Intercept shows estimates for the control group, and N/m is number of observations (N) and number of pairs (m). Square brackets show bootstrapped 95% confidence intervals based on 1000 replications drawing observations (N) with replacement. Model specification is a mixed-effects model where Pair, the categorical variable identifying matched pairs, is a random intercept (see Equation 4).

	Base Model **(1)**	Base Model with harvest year (2)	Base Model with district control (3)
(Intercept)	8.9703	8.9997	9.0020
	[8.9403, 8.9967]	[8.9734, 9.0293]	[8.9606, 9.0427]
Treat	0.0029	0.0287	0.0287
	[0.0008, 0.0051]	[0.0251, 0.0317]	[0.0257, 0.0319]
HarvestYear2		-0.0534	-0.0534
		[-0.0566, -0.0497]	[-0.0564, -0.0500]
Treat:HarvestYear2		-0.0473	-0.0473
		[-0.0518, -0.0430]	[-0.0514, -0.0429]
DistrictKondoa			-0.0048
			[-0.0621, 0.0524]
Obs. (N/m)	(41031/31)	(41031/31)	(41031/31)
R2 (total)	0.4301	0.4922	0.4922

4.3 Effects of Treatment on Prices in the Lean Season

The average treatment effects for the two harvest cycles are also mirrored in the results for the lean season. Specifically, the results show that the effect of improved on-farm storage on local market prices is highest in the lean season, which corresponds to the time period of strong price changes in both harvest cycles.

Table 2 reports estimates based on Equation 5 with sample splits for harvest cycle year one (Column 1-2) and harvest cycle year two (Columns 3-4). In the first harvest cycle, the harvest cycle with a pattern of overall decreasing prices, the intervention increased local market prices by 2.75% on average in the lean season relative to prices in the control markets (see Table 2, Column 2). In the second harvest cycle, the year of overall price increases, the intervention decreased lean season prices by 2.4% on average, relative to prices in the control markets (see Table 2, Column 4). The effects are statistically significant at the 5% level. The results are again robust to a model specification based on cluster-level mean prices (see Table SI-2).

Table 2: **Treatment effect on market prices, dependent on harvest, post-harvest and lean season.** The dependent variable is local maize price, measured weekly through SMS-based mobile phone surveys. Treat is a cluster-level indicator for treatment assignment showing the intent-to-treat (ITT) effect. Season is a categorical variable indicating price observations in the harvest, post-harvest and lean season. Intercept shows estimates for the control group in the harvest season, and N/m is number of observations (N) and number of pairs (m). Bootstrapped 95% confidence intervals based on 1000 replications are reported in square brackets. Model specification is a mixed-effects model where Pair, the categorical variable identifying matched pairs, is a random intercept (see Equation 5).

	Harvest Cycle Year 1		**Harvest Cycle Year 2**	
	Base Model (1)	Base Model with Seasons (2)	Base Model (3)	Base Model with Seasons (4)
(Intercept)	8.9963	9.0362	8.9457	8.8057
	[8.9635, 9.0252]	[9.0087, 9.0664]	[8.9110, 8.9850]	[8.7717, 8.8397]
Treat	0.0287	0.0111	-0.0186	-0.0043
	[0.0262, 0.0316]	[0.0065, 0.0157]	[-0.0219, -0.0154]	[-0.0087, 0.0007]
seasonPostHarvest		-0.0076		0.1142
		[-0.0126, -0.0024]		[0.1093, 0.1190]
seasonLean		-0.1013		0.3462
		[-0.1060, -0.0965]		[0.3407, 0.3518]
Treat:seasonPostHarvest		0.0241		-0.0210
		[0.0174, 0.0302]		[-0.0278, -0.0136]
Treat:seasonLean		0.0275		-0.0240
		[0.0210, 0.0339]		[-0.0309, -0.0167]
Obs. (N/m)	(18007/31)	(18007/31)	(23024/31)	(23024/31)
R2 (total)	0.5813	0.6327	0.4890	0.7754

4.4 Effects of Treatment on Seasonal Price Gap

The results show that the effects of improved on-farm storage on the seasonal price trend and on prices in the lean season, also translate into a reduction of the seasonal price gap, i.e. the difference between the highest and lowest monthly prices in the harvest cycle. In the observation period, the seasonal price gap is 33% on average, which is in line with estimates reported in the literature. Kaminski et al. (2016) find an average seasonal price gap of 27% for a 19-year observation period in Tanzania.

Table 3 presents estimates based on Equation 6. In the first harvest cycle, improved on-farm storage reduced the seasonal price gap by 5.1 percentage points (i.e. by 16 percent), on average. The reduction is statistically significant at the 5% level (see Table 3, Column 2). The results are robust when the seasonal price gap is calculated based on the difference between the highest and lowest weekly instead of monthly prices (see Table 3, Column 5). In the second harvest year, for which data collection is on-going, the treatment coefficient is again negative, yet not statistically significant.

It is notable that the estimated seasonal price gaps are higher when using weekly price data, as compared to averaged monthly prices. This points to the possibility that literature estimates on seasonal food price gaps, which are based on monthly data, may underestimate their extent.

Table 3: **Effect of treatment on seasonal price gap.** The dependent variable is the seasonal price gap, based on average monthly prices on the left-hand side, and, for comparison, based on weekly prices, on the right-hand side. Treat is a cluster-level indicator for treatment assignment showing the intent-to-treat (ITT) effect. Intercept shows estimates for the control group, and N/m is number of observations (N) and number of pairs (m). Square brackets show bootstrapped 90% and 95% confidence intervals based on 500 replications drawing observations (N, i.e. clusters) with replacement. Model specification is a mixed-effects model where Pair, the categorical variable identifying matched pairs, is a random intercept (see Equation 6).

	Based on Monthly Prices			**Based on Weekly Prices**		
	Full Observation Period (1)	Harvest Cycle Y1 (2)	Harvest Cycle Y2 (3)	Full Observation Period (4)	Harvest Cycle Y1 (5)	Harvest Cycle Y2 (6)
(Intercept)	0.5344	0.3299	0.5019	0.6496	0.4168	0.6244
Treat	-0.0276	-0.0516	-0.0240	-0.0371	-0.0544	-0.0421
CI 95 Treat	[-0.0914, 0.0360]	[-0.1046, -0.0057]	[-0.1011, 0.0469]	[-0.1038, 0.0321]	[-0.1102, 0.0072]	[-0.1060, 0.0246]
CI 90 Treat	[-0.0812, 0.0229]	[-0.0971, -0.0109]	[-0.0828, 0.0334]	[-0.0966, 0.0178]	[-0.1058, -0.0053]	[-0.0926, 0.0234]
N/m	62/31	62/31	62/31	62/31	62/31	62/31
R2 (total)	0.3421	0.1199	0.3007	0.3356	0.1738	0.3737

4.5 Effects of Treatment on Price Volatility

Turning to the effect of storage on price volatility, the results show that improved on-farm storage reduced price volatility over the course of the full observation period, as well as in the first harvest cycle.

In the full observation period, monthly maize price volatility is 0.090 and weekly price volatility is 0.068 in the study sample (see Table 4, Column 1-2). To provide some context, one of the few studies assessing food price volatility in Sub-Saharan African countries reports average maize price volatility of 0.114 from 2003-2006, and of 0.122 in the years 2007-2010, during the global food price spikes (Minot, 2014). They further estimate that price volatility in international markets was lower in these time periods (0.054 and 0.082, respectively). Their analysis is based on monthly price data. The comparison indicates that price volatility measured in the here presented paper is not particularly high.

For the full harvest cycle, the treatment reduced monthly price volatility from 0.090 to 0.081. The result is significant at the 10% level (see Table 4, Column 1, based on Equation 6). The results is only statistically significant for monthly price volatility in the full observation period. Additionally, the effect appears to be more pronounced in the first harvest cycle where the treatment reduced both monthly and weekly price volatility (Columns 2 & 5).

Table 4: **Effect of treatment on price volatility.** The dependent variable is weekly price volatility (Column 1,3,5), and monthly price volatility (Column 2,4,6), measured as the standard deviation of weekly and monthly returns, respectively, for each experimental cluster for the entire observation period (Column 1 & 2), and, for the harvest cycle in year one (Columns 3 & 4) and year two (Columns 5 & 6). Treat is a cluster-level indicator for treatment assignment showing the intent-to-treat (ITT) effect. Intercept shows estimates for the control group, and N/m is number of observations (N) and number of pairs (m). Square brackets show bootstrapped 95% confidence intervals based on 500 replications drawing observations (N, i.e. clusters) with replacement. Model specification is a mixed-effects model where pair, the categorical variable identifying matched pairs, is a random effect (see Equation 6).

	Based on Monthly Prices			**Based on Weekly Prices**		
	Full Observation Period (1)	Harvest Cycle Y1 (2)	Harvest Cycle Y2 (3)	Full Observation Period (4)	Harvest Cycle Y1 (5)	Harvest Cycle Y2 (6)
(Intercept)	0.0904	0.0765	0.0908	0.0686	0.0713	0.0635
Treat	-0.0099	-0.0141	-0.0032	-0.0044	-0.0126	0.0022
CI 95 Treat	[-0.0202, 0.0004]	[-0.0265, -0.0033]	[-0.0178, 0.0102]	[-0.0164, 0.0082]	[-0.0248, 0.0009]	[-0.0107, 0.0158]
CI 90 Treat	[-0.0186, -0.0017]	[-0.0247, -0.0046]	[-0.0143, 0.0076]	[-0.0151, 0.0056]	[-0.0238, -0.0019]	[-0.0080, 0.0156]
N/m	62/31	62/31	62/31	62/31	62/31	62/31
R2 (total)	0.2348	0.3839	0.1907	0.2896	0.4010	0.1937

5 Discussion and Conclusion

This is the first paper to empirically document that improved on-farm storage can affect local markets in segmented markets and reduce seasonal price gaps. In contrast to existing empirical work, the results suggest that the absence of suitable storage technologies are an important limiting factor for smallholder farmers to make use of intertemporal arbitrage opportunities.

Prior empirical work focused on liquidity constraints to arbitrage. The one empirical study assessing the effects of a credit intervention on local market prices only shows significant effects on harvest time prices (Burke et al., 2019). However, their study finds no effect for the seasonal price trend or for lean season prices. Although post-harvest storage losses would be consistent with these findings, Burke et al. (2019) state that "it appears unlikely that storage is constrained by either the fixed or marginal costs of storing additional bags, nor by grain losses due to moisture or pests when grain is stored for many months" (p. 796). In stark contrast, this paper finds that an intervention to improve on-farm storage has significant effects on seasonal prices and on prices in the lean season.

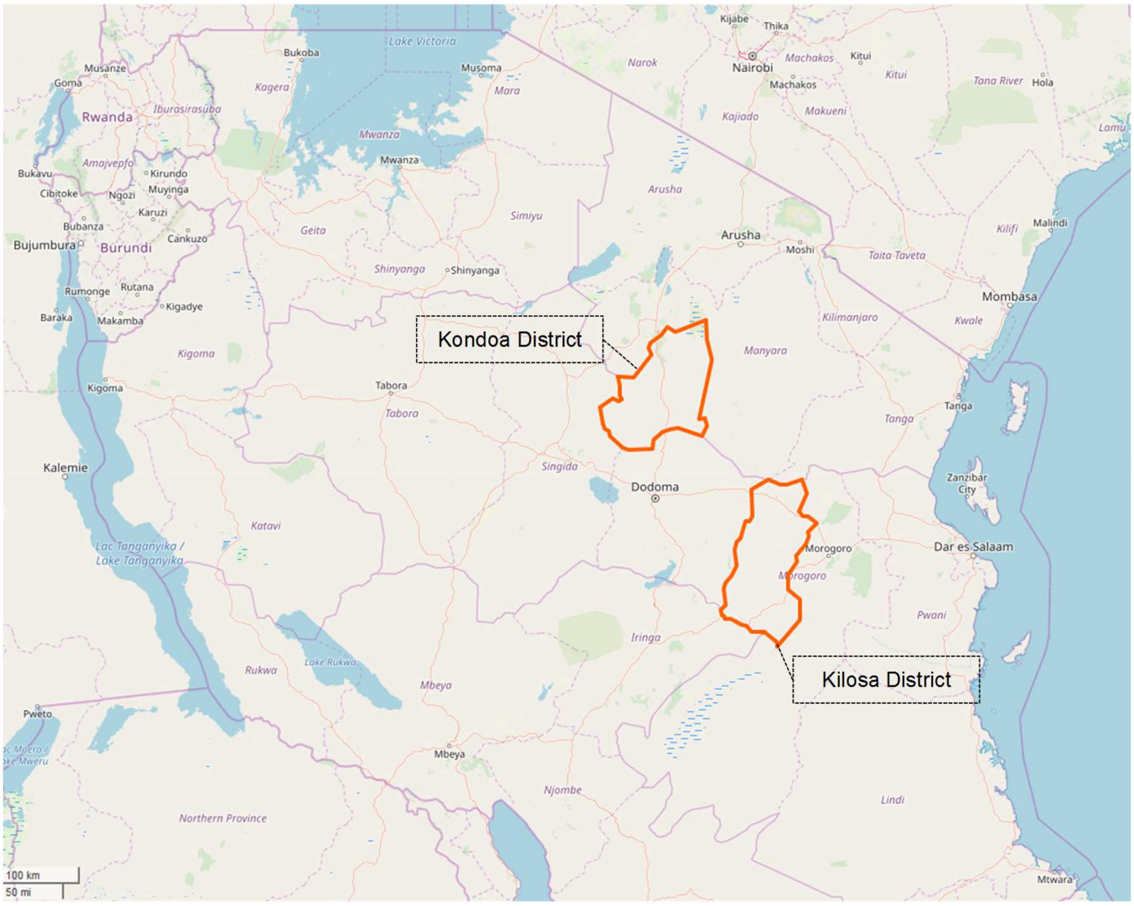
This paper has further demonstrated the benefits and feasibility of collecting weekly price data from remote rural areas via mobile-phone based SMS surveys. Collecting the price dataset at hand would not have been feasible with traditional modes of data collection. However, despite the high frequency of the data collected, the results presented in this paper are clearly limited by a short observation period of one harvest cycle and the rather narrow geographic focus. It remains to be assessed whether the reduction of the seasonal price gap shown here can be generalized to a situation of increasing market prices, and in other geographic locations, which is left open for future research.

These limitations notwithstanding, the here presented results suggest that it is premature to disregard the role of improved on-farm storage as an option to reduce seasonal price gaps and their adverse effects on poverty and food consumption (e.g. Bellemare, Barrett, & Just, 2013; Dercon & Krishnan, 2000; Kaminski et al., 2016). This adds to growing evidence on the direct welfare benefits of improved on-farm storage for adopting farming households, particularly food security (e.g., Brander et al., 2019; Tesfaye & Tirivayi, 2018; Gitonga, Groote, Kassie, & Tefera, 2013; Bokusheva et al., 2012). The promotion of improved on-farm storage may hence present a policy option for developing countries to contribute to more stable food prices in local markets and to further farming household's food security. Specifically, import duties and value added taxes currently levied on hermetic storage technologies could be adjusted to match the preferential rules commonly applied to agricultural production inputs, such as seeds and fertilizers, in Sub-Saharan Africa.

Taken together, the results reinforce the call to consider the promotion of improved on-farm storage as a policy and development option not only to further year-round food security, but also to reduce the seasonality of food prices. These results are of high relevance as the world strives to achieve the goals of the 2030 Agenda for Sustainable Development to eliminate hunger and poverty.

Supplementary Information

Figure SI-1: Map of Study Areas in Tanzania



Notes: Figure shows the two study districts in Tanzania. Upper shape shows the administrative district boundaries for Kondoa, the less integrated markets, and lower shape shows the district boundaries of Kilosa, the more integrated market. Source of geographic data: https://www.openstreetmap.org

Table SI-5: **Effects of treatment on market prices – based on cluster-level mean prices.** The dependent variable is mean weekly maize prices per experimental cluster, measured for the full observation period (Sept 2017-June 2019), through SMS-based mobile phone surveys amongst study participants. Treat is a cluster-level indicator for treatment assignment showing the intent-to-treat (ITT) effect. HarvestYear is a dummy variable indicating the second harvest year (from July 2018). Intercept shows estimates for the control group, and N/m is number of observations (N) and number of pairs (m). Square brackets show bootstrapped 95% confidence intervals based on 1000 replications drawing observations (N) with replacement. Model specification is a mixed-effects model where Pair, the categorical variable identifying matched pairs, is a random intercept (see Equation 7).

	Base Model **(1)**	Base Model with harvest year (2)	Base Model with district control (3)
(Intercept)	8.9704	8.9997	9.0020
	[8.9399, 8.9974]	[8.9699, 9.0303]	[8.9642, 9.0442]
Treat	0.0029	0.0287	0.0287
	[-0.0062, 0.0127]	[0.0155, 0.0414]	[0.0143, 0.0435]
HarvestYear2		-0.0534	-0.0534
		[-0.0667, -0.0402]	[-0.0677, -0.0394]
Treat:HarvestYear2		-0.0473	-0.0473
		[-0.0660, -0.0291]	[-0.0664, -0.0270]
DistrictKondoa			-0.0048
			[-0.0620, 0.0534]
Obs. (N/m)	(5422/31)	(5422/31)	(5422/31)
R2 (total)	0.1716	0.2144	0.2144

Table SI-6: **Treatment effect on market prices, dependent on harvest, post-harvest and lean season.** The dependent variable is mean weekly maize price per cluster, measured through SMS-based mobile phone surveys. Treat is a cluster-level indicator for treatment assignment showing the intent-to-treat (ITT) effect. Season is a categorical variable indicating price observations in the harvest, post-harvest and lean season. Intercept shows estimates for the control group in the harvest season, and N/m is number of observations (N) and number of pairs (m). Bootstrapped 95% confidence intervals based on 1000 replications are reported in square brackets. Model specification is a mixed-effects model where Pair, the categorical variable identifying matched pairs, is a random intercept (see Equation 8).

	Harvest Cycle Year 1		**Harvest Cycle Year 2**	
	Base Model (1)	Base Model with Seasons (2)	Base Model (3)	Base Model with Seasons (4)
(Intercept)	8.9965	9.0363	8.9458	8.8057
	[8.9638, 9.0273]	[9.0069, 9.0670]	[8.9112, 8.9837]	[8.7682, 8.8408]
Treat	0.0287	0.0111	-0.0186	-0.0043
	[0.0184, 0.0397]	[-0.0051, 0.0270]	[-0.0329, -0.0048]	[-0.0204, 0.0117]
seasonPostHarvest		-0.0076		0.1143
		[-0.0228, 0.0085]		[0.0974, 0.1316]
seasonLean		-0.1014		0.3462
		[-0.1173, -0.0850]		[0.3291, 0.3654]
Treat:seasonPostHarvest		0.0241		-0.0210
		[0.0022, 0.0453]		[-0.0447, 0.0033]
Treat:seasonLean		0.0275		-0.0240
		[0.0073, 0.0515]		[-0.0508, 0.0011]
Obs. (N/m)	(2468/31)	(2468/31)	(2954/31)	(2954/31)
R2 (total)	0.3378	0.4092	0.1995	0.5810

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