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STOCKS AND STORAGE: EFFECTS OF IMPROVED ON-FARM STORAGE ON LOCAL FOOD PRICES AND SEASONAL FOOD SECURITY, AND EFFECTS OF TRADE POLICIES ON GLOBAL FOOD PRICE VOLATILITY

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Abstract

Eradicating hunger and malnutrition have gained increasing attention in the past decade, which is reflected in their prominent inclusion in the 2030 Agenda for Sustainable Development, adopted in 2015. However, progress has been limited.

The prevalence of severe food insecurity is highest in Sub-Saharan Africa, where the seasonality of harvests leads to fluctuations in food insecurity, particularly in the lean season, the time before the harvest is brought in. In the first paper, it is argued that addressing seasonal food insecurity requires consideration of post-harvest losses during storage, a topic often neglected in the literature. The paper presents an experimental assessment where an improved storage technology that can reduce post-harvest losses is randomly allocated to farmers groups in two districts in Tanzania. The results show that the improved on-farm storage technology reduces seasonal food insecurity. The effect is most pronounced in the lean season.

The second paper addresses seasonal food price gaps, the differences between the highest and lowest prices in a harvest cycle. Seasonal price gaps can have adverse effects on food security and poverty, and their extent in Sub-Saharan Africa suggests that intertemporal arbitrage is constrained. The paper develops and experimentally analyses the argument that post-harvest storage losses constrain arbitrage. In Tanzania, smallholder farmers are randomly allocated an improved storage technology that limits post-harvest losses even in extended time of storage. Local market prices are tracked weekly. The results document significant effects of improved on-farm storage on local market prices, and a reduction of the seasonal price gap in the observation period.

Currently, the most prominent political response to volatility and fluctuations of food prices are trade policy changes by national governments, which is the focus of the third paper. Though there is a widespread concern that such actions exacerbate global food price volatility, there is little empirical evidence to underpin this claim. The paper analyzes the effects of national trade policies on volatility of food prices in global markets, using an original dataset on announced trade policy changes in the time period 2005-2017. The result show that the announcement of trade policy changes leads to short-term increases in global food price volatility. However, the effects show little persistence and are confined to periods of low stocks.

Overall, the results of this dissertation point to the need to give increasing attention to improved on-farm storage and adequate stocks in policy, practice and research on food security and food prices, and, by extension, in implementing the 2030 Agenda for Sustainable Development.

Zusammenfassung

Das Vorhaben, Hunger und Mangelernährung ein Ende zu bereiten, hat in der vergangenen Dekade zunehmende Aufmerksamkeit erhalten, was sich in der prominenten Aufnahme dieses Themas in der im Jahr 2015 verabschiedeten Agenda 2030 für nachhaltige Entwicklung widerspiegelt. Allerdings sind wenig Fortschritte zu verzeichnen.

Die Prävalenz schwerer Ernährungsunsicherheit ist in Subsahara-Afrika am höchsten, wo die Saisonalität des Erntezyklus für Schwankungen in der Ernährungsunsicherheit sorgt, vor allem in der «lean season» («magere Zeit»), dem Zeitraum, bevor eine Ernte eingebracht werden kann. Die erste Forschungsarbeit argumentiert, dass saisonale Ernährungsunsicherheit angegangen werden kann, wenn die Rolle von Nachernteverlusten während der Lagerung berücksichtigt wird - ein in der Literatur oft vernachlässigter Aspekt. In der Forschungsarbeit werden die Ergebnisse eines Experimentes vorgestellt, in dem zufällig ausgewählte Bauerngruppen in zwei Distrikten in Tansania eine verbesserte und die Nachernteverluste reduzierende Lagerungstechnologie erhalten. Die Ergebnisse zeigen, dass die verbesserte Lagerungstechnologie saisonale Ernährungsunsicherheit verringert. Die Effekte treten am Stärksten in der «lean season» hervor.

Die zweite Forschungsarbeit behandelt saisonale Preisunterschiede von Nahrungsmitteln, also die Differenz zwischen dem höchsten und tiefsten Preis innerhalb eines Erntezyklus. Diese Preisunterschiede können negative Folgen für Armut und Ernährungssicherheit haben. Das Ausmass saisonaler Preisunterschiede in Subsahara-Afrika spricht dafür, dass intertemporale Arbitrage eingeschränkt ist. Die Forschungsarbeit entwickelt und testet das Argument, dass dies auf Nachernteverluste bei der Lagerung zurückzuführen ist. Bauerngruppen in Tansania erhalten zufällig ausgewählt eine verbesserte Lagerungstechnologie, welche Nachernteverluste auch bei längerer Lagerungszeit minimiert. Lokale Marktpreise werden wöchentlich gemessen. Die Ergebnisse dokumentieren signifikante Effekte von verbesserter Lagerung auf lokale Marktpreise sowie eine Reduktion saisonaler Preisunterschiede im Beobachtungszeitraum.

Im Fokus der dritten Forschungsarbeit stehen handelspolitische Interventionen, die im Moment die bedeutendste politische Reaktion auf volatile Nahrungsmittelpreise darstellen. Eine weitverbreitete Sorge besteht jedoch darin, dass diese Interventionen die Volatilität von globalen Nahrungsmittelpreisen noch verschlimmern, obwohl hierzu kaum empirische Evidenz vorhanden ist. Die Forschungsarbeit analysiert die Auswirkungen nationaler Handelspolitik auf die Volatilität globaler

Nahrungsmittelpreise, basierend auf einem neuen Datensatz zu Ankündigungen von Veränderungen in der Handelspolitik im Zeitraum von 2005 bis 2017. Die Ergebnisse zeigen, dass die Ankündigungen von Veränderungen in der Handelspolitik zu kurzfristiger Erhöhung der Volatilität von globalen Nahrungsmittelpreisen führen. Diese Effekte sind jedoch wenig persistent und begrenzt auf Zeiten niedriger Lagerbestände.

Insgesamt weisen die Ergebnisse dieser Dissertation darauf hin, dass verbesserter Lagerung und ausreichenden Lagerbeständen vermehrte Aufmerksamkeit gebührt sowohl in Politik, Praxis und Forschung zu Ernährungssicherheit und Nahrungsmittelpreisen als auch entsprechend bei der Umsetzung der Agenda 2030 für nachhaltige Entwicklung.

Acknowledgments

This dissertation was made possible thanks to the support, inspiration and motivation from numerous individuals and institutions. Developing this thesis was an enriching process not only in terms of the topics covered but also with regards to collaboration and exchange with a wide set of people from diverse backgrounds.

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Zurich, April 2019 *Michael Brander*

To my family.

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1 Introduction

Food security and the ambition to eradicate hunger and malnutrition have gained increasing prominence in the past decade, ever since the global food price crises in 2008. These common goals were reflected in the 2030 Agenda for Sustainable Development, which was adopted in 2015 and provides a blueprint for a world free from hunger and poverty where natural resources are maintained and protected.

Current efforts to ending hunger emphasize increasing agricultural production and productivity, whereas reducing post-harvest losses receives much less attention. This is surprising as reducing post-harvest losses are commonly described as one of greatest source of inefficiencies in food production (Lybbert & Sumner, 2012). The emphasis on increasing agricultural production can be traced back to the "Green Revolution". Especially in Asian countries, an intensification of agriculture and improved seed varieties had resulted in significant reductions of food insecurity, but also came with substantial environmental costs. Much of the development efforts and agricultural policies in the past decades have aimed at replicating this experience in other regions, especially in Sub-Saharan Africa. Yet, progress has been limited. The prevalence of severe food insecurity in the world has increased again in recent years and is most pronounced in Sub-Saharan Africa.

The neglect of post-harvest losses is also evident in the current global policy debate. In the 2030 Agenda, for example, reducing food losses and waste is included in an unspecific target, which is not directly linked to food insecurity. This can be partly attributed to contradictory claims on the benefits of reduced post-harvest losses for food security coupled with the absence of robust, empirical evidence. In an influential World Bank report, the benefits of gains from better post-harvest handling were recently questioned based on the argument that large post-harvest losses in Sub-Saharan Africa are a plausibly false myth (Christiaenesen & Demery, 2017). In contrast, organizations like the United Nations World Food Programme stress that post-harvest losses are a major cause of hunger for millions of families worldwide, and that reducing post-harvest losses is consequentially key to achieve a world free of hunger as part of the Agenda 2030 for Sustainable Development (World Food Programme, 2015). This divergence illustrates the need for robust, empirical analysis on the socio-economic and food security impacts of reduced post-harvest losses and their potential impact to inform the global policy debate on reducing hunger.

The first and second paper of this dissertation aim to address these gaps and present the results of the first randomized control trial on the effects of an improved on-farm storage technology on seasonal food insecurity (Paper 1) and on local market prices (Paper 2). In the experiment, smallholder farmers in two districts of Tanzania, clustered in farmers groups, were randomly allocated an improved on-farm storage technology and training in their use. The technology, hermetic storage bags, is, in principle, able to minimize post-harvest storage losses. Yet, their actual impact on food insecurity strongly depends on how the technology is been put to use by smallholder farmers, which has not been studied so far.

In the first paper, it is argued that reducing food insecurity requires not only increased agricultural production, as is commonly contended, but also reducing post-harvest losses during storage. Food insecurity tends to fluctuate with harvest seasonality, often increasing in the lean season, the time before the new harvest is brought in. An improved on-farm storage technology may enable farmers to store their self-produced crops longer without risks of post-harvest storage losses. The food security effects of improved on-farm storage are hence expected to be most pronounced in the lean season. To assess these seasonally dependent effects, household's food insecurity is tracked on a quarterly basis using SMS-based mobile phone surveys.

The second paper considers the role of improved on-farm storage in moderating seasonal food price fluctuations. In Sub-Saharan Africa, food prices show strong and recurring seasonal fluctuations. These seasonal food price gaps, which are the differences between the highest and lowest prices in a harvest cycle, have important consequences for poverty and food security as income from agricultural production and food expenditures both have considerable shares in household's budgets. The extent of seasonal food price gaps implies that intertemporal arbitrage is constrained. In the literature, limits to arbitrage are commonly attributed to credit and liquidity constraints. Yet, prior experimental research finds little support for this argument. Instead, the second paper argues that post-harvest storage losses constrain farmer's intertemporal arbitrage, and thereby contribute to seasonal food price gaps. To analyse market effects, local prices of maize, the staple food in the project areas, are tracked on a weekly frequency, using SMS-based mobile phone surveys.

Thus far, the dominant national policy to stabilize domestic food prices are national trade policy interventions, including in Tanzania. Governments aim to stabilize food prices in order to avert adverse effects on domestic consumers and producers. However, there is a wide-spread concern that national trade policy interventions in turn amplify food price volatility in global markets, which can render their policy actions ineffective and imply adverse effects on other countries. This has led to growing calls on countries to refrain from national trade policy interventions in the face of volatile global food prices. Yet, the empirical evidence underpinning this concern is limited. The third paper addresses this research gap by using an original, new dataset on the announcement of trade policy events for the world's most important staple crops from 2005 to 2017. The paper presents an empirical analysis on the announcement effects of different types of trade policy changes on global food price volatility and explores whether stock levels could moderate effects.

Taken together, this dissertation addresses pertinent topics on food security and food prices to inform research, policy, and practice on agriculture and rural development. The thesis comprises of three self-contained, yet thematically linked papers, which are presented in chapters 2, 3 and 4. Chapter 5 concludes and derives policy implications.

References:

Christiaensen, L., & Demery, L. (2017). *Agriculture in Africa: Telling Myths from Facts.* The World Bank. Retrieved from http://documents.worldbank.org/curated/en/681121528784639307/pdf/Agriculture-in-Africa-Telling-Myths-from-Facts-2017.pdf

Lybbert, T. J., & Sumner, D. A. (2012). Agricultural technologies for climate change in developing countries: Policy options for innovation and technology diffusion. *Food Policy*, *37*(1), 114–123. https://doi.org/10.1016/j.foodpol.2011.11.001

World Food Programme. (2015). *Zero Loss for Zero Hunger: WFP's Work to Prevent Post-Harvest Food Losses.* Retrieved from http://documents.wfp.org/stellent/groups/public/documents/reports/wfp289788.pdf

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Improved on-farm storage reduces seasonal food insecurity of smallholder farmer households – Evidence from a Randomized Control Trial in Tanzania

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Abstract

Ending hunger is a key goal of the 2030 Agenda for Sustainable Development, adopted in 2015. This goal notwithstanding, the prevalence of severe food insecurity of the world's population has increased. It is highest in Sub-Saharan Africa, where the seasonality of harvests leads to fluctuations in food insecurity, particularly in the lean season, the time before the harvest is brought in. We posit that addressing seasonal food insecurity requires not only increased food production, as is commonly argued, but also consideration of post-harvest losses during storage. Here we present the results of a randomized control trial on the effects of improved on-farm storage on seasonal food insecurity. Our intervention provided farming households from two districts in Tanzania with hermetic storage bags that can help reduce storage losses. The results show that the intervention reduced the proportion of severely food insecure households by 40% on average in the lean season, and by 21% in the full seasonal cycle, with households of female participants benefiting most from the intervention. These findings demonstrate that a simple and inexpensive technology could contribute strongly to reducing seasonal food insecurity and improving smallholder farmers' year-round access to food.

1 Introduction

Ending hunger and ensuring access to food all year round is a key objective of the 2030 Agenda for Sustainable Development (Transforming our world: the 2030 Agenda for Sustainable Development, 2015). Yet, in the three years since the adoption of the Agenda in 2015, the prevalence of severe food insecurity has increased from 8.4 to 10.2% of the world's population (FAO, 2018). The prevalence of food insecurity is highest in Sub-Saharan Africa, with 29.8% of the population affected by severe food insecurity (FAO, 2018). The United Nations Food and Agriculture Organization warns that without increased efforts, the SDG goal of ending hunger will be missed by far.

In Sub-Saharan Africa, about 70–80% of farms are less than two hectares in size (Lowder, Skoet, & Raney, 2016). These small-scale farming households depend on food and income from their annual or semi-annual harvests. It is well established that the seasonality of harvests leads to fluctuations in food insecurity. Food insecurity and malnutrition have been shown to increase in the lean season, the time shortly before a new harvest is brought in (e.g. Christian & Dillon, 2018; Abizari, Azupogo, Nagasu, Creemers, & Brouwer, 2017; Hirvonen, Taffesse, & Worku Hassen, 2016; Kaminski, Christiaensen, & Gilbert, 2016; Becquey et al., 2012; Savy, Martin-Prével, Traissac, Eymard-Duvernay, & Delpeuch, 2006). Much less is known about the specific mechanisms leading to fluctuations in food insecurity and options for mitigating this problem.

One prominent string of research argues that seasonal changes in food consumption are a consequence of credit and liquidity constraints, which compel households to sell their harvest early. As prices often increase after harvest and peak in the lean season, many households lack the resources to buy similar quantities later, explaining lower lean season consumption. A range of empirical studies have shown that credit and liquidity constraints indeed cause households to sell early (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). However, studies assessing the effects of access to credits or loans on consumption or food security in the lean season do not find statistically significant effects (e.g. Burke et al., 2019; Fink et al., 2018; Basu & Wong, 2015).

We posit that addressing seasonal food insecurity requires consideration of post-harvest losses during storage. Independent of liquidity and credit constraints, households would only store their harvest until the lean season if expected price increases outweigh the expected quantities lost during storage. Yet, post-harvest losses during storage are substantial in Sub-Saharan Africa. A meta-analysis of measurements based on grain samples estimates maize post-harvest losses of 25.6% on average (Affognon, Mutungi, Sanginga, & Borgemeister, 2015). These post-harvest losses mainly occur during storage when insect infestation and mold damage the harvested produce (Affognon et al., 2015). Reducing storage losses would not only make an extended duration of storage more profitable for households, but also increase the quantity available for consumption, especially in the lean season. Hence, we argue that limiting post-harvest losses during storage could contribute to mitigating seasonal food insecurity.

To assess whether and how much reducing post-harvest losses could help improve seasonal food security we randomly allocated a technology for improved storage to smallholder farming households in Tanzania, clustered at farmers group level, and tracked their food security during one seasonal cycle. The intervention consisted of hermetic storage bags, which have been shown to effectively reduce post-harvest losses in stored produce, mainly grains, even in extended periods of storage (e.g. Abass et al., 2018; Murdock, Margam, Baoua, Balfe, & Shade, 2012; Groote et al., 2013; Baoua, Amadou, & Murdock, 2013; Chigoverah & Mvumi, 2016; Likhayo, Bruce, Mutambuki, Tefera, & Mueke, 2016). Hermetic storage limits atmospheric oxygen, which causes desiccation of insects and other pests that damage stored grains (Murdock et al., 2012). In our field experiment we did not manipulate credit or liquidity constraints, as we focus on the effects of improved storage given the normal credit and liquidity situation in our sample. For details, see the Methods section.

Our research contributes to filling an important knowledge gap. Prior research has shown that improved storage conditions can, in principle, increase storage quantity and storage duration (e.g. Aggarwal, Francis, & Robinson, 2018; Omotilewa, Ricker-Gilbert, Ainembabazi, & Shively, 2018). Yet, it does not offer an assessment of the de facto effects of improved storage on seasonal food security (Sheahan & Barrett, 2017), which strongly depend on how storage technologies are used and how their employment affects consumption and market behaviour. Partial exceptions include observational studies from Kenya and Central America showing that households using hermetic metal silos store their maize longer and benefit from an additional 5-6 weeks of adequate food provision over the year (Gitonga, Groote, Kassie, & Tefera, 2013; Bokusheva et al., 2012). Here we present the results of the first experimental study that assesses the impacts of improved on-farm storage on seasonal food security.

2 Results

To estimate the effects of improved on-farm storage on household food security, we randomly allocated hermetic storage bags and training in their use to some households (treatment group), but not others (control group). The hermetic bags were provided as a loss-reducing storage alternative to the commonly used polypropylene bags. The experiment was implemented as a matched-pair, cluster randomized control trial in two districts of Tanzania (Kilosa and Kondoa), with 1023 participating farmers clustered in 62 farmers groups, and matched in 31 pairs. Households in treatment clusters received five hermetic storage bags per household, with a capacity to store about 100kg of maize in each bag. No intervention was conducted for farmers groups assigned to the control group during the duration of this study. We measured severe food insecurity with quarterly rounds of the reduced Coping Strategies Index (rCSI) over the course of fifteen months (c.f. Maxwell, Vaitla, & Coates, 2014; Maxwell, Caldwell, & Langworthy, 2008), using SMS-based mobile phone surveys. We estimate the intent-to-treat (ITT) effect as the weighted average of within-pair mean differences between treatment and control groups (Imai, King & Nall, 2009).

2.1 Seasonal Changes in Severe Food Insecurity and Treatment Effects

The results show that the experimental treatment reduces the prevalence of severe food insecurity, and that the ITT effect is contingent on seasonality. For each seasonal measurement, the prevalence of severe food insecurity is calculated as the proportion of households that are severely food insecure at that time.

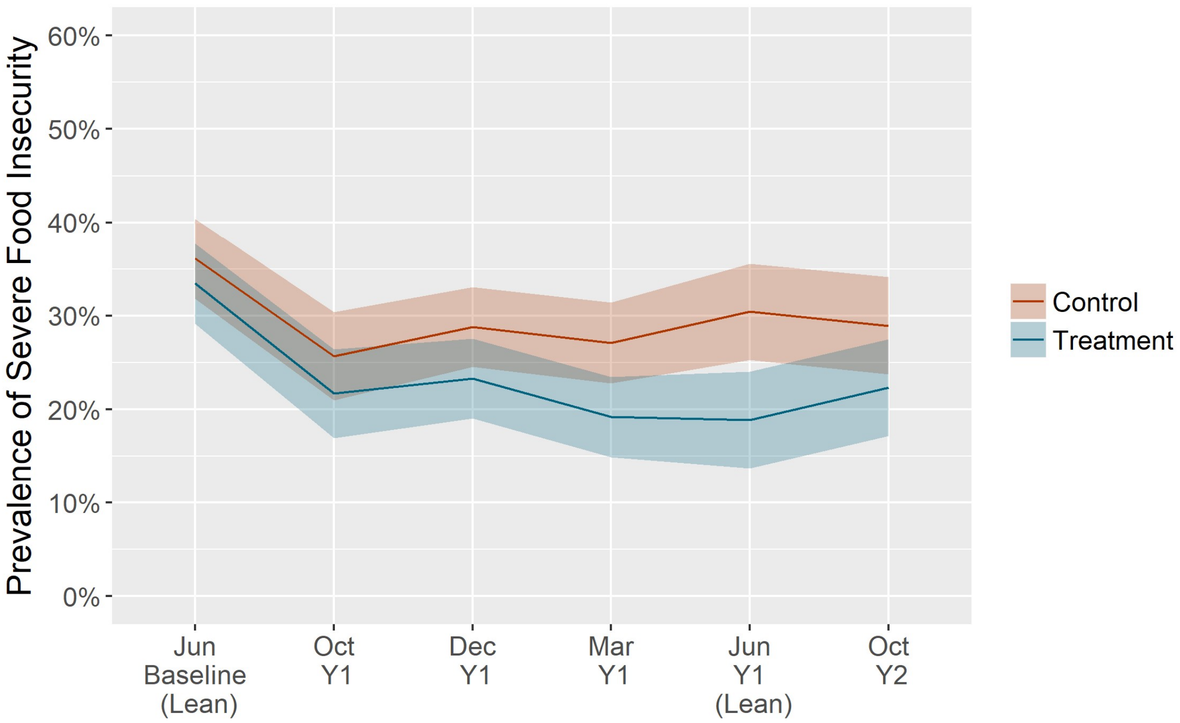
In the control group, prevalence of severe food insecurity increases relatively steadily after the year's first harvest, and peaks in the lean season (June Y1), before decreasing again as the year's second harvest is brought in (see Figure 1). The prevalence of severe food insecurity is highest in the lean season when an estimated 30% of households in the control group are severely food insecure (June Y1, Table 1). This figure is similar to the estimate of 29.2% for Eastern Africa, reported by the Food and Agriculture of the United Nations, albeit for 2017 and measured only through a 12-month recall period (FAO, 2018).[1]

In stark contrast to the control group, in the treatment group severe food insecurity remains stable and slightly decreases after harvest. The treatment leads to a

[1] The Food and Agriculture of the United Nations only reports regionally aggregated values for its Prevalence of Severe Food Insecurity in most cases, including Tanzania.

statistically significant reduction of the prevalence of severe food insecurity in the third (March Y1) and fourth quarterly measurement (June Y1). The latter covers the lean season. A statistically significant ITT effect is observed earlier in one of the districts, namely in the second quarterly measurement (December Y1) in Kilosa, whereas the treatment effect appears in the third quarterly measurement (March Y1) in Kondoa. Because the two districts are in different agro-ecological zones, the timing of harvests did not coincide in the study period. One of the districts, Kondoa, experienced a delayed harvest at the beginning of the observation period due to climatic conditions. One plausible explanation for our result is that the number of months of storage after harvest was shorter in Kondoa than Kilosa, and hence the treatment effect of improved-on farm storage appears with a delay.

Figure 1: Comparison of prevalence of severe food insecurity in treatment and control for different seasonal measurements



Notes: The horizontal axis indicates measurement point within our observation period. The vertical axis represents the prevalence of severe food insecurity expressed as the percentage of severely food insecure households. Lines based on point estimates according to cluster-level assignment to control (red lines) or treatment (blue lines). Shades represent clustered standard errors.

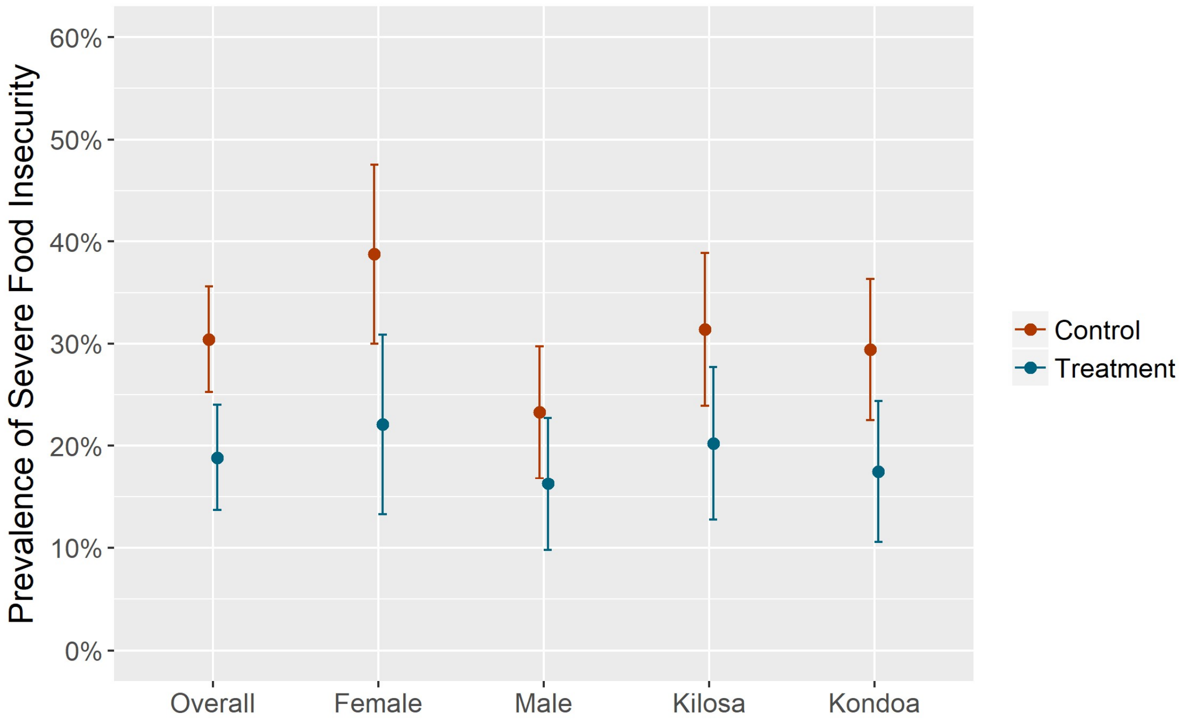
2.2 Effects on Severe Food Insecurity in the Lean Season

Our results show that the experimental intervention reduced the prevalence of severe food insecurity in the lean season. Lean season food insecurity is measured for June (Y1), right before the new harvest was brought in. Specifically, the treatment reduced by 40% the proportion of severely food insecure households, on average, in the lean season (see Figure 2; Table 1). The effect is statistically significant at the 5% level.

We further analyse gender differences of the ITT effect as it is well established that female farmers have more limited access to agricultural assets and inputs than male farmers (Conceição, Levine, Lipton, & Warren-Rodríguez, 2016), and, as a result, lower agricultural productivity, particularly in Sub-Saharan Africa (Food and Agriculture Organization of the United Nations, 2011). Both could, in principle, influence the effects of the intervention on severe food insecurity. As suggested by Doss (2014), we measure gender differences by the sex of participating farmers rather than by the sex of the household head (see Methods for details). Our results show that the ITT effect in the lean season is higher for households of female participants as compared to households of male participants (see Figure 2). Among households of female participants, the intervention reduced the proportion of severely food insecure households by 43%, on average, in the lean season. In contrast, the intervention reduced by 30% the proportion of severely food insecure households of male participants, on average (see Table 1). However, only the ITT effect for households of female participants is statistically significant.

The overall results for the lean season uphold when adopting a difference-in-difference estimation approach accounting for two-fold effects: differences at baseline and differences in the first measure after provision of the treatment to account for a placebo-like effect (see Table 1). Because our baseline survey was conducted prior to random assignment to treatment or control, it is independent of assignment to experimental conditions. We use household differences between the baseline and the corresponding measurement one year later (Baseline-June), and find that the estimator from this difference-in-difference analysis indicates a slightly reduced ITT effect. The effect remains statistically significant at the 10% level. Moreover, the first quarterly survey was conducted immediately after the experimental intervention, which coincides with the time after harvest where we do not yet expect a treatment effect. An effect could hence indicate a placebo-like effect in the treatment group (see King et al., 2009). We use household differences between the first quarterly survey and the lean season measurement (October-June) to test for such effects. Again, the estimator from this second difference-in-difference approach shows a slightly reduced ITT effect and remains statistically significant at the 10% level. These results enhance our confidence that the observed ITT effects are very unlikely to be due to pre-existing differences at baseline or a placebo-like pattern. However, in both robustness checks, the reported asymmetric effects for gender are not statistically significant, which suggests that our gender-specific differences should be interpreted with some caution.

Figure 2: Effect of cluster-level assignment of improved on-farm storage on the prevalence of severe food security in the lean season



Notes: The horizontal axis indicates (from left to right) effects for all households, effects for households of female and male participants, and effects for households located in Kilosa and Kondoa districts. The vertical axis represents the prevalence of severe food insecurity expressed as the percentage of severely food insecure households in the lean season. Points represent point estimates according to cluster-level assignment to control (red points) or treatment (blue lines). Whiskers represent clustered standard errors.

Table 1: **Effects of improved on-farm storage on the prevalence of severe food insecurity in seasonal measurements.** Prevalence of severe food insecurity expressed as the ratio of severely food insecure households in the full seasonal cycle (1=100% prevalence). ITT=Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed t test. Sample sizes for pairs (m) and total number of observations (n) for full sample I, and sample splits II-V (Sample/m/n): I/31/671; II/29/339; III/31/329; IV/16/338; V/15/333.

	Baseline and Seasonal Measurements						Lean Season Difference-in-Difference	
	Jun BL (Lean)	Oct Y1	Dec Y1	Mar Y1	Jun Y1 (Lean)	Oct Y2	Jun Y1 - Jun BL	Jun Y1 - Oct Y1
I. All Households (HH)								
Control Group	0.36	0.26	0.29	0.27	0.30	0.29	-0.06	0.05
ITT	-0.03	-0.04	-0.06	-0.08	-0.12	-0.07	-0.09	-0.08
t-statistic	-0.62	-0.85	-1.29	-1.84	-2.25	-1.27	-1.47	-1.50
p-value	0.27	0.20	0.10	0.03	0.01	0.10	0.07	0.07
II. Female Participant's HH								
Control Group	0.40	0.35	0.35	0.30	0.39	0.34	-0.01	0.04
ITT	-0.06	-0.07	-0.08	-0.11	-0.17	-0.09	-0.10	-0.10
t-statistic	-0.87	-0.92	-1.12	-1.39	-1.90	-1.01	-1.02	-1.18
p-value	0.19	0.18	0.13	0.08	0.03	0.16	0.15	0.12
III. Male Participant's HH								
Control Group	0.32	0.18	0.23	0.23	0.23	0.25	-0.09	0.05
ITT	0.03	-0.04	-0.03	-0.01	-0.07	-0.05	-0.10	-0.03
t-statistic	0.51	-0.65	-0.52	-0.14	-1.09	-0.68	-1.18	-0.39
p-value	0.30	0.26	0.30	0.45	0.14	0.25	0.12	0.35
IV. Households in Kilosa								
Control Group	0.33	0.26	0.29	0.27	0.31	0.31	-0.02	0.05
ITT	-0.03	-0.03	-0.08	-0.08	-0.11	-0.05	-0.08	-0.08
t-statistic	-0.55	-0.37	-1.20	-1.26	-1.50	-0.64	-1.04	-1.14
p-value	0.29	0.36	0.11	0.10	0.07	0.26	0.15	0.13
V. Households in Kondoa								
Control Group	0.39	0.25	0.29	0.27	0.29	0.26	-0.09	0.04
ITT	-0.02	-0.05	-0.03	-0.08	-0.12	-0.08	-0.10	-0.07
t-statistic	-0.36	-0.89	-0.61	-1.27	-1.73	-1.25	-1.09	-0.99
p-value	0.36	0.19	0.27	0.10	0.04	0.11	0.14	0.16

2.3 Food Insecurity in the Full Seasonal Cycle

Our results demonstrate that the treatment effects observed for the specific seasonal measurements, peaking in the lean season, also translate into a reduction of the prevalence of severe food insecurity in the full seasonal cycle. We estimate the prevalence for the full seasonal cycle as the percentage of households where at least one out of four seasonal measurements had values classified as severely food insecure.

In our control group sample, the prevalence of severe food insecurity in the full seasonal cycle is 53% which means that around half of the study population are severely food insecure at least at one point of the full season (see Table 2). The figure is higher than the prevalence of severe food insecurity in the lean season (30%). The difference implies that 23% of study households were not severely food insecure in the lean season, but in at least one of the remaining three seasonal measurements.

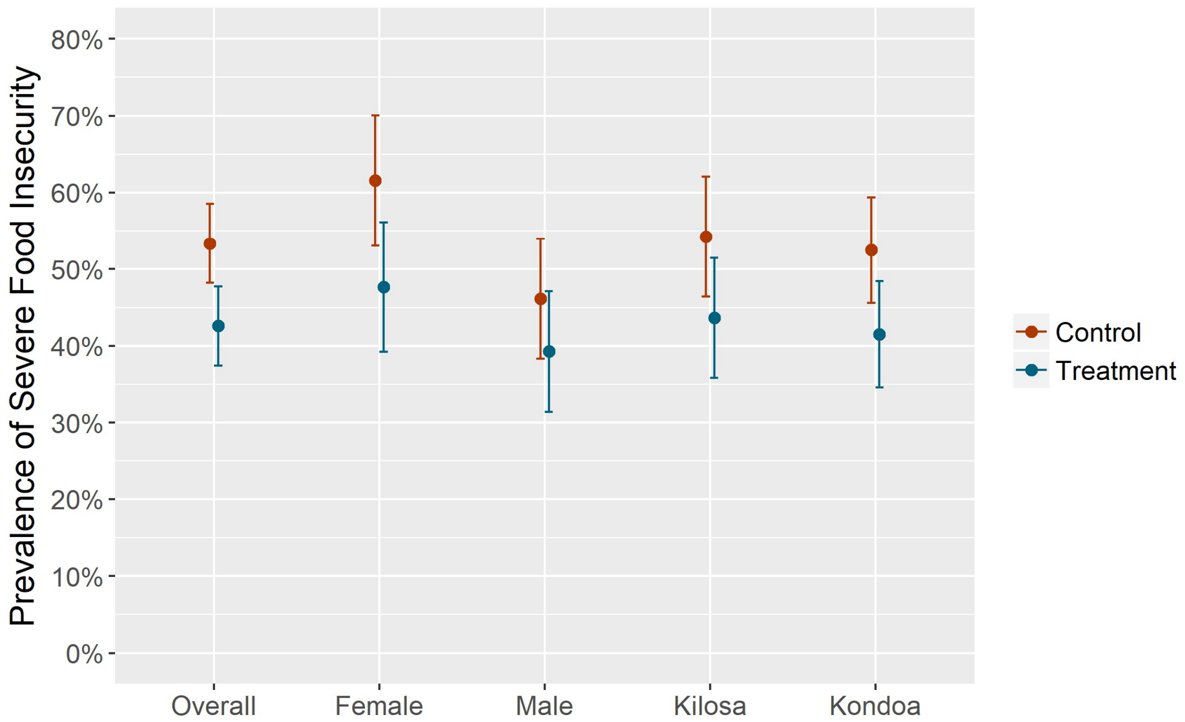
For the full seasonal cycle, our results show that the intervention reduced by 21% the proportion of severely food insecure households, on average. The ITT is statistically significant at the 5% level. Our results imply that the experimental treatment smoothens the prevalence of food insecurity in the observation season.

Table 2: **Effects of improved on-farm storage on the full season's prevalence of severe food insecurity.** Prevalence of severe food insecurity expressed as the ratio of severely food insecure households in the full seasonal cycle (1=100% prevalence). ITT=Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed t test. Sample sizes for pairs (m) and total number of observations (n) for full sample I, and sample splits II-V (Sample/m/n): I/31/671; II/29/339; III/31/329; IV/16/338; V/15/333.

	Control Group	ITT	m	n	t-statistic	p-value
Full						
Overall	0.53	-0.11	31	671	-2.08	0.02
Gender						
Female	0.62	-0.14	29	339	-1.64	0.05
Male	0.46	-0.07	31	329	-0.88	0.19
District						
Kilosa	0.54	-0.11	16	338	-1.36	0.09
Kondoa	0.52	-0.11	15	333	-1.59	0.06

Our results further show that the ITT effect size is again different for households of female and male participants (see Figure 3). Among households of female participants, the treatment reduced the proportion of severely food insecure households by 23%, on average in the full seasonal cycle. In contrast, the intervention reduced by 15% the proportion of severely food insecure households among male participants. Yet, only the ITT effect for households of female participants is statistically significant.

Figure 3: Effect of cluster-level assignment of improved on-farm storage on the prevalence of severe food security in the full seasonal cycle



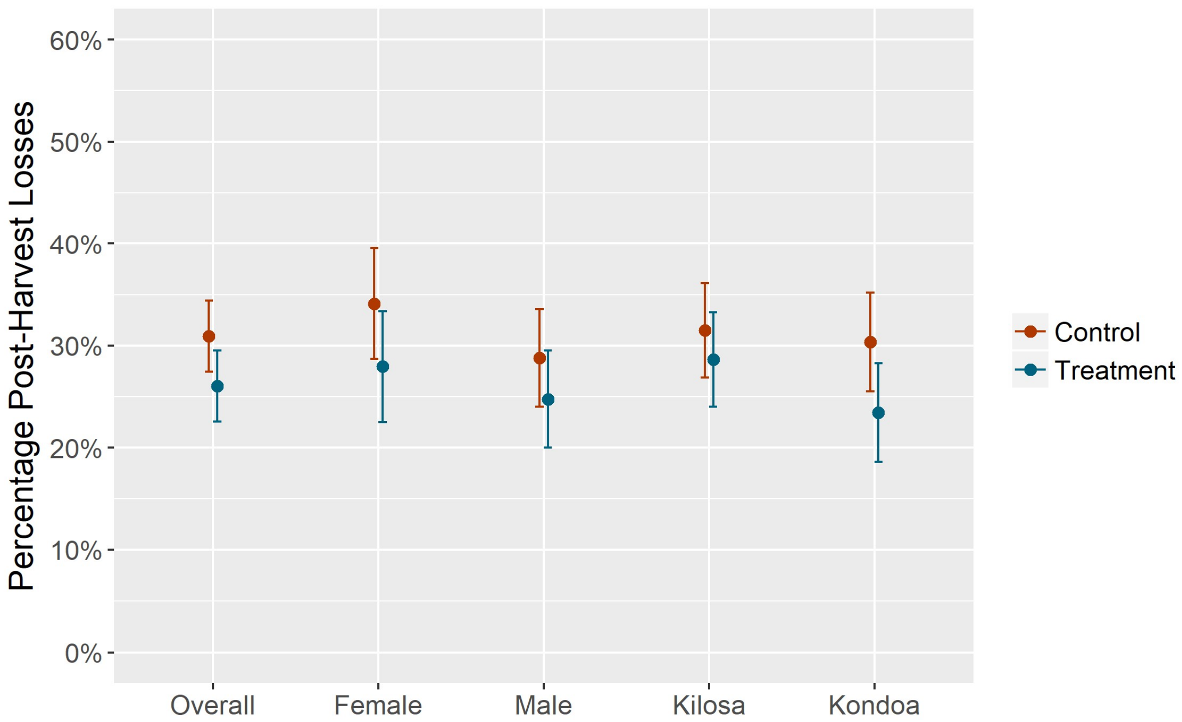
Notes: The horizontal axis indicates (from left to right) effects for all households, effects for households of female and male participants, and effects for households located in Kilosa and Kondoa districts. The vertical axis represents the prevalence of severe food insecurity expressed as the percentage of severely food insecure households in the full seasonal cycle. Points represent point estimates according to cluster-level assignment to control (red points) or treatment (blue lines). Whiskers represent clustered standard errors.

2.4 Effects on Post-Harvest Losses

Our expectation was that improved on-farm storage would lead to reduced post-harvest losses, and hence would enable households to better smooth their food consumption, and, by extension, food security throughout the agricultural season. Our results show that the treatment did effectively reduce post-harvest losses.

We use a farmer self-assessment of post-harvest losses incurred during the seasonal cycle, and follow the methodology used in Kaminski and Christiaensen (2014), which are part of the World Bank's Living Standard Measurement Survey's (LSMS) agricultural module. We find that farmer self-reported post-harvest losses are 31% on average for control group households. The intervention reduced post-harvest losses by 16%, on average (see Figure 4; Table SI-1). The level of losses incurred are similar to the estimates by Affognon et al. (2015), who report maize post-harvest losses of 25.6%, on average, in Sub-Saharan Africa. Yet, they are well above the estimates of Kaminski and Christiaensen (2014) who estimate post-harvest losses of between 1.4 and 5.9% in Tanzania. While the latter study uses the same methodology as we use here, the former is a meta-analysis of loss estimates based on grain samples.

Figure 4: Effect of cluster-level assignment of improved storage on post-harvest losses



Notes: The horizontal axis indicates effects for (from left to right) all households, households of female and male participants, for households located in Kilosa and Kondoa. The vertical axis represents the percentage of post-harvest losses, according to farmer self-assessments. Points represent point estimates according to cluster-level assignment to control (red points) or treatment (blue lines). Whiskers are standard errors.

3 Discussion

Current efforts to attain the 2030 Agenda for Sustainable Development goal of ending hunger prioritize increases in agricultural production, whereas post-harvest losses have received much less attention (Kitinoja, Saran, Roy, & Kader, 2011). Our results suggest that improved on-farm storage substantially reduces the proportion of seasonally food insecure smallholder households. Such positive impacts on food security have rarely been documented in prior research on agricultural production interventions. Positive food security effects have thus far only been documented for the provision of improved seeds (mainly orange-fleshed sweet potatoes) as shown in a meta-analysis for Sub-Saharan Africa (Stewart et al., 2015). Our results thus highlight the need for greater consideration of improved on-farm storage as a means for reducing severe food insecurity. Our findings further suggest that seasonal food insecurity problems require more attention, both in research and on the ground. While this is often challenging for researchers due to the high costs of high-frequency data collection, the approach we used – SMS based mobile phone surveys – turned out to be quite cost-efficient.

Our results also indicate that the food security benefits from improved on-farm storage are higher for households of female participants than male participants. However, while the treatment effect we observed is substantial, it does not remain statistically significant in all model specifications, and further research is required before clear-cut policy conclusions can be drawn. One potential explanation for gender differences is that, in Tanzania, food cultivation, preparation, and storage are most often handled by women, and female participants can thus make better use of the means we provided through our experimental intervention. Improving the understanding of gender differences, as manifest in treatment effect sizes, and their determinants, will be highly relevant for post-harvest loss reduction policies, programmes, and strategies. Of similar relevance is estimating the marginal effects of training on improved on-farm storage, which would allow to separate training and technology effects. Our design estimates joint effects of the provision of the improved on-farm storage technology effects and training in improved on-farm storage.

Prior research has produced contradictory results regarding levels of post-harvest losses, especially when comparing farmer self-reported information with losses measured based on grain samples (c.f. Affognon et al., 2015; Kaminski & Christiaensen, 2014). This divergence in findings led Christiaensen and Demery (2017) to add a cautionary note about the gains from better post-harvest handling, such as improved on-farm storage. Clearly, measurement of post-harvest losses, including self-reported measurements used in our study, come with limitations and remain to be cross-checked further. Yet, our results, notably those based on the same methodology as used in Kaminski and Christiaensen (2014), indicate that post-harvest losses in our study population are substantial, and much higher than estimates for the national maize harvest in Tanzania, based on nationally representative surveys. While some part of this difference can certainly be attributed to sample selection, it also raises questions about the external validity of our results. While generalizability is, of course, a common issue with all location-specific field experiments in the natural and social sciences, it will be important to use similar study designs to examine the effects of improved on-farm storage on food security in other areas of Tanzania as well as other countries in Sub-Sahara Africa and elsewhere. It would also be very interesting to expand the focus of such research to outcomes other than food security per se, such as poverty levels as well as nutritional and health outcomes.

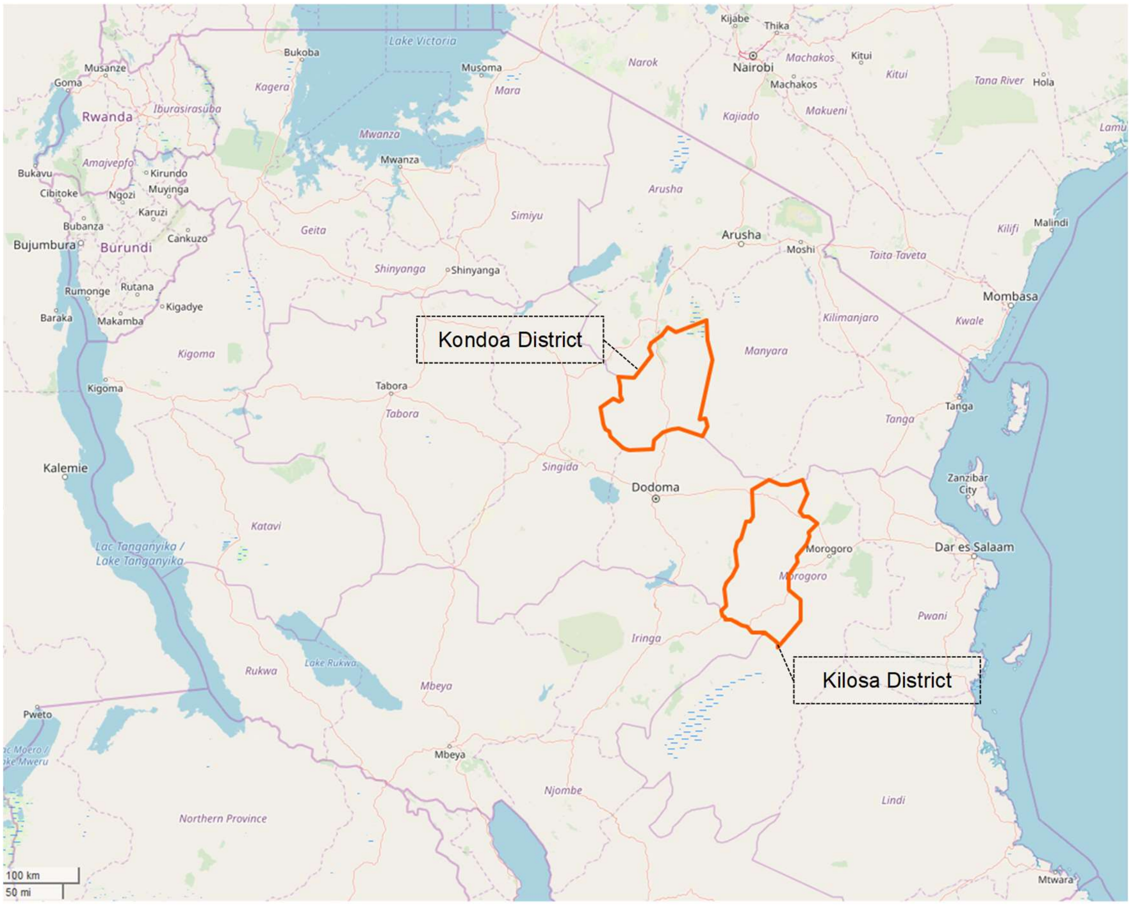
These limitations notwithstanding, we hope that our study, which is the first RCT to look into the effects of improved on-farm storage on food security, paves the way for more research in this area. Such research can contribute in important ways to the larger debate on how to achieve the 2030 Agenda goal of ending hunger, and how much should be invested into reducing post-harvest losses, in addition to measures focusing on increasing food production.

4 Methods

4.1 Experimental Design

The experiment was implemented in two districts of Tanzania selected due to their agro-ecological and market access differences. Kondoa is relatively remote, while Kilosa is close to Dar es Salaam and the major transit routes (road/sea). Yet, both districts bring in one maize harvest per year, and maize is the staple food in both, facilitating comparisons. Figure 5 shows a map of the study areas.

Figure 5: Map of Study Areas in Tanzania



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

We used a matched-pair, cluster-randomization design as discussed in Imai, King and Nall (2009). Their results show that from the perspective of efficiency, power, bias and robustness, pairing should be done whenever feasible.

Clustering was done at the level of farmer groups (organizations). An initial list of 70 farmer groups (35 in Kilosa district, 35 in Kondoa district) was proposed by non-governmental organization Helvetas Swiss Intercooperation (hereinafter called Helvetas)[2], the intervention partner. Prior to the random allocation, 67 farmer groups were visited by enumerators from Sustainable Agriculture Tanzania, an independent non-governmental organization, and informed about the research and offered to participate. Data collection and interventions were separated, and participants were

[2] Helvetas is an independent Swiss development organization (www.helvetas.org). In Tanzania, Helvetas has been active since the 1970s. The interventions for our study were implemented by the team of the "Grain Postharvest Loss Prevention" project, which is carried out by Helvetas as a mandate from the Swiss Agency for Development and Cooperation Helvetas Swiss Intercooperation .

assured that individual data will not be shared with intervention partners. On average, 93% of farmers approached in farmers group visits gave their consent to participate. All members of the visited farmers groups were eligible to participate. For three farmer groups, all located in Kondoa district, attempts to schedule a visit were not successful. Additionally, two groups in Kilosa were excluded as some individuals were members in both groups.

We subsequently paired clusters based on baseline variables prior to randomization, namely average distance to market (walking time in minutes, from the pre-baseline survey), soil type, and a regional dummy (district). These variables were expected to strongly correlate with future outcomes studied, namely food security (c.f. Bruhn & McKenzie, 2009). The latter two variables were necessary matches in each pair, while average distance to market was used to allocate clusters in these strata through an "optimal greedy" algorithm using the R package "blockTools" (Moore & Schnakenberg; see also Balance Table SI-2). After assignment of the experimental clusters to matched pairs, we ran an automated random allocation, using a random number seed, to assign the clusters in each matched pair to treatment and control conditions, respectively.

The intervention for treatment groups consisted of five hermetic storage bags, of the brand "Purdue Improved Crop Storage (PICS)", with the capacity to store approximately 100kg of maize, per household in each treatment group, and three standardized training sessions on improved on-farm storage and the use of hermetic storage technologies. The interventions were carried out by Helvetas between July and October 2017, i.e. shortly before and after the harvest was brought in. The control group farmer did not participate in the intervention, yet they were also not prevented from purchasing hermetic storage bags on the market (see section 4.5 for discussion on experimental compliance).

4.2 Measurement

We follow the definition of the Food and Agriculture Organization of the United Nations (2010) that "food insecurity exists when people do not have adequate physical, social or economic access to food" (p.8).[3] We measured food insecurity through the

[3] This definition builds on the most commonly definition of food security as adopted at the World Food Summit (1996) which is that "food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (Para. 1).

reduced Coping Strategies Index (rCSI) (Maxwell et al., 2008; Maxwell et al., 2014). The rCSI is a 5-item questionnaire that assesses the magnitude of measures taken by households to deal with stresses from food insecurity (Maxwell et al., 2008; see Table SI-3 for questionnaire). We chose the rCSI due to its ability to capture short-term changes in food insecurity, which is critical to assessing seasonal fluctuations in food insecurity (Maxwell et al., 2014). The rCSI items include information on eating less expensive or less preferred food, reducing number of meals per day, limiting portion size, restricting consumption by adults in the households, and borrowing food and money from friends and relatives (Maxwell et al., 2008). For each item, respondents indicate the frequency in days over the past 30 days. Standard weights are used according to the severity of these coping strategies (Vaitla et al., 2017, see Table SI-2 for details). Thresholds proposed in the literature are used to classify rCSI values into food (in)security categories (Vaitla et al., 2017): a) Food secure or mildly food insecure (rCSI values 0-4), b) Moderately food insecure (5-10), and c) Severely food insecure (>=11). We apply the threshold for severe food insecurity in our analysis. Our results are robust to using alternative thresholds as proposed by Maxwell, Vaitla and Coates (2014). Table SI-4 presents the respective robustness checks. We rescale the 30-day recall window used in our survey, compared to their 7-days recall window, and use the lower bounds for the thresholds to not underestimate food insecurity. Data for the rCSI was collected on a quarterly basis.

To measure self-reported post-harvest losses (PHL), we adopt the same questions and approach used in Kaminski and Christiaensen (2014) to facilitate comparison with their measurements from 2010 in Tanzania, Malawi and Uganda as part of the World Bank's Living Standard Measurement Survey's (LSMS) agricultural module. The two questions used are 1) "Was any portion of the production lost post-harvest to rotting, insects, rodents, etc?", and if yes, 2) "Out of 10 units of maize, how many were lost?". We restrict our questions to maize as the crop of interest. We used the original questions asked in Swahili, the language in our study regions. In contrast to what is specified in Kaminski and Christiaensen, their Swahili version of the question did not include "theft" as one type of losses. Clearly, these post-harvest loss estimates need to be viewed with some caution as the approach is yet to be validated further, e.g. by contrasting self-reported values with actual grain samples, which has not been done so far. However, because our interest mainly lies in comparing differences in self-reported PHL between the experimental conditions, the self-reported PHL are suitable for our purpose. The PHL survey was conducted in October 2018 (Oct Y2).

We report gender differences based on the sex of participating farmers. Our measure of gender hence reflects whether a male or female farmer has participated in the study. In case their farmers group was randomly assigned to treatment, the gender measure correspondingly reflects whether a male or female farmer has received the treatment. We purposely do not analyse gender differences by the sex of the household head, which is done in many studies (Doss, 2014). Analysing gender differences by sex of the household head has important empirical drawbacks (Doss, 2014), which have been shown to lead to results that underestimate gender differences in agriculture (Peterman, Quisumbing, Behrman, & Nkonya, 2011). In male headed households, women are most often present and are likewise involved in or lead agricultural production. In contrast, men are rarely present in female-headed households. In our case, using sex of household head as gender indicator would hence mask the sex of the person who has participated in our study. Moreover, analysing gender differences by sex of study participants is more informative for policy recommendations and development programmes. It shows whether the sex of the person that receives the experimental intervention moderate's treatment effects, which can inform the design and targeting of interventions.

4.3 Survey Methods

All data, including the baseline, were collected through SMS-based mobile phone surveys, an efficient method for collecting data at high frequency, which is essential for variables with seasonal fluctuations and limited recall periods, where information can be remembered with sufficient precision by study participants. This approach also allowed us to collect data within a relatively short time period: in our case, SMS surveys were open for completion for only 5 days, limiting the extent to which short-term fluctuations (e.g. in food insecurity) might lead to inconsistent measurements. Measuring the rCSI, our main outcome variable, via SMS-based mobile phone surveys, has been extensively tested, especially by the United Nations World Food Programme (c.f. Mock, Singhal, Olander, Pasquier, & Morrow, 2016; Morrow, Mock, Bauer, & Browning, 2016).

Relative to traditional face-to-face interviews, the cost savings of mobile surveys are extremely high, particularly when collecting high frequency panel data in a large and geographically dispersed sample. The phone numbers of survey participants were collected during recruitment of farmers groups. As an incentive for participation and responding to the SMS surveys, respondents received a phone credit (airtime) of 1 USD after completing a survey. Both treatment and control group participants received equal airtime payouts after survey completion. Furthermore, prior research also indicates that response bias, e.g. due to social desirability relating to sensitive questions, is reduced in self-administered surveys, such as SMS-based surveys, where no personal interaction with interviewers exists (c.f. Krumpal, 2013, for an overview).

4.4 Missingness and Attrition

Our choice of data collection via SMS-based surveys enables frequent measurement of our main outcome variable (severe food insecurity). Yet, our mode of data collection might result in a higher degree of missing data for a given measurement round relative to what would be expected in traditional face-to-face surveys. If missingness in outcome data is systematically related to potential outcomes, inference may be biased (Gerber & Green, 2012).

We consider these concerns as follows: When outcome data is missing for a whole cluster, the matched-pair design allows us to exclude both, the cluster with the missing data, and corresponding cluster in the same pair. This procedure precludes the risk of bias regardless of the missing data mechanism (Imai et al., 2009). In this study, we exclude one cluster in Kondoa, where participants ceased to respond to the survey after the initial recruitment. Our full sample therefore consists of 31 matched pairs, i.e. 62 clusters, overall.

However, for missing individual-level data within clusters, list-wise deletion requires the restrictive assumption that data is “missing completely at random” (Blackwell, Honaker, & King, 2017a). Instead, we adopt a more conservative assumption that data is “missing at random” (MAR), i.e. the missing values may depend on observed values in the data but not on unobservables (Blackwell et al., 2017a), and use multiple imputation techniques for missing values. 671 individuals participated in at least one of the quarterly food security surveys and multiple imputation is restricted to this panel. We generate 50 imputations for each of the missing values in the data and rerun our analysis with these 50 datasets (see section 4.5). The multiple imputation is implemented with the R-package Amelia II, according to Blackwell, Honaker, and King (2017a, 2017b). This approach to addressing the problem of missing outcome data in a field experiment is also used, for example, by King et al. (2009). In our analysis, results based on multiple imputation provide more conservative treatment effect estimates compared to list-wise deletion (c.f. Table SI-5, for comparison).

4.5 Quantities of Interest

To analyse treatment effects for the full sample and subgroups, we follow Imai, King and Nall (2009). We calculate the intent-to-treat (ITT) effect for all outcome variables of interest (Gerber & Green, 2012). The ITT is the total effect of the treatment on the outcomes of interest, regardless of experimental compliance, and offers a conservative estimation of the average effect of an intervention to improve on-farm storage. At the same time, the ITT is also the most realistic quantity when it comes to gauging the potential impacts of efforts to promote improved on-farm storage, such as in development programmes and policies where experimental compliance, in most cases, cannot be assured and may not even be desirable. We also examined treatment effect for subgroups of our sample, namely the two districts and male and female study participants. For the lean season ITT, we further calculated two-fold difference-in-differences: household differences between the lean season baseline and the lean season after treatment, and household differences between the first measurement immediately after experimental intervention and the lean season.

The ITT is calculated through a point estimator as a weighted average of within-pair mean differences between treatment and control groups (Imai et al., 2009):

$$\begin{aligned}\hat{\psi}(\widetilde{w}_k) \equiv \frac{1}{\sum_{k=1}^{m} w_k} \sum_{k=1}^{m} w_k \Bigg\{ Z_k \left(\frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} - \frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} \right) \\ + (1 - Z_k) \left(\frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} - \frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} \right) \Bigg\},\end{aligned} \tag{1}$$

where index for pairs is by k, clusters within each pair by j, and units within each cluster by i. Z_k denotes whether the first ($Z_k = 1$) or second cluster ($Z_k = 0$) in each of the m pairs was randomly assigned to treatment. We use arithmetic weights, such that the weight $(w_k) = n_{1k} + n_{2k}$, which corresponds to the sum of the n observations of the two clusters in each pair indexed by k. The variance estimator is (Imai et al., 2009):

$$\begin{aligned}\hat{\sigma}(\widetilde{w}_k) \equiv \frac{m}{(m-1)n^2} \sum_{k=1}^{m} \Bigg[\widetilde{w}_k \Bigg\{ Z_k \left(\frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} - \frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} \right) \\ + (1 - Z_k) \left(\frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} - \frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} \right) \Bigg\} - \frac{n \hat{\psi}(\widetilde{w}_k)}{m} \Bigg]^2.\end{aligned} \tag{2}$$

Supplementary Information

Table SI-1: **Effects of improved on-farm storage on post-harvest losses (PHL)**. Percentage of post-harvest losses expressed as the ratio of severely food insecure households in the full seasonal cycle (1=100% prevalence). ITT=Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed t test. Sample sizes for pairs (m) and total number of observations (n) for full sample I, and sample splits II-V (Sample/m/n): I/31/671; II/29/339; III/31/329; IV/16/338; V/15/333.

	Seperate Measurement of PHL		**Combined Measurement of PHL**
	PHL Dummy	**PHL Percentage**	**PHL Percentage**
I. All Households (HH)			
Control Group	0.74	35.04	30.93
ITT	-0.11	-2.40	-4.88
t-statistic	-2.42	-0.68	-1.41
p-value	0.01	0.25	0.08
II. Female Participant's HH			
Control Group	0.78	38.52	34.11
ITT	-0.14	-5.42	-6.16
t-statistic	-1.96	-1.00	-1.13
p-value	0.03	0.16	0.13
III. Male Participant's HH			
Control Group	0.71	32.43	28.78
ITT	-0.08	0.69	-4.01
t-statistic	-1.26	0.14	-0.84
p-value	0.10	0.45	0.20
IV. HH in Kilosa			
Control Group	0.76	36.34	31.50
ITT	-0.12	0.30	-2.87
t-statistic	-2.06	0.07	-0.62
p-value	0.02	0.47	0.27
V. HH in Kondoa			
Control Group	0.71	33.72	30.35
ITT	-0.09	-5.14	-6.91
t-statistic	-1.43	-0.98	-1.43
p-value	0.08	0.16	0.08

Table SI-2: **Balance of baseline characteristics between experimental groups.** Table shows a comparison of baseline characteristics in experimental groups by study district. The variables "study district" and "distance to market" were used for pair-wise matching.

Study District	Experimental Group	Number of Households	Number of Groups	Mean Group Size	Ratio of Female Participants	Mean Distance to Market
Kilosa	Control	166	16	10,38	0,56	62,95
	Treatment	172	16	10,75	0,34	63,86
Kondoa	Control	155	15	10,33	0,54	102,09
	Treatment	178	15	11,87	0,51	85,88

Table SI-3: **Items for the reduced Coping Strategies Index (rCSI) and respective weights as implemented via SMS-based mobile phone surveys.** Question items and weights according to Vaitla et al. (2017).

#	Category	Question	Item Weight
1	Introduction	For the next 5 questions reply only with the number of days your household took action because there was not enough food or money to buy food. Reply 1 to continue	
2	Less Expensive Food	In the past 30 days, how many days did your household rely on less preferred or less expensive food due to lack of food/money? Reply number of days 0-30	1
3	Borrow and Get Help	In the past 30 days, how many days did your household borrow food or rely on help from a friend or relative due to lack of food/money? Reply number of days 0-30	2
4	Reduce Number of Meals	In the past 30 days, how many days did your household reduce the number of meals eaten in a day due to lack of food/money? Reply number of days 0-30	1
5	Limit Portion Size	In the past 30 days, how many days did your household limit portion sizes at mealtime due to lack of food/money? Reply number of days 0-30	1
6	Restrict Consumption	In the past 30 days, how many days did your household restrict consumption by adults so children could eat due to lack of food/money? Reply number of days 0-30	3

Table SI-4: **Robustness checks for the effects of improved on-farm storage on the prevalence of severe food insecurity in the full season and in seasonal measurements using an alternative severe food insecurity threshold.** Prevalence of severe food insecurity expressed as the ratio of severely food insecure households in the full seasonal cycle (1=100% prevalence). Prevalence based on alternative threshold for severe food insecurity (>18) proposed in Maxwell, Vaitla and Coates (2014). ITT=Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed t test. DiD means Difference-in-Difference. Sample sizes for pairs (m) and total number of observations (n) for full sample I, and sample splits II-V (Sample/m/n): I/31/671; II/29/339; III/31/329; IV/16/338; V/15/333.

	Full Season	Baseline and Seasonal Measurements						Lean Season DiD	
	Y1	Jun BL (Lean)	Oct Y1	Dec Y1	Mar Y1	Jun Y1 (Lean)	Oct Y2	Jun Y1 Jun BL	Jun Y1 - Oct Y1
I. All Households (HH)									
Control Group	0.37	0.21	0.15	0.17	0.15	0.19	0.16	-0.02	0.04
ITT	-0.08	-0.02	-0.03	-0.03	-0.06	-0.08	-0.02	-0.06	-0.05
t-statistic	-1.64	-0.54	-0.76	-0.82	-1.61	-2.10	-0.35	-1.26	-1.28
p-value	0.05	0.30	0.22	0.21	0.05	0.02	0.36	0.10	0.10
II. Female Participant's HH									
Control Group	0.44	0.26	0.21	0.20	0.16	0.25	0.22	-0.01	0.04
ITT	-0.11	-0.06	-0.06	-0.04	-0.07	-0.12	-0.05	-0.06	-0.06
t-statistic	-1.56	-0.79	-0.98	-0.62	-1.24	-1.84	-0.64	-0.78	-0.87
p-value	0.06	0.21	0.16	0.27	0.11	0.03	0.26	0.22	0.19
III. Male Participant's HH									
Control Group	0.30	0.18	0.10	0.14	0.14	0.14	0.13	-0.04	0.04
ITT	-0.04	0.03	-0.01	-0.02	-0.04	-0.04	0.00	-0.07	-0.03
t-statistic	-0.59	0.50	-0.10	-0.43	-0.73	-0.74	-0.02	-0.98	-0.53
p-value	0.28	0.31	0.46	0.33	0.23	0.23	0.49	0.16	0.30
IV. HH in Kilosa									
Control Group	0.37	0.25	0.14	0.17	0.16	0.20	0.19	-0.05	0.06
ITT	-0.07	-0.05	0.00	-0.05	-0.06	-0.08	-0.01	-0.03	-0.08
t-statistic	-1.05	-0.99	-0.07	-0.79	-1.35	-1.51	-0.09	-0.51	-1.41
p-value	0.15	0.16	0.47	0.22	0.09	0.07	0.46	0.31	0.08
V. HH in Kondoa									
Control Group	0.36	0.18	0.15	0.16	0.15	0.17	0.14	0.00	0.02
ITT	-0.08	0.01	-0.05	-0.01	-0.05	-0.07	-0.02	-0.08	-0.02
t-statistic	-1.23	0.25	-1.14	-0.30	-0.90	-1.40	-0.46	-1.19	-0.38
p-value	0.11	0.40	0.13	0.38	0.18	0.08	0.32	0.12	0.35

Table SI-5: **Robustness checks for the effects of improved on-farm storage on the prevalence of severe food insecurity in the full season and in seasonal measurements using only data with complete observations for all measurements.** Prevalence of severe food insecurity expressed as the ratio of severely food insecure households in the full seasonal cycle (1=100% prevalence). ITT=Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed t test. DiD means Difference-in-Difference. Sample sizes for pairs (m) and total number of observations (n) for full sample I, and sample splits II-V (Sample/m/n): I/25/215; II/13/71; III/20/105; IV/13/105; V/12/110.

	Full Season	Baseline and Seasonal Measurements						Lean Season DiD	
	Y1	Jun BL (Lean)	Oct Y1	Dec Y1	Mar Y1	Jun Y1 (Lean)	Oct Y2	Jun Y1 - Jun BL	Jun Y1 - Oct Y1
I. All Households (HH)									
Control Group	0.42	0.33	0.23	0.28	0.24	0.32	0.25	-0.01	0.08
ITT	-0.13	0.04	-0.03	-0.05	-0.06	-0.18	-0.05	-0.22	-0.15
t-statistic	-1.62	0.55	-0.38	-0.79	-0.96	-2.12	-0.72	-2.43	-2.30
p-value	0.05	0.29	0.35	0.21	0.17	0.02	0.24	0.01	0.01
II. Female Participant's HH									
Control Group	0.55	0.35	0.41	0.42	0.27	0.45	0.24	0.10	0.04
ITT	-0.18	0.09	-0.13	-0.11	-0.01	-0.22	0.01	-0.31	-0.09
t-statistic	-1.36	0.60	-0.91	-0.79	-0.11	-1.47	0.04	-1.67	-0.87
p-value	0.09	0.28	0.18	0.22	0.46	0.07	0.48	0.05	0.19
III. Male Participant's HH									
Control Group	0.31	0.31	0.13	0.21	0.18	0.19	0.22	-0.12	0.06
ITT	-0.09	0.05	-0.02	-0.05	-0.03	-0.11	-0.06	-0.16	-0.10
t-statistic	-0.83	0.44	-0.16	-0.53	-0.30	-1.15	-0.65	-1.41	-1.24
p-value	0.20	0.33	0.44	0.30	0.38	0.13	0.26	0.08	0.11
IV. HH in Kilosa									
Control Group	0.37	0.25	0.20	0.22	0.24	0.24	0.25	-0.01	0.04
ITT	-0.11	0.05	0.04	-0.02	-0.09	-0.10	-0.03	-0.15	-0.14
t-statistic	-0.96	0.49	0.39	-0.18	-1.36	-0.90	-0.30	-1.37	-1.48
p-value	0.17	0.31	0.35	0.43	0.09	0.19	0.38	0.08	0.07
V. HH in Kondoa									
Control Group	0.48	0.41	0.26	0.33	0.25	0.39	0.25	-0.02	0.13
ITT	-0.14	0.04	-0.10	-0.09	-0.02	-0.25	-0.08	-0.29	-0.15
t-statistic	-1.29	0.30	-0.91	-0.90	-0.24	-2.02	-0.69	-2.00	-1.72
p-value	0.10	0.38	0.18	0.18	0.40	0.02	0.24	0.02	0.04

References

Abass, A. B., Fischler, M., Schneider, K., Daudi, S., Gaspar, A., Rüst, J., . . . Msola, D. (2018). On-farm comparison of different postharvest storage technologies in a maize farming system of Tanzania Central Corridor. *Journal of Stored Products Research*, *77*, 55–65. https://doi.org/10.1016/j.jspr.2018.03.002

Abizari, A.-R., Azupogo, F., Nagasu, M., Creemers, N., & Brouwer, I. D. (2017). Seasonality affects dietary diversity of school-age children in northern Ghana. *PLOS ONE*, *12*(8), e0183206. https://doi.org/10.1371/journal.pone.0183206

Affognon, H., Mutungi, C., Sanginga, P., & Borgemeister, C. (2015). Unpacking Postharvest Losses in Sub-Saharan Africa: A Meta-Analysis. *World Development*, *66*, 49–68. https://doi.org/10.1016/j.worlddev.2014.08.002

Aggarwal, S., Francis, E., & Robinson, J. (2018). Grain today, gain tomorrow: Evidence from a storage experiment with savings clubs in Kenya. *Journal of Development Economics*, *134*, 1–15. https://doi.org/10.1016/j.jdeveco.2018.04.001

Baoua, I. B., Amadou, L., & Murdock, L. L. (2013). Triple bagging for cowpea storage in rural Niger: Questions farmers ask. *Journal of Stored Products Research*, *52*, 86–92. https://doi.org/10.1016/j.jspr.2012.12.004

Basu, K., & Wong, M. (2015). Evaluating seasonal food storage and credit programs in east Indonesia. *Journal of Development Economics*, *115*, 200–216. https://doi.org/10.1016/j.jdeveco.2015.02.001

Becquey, E., Delpeuch, F., Konaté, A. M., Delsol, H., Lange, M., Zoungrana, M., & Martin-Prevel, Y. (2012). Seasonality of the dietary dimension of household food security in urban Burkina Faso. *British Journal of Nutrition*, *107*(12), 1860–1870. https://doi.org/10.1017/S0007114511005071

Blackwell, M., Honaker, J., & King, G. (2017a). A Unified Approach to Measurement Error and Missing Data: Details and Extensions. *Sociological Methods and Research*, *46*(3), 342–369. Retrieved from http://journals.sagepub.com/doi/full/10.1177/0049124115589052

Blackwell, M., Honaker, J., & King, G. (2017b). A Unified Approach to Measurement Error and Missing Data: Overview and Applications. *Sociological Methods and Research*, *46*(3), 303–341. Retrieved from http://journals.sagepub.com/doi/full/10.1177/0049124115585360

Bokusheva, R., Finger, R., Fischler, M., Berlin, R., Marín, Y., Pérez, F., & Paiz, F. (2012). Factors determining the adoption and impact of a postharvest storage technology. *Food Security*, *4*(2), 279–293. https://doi.org/10.1007/s12571-012-0184-1

Bruhn, M., & McKenzie, D. (2009). In Pursuit of Balance: Randomization in Practice in Development Field Experiments. *American Economic Journal: Applied Economics*, *1*(4), 200–232.

Burke, M., Bergquist, L. F., & Miguel, E. (2019). Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets. *The Quarterly Journal of Economics*, *134*(2), 785–842. https://doi.org/10.1093/qje/qjy034

Chigoverah, A. A., & Mvumi, B. M. (2016). Efficacy of metal silos and hermetic bags against stored-maize insect pests under simulated smallholder farmer conditions. *Journal of Stored Products Research*, *69*, 179–189. https://doi.org/10.1016/j.jspr.2016.08.004

Christiaensen, L., & Demery, L. (2017). *Agriculture in Africa: Telling Myths from Facts*: The World Bank. Retrieved from http://documents.worldbank.org/curated/en/681121528784639307/pdf/Agriculture-in-Africa-Telling-Myths-from-Facts-2017.pdf

Christian, P., & Dillon, B. (2018). Growing and Learning When Consumption Is Seasonal: Long-Term Evidence From Tanzania. *Demography*, *55*(3), 1091–1118. https://doi.org/10.1007/s13524-018-0669-4

Conceição, P., Levine, S., Lipton, M., & Warren-Rodríguez, A. (2016). Toward a food secure future: Ensuring food security for sustainable human development in Sub-Saharan Africa. *Food Policy*, *60*, 1–9. https://doi.org/10.1016/j.foodpol.2016.02.003

Dillon, B. (2017). Selling Crops Early to Pay for School: A Large-Scale Natural Experiment in Malawi. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.2848003

Doss, C. (2014). Data Needs for Gender Analysis in Agriculture. In A. R. Quisumbing, R. Meinzen-Dick, T. L. Raney, A. Croppenstedt, J. A. Behrman, & A. Peterman (Eds.), *Gender in Agriculture: Closing the Knowledge Gap* (pp. 55–68). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-017-8616-4_3

FAO. (2010). *Addressing food insecurity in protracted crises. The state of food insecurity in the world: Vol. 2010.* Rome: FAO.

FAO. (2018). *Building climate resilience for food security and nutrition. The state of food security and nutrition in the world: Vol. 2018.* Rome: FAO.

Fink, G., Kelsey, J., & Felix, M. (2018). *Seasonal Credit Constraints and Agricultural Labor Supply: Evidence from Zambia* (NBER Working Paper No. 20218).

Food and Agriculture Organization of the United Nations. (2011). *Women in agriculture: Closing the gender gap for development. The state of food and agriculture: 2010/11.* Rome: FAO.

Gerber, A. S., & Green, D. P. (2012). *Field experiments: Design, analysis, and interpretation* (1. ed.). New York, NY: Norton.

Gitonga, Z. M., Groote, H. de, Kassie, M., & Tefera, T. (2013). Impact of metal silos on households' maize storage, storage losses and food security: An application of a propensity score matching. *Food Policy*, *43*, 44–55. https://doi.org/10.1016/j.foodpol.2013.08.005

Groote, H. de, Kimenju, S. C., Likhayo, P., Kanampiu, F., Tefera, T., & Hellin, J. (2013). Effectiveness of hermetic systems in controlling maize storage pests in Kenya. *Journal of Stored Products Research*, *53*, 27–36. https://doi.org/10.1016/j.jspr.2013.01.001

Helvetas Swiss Intercooperation. Tanzania: Increase Food Security and income for farming households. Retrieved from https://www.helvetas.org/en/switzerland/what-we-do/how-we-work/our-projects/africa/tanzania/tanzania-storage-food-products

Hirvonen, K., Taffesse, A. S., & Worku Hassen, I. (2016). Seasonality and household diets in Ethiopia. *Public Health Nutrition*, *19*(10), 1723–1730. https://doi.org/10.1017/S1368980015003237

Imai, K., King, G., & Nall, C. (2009). The Essential Role of Pair Matching in Cluster-Randomized Experiments, with Application to the Mexican Universal Health Insurance Evaluation. *Statistical Science*, *24*(1), 29–53. https://doi.org/10.1214/08-STS274

Kadjo, D., Ricker-Gilbert, J., Abdoulaye, T., Shively, G., & Baco, M. N. (2018). Storage losses, liquidity constraints, and maize storage decisions in Benin. *Agricultural Economics*, *49*(4), 435–454. https://doi.org/10.1111/agec.12427

Kaminski, J., & Christiaensen, L. (2014). Post-harvest loss in sub-Saharan Africa—what do farmers say? *Global Food Security*, *3*(3-4), 149–158. https://doi.org/10.1016/j.gfs.2014.10.002

Kaminski, J., Christiaensen, L., & Gilbert, C. L. (2016). Seasonality in local food markets and consumption: evidence from Tanzania. *Oxford Economic Papers*, *68*(3), 736–757. https://doi.org/10.1093/oep/gpw013

King, G., Gakidou, E., Imai, K., Lakin, J., Moore, R. T., Nall, C., . . . Llamas, H. H. (2009). Public policy for the poor? A randomised assessment of the Mexican universal health insurance programme. *The Lancet*, *373*(9673), 1447–1454. https://doi.org/10.1016/S0140-6736(09)60239-7

Kitinoja, L., Saran, S., Roy, S. K., & Kader, A. A. (2011). Postharvest technology for developing countries: challenges and opportunities in research, outreach and advocacy. *Journal of the Science of Food and Agriculture*, *91*(4), 597–603. https://doi.org/10.1002/jsfa.4295

Krumpal, I. (2013). Determinants of social desirability bias in sensitive surveys: A literature review. *Quality & Quantity*, *47*(4), 2025–2047. https://doi.org/10.1007/s11135-011-9640-9

Likhayo, P., Bruce, A. Y., Mutambuki, K., Tefera, T., & Mueke, J. (2016). On-Farm Evaluation of Hermetic Technology Against Maize Storage Pests in Kenya. *Journal of Economic Entomology*, *109*(4), 1943–1950. https://doi.org/10.1093/jee/tow134

Lowder, S. K., Skoet, J., & Raney, T. (2016). The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide. *World Development*, *87*, 16–29. https://doi.org/10.1016/j.worlddev.2015.10.041

Maxwell, D., Caldwell, R., & Langworthy, M. (2008). Measuring food insecurity: Can an indicator based on localized coping behaviors be used to compare across contexts? *Food Product Composition, Consumer Health, and Public Policy*, *33*(6), 533–540. https://doi.org/10.1016/j.foodpol.2008.02.004

Maxwell, D., Vaitla, B., & Coates, J. (2014). How do indicators of household food insecurity measure up? An empirical comparison from Ethiopia. *Food Policy*, *47*, 107–116. https://doi.org/10.1016/j.foodpol.2014.04.003

Mock, N., Singhal, G., Olander, W., Pasquier, J.-B., & Morrow, N. (2016). mVAM: A New Contribution to the Information Ecology of Humanitarian Work. *Procedia Engineering*, *159*, 217–221. https://doi.org/10.1016/j.proeng.2016.08.164

Morrow, N., Mock, N., Bauer, J.-M., & Browning, J. (2016). Knowing Just in Time: Use Cases for Mobile Surveys in the Humanitarian World. *Procedia Engineering*, *159*, 210–216. https://doi.org/10.1016/j.proeng.2016.08.163

Moore, R. T., & Schnakenberg, K. *Package 'blockTools'.* Retrieved from https://cran.r-project.org/web/packages/blockTools/index.html

Murdock, L. L., Margam, V., Baoua, I., Balfe, S., & Shade, R. E. (2012). Death by desiccation: Effects of hermetic storage on cowpea bruchids. *Journal of Stored Products Research*, *49*, 166–170. https://doi.org/10.1016/j.jspr.2012.01.002

Omotilewa, O. J., Ricker-Gilbert, J., Ainembabazi, J. H., & Shively, G. E. (2018). Does improved storage technology promote modern input use and food security? Evidence from a randomized trial in Uganda. *Journal of Development Economics*, *135*, 176–198. https://doi.org/10.1016/j.jdeveco.2018.07.006

Peterman, A., Quisumbing, A., Behrman, J., & Nkonya, E. (2011). Understanding the Complexities Surrounding Gender Differences in Agricultural Productivity in Nigeria and Uganda. *Journal of Development Studies*, *47*(10), 1482–1509. https://doi.org/10.1080/00220388.2010.536222

Savy, M., Martin-Prével, Y., Traissac, P., Eymard-Duvernay, S., & Delpeuch, F. (2006). Dietary diversity scores and nutritional status of women change during the seasonal food shortage in rural Burkina Faso. *The Journal of Nutrition*, *136*(10), 2625–2632. https://doi.org/10.1093/jn/136.10.2625

Sheahan, M., & Barrett, C. B. (2017). Review: Food loss and waste in Sub-Saharan Africa. *Food Policy*, *70*, 1–12. https://doi.org/10.1016/j.foodpol.2017.03.012

Stephens, E. C., & Barrett, C. B. (2011). Incomplete Credit Markets and Commodity Marketing Behaviour. *Journal of Agricultural Economics*, *62*(1), 1–24. https://doi.org/10.1111/j.1477-9552.2010.00274.x

Stewart, R., Langer, L., Rebelo Da Silva, N., Muchiri, E., Zaranyika, H., Erasmus, Y., . . . de Wet, T. (2015). The effects of training, innovation and new technology on African smallholder farmers' wealth and food security. *Campbell Systematic Reviews*, *2015:16.* https://doi.org/10.4073/csr.2015.16

Transforming our world: the 2030 Agenda for Sustainable Development, United Nations General Assembly 10/21/2015.

Vaitla, B., Coates, J., Glaeser, L., Hillbruner, C., Biswal, P., & Maxwell, D. (2017). The measurement of household food security: Correlation and latent variable analysis of alternative indicators in a large multi-country dataset. *Food Policy*, *68*, 193–205. https://doi.org/10.1016/j.foodpol.2017.02.006

World Food Summit (1996). *Report of the World Food Summit: 13-17 November 1996.* FAO, Rome.

3 Brander, M. (2019): Does improved on-farm storage reduce seasonal food price gaps? Experimental evidence from Tanzanian markets

Does improved on-farm storage reduce seasonal food price gaps? Experimental evidence from Tanzanian markets

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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. The results document significant effects of improved on-farm storage on local market prices. Improved on-farm storage reduced the seasonal price gap by 16% on average in the observed harvest 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. 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.

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 (see for a meta-analysis 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. 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. For comparison, results based on uncorrected data are shown in the Supplementary Information.

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),

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

where $p_{s,m}$ 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 seasonal price trends, an interaction between T_{jk} and $Hweek$ is included in the model specification in Equation 3, where $Hweek$ is a linear time trend for the number of weeks after harvest,

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

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

To estimate effects on lean season prices, an interaction between T_{jk} and a dummy variable $Lean$ is included in the model specification in Equation 3, where $Lean$ indicates the lean season:

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

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

To estimate the ITT on the difference between storage levels at the start and at the end of the lean season, the sample is restricted to these two measurement rounds, and an interaction between T_{jk} and $EndLean$ is included in the model specification in Equation 3, where $EndLean$ is a dummy variable indicating whether the measurement was at the end of the lean season:

$$Y_{ijk} = \tau_1 T_{jk} + \gamma EndLean + \tau_2 (T_{jk} * EndLean) + \alpha_k + \epsilon_{ijk}, \tag{6}$$

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

$$Y_{jk} = \tau T_{jk} + \alpha_k + \epsilon_{jk}, \tag{7}$$

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 seasonal price trends based on cluster-level mean prices, the interaction between T_{jk} and $Hweek$ is added to the model specification in Equation 6:

$$Y_{jk} = \tau_1 T_{jk} + \gamma Hweek_t + \tau_2 (T_{jk} * Hweek_t) + \alpha_k + \epsilon_{jk}, \tag{8}$$

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

Model estimates for each study district are presented, wherever sample size permits, based on the respective sample splits. District dummies were already used for matching of pairs and represent prior beliefs on their moderation of treatment effects. 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 regions during the observation period. 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. The price decrease is more pronounced in Kondoa, the less integrated markets, as compared to the more integrated markets in Kilosa. Such 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] In the observation period, 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 1A).

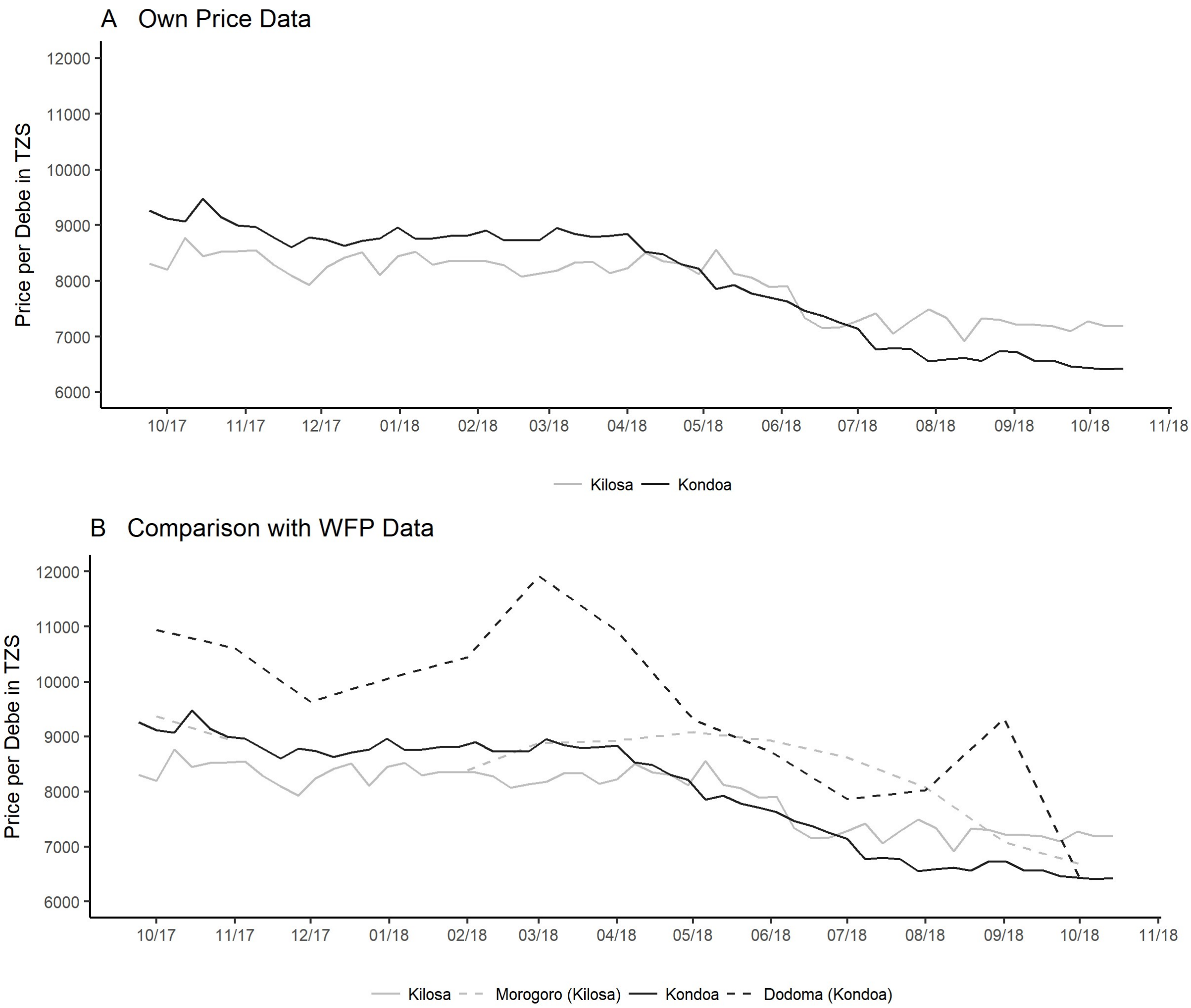
[1] See for example price data from World Food Programme (2019)

One plausible explanation for the decreasing price trend in the observation period, 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.

Figure 1B contrasts the weekly price data collected via SMS-based mobile phone survey with price data for each study district's regional capital (Dodoma for Kilosa district; Morogoro for Kilosa district) from WFP (World Food Programme, 2019). In terms of regional breakdown, the prices collected by WFP are most comparable to the data used in this paper, among all publicly available data. However, the WFP prices refer to wholesale prices, have missing observations and are available on a monthly frequency only. Nevertheless, a similar price pattern is observed.

The figure also suggests that prices in Kilosa (black line) are closer to prices in its regional capital Morogoro (black dashed-line), while the price differences observed between Kondoa (grey) and its regional capital Dodoma (grey dashed-line) are more substantial. Higher differences between price curves is what would be expected for the less integrated market of Kondoa. The comparison also documents the strengths of the data collection approach followed in this paper for gathering highly localized price data, weekly frequency and continuous observation over the study period.

Figure 1: Market prices in the two study districts (A) based on own weekly data and (B) comparison with WFP monthly data for regional capitals



Notes: Maize prices per debe (approx. 19kg) in Tanzanian Shilling (TZS) for (A) the two study districts based on own data, and (B) comparison of own data with data from the World Food Programme (WFP) for regional capitals. Solid lines in (A) and (B) represent own weekly price data per debe in Tanzanian Shilling (TZS), collected via SMS-based mobile phone surveys amongst study participants from the control groups (see Chapter 3.4). Dashed lines in (B) represent monthly price data available from the World Food Programme (2019). The grey lines show data for the Kilosa district in (A) and (B) and its regional capital Morogoro (B). The black lines represent price data for the Kondoa district in (A) and (B), and its regional capital Dodoma (B). World Food Programme prices scaled to one debe (19kg).

4.2 Effects of Treatment on Price Trend

For decreasing market prices, the expectation is that improved on-farm storage results in additional market demand, which in turn leads to higher prices. The effect of on-farm storage is anticipated to be more pronounced in markets that are less integrated where local supply and demand shifts more strongly influence local market prices.

Figure 2 illustrates that prices in treatment and control markets follow a similar trend of decreasing prices in the observed harvest cycle from September 2017 until July 2018. 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 are similar at the start of the observation period before prices in treatment markets increase relative to control.

The differences in weekly prices for treatment and control markets are shown in Figure 3. Consistent with the hypothesis, the difference between treatment and control prices is more pronounced in Kondoa, the less integrated markets, as compared to Kilosa. In Kondoa, prices in treatment and control diverge almost immediately after the completion of the intervention (Early October 2017, see Figure 3B). Thereafter, treatment prices in Kondoa are consistently higher than control prices and only converge in the second-year harvest period. In contrast, in the more integrated markets, Kilosa, prices remain similar in treatment and control markets until February, yet then also diverge in the same direction as in Kondoa (see Figure 3A). Prices in treatment markets are higher than prices in control markets for a few months, before they converge again after May shortly before the next harvest is brought in.

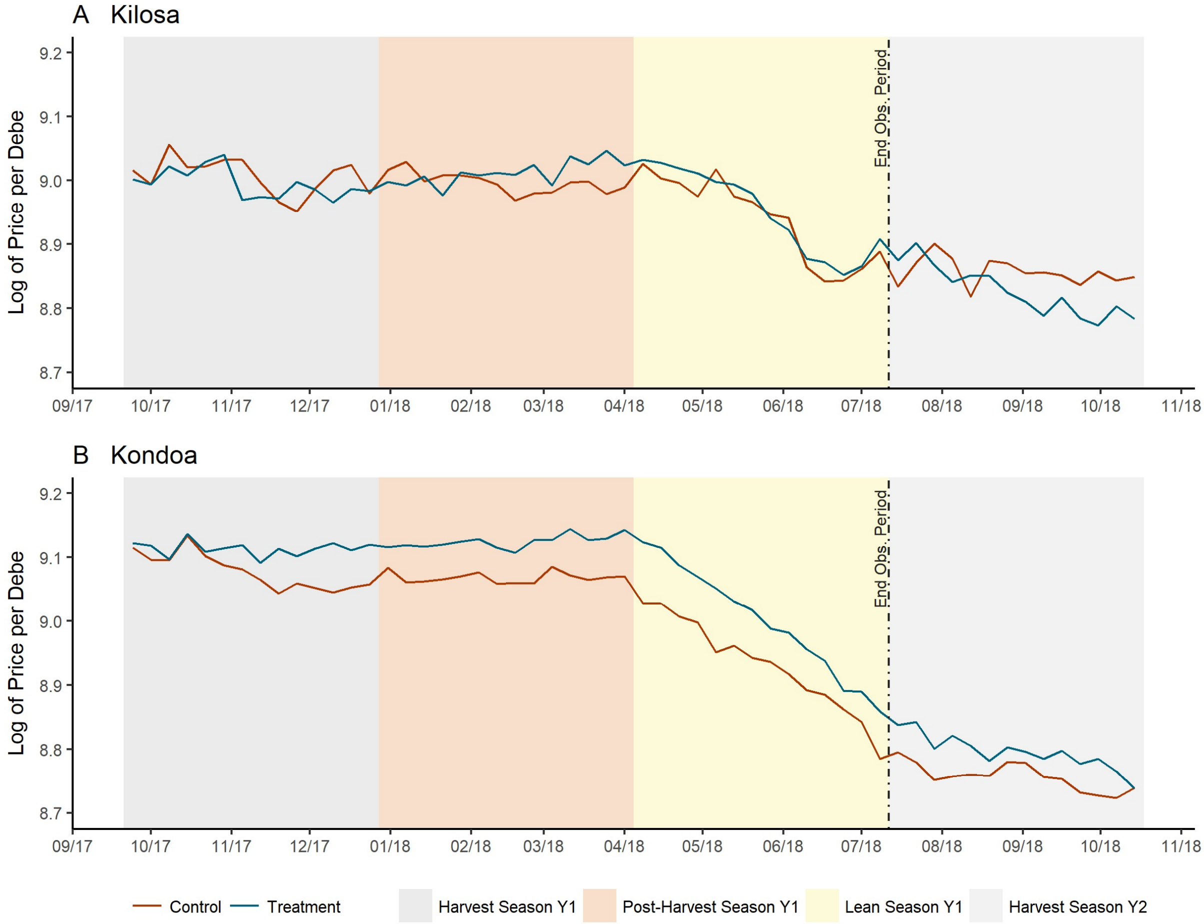
Table 1 presents the results estimated based on Equation 4, outlined in Chapter 3.6. The negative coefficient for the variable Hweek, the linear time-trend for the 42-weeks harvest cycle, shows the overall decreasing price trend, which is less pronounced in Kilosa (column 3) as compared to Kondoa (column 4). The variable Treat shows differences in the first week of measurement. In Kondoa, treatment market prices are 2.9% higher than control market prices, while in Kilosa, treatment market prices are 1.5% lower than control prices.[2] The interaction of the variable Treat with Hweek shows the experimental treatment increases prices relative to control in both study districts,

[2] Calculation example: In Kondoa, treatment market prices are 2.9% higher than control market prices, calculated as ((exp(0.029)-1)*100)

which is statistically significant at the 5% level. In line with the visual inspection, the treatment effect is smaller in Kilosa as compared to Kondoa.

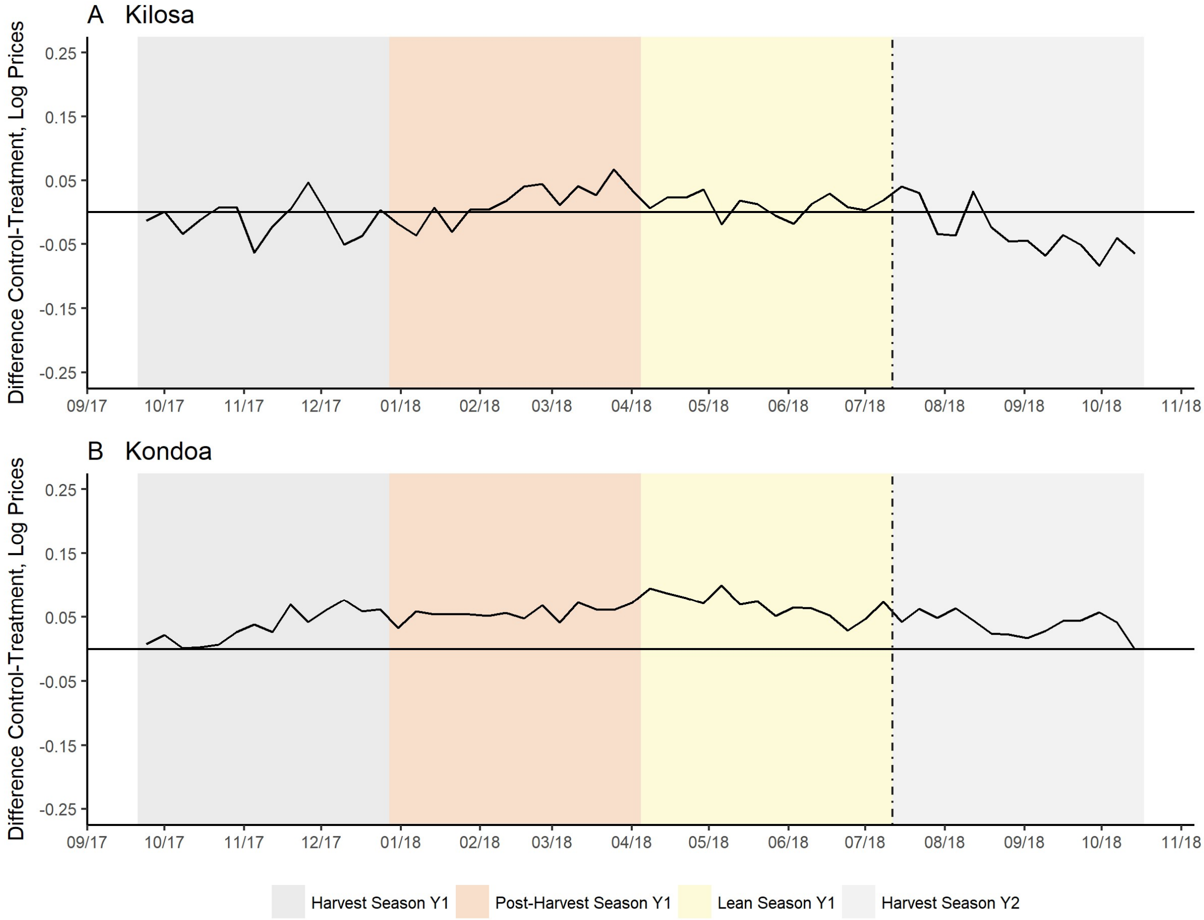
The treatment effects for the full sample and for Kondoa, though not Kilosa, are robust to an alternative model specification where the dependent variable are cluster-level mean local maize prices per week (see Figure SI-1) and if no outlier correction, as described in section 3.5, is applied (see Table SI-2). The effects for the full sample and Kondoa remain statistically significant at the 5% level, whereas treatment effects for Kilosa are no longer statistically significant in this robustness check, which also reflects the more limited magnitude of the treatment effect observed in Kilosa, the district with more integrated markets. On-site visits have reinforced this impression as the communities in which study farmers groups are located are small (around 50-100 households per community is a reasonable estimation) remote, and spatially dispersed, especially in Kondoa.

Figure 2: Development of market prices in experimental groups



Notes: Average of log local maize prices in study districts by treatment (blue line) and control (red line) groups. Calculations based on weighted observations, such that each cluster has equal weight. Colour background illustrates intraseasonal time periods where grey denotes harvest periods in 2017 (Year 1) and 2018 (Year 2), red denotes post-harvest period, and yellow shows lean period. Black dotted line shows end of observation period for this study.

Figure 3: Difference of Market Prices between Experimental Groups



Notes: Difference of log local maize prices in study districts 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 in 2017 (Year 1) and 2018 (Year 2), red denotes post-harvest period (Year 1), and yellow shows lean period (Year 1). Black dotted line shows end of observation period for this study.

Table 1: **Effects of treatment on seasonal price trend.** The dependent variable is the natural logarithm of local maize prices, measured weekly for the harvest cycle (Sept 2017-July 2018), 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. Hweek is a linear week time trend, starting at 1 with the first observation in mid-September 2017, and ending with 42 at the subsequent harvest mid-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).

	Full Sample without time trend (1)	Full Sample with time trend (2)	Kilosa Sample with time trend (3)	Kondoa Sample with time trend (4)
(Intercept)	8.9963	9.0869	9.0371	9.1412
	[8.9636, 9.0251]	[9.0587, 9.1175]	[9.0014, 9.0710]	[9.0933, 9.1874]
Treat	0.0287	0.0062	-0.0149	0.0293
	[0.0258, 0.0314]	[0.0007, 0.0113]	[-0.0235, -0.0050]	[0.0232, 0.0355]
Hweek		-0.0040	-0.0028	-0.0055
		[-0.0042, -0.0039]	[-0.0030, -0.0025]	[-0.0057, -0.0053]
Treat:Hweek		0.0010	0.0009	0.0011
		[0.0008, 0.0012]	[0.0005, 0.0013]	[0.0009, 0.0014]
Obs. (N/m)	(18007/31)	(18007/31)	(8823/16)	(9184/15)
R2 (total)	0.5813	0.6321	0.4026	0.7717

4.3 Effects of Treatment on Prices in the Lean Season

The positive and increasing treatment effect as the harvest cycle progresses, is 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, albeit only for Kondoa, the less integrated markets.

Table 2 reports estimates based on Equation 3 with sample splits by study district and seasonal time period. The intervention increased local market prices in Kilosa by 1% in the lean season, whereas the intervention increased lean season prices by 6.8% in Kondoa. The effects are statistically significant at the 5% level.

As the harvest season of year one and the post-harvest season also show significant differences in prices (see Table 2, Column 1 & 2), robustness is checked by contrasting these pre-lean season prices with prices observed in the lean season (see Equation 5). Table SI-3 presents the respective robustness check, which again shows that the treatment effect is highest in the lean season.

The full sample and the Kondoa subsample are further robust to a model specification based on cluster-level mean prices (see Table SI-4), where, however, the effects for Kilosa are not statistically significant.

Table 2: **Treatment effect on harvest, post-harvest and lean season prices.** The dependent variable is local maize price, measured weekly for the harvest cycle (Sept 2017-July 2018), through SMS-based mobile phone surveys. 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). Panels B and C report subsample estimates for the two study districts, Kondoa and Kilosa. 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 3).

	Harvest Season (1)	Post-Harvest Season (2)	Lean Season (3)
Panel A: Full Sample			
(Intercept)	9.0364	9.0268	8.9349
Treat	0.0111	0.0352	0.0386
	[0.0070, 0.0153]	[0.0308, 0.0392]	[0.0342, 0.0434]
Obs. (N/m)	5722/30	5743/31	6542/31
R2 (total)	0.6878	0.6916	0.5150
Panel B: Kilosa			
(Intercept)	9.0043	8.9920	8.9391
Treat	-0.0119	0.0155	0.0109
	[-0.0185, -0.0053]	[0.0084, 0.0216]	[0.0022, 0.0193]
Obs. (N/m)	2772/16	2860/16	3191/16
R2 (total)	0.4640	0.4355	0.3905
Panel C: Kondoa			
(Intercept)	9.0736	9.0655	8.9303
Treat	0.0364	0.0562	0.0685
	[0.0313, 0.0414]	[0.0518, 0.0606]	[0.0631, 0.0747]
Obs. (N/m)	2950/14	2883/15	3351/15
R2 (total)	0.7676	0.8044	0.6508

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 7. Improved on-farm storage reduced the seasonal price gap by 16%, on average. The reduction is statistically significant at the 5% level (see Table 3, Column 1). 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 2). It is notable that the estimated seasonal price gap is higher when using weekly price data (42%), 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. The limited sample size for this outcome variable, as prices are based on cluster-level means here (see Equation 1), restrains further sample splits by district.

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 7).

	Full Sample	
	Based on Monthly Prices (1)	Based on Weekly Prices (2)
(Intercept)	0.330	0.417
Treat	-0.052	-0.054
CI 95 Treat	[-0.102, -0.001]	[-0.117, 0.000]
CI 90 Treat	[-0.092, -0.009]	[-0.105, -0.007]
N/m	62/31	62/31
R2 (tot.)	0.120	0.174

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 a full harvest cycle. The effect is most pronounced for the lean season.

In the full harvest cycle, monthly maize price volatility is 0.077 and weekly price volatility is 0.071 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 and weekly price volatility. Monthly volatility is reduced from 0.077 to 0.063 and weekly volatility from 0.071 to 0.058, both reflecting a reduction by 1.3-1.4 percentage points, on average (see Table 4, Column 1-2, based on Equation 7). The results are statistically significant at the 5% and 10% levels, respectively.

The weekly price data enables estimates for the harvest, post-harvest and lean season. Weekly price volatility in control groups remains similar across these time periods. However, the treatment effect is again highest in the lean season (see Table 4, Column 5). In the lean season, the treatment results in a reduction of weekly price volatility by 1.9 percentage points, on average, which is statistically significant at the 5% level.

Table 4: **Effect of treatment on price volatility.** The dependent variable is monthly price volatility (Column 1), and weekly price volatility (Column 2-5), measured as the standard deviation of monthly and weekly returns, respectively, for each experimental cluster for the harvest cycle, and, on the right-hand side, for each time period. 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 effect (see Equation 7).

	Full Sample				
	Full Season		Seasonal Time Periods (Weekly Volatility)		
	Monthly Volatility (1)	Weekly Volatility (2)	Harvest Season (3)	Post-Harvest Season (4)	Lean Season (5)
(Intercept)	0.077	0.071	0.070	0.066	0.070
Treat	-0.014	-0.013	-0.009	-0.011	-0.019
	[-0.026, -0.002]	[-0.026, 0.001]	[-0.024, 0.007]	[-0.029, 0.006]	[-0.034, -0.004]
N/m	62/31	62/31	58/29	58/29	62/31
R2 (tot.)	0.384	0.401	0.373	0.392	0.095
CI 90 Treat	[-0.024, -0.004]	[-0.023, -0.002]	[-0.022, 0.004]	[-0.026, 0.003]	[-0.031, -0.006]

4.6 Effects of Treatment on Household Storage Levels

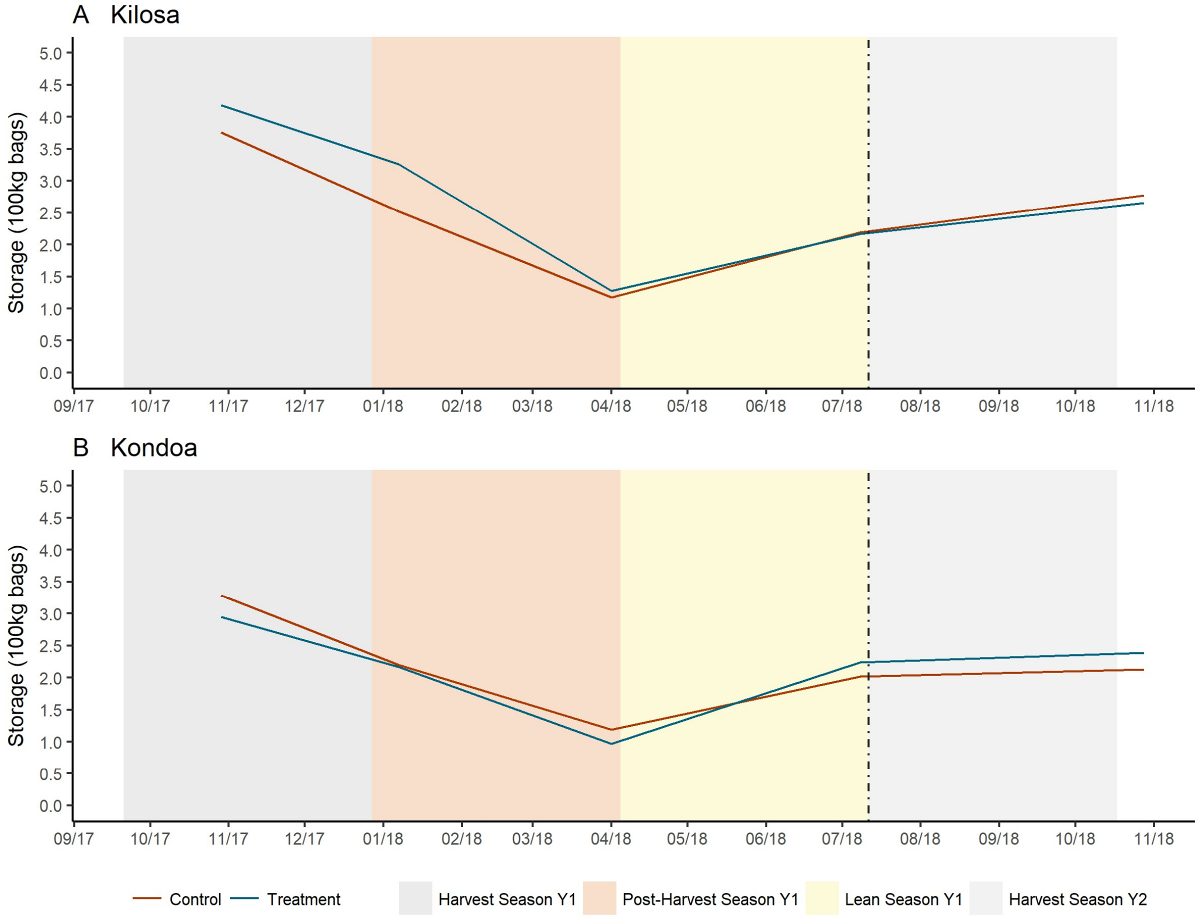
The hypothesis is that improved on-farm storage creates additional market demand in times of falling prices. Smallholder farmers are expected to more strongly increase their stocks in times of falling prices, as compared to farmers in the control condition. In the observation period, the time of decreasing prices corresponds to the lean season for both study districts. The results presented in Table 5 are consistent with this hypothesis, albeit only for the less integrated markets of Kondoa.

The seasonal development of storage levels, in number of bags of 100kg maize, in treatment and control households is illustrated in Figure 4. On average, storage is higher in Kilosa than Kondoa (see also Table SI-5). These differences may reflect the higher agricultural productivity in Kilosa. In both districts, storage levels show a decreasing trend in the harvest and post-harvest season, before they increase again in the lean season, the time when prices decrease.

In Kilosa, the more integrated markets, the lean season stock increase is very similar in treatment and control households (c.f. Figure 4A). In contrast, the results for Kondoa show that between the start and end of the lean season, treatment groups more strongly increased their storage as compared to control groups (see Figure 4B). Such an increase of storage is consistent with the expectation that improved on-farm storage leads to additional market demand in times of falling prices.

The observation is mirrored in Table 5, which reports estimates based on Equation 6. For Kondoa (Column 4), the positive coefficient for the interaction between the variables Treat and EndLean shows that the lean season stock increase is higher for treatment as compared to control. Specifically, the estimated storage increase in Kondoa is 49% higher for treatment as compared to control, which corresponds to about 50kg of additional maize demand per household, on average. The effect is statistically significant at the 5% level, and robust to estimating the model based on data where no outlier correction is applied (see Table SI-6).

Figure 4: Effects on storage levels in experimental groups



Notes: Weighted means of number of storage bags of 100kg kept by study households in control (red line) and treatment (blue line). Calculations based on weighted observations, such that each cluster has equal weight. Colour background illustrates intraseasonal time periods where grey denotes harvest periods in 2017 (Year 1) and 2018 (Year 2), red denotes post-harvest period (Year 1), and yellow shows lean period (Year 1). Black dotted line shows end of observation period for this study.

Table 5: **Effects of treatment on household storage levels before and after the lean season.** The dependent variable is the number of bags of 100kg of maize stored by households of study participants in the lean season. Treat is a cluster-level indicator for treatment assignment. EndLean is a dummy variable indicating whether the measurement was at the start of the lean season (early April 2018) or at the end of the lean season (July 2018). 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 6).

	Full Sample Start and End Lean Season (1)	Full Sample with End Lean Dummy (2)	Kilosa Sample with End Lean Dummy (3)	Kondoa Sample with End Lean Dummy (4)
(Intercept)	1.6299	1.1853	1.1771	1.1947
	[1.4383, 1.8417]	[0.9918, 1.4285]	[0.8946, 1.4325]	[0.8389, 1.5571]
Treat	0.0202	-0.0456	0.0960	-0.2199
	[-0.1456, 0.1598]	[-0.2340, 0.1451]	[-0.1772, 0.3846]	[-0.4639, 0.0159]
EndLean		0.9363	0.9943	0.8988
		[0.7307, 1.1216]	[0.6872, 1.2974]	[0.6206, 1.2054]
Treat:EndLean		0.1365	-0.1245	0.4395
		[-0.1429, 0.4121]	[-0.5352, 0.2652]	[0.0581, 0.7903]
N (Obs/Pair)	645/31	645/31	318/16	327/15
R2 (total)	0.2729	0.4774	0.3966	0.5829

5 Discussion and Conclusion

This is the first paper to empirically document that improved on-farm storage can reduce seasonal price gaps. Specifically, the intervention reduced the seasonal price gap by 16% in the observation period. 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 the seasonal price trend and on prices in the lean season.

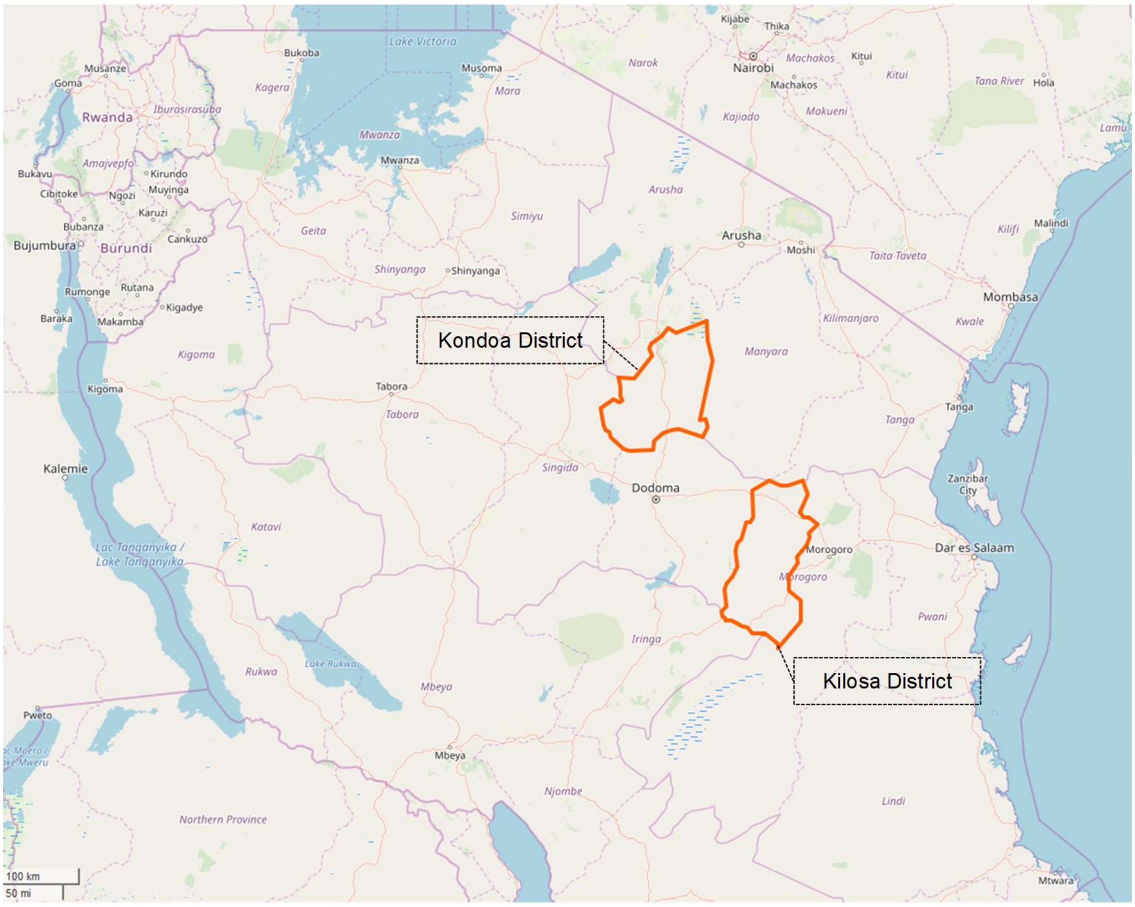
Moreover, this paper documents seasonal changes in household's storage decisions, which substantiates the results reported for price effects. The observed differences in storage levels are consistent with the hypothesis that an improved on-farm storage technology reduces the otherwise prevailing physical limits to intertemporal arbitrage. Although household storage levels were measured at a lower frequency (quarterly), compared to the price data (weekly), the results show that the intervention led to an increase in the amount of maize stored in the lean season for the district with less integrated markets. This increase reflects the expectation that in times of falling prices farmers increase their stocks. The fact that these effects are substantially more pronounced in Kondoa suggest higher marginal benefits of improved storage in less integrated markets, where intra- and interregional trade are more costly, and post-harvest storage loss may be more difficult. The results in Brander et al. (2019) lend support to the latter argument as they indicate that improved on-farm storage reduces post-harvest losses more substantially in Kondoa, which are the less integrated markets in this study.

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-1: **Effects of treatment on seasonal price trend based on weekly cluster-level mean prices.** The dependent variable is the natural logarithm of mean local maize price for each experimental cluster, measured weekly for the harvest cycle (Sept 2017-July 2018), through SMS-based mobile phone surveys amongst study participants. Treat is a cluster-level indicator for treatment assignment. Hweek is a linear week time trend, starting at 1 with the first observation in mid-September 2017, and ending with 42 at the subsequent harvest mid-July 2018. 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 8).

	Full Sample without time trend (1)	Full Sample with time trend (2)	Kilosa Sample with time trend (3)	Kondoa Sample with time trend (4)
(Intercept)	8.9965	9.0871	9.0376	9.1413
	[8.9642, 9.0265]	[9.0575, 9.1189]	[9.0005, 9.0758]	[9.0926, 9.1872]
Treat	0.0287	0.0062	-0.0149	0.0293
	[0.0185, 0.0389]	[-0.0133, 0.0246]	[-0.0456, 0.0161]	[0.0080, 0.0500]
Hweek		-0.0041	-0.0028	-0.0055
		[-0.0046, -0.0035]	[-0.0036, -0.0019]	[-0.0061, -0.0049]
Treat:Hweek		0.0010	0.0009	0.0011
		[0.0003, 0.0018]	[-0.0003, 0.0022]	[0.0003, 0.0019]
N (Obs/Pair)	(2468/31)	(2468/31)	(1282/16)	(1186/15)
R2 (total)	0.3378	0.4101	0.2123	0.6046

Table SI-2: **Effects of treatment on seasonal price trend – without outlier correction.** The dependent variable is the natural logarithm of local maize prices (without outlier correction), measured weekly for the harvest cycle (Sept 2017-July 2018), 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. Hweek is a linear week time trend, starting at 1 with the first observation in mid-September 2017, and ending with 42 at the subsequent harvest mid-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 Equ. 4).

	Full Sample without time trend (1)	Full Sample with time trend (2)	Kilosa Sample with time trend (3)	Kondoa Sample with time trend (4)
(Intercept)	8.9825	9.0570	8.9810	9.1396
	[8.9443, 9.0157]	[9.0201, 9.0941]	[8.9467, 9.0168]	[9.0808, 9.1939]
Treat	0.0158	-0.0009	0.0407	-0.0467
	[0.0108, 0.0206]	[-0.0108, 0.0094]	[0.0266, 0.0569]	[-0.0621, -0.0332]
Hweek		-0.0033	-0.0021	-0.0047
		[-0.0037, -0.0030]	[-0.0026, -0.0017]	[-0.0051, -0.0043]
Treat:Hweek		0.0008	-0.0007	0.0024
		[0.0004, 0.0012]	[-0.0013, -0.0002]	[0.0019, 0.0030]
Obs. (N/m)	(18680/31)	(18680/31)	(9187/16)	(9493/15)
R2 (total)	0.3517	0.3759	0.2483	0.3965

Table SI-3: **Effects of treatment on prices in the lean season.** The dependent variable is the natural logarithm of local maize price, measured weekly for the harvest cycle (Sept 2017-July 2018), through SMS-based mobile phone surveys. Treat is a cluster-level indicator for treatment assignment showing the intent-to-treat (ITT) effect. Lean is an indicator for observations in the lean season time period. Intercept shows estimates for the control group, 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).

	Full Sample (1)	Kilosa (2)	Kondoa (3)
(Intercept)	9.0323	8.9971	9.0706
	[9.0011, 9.0605]	[8.9665, 9.0293]	[9.0198, 9.1243]
Treat	0.0233	0.0019	0.0466
	[0.0203, 0.0265]	[-0.0039, 0.0068]	[0.0426, 0.0504]
Lean	-0.0975	-0.0580	-0.1403
	[-0.1022, -0.0935]	[-0.0646, -0.0509]	[-0.1447, -0.1358]
Treat:Lean	0.0153	0.0090	0.0220
	[0.0097, 0.0208]	[0.0002, 0.0172]	[0.0160, 0.0276]
N (Obs/Pair)	18007/31	8823/16	9184/15
R2 (total)	0.6318	0.3953	0.7779

Table SI-4: **Treatment effect on harvest, post-harvest and lean season prices based on weekly cluster-level mean prices.** The dependent variable is the natural logarithm of mean local maize price for each experimental cluster, measured weekly for the harvest cycle (Sept 2017-July 2018), through SMS-based mobile phone surveys. 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). Panels B and C report subsample estimates for the two study districts, Kondoa and Kilosa. 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 7).

	Harvest Season (1)	Post-Harvest Season (2)	Lean Season (3)
Panel A: Full Sample			
(Intercept)	9.0367	9.0275	8.9349
Treat	0.0111	0.0352	0.0386
	[-0.0018, 0.0252]	[0.0216, 0.0482]	[0.0220, 0.0580]
Obs. (N/m)	790/30	814/31	864/31
R2 (total)	0.5033	0.5333	0.2669
Panel B: Kilosa			
(Intercept)	9.0047	8.9936	8.9391
Treat	-0.0119	0.0155	0.0109
	[-0.0331, 0.0074]	[-0.0054, 0.0370]	[-0.0170, 0.0397]
Obs. (N/m)	414/16	420/16	448/16
R2 (total)	0.2892	0.2589	0.1674
Panel C: Kondoa			
(Intercept)	9.0737	9.0657	8.9303
Treat	0.0364	0.0562	0.0685
	[0.0190, 0.0525]	[0.0433, 0.0681]	[0.0485, 0.0868]
Obs. (N/m)	376/14	394/15	416/15
R2 (total)	0.6078	0.7346	0.4374

Table SI-5: **Effects of treatment on household storage levels.** The dependent variable is the number of bags of 100kg of maize stored by households of study participants in the full observation period (Column 1) and for each survey round (Columns 2-5). Sub-panels identify the two study districts, namely Kondoa and Kilosa. Surveys were implemented by the first week of the months indicated. Square brackets show bootstrapped 95% confidence intervals. Model specification is a mixed-effects model where Pair, the categorical variable identifying matched pairs, is a random effect (see Equation 3).

	Full Season	Nov 17	Jan 18	Apr 18	Jul 18
		Mid	Start	Start	End
		Harvest	Post-Harvest	Lean	Lean
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
(Intercept)	2.3170	3.5280	2.3601	1.1815	2.1083
Treat	0.1138	0.0606	0.3560	-0.0456	0.0909
	[-0.0253, 0.2629]	[-0.2634, 0.3641]	[0.1257, 0.6049]	[-0.1628, 0.0820]	[-0.1559, 0.3325]
Obs. (N/m)	1314/31	342/29	327/28	362/29	283/27
R2 (total)	0.2821	0.5301	0.3317	0.4424	0.2422
Panel B: Kilosa					
(Intercept)	2.3972	3.7548	2.5232	1.1771	2.1915
Treat	0.3046	0.4329	0.7388	0.0960	-0.0285
	[0.0741, 0.5439]	[-0.1750, 1.0287]	[0.3182, 1.1446]	[-0.1201, 0.3015]	[-0.4246, 0.3545]
Obs.	614/16	149/15	147/14	181/16	137/14
R2 (total)	0.0727	0.3314	0.1470	0.0084	0.3533
Panel C: Kondoa					
(Intercept)	2.2215	3.2849	2.1971	1.1869	2.0187
Treat	-0.0948	-0.3383	-0.0268	-0.2199	0.2195
	[-0.2509, 0.0672]	[-0.6722, 0.0284]	[-0.2932, 0.2607]	[-0.3741, -0.0798]	[-0.1533, 0.5863]
Obs.	700/15	193/14	180/14	181/13	146/13
R2 (total)	0.4560	0.6553	0.3969	0.6859	0.0839

Table SI-6: **Effects of treatment on household storage levels before and after the lean season – without outlier correction.** The dependent variable is the number of bags of 100kg of maize stored by households of study participants in the lean season without outlier correction applied. Treat is a cluster-level indicator for treatment assignment. EndLean is a dummy variable indicating whether the measurement was at the start of the lean season (early April 2018) or at the end of the lean season (July 2018). 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 6).

	Full Sample Start and End Lean Season (1)	Full Sample with End Lean Dummy (2)	Kilosa Sample with End Lean Dummy (3)	Kondoa Sample with End Lean Dummy (4)
(Intercept)	13.7558	23.8202	22.1117	25.9348
	[7.4660, 20.1867]	[16.3264, 31.4077]	[12.1275, 32.3134]	[16.2356, 36.0602]
Treat	-11.3613	-22.1302	-20.3359	-24.3385
	[-18.3040, -4.3911]	[-31.2105, -12.3387]	[-31.3555, -9.2514]	[-37.2433, -11.2852]
EndLean		-20.5149	-19.1489	-22.4953
		[-30.1051, -10.3576]	[-30.0372, -7.5464]	[-36.5569, -8.2093]
Treat:EndLean		21.9223	20.8317	23.4269
		[6.8700, 36.2020]	[4.1032, 35.5037]	[1.7734, 44.4258]
N (Obs/Pair)	698/31	698/31	349/16	349/15
R2 (total)	0.0879	0.1247	0.2497	0.0565

References

Abass, A. B., Fischler, M., Schneider, K., Daudi, S., Gaspar, A., Rüst, J., . . . Msola, D. (2018). On-farm comparison of different postharvest storage technologies in a maize farming system of Tanzania Central Corridor. *Journal of Stored Products Research*, *77*, 55–65. https://doi.org/10.1016/j.jspr.2018.03.002

Affognon, H., Mutungi, C., Sanginga, P., & Borgemeister, C. (2015). Unpacking Postharvest Losses in Sub-Saharan Africa: A Meta-Analysis. *World Development*, *66*, 49–68. https://doi.org/10.1016/j.worlddev.2014.08.002

Baoua, I. B., Amadou, L., & Murdock, L. L. (2013). Triple bagging for cowpea storage in rural Niger: Questions farmers ask. *Journal of Stored Products Research*, *52*, 86–92. https://doi.org/10.1016/j.jspr.2012.12.004

Basu, K., & Wong, M. (2015). Evaluating seasonal food storage and credit programs in east Indonesia. *Journal of Development Economics*, *115*, 200–216. https://doi.org/10.1016/j.jdeveco.2015.02.001

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Bellemare, M. F., Barrett, C. B., & Just, D. R. (2013). The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia. *American Journal of Agricultural Economics*, *95*(4), 877–899. https://doi.org/10.1093/ajae/aat018

Bokusheva, R., Finger, R., Fischler, M., Berlin, R., Marín, Y., Pérez, F., & Paiz, F. (2012). Factors determining the adoption and impact of a postharvest storage technology. *Food Security*, *4*(2), 279–293. https://doi.org/10.1007/s12571-012-0184-1

Brander, M., Bernauer, T., & Huss, M. (2019). *Improved on-farm storage reduces seasonal food insecurity of smallholder farmer's households – Evidence from a Randomized Control Trial in Tanzania* (Working Paper).

Bruhn, M., & McKenzie, D. (2009). In Pursuit of Balance: Randomization in Practice in Development Field Experiments. *American Economic Journal: Applied Economics*, *1*(4), 200–232.

Burke, M., Bergquist, L. F., & Miguel, E. (2019). Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets *The Quarterly Journal of Economics*, *134*(2), 785–842. https://doi.org/10.1093/qje/qjy034

Cafiero, C., Bobenrieth H., E. S.A., Bobenrieth H., J. R.A., & Wright, B. D. (2011). The empirical relevance of the competitive storage model. *Journal of Econometrics*, *162*(1), 44–54. https://doi.org/10.1016/j.jeconom.2009.10.008

Chigoverah, A. A., & Mvumi, B. M. (2016). Efficacy of metal silos and hermetic bags against stored-maize insect pests under simulated smallholder farmer conditions. *Journal of Stored Products Research*, *69*, 179–189. https://doi.org/10.1016/j.jspr.2016.08.004

Coulter, J., & Golob, P. (1992). Cereal marketing liberalization in Tanzania. *Food Policy*, *17*(6), 420–430. https://doi.org/10.1016/0306-9192(92)90074-8

Davis, B., Di Giuseppe, S., & Zezza, A. (2017). Are African households (not) leaving agriculture? Patterns of households' income sources in rural Sub-Saharan Africa. *Food Policy*, *67*, 153–174. https://doi.org/10.1016/j.foodpol.2016.09.018

Deaton, A., & Laroque, G. (1992). On the Behaviour of Commodity Prices. *The Review of Economic Studies*, *59*(1), 1. https://doi.org/10.2307/2297923

Deaton, A., & Laroque, G. (1996). Competitive Storage and Commodity Price Dynamics. *Journal of Political Economy*, *104*(5), 896–923. https://doi.org/10.1086/262046

Dercon, S., & Krishnan, P. (2000). Vulnerability, seasonality and poverty in Ethiopia. *Journal of Development Studies*, *36*(6), 25–53. https://doi.org/10.1080/00220380008422653

Dillon, B. (2017). Selling Crops Early to Pay for School: A Large-Scale Natural Experiment in Malawi. *SSRN Electronic Journal*. Advance online publication. https://doi.org/10.2139/ssrn.2848003

Fink, G., Kelsey, J., & Felix, M. (2018). *Seasonal Credit Constraints and Agricultural Labor Supply: Evidence from Zambia* (NBER Working Paper No. 20218).

Frelat, R., Lopez-Ridaura, S., Giller, K. E., Herrero, M., Douxchamps, S., Djurfeldt, A. A., . . . van Wijk, M. T. (2015). Drivers of household food availability in sub-Saharan Africa based on big data from small farms. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(2), 458–463. https://doi.org/10.1073/pnas.1518384112

Gerber, A. S., & Green, D. P. (2012). *Field experiments: Design, analysis, and interpretation* (1. ed.). New York, NY: Norton.

Gilbert, C. L., Christiaensen, L., & Kaminski, J. (2017). Food price seasonality in Africa: Measurement and extent. *Food Product Composition, Consumer Health, and Public Policy*, *67*, 119–132. https://doi.org/10.1016/j.foodpol.2016.09.016

Gitonga, Z. M., Groote, H. de, Kassie, M., & Tefera, T. (2013). Impact of metal silos on households' maize storage, storage losses and food security: An application of a propensity score matching. *Food Policy*, *43*, 44–55. https://doi.org/10.1016/j.foodpol.2013.08.005

Groote, H. de, Kimenju, S. C., Likhayo, P., Kanampiu, F., Tefera, T., & Hellin, J. (2013). Effectiveness of hermetic systems in controlling maize storage pests in Kenya. *Journal of Stored Products Research*, *53*, 27–36. https://doi.org/10.1016/j.jspr.2013.01.001

Gustafson, R. L., States, U., & Agriculture, D. o. (1958). *Carryover levels for grains: A method for determining amounts that are optimal under specified conditions*. Washington: U.S. Dept. of Agriculture.

Hill, J., & Scott, M. (2009). Comment: The Essential Role of Pair Matching. *Statistical Science*, *24*(1), 54–58. https://doi.org/10.1214/09-STS274A

Imai, K., King, G., & Nall, C. (2009a). Rejoinder: Matched Pairs and the Future of Cluster-Randomized Experiments. *Statistical Science*, *24*(1), 65–72. https://doi.org/10.1214/09-STS274REJ

Imai, K., King, G., & Nall, C. (2009b). The Essential Role of Pair Matching in Cluster-Randomized Experiments, with Application to the Mexican Universal Health Insurance Evaluation. *Statistical Science*, *24*(1), 29–53. https://doi.org/10.1214/08-STS274

Kadjo, D., Ricker-Gilbert, J., Abdoulaye, T., Shively, G., & Baco, M. N. (2018). Storage losses, liquidity constraints, and maize storage decisions in Benin. *Agricultural Economics*, *49*(4), 435–454. https://doi.org/10.1111/agec.12427

Kaminski, J., Christiaensen, L., & Gilbert, C. L. (2016). Seasonality in local food markets and consumption: evidence from Tanzania. *Oxford Economic Papers*, *68*(3), 736–757. https://doi.org/10.1093/oep/gpw013

Likhayo, P., Bruce, A. Y., Mutambuki, K., Tefera, T., & Mueke, J. (2016). On-Farm Evaluation of Hermetic Technology Against Maize Storage Pests in Kenya. *Journal of Economic Entomology*, *109*(4), 1943–1950. https://doi.org/10.1093/jee/tow134

Minot, N. (2014). Food price volatility in sub-Saharan Africa: Has it really increased? *Food Policy*, *45*, 45–56. https://doi.org/10.1016/j.foodpol.2013.12.008

Mitra, S., & Boussard, J.-M. (2012). A simple model of endogenous agricultural commodity price fluctuations with storage. *Agricultural Economics*, *43*(1), 1–15. https://doi.org/10.1111/j.1574-0862.2011.00561.x

Moore, R. T., & Schnakenberg, K. Package 'blockTools'. Retrieved from https://cran.r-project.org/web/packages/blockTools/index.html

Mulangu, F., Chauvin, N., & Porto, G. (2012). *Food Production and Consumption Trends in Sub-Saharan Africa: Prospects for the Transformation of the Agricultural Sector* (Working Paper). Retrieved from United Nations Development Programme website:
https://www.researchgate.net/profile/Francis_Mulangu2/publication/263257182_Food_Production_and_Consumption_Trends_in_Sub-Saharan_Africa_Prospects_for_the_Transformation_of_the_Agricultural_Sector/links/55f1561008aef559dc470917/

Murdock, L. L., Margam, V., Baoua, I., Balfe, S., & Shade, R. E. (2012). Death by desiccation: Effects of hermetic storage on cowpea bruchids. *Journal of Stored Products Research*, *49*, 166–170. https://doi.org/10.1016/j.jspr.2012.01.002

Newbery, D. M. G., & Stiglitz, J. E. (1981). *The theory of commodity price stabilization: A study in the economics of risk*. Oxford: Clarendon Press.

Samuelson, P. A. (1971). Stochastic Speculative Price. *Proceedings of the National Academy of Sciences*, *68*(2), 335–337. https://doi.org/10.1073/pnas.68.2.335

Stephens, E. C., & Barrett, C. B. (2011). Incomplete Credit Markets and Commodity Marketing Behaviour. *Journal of Agricultural Economics*, *62*(1), 1–24. https://doi.org/10.1111/j.1477-9552.2010.00274.x

Tesfaye, W., & Tirivayi, N. (2018). The impacts of postharvest storage innovations on food security and welfare in Ethiopia. *Food Policy*, *75*, 52–67. https://doi.org/10.1016/j.foodpol.2018.01.004

World Food Programme. (2019). vam Food Security Analysis: Economic Explorer - Prices. Retrieved from http://dataviz.vam.wfp.org/economic_explorer/

4 Brander, M., Bernauer, T., and Huss, M. (2019): Do national trade policy changes increase global food price volatility?

Do national trade policy changes increase global food price volatility?

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Abstract

Price volatility in global agricultural markets has gained increasing prominence since the world food price crises of the years 2007-08 and 2010-11. While the public and media awareness focused on rising food price levels, the political response concentrated on food price volatility. This political priority is reflected in a dedicated target on food price volatility in the 2030 Agenda for Sustainable Development. National governments have frequently resorted to agricultural trade policy interventions as a means to stabilize domestic food prices with the aim of averting adverse effects on poor consumers and agricultural producers. However, there is a widespread concern that trade policy interventions result in even more volatile global market prices. Yet, the empirical evidence behind this concern is thin. If national trade policy interventions indeed increase global price volatility, their effects most likely appear on the day that trade policy changes are announced. This paper presents the first analysis on the effects of the announcement of national trade policy changes on global food price volatility. We develop an original dataset on announcements of national trade policy changes covering the main global staple crops, namely wheat, maize, and rice, and the time period from 2005 to 2017. Our results show that the announcement of national trade policy changes, specifically restrictive export and liberal import policies, can result in increases of global food price volatility on their announcement day and a few days thereafter, yet the persistence of these trade-policy related volatility effects is short. Moreover, the results show that adequate stock levels can minimize the observed short-term effects. Our results hence provide little empirical support to the concern that national agricultural trade policies exacerbate global food price volatility.

1 Introduction

Price volatility in global agricultural markets has gained increasing prominence in the past decade. Much of this renewed attention can be attributed to the food price crises of the years 2007-08 and 2010-11 (Tadesse, Algieri, Kalkuhl, & Braun, 2014). Between 2006 and 2008 the Food and Agriculture Organization (FAO) of the United Nations' food price index rose by 38%, and between 2009 and 2011, again by 27% (Bellemare & Lee, 2016). While the ensuing public and media debate focused on these rising food price levels, the political response quickly concentrated on food price volatility (Bellemare, Barrett, & Just, 2013), that is fluctuations of food prices around their short-term trend. Policy makers around the world pushed for measures to limit food price volatility and stabilize prices (Bellemare & Lee, 2016). This shared political priority was consequentially also reflected in a dedicated target to "limit extreme food price volatility" in the 2030 Agenda for Sustainable Development, adopted in 2015 (Transforming our world: the 2030 Agenda for Sustainable Development, 2015).

The political focus on food price volatility can be explained by a shared consensus among countries that volatility is undesirable. In contrast, countries do not have such a shared consensus on the issue of high food prices as they affect countries unevenly. Food price volatility is widely seen as detrimental for producers and consumers alike, while high food prices have negative repercussions for consumers but benefit agricultural producers (HLPE, 2011). The welfare effect of high food prices hence depends on the sectoral composition of national economies. Where positive effects on agricultural producers outweigh adverse effects on food buyers, high food prices may overall have positive welfare and economic effects. The literature documents that the impact of high food prices on poverty and food security has indeed been uneven among and within countries (e.g. Headey, 2013; Headey & Martin, 2016; Ivanic, Martin, & Zaman, 2012; Ivanic & Martin, 2014; Anríquez, Daidone, & Mane, 2013).[1] In contrast, food price volatility induces price risk and uncertainty, which challenge both consumers and producer's ability to make decisions optimal for their welfare (e.g., Wossen, Berger, Haile, & Troost, 2018; Pieters & Swinnen, 2016; Dawe & Peter Timmer, 2012; Gouel, 2013). These effects are particularly detrimental in the developing world, where consumers and producers have limited options to hedge against price uncertainty (e.g. Magrini, Balié, & Morales-Opazo, 2017; Bellemare et al., 2013; Clapp, 2009; Naylor &

[1] For example, Headey and Martin (2016) show that sustained increases in food prices have often benefited the poor and likely contributed to faster global poverty reduction from the mid-2000s onward, and Headey (2013) finds that during the global food crises (2007-08), food security remained the same or even improved.

Falcon, 2010; Gilbert & Morgan, 2010). In poor countries, volatile staple food prices can induce risks for poor farmers and consumers for falling into poverty traps, limit investment in agriculture and throughout the economy, and result in reduced income and food security (e.g. Wossen et al., 2018; Bellemare et al., 2013; Dawe & Peter Timmer, 2012;). The social relevance of limiting food price volatility is illustrated in Ethiopia, where Bellemare et al. (2013) show that the average household would be willing to pay 18% of their income to fully stabilize commodity prices. Given the value of stable food prices for consumers and producers, contrasted with diverging effects of high food prices, it comes with no surprise that policy-makers emphasized measures to limit price volatility.

National governments have frequently resorted to trade policy interventions as a means to stabilize domestic food prices in the face of volatile global market prices (Gilbert & Morgan, 2010). However, there is a widespread concern that the result of these interventions are even more volatile global market prices, which in turn transmit back to domestic markets (Gilbert & Morgan, 2010). This concern is exemplified in the declaration of a summit convened at the FAO in 2008, which had reaffirmed "the need to minimise the use of restrictive measures that could increase volatility of international prices" (Food and Agriculture Organization of the United Nations, 2008, Para. 6e). These consequences for international price volatility could imply beggar-your-neighbour effects and limit the effectiveness of trade policies to create more stable domestic prices. To the extent that price volatility transmits from global markets to domestic markets, this concern is well founded. Ceballos, Hernandez, Minot, and Robles (2017) show statistically significant volatility transmission from global markets to domestic markets for wheat, rice and maize, with strongest effects for wheat. Yet, very little is known on the effects of national trade policy interventions on global price volatility in the first place.

The limited literature on the effects of trade policy interventions on global price volatility has thus far argued that restrictive trade policies have stronger effects on global food price volatility as compared to liberal trade policies, and that volatility effects are more pronounced if restrictions concern exports rather than imports (e.g. Rude and An, 2015). Based on this argument, Rude and An (2015) focus on restrictive export policies and show that export taxes and quantitative export restrictions increase global price volatility of wheat, export taxes increase price volatility of rice, but neither increases price volatility of maize and soybean. Similar results for protectionist trade policies in general, without a distinction into import and export restrictions, are shown in a simulation study for the period 1970-2010 (Ivanic & Martin, 2014). Yet, we are not aware of any study that has empirically analyzed the hypothesized diverging effects of different types of trade policies. This is especially surprising as a frequent policy of importing countries in times of high and volatile global food prices are liberal import policies. For example, for the year 2008, Demeke, Pangrazio, and Maetz (2009) find that out of 81 countries in their sample, there were more countries that reduced tariffs or import custom fees (43) than countries that restricted or banned exports of agricultural commodities (25). There is a priori no reason why import policies, specifically liberal import policies, should have no effect on price volatility.

If national trade policy interventions indeed increase global price volatility, their effects most likely appear on the day that trade policy changes are announced. This paper presents the first analysis on the comparative effects of the announcement of trade policy measures on global grain price volatility. We focus on the announcement, rather than the implementation of trade policy measures, as market participants learn about a policy change on the announcement day. In an efficient market, this information should be immediately reflected in market participants' expectations, and hence prices and volatility, while the actual implementation of changes, which is rarely on the same date, does not provide new information. Specifically, we analyse the volatility effects following the announcement of different types of national trade policy changes, including the thus far neglected effects of liberal import policies. Moreover, our analysis is based on daily data, in contrast to monthly or annual data typically used in the existing literature. To do so, we develop an original dataset of announcements of national trade policy changes for the main global staple crops, namely wheat, maize, and rice, for the period 2005-2017. Our data captures the characteristics of policies announced, coded based on an extensive and replicable media search. We estimate daily price volatility from the daily range of futures prices, i.e. the difference between the highest and the lowest price observed on a given day, at the Chicago Board of Trade (CBOT). Our daily data further permits to estimate the persistence of volatility effects by the extent to which announcements of trade policy changes continue to affect price volatility after the event day. Persistent shocks have more important policy implications as they are more likely to transmit to domestic markets where food price volatility can cause adverse effects on producers and consumers.

2 Implications of Trade Policy for Global Food Price Volatility

The extent to which trade policies translate into price volatility depends on supply and demand elasticities (Gilbert & Morgan, 2010). For a global market of staple foods, these elasticities are generally assumed to be inelastic in the short term. On the production side, supply is inelastic in the short term due to the inherently lagged response of seasonal agricultural production, and demand is inelastic due to slow changes of dietary habits and, in developing countries, the dependence on staples for basic food security (Gilbert & Morgan, 2010). Our argument hence is that import policies (demand shocks) and export policies (supply shocks) can both affect world market price volatility.

Other factors may, however, moderate the effects of trade policies on price volatility. In particular, stockholding can affect the extent to which supply and demand shocks affect price volatility, which reflects the conceptual framework of the model of competitive storage (Gustafson, States, & Agriculture, 1958; Samuelson, 1971; Newbery & Stiglitz, 1981; Deaton & Laroque, 1992, Deaton & Laroque, 1996; Cafiero, E. S.A Bobenrieth H., J. R.A. Bobenrieth H., & Wright, 2011). Stocks dampen the effects of a given consumption or production shock on price volatility. In the presence of sufficient stocks, a given shock induces less uncertainty on future price developments, which translates into more limited price volatility effects.

Yet, stocks are more effective in reducing price volatility effects of positive supply and negative demand shocks, i.e. increases in supply or reductions of demand, than of negative supply or positive demand shocks, i.e. reductions of supply or increases of demand (Wright, 2011). In the event of positive supply and negative demand shocks, stockholders respond by building up stocks, and the resulting price effect on the world market is dampened trough additional stock demand. In contrast, when a negative supply or positive demand shock affects world markets, the extent to which prices are moderated is limited by stock levels, i.e. carry-overs from past seasons that can be released. Restrictive export policies and liberal import policies represent such negative supply and positive demand shocks, and we hence expect accentuated price volatility effects for these two trade policy types.

Taken together, we hypothesize most pronounced effects of restrictive export policies and of liberal import policies on global food price volatility, particularly when stocks are low.

3 Methods

We put our arguments to an empirical test based on an original dataset on trade policy events from 2005 to 2017 for the world's most important staple crops and by estimating the storage-dependent effects of different types of trade policies on daily futures price ranges using a Conditional Autoregressive Range (CARR) model.

3.1 Conceptual Framework

We adopt a simple definition of agricultural trade policy. International trade refers to exchanges of commodities, such as goods and services, across national boundaries, whereas trade policies comprise the standards, goals, rules and regulations that govern such exchanges (Mitchell, 2008). Based on this general concept, agricultural trade policy is defined here as 1) an actual or potential decision by a national government or an institution controlled by the national government, that concerns 2) transboundary exchange in one or more agricultural commodities. The first component puts the focus on national trade policies. Trade policies by the European Union are included, as they can be understood as decisions pertaining to a group of sovereign countries. Multilateral trade agreements, such as those of the World Trade Organization (WTO), are not considered. The definition further excludes decisions of private sector traders but includes decisions by state-owned enterprises.

3.2 Case Selection

To study the influence of trade policy interventions on price volatility, we focus on wheat, maize and rice. This choice is motivated by their importance in global agricultural production, consumption and commodity trade. Maize, rice and wheat are the most important element in the human diet as they supply 42.5% of the world's food calories (Food and Agriculture Organization of the United Nations, 2016). In most developing countries, these grains provide more protein than fish or livestock products combined (Food and Agriculture Organization of the United Nations, 2016). All three crops have in the past been subject to trade policy interventions, which results in an adequate level of variation in the data and is sufficient for distinguishing the relative influence of different directions and types of trade policy interventions. We focus on a 12-year time period, from 2005 until mid 2017, which encompasses peaks in food prices observed for the years 2007 and 2008, as well as 2011, and periods of relatively stable or decreasing world market prices for grains since 2012. Currently available, comparable datasets only cover the time after 2008, for example the Global Trade Alert database (Evenett, 2009).

3.3 Empirical Estimation

Since we are interested in the announcement effects of trade policy changes (also referred to as “events” for the remainder of this paper) on food price volatility, we use an event study approach. Our empirical setting requires times series of daily volatilities.

However, volatility (i.e., the second moment of the return distribution) is generally unobservable and has to be estimated from observed prices. We estimate daily volatility for the three crops of interest from the range-based approach suggested by Parkinson (1980). Let P_τ be the price of an asset at time τ. The price range over an interval [t-1, t], defined as

$$R_t = max\{ln(P_\tau)\} - min\{ln(P_\tau)\},$$
$$\text{where } \tau \in [t-1, t],$$

is an unbiased estimator of volatility. Compared to standard return-based measures, which are based on the difference of close-to-close prices, the range-based estimator incorporates more information, as it also captures the intra-period (i.e., within day) price movements that return-based volatility measures ignore.

For our empirical design, we use the Conditional Autoregressive Range (CARR) model, initially proposed by Chou (2005). The model is a variant of the ARCH/GARCH family of models developed by Engle (1982) and Bollerslev (1986), which are widely used for modelling time series of (conditional) volatilities. The CARR model, however, is based on ranges, rather than returns, which makes the model more informationally efficient, as shown by Alizadeh, Brandt, and Diebold (2002) and Brandt and Jones (2006).

Although initially formulated as an autoregressive model, the CARR model can be extended to take additional explanatory variables into account (then termed CARRX). A CARRX model of order (p, q, l) is given by:

$$R_t = \lambda_t \varepsilon_t \,,$$
$$\lambda_t = \omega + \sum_{i=1}^{p} \alpha_i R_{t-i} + \sum_{j=1}^{q} \beta_j \lambda_{t-j} + \sum_{k=1}^{l} \gamma_k X_{t,k} \,, \tag{2}$$

where λ_t denotes the conditional mean of the range, based on all information up to time t, and ε_t is the shock to the range. The parameter ω characterizes the inherent uncertainty in the range, α describes the short-term impact of a prior shock, and β describe the long-term effect of past shocks to the range.

Exogenous variables are denoted by $X_{t,k}$. The main explanatory variable used in this paper is trade policy changes, which we code as dummy variables that take on the value 1 on the announcement day of a trade policy event, and are zero otherwise. We construct one vector of dummy variables for each type of policy events. The parameter γ measures the impact of trade policy changes on conditional volatility. Similar approaches have been used by Auer (2016) and Haase and Huss (2018), among others.

Based on our argument, a strong positive coefficient is expected for restrictive export and liberal import policies.

3.4 Data on Trade Policy

The maize, rice and wheat trade policy changes are identified through a media search and hand-coded in terms of their type and the direction of change. The coding procedure and indicators were developed by experts within our research consortium (see Appendix A.2).

The media search was done on the “Factiva” database and restricted to English-language articles on the “Reuters Newsfeed”, published between January 2005 and July 2017. As we seek to assess the effects of trade policy on global food prices, measured at the Chicago Mercantile Exchange (CME), there is little reason to assume that trade policies reported in non-English media would have effects on global markets. Search terms include keywords for classes of trade policy measures and all synonyms and singular/plural forms, and where applicable, verb forms, e.g. quota and limit, duty and duties, suspension and suspend*. The full search string is available in the code book in Appendix A.2.

The media search resulted in 27’507 articles. The date and time of publication as well as the standard reference number were automatically extracted from these articles, using an own text mining algorithm. Apart from date and time, all indicators were hand-coded by a dedicated team at the Institute of Policy and Strategy for Agriculture and Rural Development (IPSARD), after a coding training workshop. Relevance of the article was assessed as the first step. As to be expected, the media search yielded a much smaller number of relevant articles; 1’165 articles were identified as relevant. As some of these relevant articles concerned several trade policy changes or affected more than one commodity, the total number of identified trade policy events is 1’737.

For the purpose of this analysis, the authors did additional hand-coding for all identified trade policy events to flag articles that present new information as compared to previous articles on the same trade policy change Out of 1737 articles, 812 presented new information, which form the data used in this paper (see also Table A-1 in Appendix A.1, which shows the number of trade policy events by country).

3.5 Types of Trade Policy

For each article, the type of trade policy was coded, i.e. whether it is a tariff measure or a non-tariff measure, and what kind of. Tariffs are defined as “customs duties on merchandise import" (World Trade Organization, 2018). Non-tariff measures are defined as "policy measures other than ordinary customs tariffs that can potentially have an economic effect on international trade in goods, changing quantities traded, or prices or both" (United Nations Conference on Trade and Development, 2015, p. 1). We use the International Classification of Non-Tariff Measures developed by the Multi-Agency Support Team (MAST) group to classify different types of non-tariff measures (United Nations Conference on Trade and Development, 2015). We summarize some very specific sub-classifications developed by the MAST group in their higher-level groupings, thereby reducing the level of detail while maintaining the overall (aggregate) categories. The groupings, codings, and respective descriptions are available in a separate codebook for trade policy measures (see Appendix A.3).

3.6 Direction of Change

We seek to assess the effects of trade policy changes contingent on whether they are expected to increase or decrease world market demand or supply. For the purpose of a simplified coding instruction, the direction of the reported change was coded. For example, if an export tax on maize is changed from 5% to 10%, the new policy is coded as "higher" (H). On the other hand, if an import quota on rice is changed from 1 Million tonnes down to 0.5 Million tonnes, the new policy is coded as "lower" (L). Based on these coded indicators, we developed a ruleset which shows for each type of trade policy and for each direction, whether the trade policy change leads to higher or lower world market supply, or higher or lower world market demand. For example, a higher export tax is expected to lower world market supply, while a lower import quota is anticipated to lower world market demand. The rules for classification of world market effects are shown in Appendix A.4. Table 1 presents an overview of trade policy events in our dataset according to their direction and the affected crop.

Table 1: **Counts of Types of Trade Policy Events by Commodity in our Dataset.** Numbers show counts of total trade policy events recorded for the observation period.

	Liberal Import *(Higher World Market Demand)*	**Restrictive Export** *(Lower World Market Supply)*	**Restrictive Import** *(Lower World Market Demand)*	**Liberal Export** *(Higher World Market Supply)*	**Total**
Wheat	95	94	47	108	**344**
Maize	53	69	21	69	**212**
Rice	44	90	38	84	**256**
Total	**192**	**253**	**106**	**261**	**812**

3.7 Grain Price Data

To proxy for global grain prices, and their volatilities, respectively, we use the prices of nearby futures contracts (i.e., contracts with the shortest time to maturity) traded at the Chicago Board of Trade (CBOT), which is part of the CME. This choice reflects the assumption that the analysis of food price volatility, as done in this paper, requires daily price observations. Such data is not available for (the generally unobservable) spot markets, in particular at the global level. The contracts traded at the CBOT are characterised by high trading volumes, and usually provide the highest liquidity compared to other exchanges, in particular for wheat and maize (termed "corn" at the CBOT). They are therefore typically the preferred contracts for global actors, even outside the US, for the purpose of hedging against future price risks. These characteristics make them a suitable estimate for global grain prices, which are the basis for our estimates on daily price volatility.

The futures price data was obtained from the Thomson Reuters Datastream. To calculate our volatility measure, we gather the highest and lowest price recorded by the exchange for each trading day. The sample period starts in January 2005, which coincides with the start of the data collected on trade policy announcements. The end of the sample period is March 2018 for each commodity. This enables us to analyse the volatility dynamics in the time following the last trade policy announcement in our dataset (June 2017).

3.8 Stocks Data

We identify periods of high and low stocks from the stock-to-use ratio, which is measured as the end of period stock level, divided by the period consumption. Specifically, we classify a month as a low stock period if the stocks-to-use level is below the first quintile during the observation period (2005-2017). We use stocks-to-use data for the United States, which is compiled by the United States Department for Agriculture (USDA) and available at monthly frequency from their World Supply and Demand Estimates report (USDA FAS, 2018). Data for global stock-to-use estimates are only available on an annual frequency. However, United States stocks data may be a more relevant indicator for our analysis, given that price volatility is measured here as the daily range of futures prices at the Chicago Mercantile Exchange.

4 Results

4.1 Grain Trade Policy Events 2005-2017

In the observation period, the global trade of maize, rice and wheat was subject to frequent trade policy events as well as changing patterns in price volatility. Figure 1 summarizes the number of trade policy events in each month during the observation period, and shows the daily price ranges for each commodity.

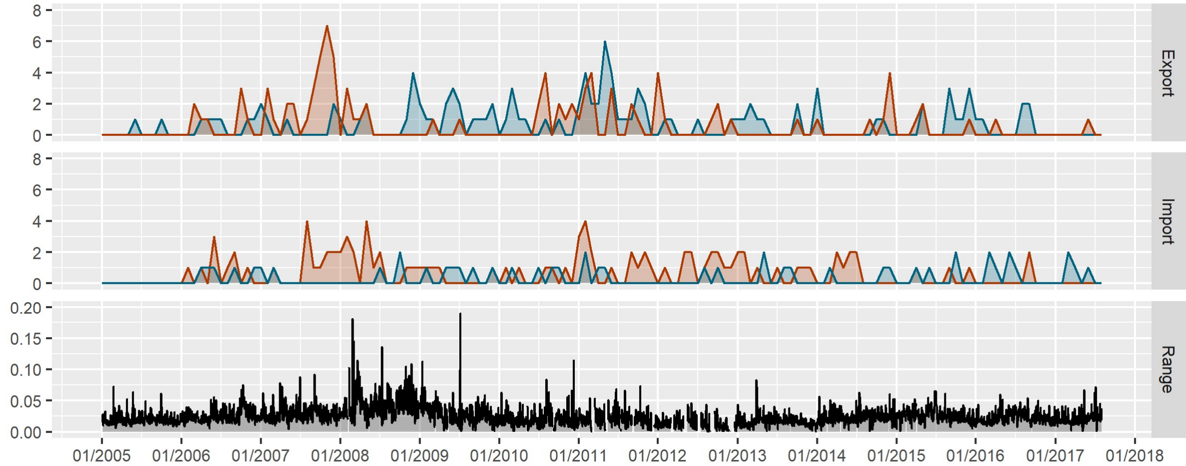
Compared to maize and rice, wheat was subject to a higher number of trade policy changes (see also Table 1). Although announcements of trade policy events occur over the entire observation period, the number of announcements is particularly clustered in the years 2007 and 2011 for the three grains. The figure also indicates that price volatility is highly time varying and reaches a peak during the years 2008 and 2009, the time of the global food price crisis, suggesting that increases in volatility were preceded by more frequent trade policy events in the months before.

The figure further discriminates between export-related (upper panel) and import-related trade policy events (middle panel), as well as the direction of trade policy events in terms of their expected effect on world market supply and demand. Trade policies that represent a negative supply or a positive demand shock, for which we expect pronounced volatility effects, are shown with red lines. For example, a higher number of events that imply a negative supply or a positive demand shock (red lines) is observed for the year 2007, whereas more events that imply a positive supply or a negative demand shock (blue lines) occurred in 2009.

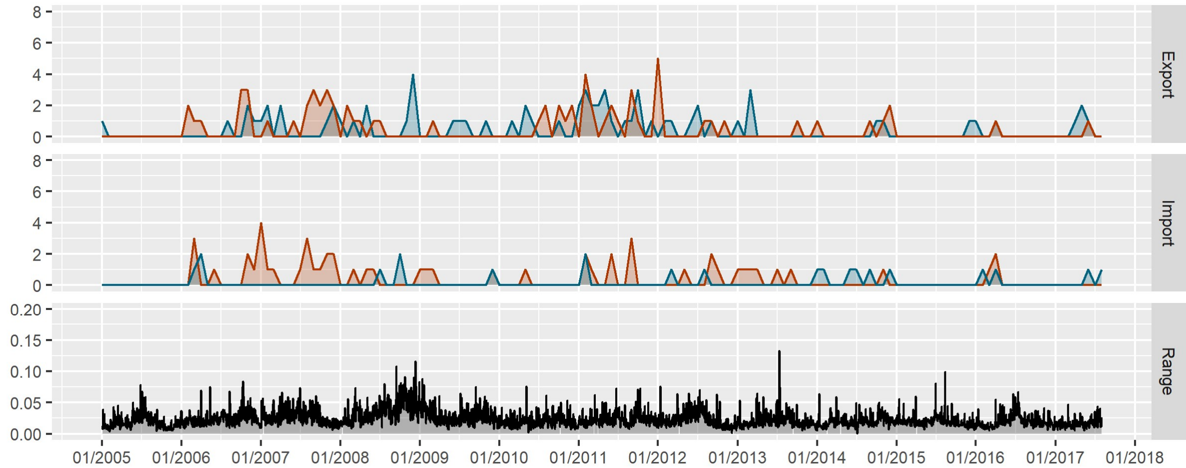
The results obtained from the CARR model mirror the impressions from the visual inspection of our data on price volatility. For all three commodities, price volatility was slightly higher in spike years (2007/08), although the increase is only statistically significant for maize (see Table 2, last Column). Overall, the impact of a prior shock to next day's volatility is similar for wheat and maize, but higher for rice, as indicated by a higher alpha value. Correspondingly, the long-term effect of shocks is smaller for rice, as compared to wheat and maize, which is indicated by a lower beta value. The omega, alpha and beta coefficients reported in Table 2 remain almost identical in all augmented model specifications (i.e., augmented with policy dummy variables) presented in this paper. For the sake of brevity, we only report the coefficients for the exogenous variables added to the model. The complete results are available upon request from the authors.

Figure 1: Frequency and Direction of Trade Policy Events from 2005-2017

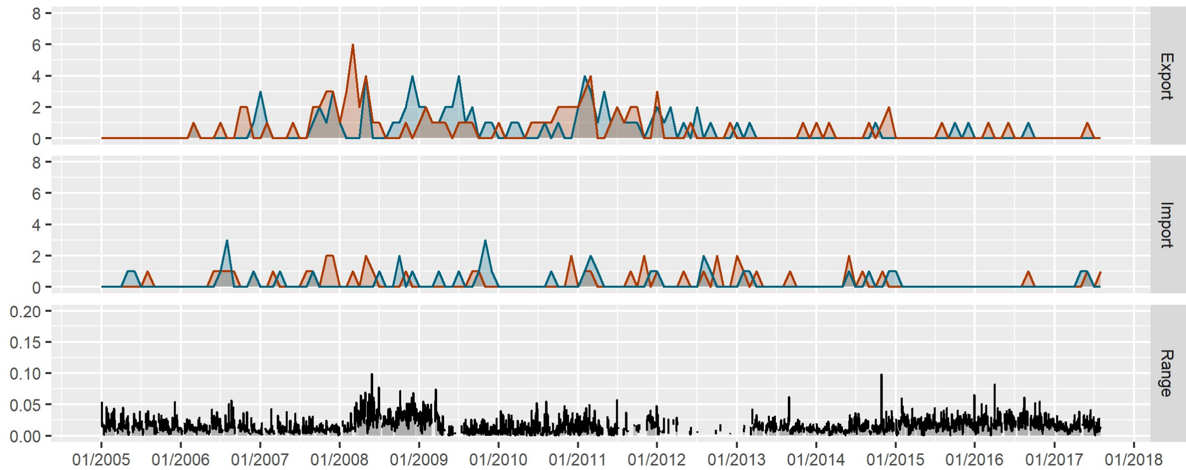
a) Wheat



b) Maize



c) Rice



Note: Trade policy events and price ranges (volatility) for a) wheat, b) maize, and c) rice. For each commodity, the upper and middle panels show counts of monthly trade policy events affecting exports (upper) and imports (middle), and the lower panel shows daily futures price range. For upper and middle panels, red lines show trade policy events that represent a negative supply or a positive demand shock, and blue lines show events that imply positive supply or negative demand shocks.

Table 2: **CARR model estimates for the observation period and effects of years 2007/2008**. Table shows CARR model estimates with effect of spike year 2007 and 2008 as exogenous dummy variable. First row for each crop shows coefficients, second row shows p-values. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

		omega	**alpha**	**beta**	**2007/2008**
Wheat	Coefficient	0.0003**	0.1348***	0.8626***	0.0002
	p-value	0.0106	0.0000	0.0000	0.2870
Maize	Coefficient	0.0003***	0.1459***	0.8382***	0.0002*
	p-value	0.0001	0.0000	0.0000	0.0813
Rice	Coefficient	0.0007***	0.2461***	0.7331***	0.0001
	p-value	0.0014	0.0000	0.0000	0.6382

4.2 Announcement Day Effects

We hypothesize that the announcement of restrictive export and of liberal import policies leads to pronounced increases in global grain price volatility, particularly when stocks are low. These effects should be highest on the announcement day, which is the day when the information of the trade policy event was first communicated, and thus available to market participants. If no futures contracts were traded that day, the announcement day reflects the next date when futures contracts were traded again.

Columns 1 and 2 of Table 3 present the effects of the announcement of restrictive export policies and liberal import policies. Announcement effects of policies where we expect more limited effects, i.e. liberal export policies and restrictive import policies, are displayed in Columns 3 and 4. Consistent with our expectation, our results suggest that the announcements of different types of trade policy changes have distinct effects on price volatility. We further find heterogenous effects for the different crops.

While the announcement of restrictive export policies significantly increases the price volatility of wheat on the announcement day, the coefficient for the announcement of liberal import policies is not statistically significant. In contrast, for maize, announcements of liberal import policies significantly increase price volatility, whereas no statistically significant effects are observed for restrictive export policies. Announcements effects of other types of trade policies for these two crops are insignificant on the announcement day. These results are consistent with our hypothesis that import and export policies can both affect price volatility, and that their effects are more pronounced when they induce negative supply shocks or positive demand shocks.

The opposite effect is observed for rice. Restrictive export policies and liberal import policies do not appear to affect price volatility. However, announcements of liberal export policies and of restrictive import policies show statistically significant reductions of price volatility on the announcement day. Though we had expected less pronounced effects for these trade policies that can cause positive supply and negative demand shocks, a reduction of volatility is surprising.

We further augment the analysis to consider effects of trade policy events conditional on the prevailing stock level (see Table 4). We identify periods of high and low stocks from the stock-to-use ratio, and classify a month as a low stock period if the stocks-to-use level is below the first quintile during the observation period (see Chapter 3.8). The results are robust to an alternative stock-to-use threshold (see Table A-2, Appendix A.1).

The results show, as expected, that stocks moderate the effects of announcements of trade policies for wheat and rice, but stocks do not appear to substantially moderate effects for maize (see Table 4). For wheat, the results indicate that announcements of protectionist export policies and of liberal import policies only significantly increase price volatility on the announcement day if they fall into periods of low stocks, which is consistent with our hypothesis. In the case of announcements of liberal import policies when stocks are high, the results show a statistically significant reduction of announcement day price volatility. The results for rice suggest that the reported surprising effects of the announcements of liberal export and protectionist import policies, are concentrated on periods of high stocks. For maize, the coefficients for the respective effects for announcements concerning trade policies on maize are similar for low and high stocks.

To summarize, our results show that the announcement of restrictive export policies leads to statistically significant increases in volatility for wheat, whereas the announcement of liberal import policies increases price volatility for both maize and wheat, though the latter only when stocks are low. Surprisingly, for rice, we do not find statistically significant effects for these policies, though we find that liberal export policies and restrictive import policies lead to a statistically significant reduction in price volatility, albeit only so when stocks are high. These results lend support to our argument that both import and export policies can have effects on global food price volatility on the announcement day.

Table 3: **Effects of Import and Export Policy Announcements on Price Volatility.** The table reports CARRX model coefficients of the exogenous variables (i.e., policy dummies) by type of trade policy (positive export and import, as well as negative export and import trade policy shocks), crop, and the prevailing stock level at the time of the announcement. Coefficients show effect on global food price volatility by commodity. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

		Liberal Import	**Restrictive Export**	**Restrictive Import**	**Liberal Export**
		(1)	**(2)**	**(3)**	**(4)**
Wheat	Coefficient	-0.0007	0.0013**	-0.0004	-0.0005
	p-value	0.1948	0.0377	0.6405	0.3346
Maize	Coefficient	0.0012*	0.0007	0.0010	0.0003
	p-value	0.0886	0.2331	0.3470	0.6499
Rice	Coefficient	0.0004	-0.0003	-0.0017**	-0.0016***
	p-value	0.6591	0.6596	0.0316	0.0022

Table 4: **Comparison of the Effect of Trade Policy Events in Low and High Stock Periods.** The table reports CARRX model coefficients of the exogenous variables (i.e., policy dummies) by type of trade policy, crop, and the prevailing stock level at the time of the announcement. First row for each crop shows coefficients, second row shows p-values. Coefficients show effect on global food price volatility by commodity. Threshold for low stocks set at the 0.2 percentile. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

	Liberal Import		**Restrictive Export**		**Restrictive Import**		**Liberal Export**	
	(1)		**(2)**		**(3)**		**(4)**	
	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks
Wheat	0.0021*	-0.0014**	0.0019**	0.0007	0.0009	-0.0005	-0.0003	-0.0005
	0.0761	0.0113	0.0429	0.3734	0.8199	0.5913	0.8493	0.3571
Maize	0.0011	0.0011	0.0005	0.0011	0.0017	0.0007	0.0010	-0.0005
	0.3189	0.1829	0.3837	0.1107	0.4473	0.5213	0.1888	0.4588
Rice	0.0006	0.0003	-0.0004	-0.0008	0.0016	-0.0022***	-0.0005	-0.0022***
	0.7768	0.7267	0.5684	0.2562	0.5561	0.0068	0.7017	0.0006

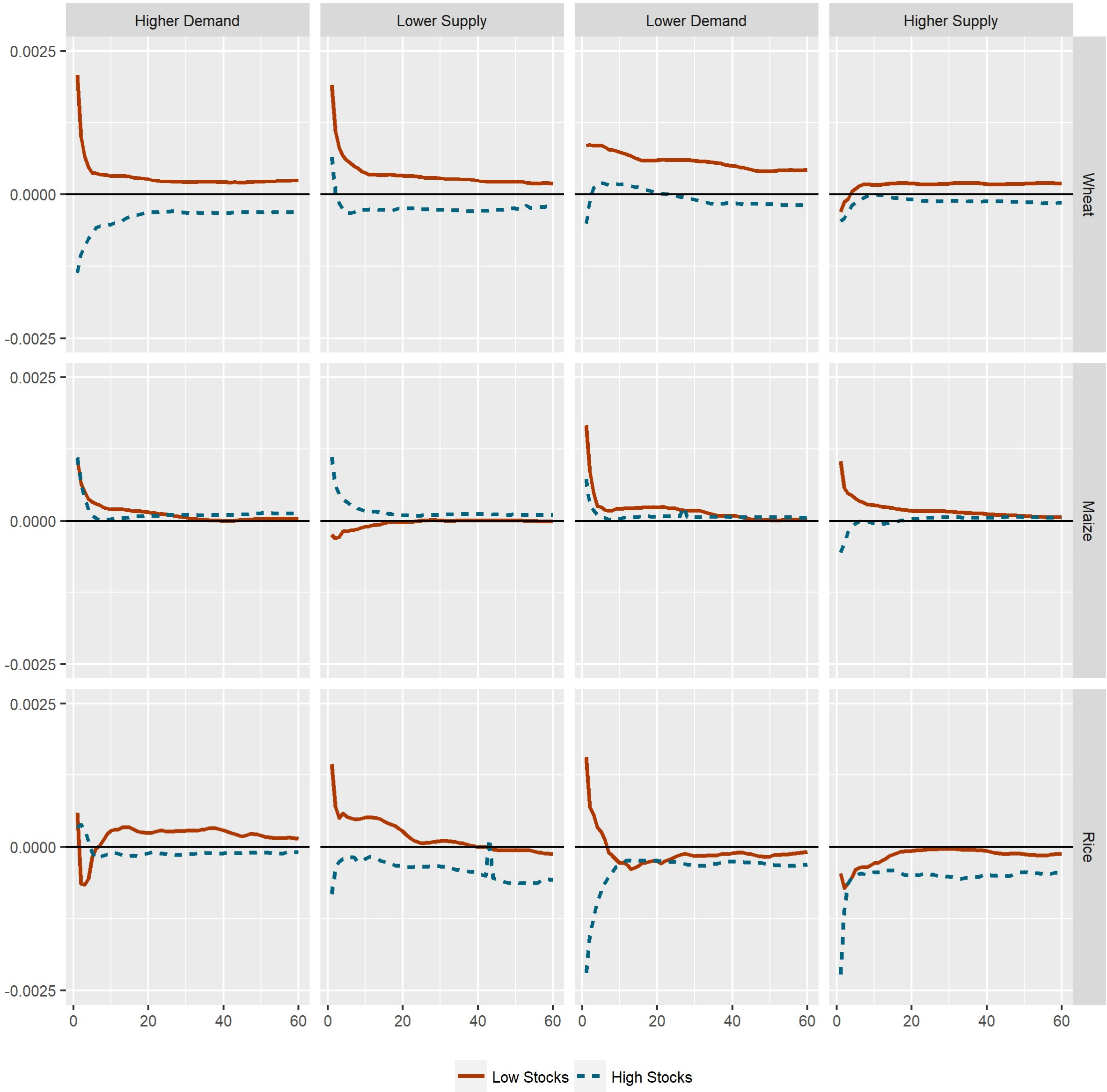
4.3 Persistence of Event Effects

From a policy perspective, the persistence of price volatility effects are of particular importance as longer-term shocks are more likely to cause adverse effects on producers and consumers. To analyze the persistence of effects, we gradually extend the event window beyond the announcement day. Specifically, we consecutively add one or more days to the corresponding dummy variable in the CARR model and re-estimate the model for each extended window.

Figure 2 shows results for the persistence of price volatility shocks induced by announcements of different types of trade policies, dependent on levels of stocks. Visual inspection shows that the induced shocks persist only for a few days after the announcement day. The effects quickly tend to zero as the event window is extended. In almost all combinations of types of trade policies announced and crops studied, the increase in event window price volatility is negligible after 10 days. The shocks tend to persist slightly longer if stocks are low (red, solid line) compared to high stocks (blue, dashed line).

Effect estimates for selected event windows are shown in Table 5. They mirror the insight from visual inspection. Coefficients decrease quickly with extension of the event window, and shocks are slightly more persistent for wheat and rice, as compared to maize. The results remain robust when using an alternative threshold for the distinction in low and high stock periods (see Table A-3, Appendix A.1).

Figure 2: Persistence of Abnormal Price Volatility Across Different Types of Trade Policies and Crops



Note: Model coefficients by type of trade policy and crop. Each sub-panel shows estimates by trade policy type (vertical), and by crop (horizontal). For each sub-panel, the red line shows effects in periods of low stocks, the blue, dashed line shows effects when stocks are high, x-axis shows the number of days for the event window estimated, and y-axis are effects on price volatility, expressed as the coefficients from model estimates.

Table 5: **Persistence of Trade Policy Induced Price Volatility.** The table reports CARRX model coefficients of the exogenous variables (i.e., policy dummies) by type of trade policy, crop, and the prevailing stock level at the time of the announcement. The variable "d" denotes the number of consecutive days after the policy announcement included in the dummy variable of the respective model specification. "W" denotes wheat, "M" denotes maize, and "R" denotes rice. The threshold for low stocks is set at the 0.2 percentile. Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1. For easier readability, p-values are not reported, but are available from the authors upon request.

		Liberal Import		**Restrictive Export**		**Restrictive Import**		**Liberal Export**	
		(1)		**(2)**		**(3)**		**(4)**	
	d	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks
W	**1**	0.0021*	-0.0014**	0.0019**	0.0007	0.0009	-0.0005	-0.0003	-0.0005
	3	0.0007	-0.0009***	0.0008**	-0.0002	0.0009	0.0001	-0.0001	-0.0003
	5	0.0004	-0.0007***	0.0006**	-0.0003*	0.0009	0.0002	0.0001	-0.0001
	10	0.0003*	-0.0005***	0.0004*	-0.0003***	0.0007	0.0002	0.0002	-0.0000
	20	0.0003**	-0.0003***	0.0003**	-0.0002***	0.0006**	0.0000	0.0002	-0.0001
	60	0.0002**	-0.0003***	0.0002*	-0.0002***	0.0004**	-0.0002***	0.0002*	-0.0001
M	**1**	0.0011	0.0011	-0.0002	0.0011	0.0017	0.0007	0.0010	-0.0005
	3	0.0005	0.0004	-0.0003	0.0005	0.0005	0.0002	0.0005	-0.0002
	5	0.0003	0.0001	-0.0002	0.0003*	0.0002	0.0001	0.0004*	-0.0000
	10	0.0002	0.0000	-0.0001	0.0002	0.0002	0.0000	0.0003**	-0.0000
	20	0.0001	0.0001	-0.0000	0.0001	0.0002	0.0001	0.0002*	0.0000
	60	0.0000	0.0001**	-0.0000	0.0001*	0.0000	0.0001	0.0001	0.0001
R	**1**	0.0006	0.0003	0.0014	-0.0008	0.0016	-0.0022***	-0.0005	-0.0022***
	3	-0.0007	0.0003	0.0005	-0.0003	0.0006	-0.0012***	-0.0006	-0.0006**
	5	-0.0002	-0.0001	0.0005	-0.0002	0.0003	-0.0008***	-0.0004	-0.0005**
	10	0.0003	-0.0001	0.0005	-0.0002	-0.0003	-0.0003	-0.0003	-0.0004***
	20	0.0002	-0.0001	0.0003	-0.0003***	-0.0002	-0.0002*	-0.0001	-0.0005***
	60	0.0001	-0.0001	-0.0001	-0.0006***	-0.0001	-0.0003**	-0.0001	-0.0005***

5 Discussion and Conclusion

In the past decade, national governments have frequently used trade policy interventions with the intention to stabilize domestic food prices and avert negative welfare effects of volatile global food prices. These policies were argued to exacerbate global price volatility, and blamed as beggar-your-neighbour policies, although the existing empirical evidence is scarce on this topic. Our results do not lend support to this argument. Although we find that the announcement of trade policy changes can affect price volatility on the announcement day, consistent with our expectations, these effects are short-term and have very limited persistence.

Our results show that the announcement of trade policy changes can increase global food price volatility on the announcement day and a few days thereafter, however, only in time periods of low stocks. When stocks are low, restrictive export policies increase global price volatility of wheat, but not for rice and maize, and liberal import policies increase global price volatility of wheat and maize, but again not for rice. We do not find any statistically significant increases of price volatility for either wheat, maize or rice in times of high stocks. This result is consistent with our argument that stocks can dampen the effects of a given trade policy shock on price volatility.

An important contribution of this paper is the finding that liberal import policies can increase short-term price volatility. This stands in stark contrast to the existing literature, which had argued, but not empirically tested, that liberal import policies "likely had little effect on world price volatility" (Rude & An, 2015, p. 84). The finding has potential implications for the broader literature on the effects of trade policies on price levels. Studies in this strand of research, likewise, either analyze effects of export restrictions or protectionist measures in general, often concluding that trade policy interventions have strong effects on rice and wheat price increases, but only small effects on high maize price levels (e.g. Yu, Tokgoz, Wailes, & Chavez, 2011; Anderson & Nelgen, 2012; Martin & Anderson, 2012; Jensen & Anderson, 2015). Clearly, using our newly established dataset to study effects on food price levels is an opportunity for further research. The dataset used here provides ample opportunities in this direction.

Our empirical setup has important implications for the findings on rice price volatility, where we do not find statistically significant effects following the announcements of restrictive export and liberal import policies, even when stocks are low. This is surprising as it is frequently argued that both global rice demand and supply are the most inelastic of the staple crops studied here, and we consequentially would anticipate that the announcements of restrictive export policies and liberal import policies lead to pronounced effects on price volatility. However, results from an earlier study by Rude and An (2015) had also pointed to mixed-effects for rice as they show that while export taxes increase rice price volatility, quantitative export restrictions do not have effects. Moreover, our results even show statistically significant reductions in rice price volatility for liberal export and restrictive import policies, though only when stocks are high. A possible explanation lies in the structure of the rice market, which is distinctly different to wheat and maize markets. Only a small fraction of rice is traded internationally "as rice is mostly consumed where it is produced" (Timmer, 2010, p. 3). This implies that trade policies may only affect a relatively small quantity of total global rice consumption and production, and its effects on inducing price uncertainty may hence also be small. At the same time, the limited international trade gives rise to an important caveat concerning our results on rice. As rice is only thinly traded in futures markets (Timmer, 2010), CBOT futures prices may be less representative as proxy for spot market prices for rice as compared to maize or wheat.

While our study analyses the effects of trade policy changes on global food price volatility, it does not empirically address the mechanisms that cause national trade policy changes. Trade policy changes may be announced as a response to past global price volatility, but could also be due to other factors, such as direct national food security concerns. Trade policy may well be endogenous to price volatility. As our study focuses on daily data, such endogeneity, however, is unlikely to affect the here presented results. It is reasonable to assume that trade policy changes on a given day are not the result of same day price volatility. Lead-lag relationships between the two variables are an interesting topic itself, which is, however, left open for future research. Furthermore, this study does not consider whether excess speculation in futures markets may reduce the effects of trade policy events on global food price volatility (e.g., Haase and Huss, 2018).

These limitations notwithstanding, our results suggest that while trade policy changes, specifically restrictive export and liberal import policies, can indeed result in increases of global food price volatility on their announcement day and a few days thereafter, the persistence of these trade-policy related volatility effects is short. Such short-term effects are unlikely to be a major concern for food security and livelihoods of agricultural producers and poor consumers in developing countries. Our results hence do not provide empirical evidence that underpins the widespread political concern that agricultural trade policies exacerbate global food price volatility. The results further highlight that adequate stock levels can minimize such short-term effects, and further reduce their persistence. For policy-makers aiming to reduce food price volatility, for example as part of the 2030 Agenda for Sustainable Development, our results imply that adequate stock levels can buffer short-term volatility effects of trade policy events.

A. Appendix

A.1 Supplementary Tables

Table A-1: **Counts of Trade Policy Events by Country in our Dataset.** Numbers show counts of total trade policy events recorded for the observation period.

	Country Name	**Event Count**
1	Russian Federation	131
2	Ukraine	111
3	India	94
4	Argentina	62
5	European Union	49
6	China	41
7	Viet Nam	32
8	Indonesia	27
9	Morocco	27
10	Egypt	25
11	Bangladesh	21
12	Pakistan	18
13	Philippines	16
14	Brazil	15
15	Kazakhstan	12
16	Korea, Republic of	12
17	Tanzania, United Republic of	10
18	Serbia	8
19	Taiwan, Province of China	8
20	Zambia	8
21	Canada	6
22	Iran, Islamic Republic of	6
23	Algeria	5
24	Turkey	5
25	Croatia	4

Table A-1 - Continued

	Country Name	Event Count
26	Kenya	4
27	Mexico	4
28	Nigeria	4
29	Paraguay	4
30	Burundi	3
31	Cameroon	3
32	Guatemala	3
33	Malawi	3
34	Zimbabwe	3
35	Australia	2
36	Colombia	2
37	Japan	2
38	Myanmar	2
39	Nepal	2
40	Peru	2
41	Romania	2
42	Saudi Arabia	2
43	South Africa	2
44	Syrian Arab Republic	2
45	Bulgaria	1
46	Cambodia	1
47	Chile	1
48	Ecuador	1
49	Iraq	1
50	Lebanon	1
51	Sri Lanka	1
52	Thailand	1

Table A-2: **Effects of Import and Export Policy Announcements on Price Volatility - Alternative Stock Threshhold.** The table reports CARRX model coefficients of the exogenous variables (i.e., policy dummies) by type of trade policy (positive export and import, as well as negative export and import trade policy shocks), crop, and the prevailing stock level at the time of the announcement. Coefficients show effect on global food price volatility by commodity. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

	Liberal Import		**Restrictive Export**		**Restrictive Import**		**Liberal Export**	
	(1)		**(2)**		**(3)**		**(4)**	
	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks
Wheat	0.0024**	-0.0017***	0.0021**	0.0005	0.0016	-0.0008	0.0006	-0.0006
	0.0263	0.0020	0.0233	0.5453	0.5050	0.4277	0.6741	0.2545
Maize	0.0005	0.0015*	-0.0002	0.0012*	0.0021	0.0005	0.0008	-0.0005
	0.6345	0.0821	0.8093	0.0932	0.2838	0.6878	0.2815	0.5431
Rice	-0.0012	0.0013	0.0006	-0.0008	0.0011	-0.0022***	-0.0001	-0.0025***
	0.3589	0.2882	0.6040	0.3276	0.6397	0.0058	0.9011	0.0002

Table A-3: **Persistence of Trade Policy Induced Price Volatility - Alternative Stock Threshold.** The table reports CARRX model coefficients of the exogenous variables (i.e., policy dummies) by type of trade policy, crop, and the prevailing stock level at the time of the announcement (threshold for low stocks set at the 0.3 percentile). The variable “d” denotes the number of consecutive days after the policy announcement included in the dummy variable of the respective model specification. “W” denotes wheat, “M” denotes maize, and “R” denotes rice. The threshold for low stocks is set at the 0.2 percentile. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. For easier readability, p-values are not reported, but are available from the authors upon request.

		Liberal Import (1)		**Restrictive Export (2)**		**Restrictive Import (3)**		**Liberal Export (4)**	
	d	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks	Low Stocks	High Stocks
W	**1**	0.0024**	-0.0017***	0.0021**	0.0005	0.0016	-0.0008	0.0006*	-0.0006
	3	0.0008**	-0.0010***	0.0009**	-0.0002	0.0011	0.0000	0.0002	-0.0004*
	5	0.0005*	-0.0008***	0.0006**	-0.0004**	0.0009	0.0001	0.0003	-0.0002
	10	0.0004**	-0.0006***	0.0004*	-0.0003***	0.0006**	0.0001	0.0002	0.0000
	20	0.0003***	-0.0004***	0.0003**	-0.0003***	0.0005*	0.0000	0.0002*	-0.0001*
	60	0.0003***	-0.0004***	0.0002**	-0.0002***	0.0003**	-0.0002***	0.0003***	-0.0002***
M	**1**	0.0005	0.0015*	-0.0002	0.0012*	0.0021	0.0005	0.0008	-0.0005
	3	0.0002	0.0006*	-0.0002	0.0005*	0.0005	0.0002	0.0004	-0.0002
	5	0.0002	0.0002	-0.0001	0.0003*	0.0002	0.0001	0.0003	0.0000
	10	0.0001	0.0001	-0.0001	0.0002	0.0001	0.0001	0.0002	0.0000
	20	0.0001	0.0001	0.0000	0.0001	0.0000	0.0001	0.0001	0.0001
	60	0.0000	0.0001*	0.0000	0.0001	0.0000	0.0001	0.0000	0.0001
R	**1**	-0.0012	0.0013	0.0006	-0.0008	0.0011	-0.0022***	-0.0001	-0.0025***
	3	-0.0007	0.0006	0.0003	-0.0003	0.0006	-0.0013***	-0.0005	-0.0007**
	5	-0.0003	0.0001	0.0003	-0.0002	0.0003	-0.0008***	-0.0003	-0.0006***
	10	0.0001	-0.0001	0.0002	-0.0002	0.0000	-0.0004*	-0.0002	-0.0005***
	20	0.0000	-0.0001	0.0001	-0.0003**	-0.0001	-0.0003*	0.0000	-0.0005***
	60	0.0001	-0.0001	-0.0001	-0.0005***	0.0001	-0.0003***	0.0000	-0.0005***

A.2 Codebook

The media search was done on the "Factiva" database and restricted to English-language articles on the "Reuters Newsfeed", published between January 2005 and July 2017 (see Chapter 3.4). The following search string was used:

(non-tariff or pre-shipment inspection* or trade-protective or antidumping or countervailing or licencing or licence* or quota* or prohibition* or ban or bans or banned or suspend* or restraint* or price-control* or tax or taxes or customs charge* or custom* or minimum price* or reference price* or export-price restraint* or variable charge* or customs surcharge* or duty or duties or internal tax or internal taxes or internal charge* or trade finance or trade financing or affecting competition or local content* or locali?ation or trade-balancing or distribution restriction* or post-sales service* or subsidies or subsidy or loan* or grant* or procurement* or rules of origin or rule of origin or quantitative restriction* or permit* or registration* or state-trading* or state trad* or re-export* or re-import*) and (import or imports or export or exports) and (wheat or maize or corn or rice)*

The following presents the coding guidance used by the research team, which can also serve to replicate the data collection and measurement.

General Rule:

- Type HELP if you don't know how to fill-out a specific cell and require assistance

a) Information Reference Number

Explanation: The variable contains the unique reference number assigned to each article. The number can be found at the very end of each media article, and looks for example like this "LBA0000020061009e2a90018a". Copy-paste the full string.

Coding:

- Copy-paste the information reference number, e.g. LBA0000020061009e2a90018a

b) Relevance of the Article:

Explanation: This variable pertains to whether the media article actually deals with agricultural trade policy. To be relevant, the article needs to deal with a) an actual or potential decision by a national government or an institution controlled by the national government, AND b) the decision affects the policy regime governing the transboundary exchange in rice, wheat or maize. For example, an article may describe ongoing negotiations in the World Trade Organization (WTO) on global trade liberalization. While that article may affect trade between countries, possible WTO decisions are not decisions by a national government or institution controlled by the national government. Hence, the article is considered irrelevant, and you would code: 0. If a media article is a duplication of a previous one coded, meaning that no new information is reported, code 0 and move on to the next article.

Note that government to government sales or tenders are only to be considered relevant if they mean a change in the national policy regime. For example, if Vietnam agrees to sell rice to Indonesia despite an export ban in place, it is relevant (code 1). However, if Vietnam announces a tender for rice exports, it is not considered a trade policy change and hence irrelevant (code 0).

Coding:

- Type 1 if the article deals with an agricultural trade policy
- Type 0 if the article does NOT deal with agricultural trade policy

Logic:

If you code 0, i.e. article is not relevant, move on to the next media article!

c) Originating jurisdiction

Explanation: This variable contains the information in which country or jurisdiction a decision affecting trade policy was made. For example, an article may inform that the Government of Russia has decided to stop all exports of wheat. In this case, you would code Russia by typing its shortcode: RU. In the event, that a trade policy change is specific to a small number of countries, type all their shortcodes separated by comma (,). For example, if Cambodia, Lao and Vietnam agree on a regional trade deal to decrease import tariffs for each other, code KH,LA,VN.

Required information: List of country/jurisdiction shortcodes available at: http://www.unece.org/cefact/locode/service/location

Coding:

- Type the two-character country/jurisdiction shortcode
- Type N/A if the information is not available in the media article

Logic:

If you code N/A, i.e. the article doesn't say which country is the originator of a policy, then go to next media article

d) Date of the media article

Explanation: This variable pertains to the date of publication of the article as indicated on the article itself. You will have to fill-out three distinct cells, the first cell (column) captures the day of the month, the second cell captures the month, and the third cell the year. Coding example below applies to a possible date of a media article: 6th February 2013.

Coding:

- For the day of the month, specify the day in format dd (e.g. the 6th day of a month, type 06)
- For the month, type in format mm (e.g. if its February, type 02)
- For the year, type year in format yyyy (e.g. if its 2013, type 2013)

e) Goods affected

Explanation: This variable contains the information what products or goods are affected by the agricultural trade policy dealt with in the article. Affected products are those on which the transboundary exchange will have a potential influence. If more than one product is affected, yet not all of them are affected equally, you have to create separate entries. For example, if an article mentions that rice will be subject to a full export ban, and wheat will be subject to increased export tax, then create separate row entries for rice and maize.

Coding:

- Type W for wheat, if the trade policy affects wheat
- Type M for maize, if the trade policy affects maize/corn
- Type R for rice, if the trade policy affects rice
- If the agricultural trade policy concerns more than one product in the same way (e.g. maize and wheat), type all letters, e.g. MW or WMR (the order doesn't matter)
- If the agricultural trade policy concerns more than one product, but not all products are affected equally, copy-paste one additional row for each commodity the agricultural trade policy is related to, type the respective product code in the new fields, and continue coding for each.
- Type N/A if the information is not available in the media article

f) Tariff Measure

Explanation: This variable is a factor variable informing whether the trade policy measure is a form of import tariff or not. Import tariffs are "customs duties on merchandise imports". We distinguish between a) import tariffs on ad valorem basis (percentage of value), and b) import tariffs on a specific basis (e.g. \$7 per 100 kgs.). For example, a news article may mention that the Government of Kenya is considering to increase its tariff on import of maize from 15% to 20%. In this case, you would code for an ad valorem import tariff and type 1.

Coding:

- If the trade policy is <u>not</u> an import tariff, code: 0
- If the trade policy is an import tariff at ad valorem basis, code: 1
- If the trade policy is an import tariff on specific basis, code: 2

- If the trade policy is an import tariff, but it is not specified if the tariff is ad valorem or specific, code: 3
- Type N/A if the information is not available in the media article

Logic:

If you code 1,2 or 3, skip the next indicator (only the next indicator, NOT going to the next article)

g) Non-Tariff Measure

Explanation: This variable pertains to the codes according to the International Classification of Non-Tariff Measures. All measures other than import tariffs, are classified according to this classification. The document contains definitions and examples for each of the possible trade policy measures. If you are uncertain, you can ask for assistance from the research team. For example, if a country decides to fully ban all exports for maize, that is classified as "Export prohibition". Hence the correct code is: P11

Required information: Own summary document "Summary: International Classification of Non-Tariff Measures – Codebook.docx"

Coding:

- Type the 3 to 4 character-digit combination according to the International Classification of Non-Tariff Measures, e.g. P11
- Type HELP in case you are uncertain and would like support from the research team
- Type N/A if the information is not available in the media article
- If more than one measure is concerned, create separate rows for each measure and continue with the next indicators for each measure.

h) Direction of Change

Explanation: This variable specifies the direction in which a trade policy is being changed. For example, if an export tax on maize is changed from 5% to 10%, the new policy is coded as "higher" (H). On the other hand, if an import quota on rice is changed from 1 Million tonnes down to 0.5 Million tonnes, the new policy is coded as "lower" (L). If a country decides to lift its export ban or import ban on rice, type lower (L). On the other hand, if a country introduces an export or import ban, type higher (H). If a country decides on stricter administrative procedures, like licensing requirements, type higher.

Coding:

- H: Type H for "Higher" if the direction is an increase
- L: Type L for "Lower" if the direction is a decrease
- HELP: Type HELP if some information is available, but you don't know how to code it
- N/A: Type N/A if the information is not given in the media article

i) Implementation Status

Explanation: The implementation status variable shows where a specific policy stands in the policy process. Three categories are distinguished: 1) Measure is under consideration, but not yet decided, 2) Measure is decided, but not yet in force, 3) Measure is in force.

Coding:

- 1: Type 1 if the measure is under consideration, but not yet decided
- 2: Type 2 if the Measure is decided, but not yet in force
- 3: Type 3 if Measure is in force
- N/A: Type N/A If the article doesn't include information on the status of implementation

j) Date of implementation

Explanation: The date of implementation is a variable pertaining to the date the trade policy change is enforced. You will have to fill-out three distinct cells, the first cell (column) captures the day of the month, the second cell captures the month, and the third cell the year. Coding example below applies to a possible date of implementation: 6th February 2013.

For example, if a media article mentions that an increase of import tariffs of the Government of Tanzania will be valid from 15th of April 2013, type 15 in the day cell, 04 in the month cell, and 2013 in the year cell. If a government announces that a partial export ban will be in place starting May 2013, type 5 in the month cell and 2013 in the year cell. In case a government decides upon altered export licensing requirements, and indicates they are effective immediately, type the date of the media article according to coding instructions.

If no day, month or year is given, but any other time indication (like “in autumn”), type OTHER.

Coding:

- For the day of the month, specify the day in format dd (e.g. the 6th day of a month, type 06)
- For the month, type in format mm (e.g. if its February, type 02)
- For the year, type year in format yyyy (e.g. if its 2013, type 2013)
- OTHER: If no specific day, month or year is given (e.g. “in autumn”), type OTHER
- type N/A if no information is given

k) End date

Explanation: For temporary trade policy changes, the end date is the date the documented change will be either withdrawn or fully replaced by a further change. For permanent measures, the measure needs to be coded as "permanent" without end date. For example, if a media article mentions that an increase of import tariffs of the Government of Tanzania will be valid until 31st of December 2013, type 31 in the day field, 12 in the month field, and 2013 in the year field. If a government announces that a partial export ban will be in place until December 2013, type 12 in the month field, and 2013 in the year field. In case a government decides upon altered export licensing requirements, which are meant to be permanent, type "P" in all three date fields.

All measures that do not explicitly specify that they are temporary, have to be coded as permanent.

Coding:

- For the day of the month, specify the day in format dd (e.g. the 6th day of a month, type 06)
- For the month, type in format mm (e.g. if its February, type 02)
- For the year, type year in format yyyy (e.g. if its 2013, type 2013)
- type P if the policy is implemented permanently
- type N/A if no information is given

l) Duration

Explanation: This variable captures the amount of time that a trade policy change is announced to remain in force. This variable has to be filled out if either the implementation date or the end date is missing. It hence has only to be coded in cases where implementation date or end date lack a specific day in their dates. Accordingly, for permanent measures, the field doesn't have to be filled out.

Coding:

- If number of months is mentioned, type the number followed by M, e.g. 1M
- If number of weeks is mentioned, type the number followed by W, e.g. 4W
- If number of days is mentioned, type the number of days followed by D, e.g. 20D
- type N/A if no duration is provided

m) Information Source

Explanation: This variable identifies the source of the information reported in each media article. Two main categories of sources and their combinations are distinguished. A named source means that the source of information reported in a media article is attributed to an identified person or to an official communication from an institution (i.e. there is a name of a person, or a name of an institution). A government source means that the source is mentioned to be associated with the government. Example, a media article may state that China is will revise its import tariff on rice, according to government sources familiar with policy developments (without giving names), yet no named official confirms the information. In this case, the source is an unnamed government source, and you would type 3. If the source for the information is another newspaper or another media article, code 4 (unnamed non-government source).

Coding

- 1: Type 1 if Named Government Source: the source of the information is an identified government official or a named government institution
- 2: Type 2 if Named NON Government Source: Source of the information is an identified person or identified institution outside the government
- 3: Type 3 if Unnamed Government Source: Source of the information is an unnamed/anonymous government official or institution
- 4: Type 4 if Unnamed NON Government source: Source of the information is an unnamed/anonymous person or institution outside the government
- If more than one of the above source categories are given in an article, type each source that applies, separated by comma (,), for example: 1,3,4
- type N/A if no source information is given

A.3 Classification of Non-Tariff Measures (Summary used for Coding)

The following shows our own summary of the International Classification of Non-Tariff Measures from the MAST Group (Multi-Agency Support Team) as used for coding of the type of non-tariff measures in our dataset.

IMPORT NON-TARIFF MEASURES

A SANITARY AND PHYTOSANITARY MEASURES (SPS)

Measures that are applied to protect human or animal life from risks arising from additives, contaminants, toxins or disease-causing organisms in their food; to protect human life from plant- or animal-carried diseases; to protect animal or plant life from pests, diseases, or disease-causing organisms; to prevent or limit other damage to a country from the entry, establishment or spread of pests; and to protect biodiversity. These include measures taken to protect the health of fish and wild fauna, as well as of forests and wild flora. Note that measures for environmental protection (other than as defined above), to protect consumer interests, or for the welfare of animals are not covered by SPS.

B TECHNICAL BARRIERS TO TRADE (TBT)

Measures referring to technical regulations, and procedures for assessment of conformity with technical regulations and standards, excluding measures covered by the SPS Agreement. A technical regulation is a document which lays down product characteristics or their related processes and production methods, including the applicable administrative provisions, with which compliance is mandatory. It may also include or deal exclusively with terminology, symbols, packaging, marking or labelling requirements as they apply to a product, process or production method. A conformity assessment procedure is any procedure used, directly or indirectly, to determine that relevant requirements in technical regulations or standards are fulfilled; it may include, inter alia, procedures for sampling, testing and inspection; evaluation, verification and assurance of conformity; registration, accreditation and approval as well as their combinations.

C PRE-SHIPMENT INSPECTION AND OTHER FORMALITIES

C1 Pre-shipment inspection Compulsory quality, quantity and price control of goods prior to shipment from the exporting country, conducted by an independent inspecting agency mandated by the authorities of the importing country.

Example: A pre-shipment inspection of textile imports by a third party for verification of colours and types of materials is required.

D CONTINGENT TRADE-PROTECTIVE MEASURES

Measures implemented to counteract particular adverse effects of imports in the market of the importing country, including measures aimed at unfair foreign trade practices, contingent upon the fulfilment of certain procedural and substantive requirements.

D1 Antidumping measure

A border measure applied to imports of a product from an exporter. These imports are dumped and are causing injury to the domestic industry producing a like product, or to third countries' exporters of that product. Dumping takes place when a product is introduced into the commerce of an importing country at less than its normal value, generally where the export price of the product is less than the comparable price, in the ordinary course of trade, for the like product when destined for consumption in the exporting country. Antidumping measures may take the form of antidumping duties, or of price undertakings by the exporting firms.

Example: An antidumping duty of between 8.5 to 36.2% has been imposed on imports of biodiesel products from country A.

D2 Countervailing measure

A border measure applied to imports of a product to offset any direct or indirect subsidy granted by authorities in an exporting country where subsidized imports of that product from that country are causing injury to the domestic industry producing the like product in the importing country. Countervailing measures may take the form of countervailing duties, or of undertakings by the exporting firms or by authorities of the subsidizing country.

Example: A countervailing duty of 44.71% has been imposed by Mexico on imports of dynamic random access memory (DRAM) semiconductors from country A.

D3 Safeguard measures

A temporary border measure imposed on imports of a product to prevent or remedy serious injury caused by increased imports of that product and to facilitate adjustment. A country may take a safeguard action (i.e., temporarily suspend multilateral concessions) in respect of imports of a product from all sources where an investigation has established that increased imports of the product are causing or threatening to cause serious injury to the domestic industry that produces like or directly competitive products. Safeguard measures can take various forms, including increased duties, quantitative restrictions, and others (e.g. tariff-rate quotas, price-based measures, special levies, etc.).

E NON-AUTOMATIC LICENSING, QUOTAS, PROHIBITIONS AND QUANTITY-CONTROL MEASURES OTHER THAN FOR SPS OR TBT REASONS

Control measures generally aimed at restraining the quantity of goods that can be imported, regardless of whether they come from different sources or one specific supplier. These measures can take the form of non-automatic licensing, fixing of a predetermined quota, or through prohibitions. All measures introduced for SPS and TBT reasons are classified in chapters A and B above.

E1 Non-automatic import-licensing procedures other than authorizations for SPS or TBT reasons

An import-licensing procedure introduced, for reasons other than SPS or TBT reasons, where approval is not granted in all cases. The approval may either be granted on a discretionary basis or may require specific criteria to be met before it is granted. Example: Imports of textile products are subject to a discretionary licence.

E2 Quotas

Restriction of importation of specified products through the setting of a maximum quantity or value that is authorized for import: No imports are allowed beyond those maximums. Example: A quota of 100 tons of fish where the importation can take place any time of the year and there is no restriction on the country of origin of the product.

E3 Prohibitions other than for SPS and TBT reasons

Prohibition on the importation of specific products for reasons other than SPS (A1) or TBT (B1) reasons.

E311 Full prohibition (import ban)

Prohibition without any additional condition or qualification Example: Imports of motor vehicle with cylinder under 1500cc are not allowed, to encourage domestic production.

E312 Seasonal prohibition

Prohibition of imports during a given period of the year: This is usually applied to certain agricultural products while the domestic harvest is in abundance. Example: Imports of strawberries are not allowed from March to June each year.

E313 Temporary prohibition, including suspension of issuance of licences

Prohibition set for a given fixed period of time unrelated to a specific season: usually for urgent matters not covered under the safeguard measures above. Example: Imports of certain fish are prohibited with immediate effect until the end of the current season.

E314 Prohibition of importation in bulk

Prohibition of importation in a large-volume container: Importation is only authorized if the product is packed in a small retail container, which increases per unit cost of imports. Example: Import of wine is allowed only in a bottle of 750 ml or less.

E315 Prohibition of products infringing patents or other intellectual property rights

Prohibition of copies or imitations of patented or trademarked products. Example: Import of imitation brand handbags is prohibited.

E5 Export-restraint arrangement

An arrangement by which an exporter agrees to limit exports in order to avoid imposition of restrictions by the importing country, such as quotas, raised tariffs or any other import controls. The arrangement may be concluded at either the government or industry level. Includes Voluntary export-restraint arrangements (VERs).

Example: A bilateral quota on export of motor vehicles from country A to country B was established to avoid sanction by the latter.

E6 Tariff-rate quotas (TRQ)

A system of multiple tariff rates applicable to a same product: The lower rates apply up to a certain value or volume of imports, and the higher rates are charged on imports which exceed this amount. Example: Rice may be imported free of duty up to the first 100,000 tons, after which it is subject to a tariff rate of $1.5 per kg.

F PRICE-CONTROL MEASURES, INCLUDING ADDITIONAL TAXES AND CHARGES

Measures implemented to control or affect the prices of imported goods in order to, inter alia, support the domestic price of certain products when the import prices of these goods are lower; establish the domestic price of certain products because of price fluctuation in domestic markets, or price instability in a foreign market; or to increase or preserve tax revenue. This category also includes measures other than tariffs measures that increase the cost of imports in a similar manner, i.e. by fixed percentage or by a fixed amount. They are also known as para-tariff measures.

F1 Administrative measures affecting customs value

Setting of import prices by the authorities of the importing country by taking into account the domestic prices of the producer or consumer. It could take the form of establishing floor- and ceiling-price limits; or reverting to determined international market values. There may be different price setting, such as minimum import prices or prices set according to a reference.

F11 Minimum import prices

Pre-established import price below which imports cannot take place. Example: A minimum import price is established for fabric and apparel.

F12 Reference prices

Pre-established import price which authorities of the importing country use as reference to verify the price of imports. Example: Reference prices for agricultural products are based on the farm-gate price, which is the net value of the product when it leaves the farm, after marketing costs have been subtracted.

F2 Voluntary export-price restraints (VEPRs)

An arrangement in which the exporter agrees to keep the price of the goods above a certain level: A VEPR process is initiated by the importing country and is thus considered as an import measure. Example: The export price of video cassette tapes is set higher in order to defuse trade friction with major importing countries.

F3 Variable charges

Taxes or levies aimed at bringing the market prices of imported products in line with the prices of corresponding domestic products: Primary commodities may be charged per total weight, while charges on processed foodstuffs can be levied in proportion to the primary product contents in the final product. Example: The target price for a seed is $700 per ton; since the world price is $500, there is a levy for $200. If the world price changed to $600, the levy would change to $100.

F4 Customs surcharges

An ad hoc tax levied solely on imported products in addition to customs tariff to raise fiscal revenues or to protect domestic industries. Example: Customs surcharge, surtax or additional duty.

F5 Seasonal duties

Duties applicable at certain times of the year, usually in connection with agricultural products. Example: Imports of fresh perry pears, in bulk from 1 August to 31 December may enter free of duty, while in other months, seasonal duties applied.

F6 Additional taxes and charges levied in connection to services provided by the government

Additional charges, which are levied on imported goods in addition to customs duties and surcharges and which have no internal equivalents.7 They include: Custom-inspection, -processing and -servicing fees, merchandise-handling or -storing fees, tax on foreign exchange transactions, stamp tax, import licence fee, consular invoice fee, statistical tax ,tax on transport facilities, additional charges.

F7 Internal taxes and charges levied on imports

Taxes levied on imports that have domestic equivalents. For example, a tax on sales of products which are generally applied to all or most products.

G FINANCE MEASURES

Finance measures are intended to regulate the access to and cost of foreign exchange for imports and define the terms of payment. They may increase import costs in the same manner as tariff measures. Example: Payment of 100% of the estimated customs duty is required three months before the expected arrival of the goods to the port of entry.

H MEASURES AFFECTING COMPETITION

Measures to grant exclusive or special preferences or privileges to one or more limited group of economic operators. Example: A statutory marketing board with exclusive rights to control imports of certain grains, a canalizing agency with an exclusive right to distribute petroleum, a sole importing agency or importation reserved for specific importers regarding certain categories of goods.

I TRADE-RELATED INVESTMENT MEASURES

I1 Local content measures

Requirements to purchase or use certain minimum levels or types of domestically produced or sourced products, or restrictions on the purchase or use of imported products based on the volume or value of exports of local products. Example: In the production of automobiles, locally produced components must account for at least 50% of the value of the components used.

I2 Trade-balancing measures

Restrictions on the importation of products used in or related to local production, including in relation to the amount of local products exported; or limitations on access to foreign exchange used for such importation based on the foreign exchange inflows attributable to the enterprise in question. Example: A company may import materials and other

J DISTRIBUTION RESTRICTIONS

Distribution of goods inside the importing country may be restricted. It may be controlled through additional license or certification requirements. For Example, restriction to limit the sales of goods to certain areas within the importing country.

K RESTRICTIONS ON POST-SALES SERVICES

Measures restricting producers of exported goods to provide post-sales service in the importing country. Example: After-sales servicing on exported TV sets must be provided by a local service company of the importing country.

L SUBSIDIES (excluding export subsidies under P7)

Financial contribution by a government or public body, or via government entrustment or direction of a private body (direct or potential direct transfer of funds: e.g. grant, loan, equity infusion, guarantee; government revenue foregone; provision of goods or services or purchase of goods; payments to a funding mechanism), or income or price support, which confers a benefit and is specific (to an enterprise or industry or group thereof, or limited to a designated geographical region). Example: The government provides producers of chemicals a one-time cash grant to replace antiquated production equipment.

M GOVERNMENT PROCUREMENT RESTRICTIONS

Measures controlling the purchase of goods by government agencies, generally by preferring national providers. Example: A government office has a traditional supplier of its office equipment requirement, in spite of higher prices than similar foreign suppliers.

N INTELLECTUAL PROPERTY

Measures related to intellectual property rights in trade: Intellectual property legislation covers patents, trademarks, industrial designs, layout designs of integrated circuits, copyright, geographical indications and trade secrets. Example: Clothing with unauthorized use of trademark is sold at much lower price than the authentic products.

O RULES OF ORIGIN

Rules of origin cover laws, regulations and administrative determinations of general application applied by government of importing countries to determine the country of origin of goods. Rules of origin are important in implementing trade policy instruments such as antidumping and countervailing duties, origin marking and safeguard measures. Example: Machinery products produced in a country are difficult to fulfil the rules of origin to qualify for the reduced tariff rate of the importing country, as the parts and materials originate in different countries.

EXPORT NON-TARIFF MEASURES

P EXPORT-RELATED MEASURES

Export-related measures are measures applied by the government of the exporting country on exported goods.

P1 Export-license, -quota, -prohibition and other quantitative restrictions

Restrictions to the quantity of goods exported to a specific country or countries by the government of the exporting country for reasons such as a shortage of goods in the domestic market, regulating domestic prices, avoiding antidumping measures or for political reasons.

P11 Export prohibition

Prohibition of exports of certain products. Example: Export of corn is prohibited because of a shortage in domestic consumption.

P12 Export quotas

Quotas that limit value or volume of exports. Example: An export quota of beef is established to guarantee adequate supply in the domestic market.

P13 Licensing- or permit requirements to export

A requirement to obtain a licence or a permit by the government of the exporting country to export products. Example: Exports of diamond ores are subject to licensing by the Ministry.

P14 Export registration requirements

A requirement to register products before being exported (for monitoring purposes). Example: Pharmaceutical products need to be registered before being exported.

P19 Export quantitative restrictions (others)

P2 State-trading enterprises, for exporting; other selective export channels

P21 State-trading enterprises, for exporting Enterprises (whether or not State-owned or -controlled) with special rights and privileges not available to other entities, which influence through their purchases and sales the level or direction of exports of particular products (See also H1). Example: An export monopoly board, to take advantage of terms of sale abroad; a marketing board, to promote for export on behalf of a large number of small farmers.

P3 Export price-control measures

Measures implemented to control the prices of exported products. Example: Different prices for exports are applied from the same product sold in the domestic market (dual pricing schemes).

P4 Measures on re-export

Measures applied by the government of the exporting country on exported goods which have originally been imported from abroad. Example: Re-export of wines and spirits back to the producing county is prohibited. The practice is common in cross-border trade to avoid imposition of domestic excise tax in the producing country.

P5 Export taxes and charges

Taxes collected on exported goods by the government of the exporting country: they can be set either on a specific or an ad valorem basis. Example: An export duty on crude petroleum is levied for revenue purposes.

P6 Export technical measures

Export regulations referring to the technical specification of products and conformity assessment systems thereof: Control over the quality or other characteristics of products for export. Example: Exports of processed food products must be inspected for sanitary conditions; or certification required by the exporting country

P7 Export subsidies

Financial contribution by a government or public body, or via government entrustment or direction of a private body (direct or potential direct transfer of funds: e.g. grant, loan, equity infusion, guarantee; government revenue foregone; provision of goods or services or purchase of goods; payments to a funding mechanism), or income or price support, which confers a benefit and is contingent in law or in fact upon export performance (whether solely or as one of several conditions), including measures illustrated in annex I of the Agreement on Subsidies and Countervailing Measures and measures described in the Agreement on Agriculture. Example: All manufacturers in country A are exempt from income tax on their export profits.

A.4 Operationalization of World Market Supply and Demand Effect Variable

Table A-1: **Operationalization of World Market Effects.** This table shows the operationalization of the expected world market supply and demand effects, depending on the direction of change coded. "Dir. Lower" means that the direction of change coded was "lower", for example, an import quota was decreased. "Dir. Higher" means that a measure was increased. HD=Higher Demand, LD=Lower Demand, HS=Higher Supply, LS=Lower Supply. For some event categories, no world market supply and demand effect is known, for example, if the measure does not provide sufficient details (e.g. if only main category E is coded). In such case, NA is assigned.

Non-Tariff Measure Type		**Market Effect**	
Code	Name	Dir. Lower	Dir. High.
A	SANITARY AND PHYTOSANITARY MEASURES (SPS)	HD	LD
B	TECHNICAL BARRIERS TO TRADE (TBT)	HD	LD
C	PRE-SHIPMENT INSPECTION AND OTHER FORMALITIES	HD	LD
D	CONTINGENT TRADE-PROTECTIVE MEASURES	HD	LD
D1	Antidumping measure	HD	LD
D2	Countervailing measure	HD	LD
E	NON-AUTOMATIC LICENSING, QUOTAS, PROHIBITIONS AND QUANTITY-CONTROL MEASURES OTHER THAN FOR SPS OR TBT REASONS	NA	NA
E1	Non-automatic import-licensing procedures other than authorizations for SPS or TBT reasons	HD	LD
E2	Quotas	LD	HD
E3	Prohibitions other than for SPS and TBT reasons4	HD	LD
E311	Full prohibition (import ban)	HD	LD
E312	Seasonal prohibition	HD	LD
E313	Temporary prohibition, including suspension of issuance of licences	HD	LD
E314	Prohibition of importation in bulk	HD	LD
E315	Prohibition of products infringing patents or other intellectual property rights	HD	LD
E5	Export-restraint arrangement	HD	LD
E6	Tariff-rate quotas (TRQ)	LD	HD
F	PRICE-CONTROL MEASURES, INCLUDING ADDITIONAL TAXES AND CHARGES	HD	LD
F1	Administrative measures affecting customs value	HD	LD
F11	Minimum import prices	HD	LD
F12	Reference prices	HD	LD
F2	Voluntary export-price restraints (VEPRs)	HD	LD

Non-Tariff Measure Type		**Market Effect**	
Code	Name	Dir. Lower	Dir. High.
F3	Variable charges	HD	LD
F4	Customs surcharges	HD	LD
F5	Seasonal duties	HD	LD
F6	Additional taxes and charges levied in connection to services provided by the government	HD	LD
F7	Internal taxes and charges levied on imports	HD	LD
G	FINANCE MEASURES	NA	NA
H	MEASURES AFFECTING COMPETITION	NA	NA
I	TRADE-RELATED INVESTMENT MEASURES	NA	NA
I1	Local content measures	HD	LD
I2	Trade-balancing measures	HD	LD
J	DISTRIBUTION RESTRICTIONS	HD	LD
K	RESTRICTIONS ON POST-SALES SERVICES	HD	LD
L	SUBSIDIES (excluding export subsidies under P7)	LD	HD
M	GOVERNMENT PROCUREMENT RESTRICTIONS	HD	LD
N	INTELLECTUAL PROPERTY	HD	LD
O	RULES OF ORIGIN	HD	LD
P	EXPORT-RELATED MEASURES	NA	NA
P1	Export-license, -quota, -prohibition and other quantitative restrictions	NA	NA
P11	Export prohibition	HS	LS
P12	Export quotas	LS	HS
P13	Licensing- or permit requirements to export	HS	LS
P14	Export registration requirements	HS	LS
P19	Export quantitative restrictions (others)	HS	LS
P2	State-trading enterprises for exporting; other selective export channels	NA	NA
P3	Export price-control measures	HS	LS
P4	Measures on re-export	HS	LS
P5	Export taxes and charges	HS	LS
P6	Export technical measures	HS	LS
P7	Export subsidies	LS	HS

References

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (2002). Range-Based Estimation of Stochastic Volatility Models. *The Journal of Finance*, *57*(3), 1047–1091. https://doi.org/10.1111/1540-6261.00454

Anderson, K., & Nelgen, S. (2012). Agricultural trade distortions during the global financial crisis. *Oxford Review of Economic Policy*, *28*(2), 235–260. https://doi.org/10.1093/oxrep/grs001

Anríquez, G., Daidone, S., & Mane, E. (2013). Rising food prices and undernourishment: A cross-country inquiry. *Food Policy*, *38*, 190–202. https://doi.org/10.1016/j.foodpol.2012.02.010

Auer, B. R. (2016). How does Germany's green energy policy affect electricity market volatility? An application of conditional autoregressive range models. *Energy Policy*, *98*, 621–628. https://doi.org/10.1016/j.enpol.2016.08.037

Bellemare, M. F., Barrett, C. B., & Just, D. R. (2013). The Welfare Impacts of Commodity Price Volatility: Evidence from Rural Ethiopia. *American Journal of Agricultural Economics*, *95*(4), 877–899. https://doi.org/10.1093/ajae/aat018

Bellemare, M. F., & Lee, Y. N. (2016). Attitudes to Price Risk and Uncertainty: The Earnest Search for Identification and Policy Relevance. *Canadian Journal of Agricultural Economics/Revue Canadienne D'agroeconomie*, *64*(4), 599–612. https://doi.org/10.1111/cjag.12109

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Brandt, M. W., & Jones, C. S. (2006). Volatility Forecasting With Range-Based EGARCH Models. *Journal of Business & Economic Statistics*, *24*(4), 470–486. https://doi.org/10.1198/073500106000000206

Cafiero, C., Bobenrieth H., E. S.A., Bobenrieth H., J. R.A., & Wright, B. D. (2011). The empirical relevance of the competitive storage model. *Journal of Econometrics*, *162*(1), 44–54. https://doi.org/10.1016/j.jeconom.2009.10.008

Ceballos, F., Hernandez, M. A., Minot, N., & Robles, M. (2017). Grain Price and Volatility Transmission from International to Domestic Markets in Developing Countries. *World Development*, *94*, 305–320. https://doi.org/10.1016/j.worlddev.2017.01.015

Chou, R. Y.-T. (2005). Forecasting Financial Volatilities with Extreme Values: The Conditional Autoregressive Range (CARR) Model. *Journal of Money, Credit, and Banking*, *37*(3), 561–582. https://doi.org/10.1353/mcb.2005.0027

Clapp, J. (2009). Food Price Volatility and Vulnerability in the Global South: considering the global economic context. *Third World Quarterly*, *30*(6), 1183–1196. https://doi.org/10.1080/01436590903037481

Dawe, D., & Peter Timmer, C. (2012). Why stable food prices are a good thing: Lessons from stabilizing rice prices in Asia. *Global Food Security*, *1*(2), 127–133. https://doi.org/10.1016/j.gfs.2012.09.001

Deaton, A., & Laroque, G. (1992). On the Behaviour of Commodity Prices. *The Review of Economic Studies*, *59*(1), 1. https://doi.org/10.2307/2297923

Deaton, A., & Laroque, G. (1996). Competitive Storage and Commodity Price Dynamics. *Journal of Political Economy*, *104*(5), 896–923. https://doi.org/10.1086/262046

Demeke, M., Pangrazio, G., & Maetz, M. (2009). *Country responses to the food security crisis: Nature and preliminary implications of the policies pursued* (Initiative on Soaring Food Prices). Retrieved from Food and Agriculture Organization of the United Nations website: http://www.fao.org/fileadmin/user_upload/ISFP/pdf_for_site_Country_Response_to_the_Food_Security.pdf

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987. https://doi.org/10.2307/1912773

Evenett, S. J. (2009). Global Trade Alert: Motivation and Launch. *World Trade Review*, *8*(04), 607. https://doi.org/10.1017/S1474745609990061

Food and Agriculture Organization of the United Nations. (2008). *Declaration of the High-Level Conference on World Food Security*. Retrieved from http://www.fao.org/fileadmin/user_upload/foodclimate/HLCdocs/declaration-E.pdf

Food and Agriculture Organization of the United Nations. (2016). *Save and Grow in practice: Maize, rice, wheat : a guide to sustainable cereal production*. Rome: Food and Agriculture Organization of the United Nations.

Gilbert, C. L., & Morgan, C. W. (2010). Food price volatility. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *365*(1554), 3023–3034. https://doi.org/10.1098/rstb.2010.0139

Gouel, C. (2013). Optimal food price stabilisation policy. *European Economic Review*, *57*, 118–134. https://doi.org/10.1016/j.euroecorev.2012.10.003

Gustafson, R. L., States, U., & Agriculture, D. o. (1958). *Carryover levels for grains: A method for determining amounts that are optimal under specified conditions*. Washington: U.S. Dept. of Agriculture.

Haase, M., & Huss, M. (2018). Guilty speculators? Range-based conditional volatility in a cross-section of wheat futures. *Journal of Commodity Markets*, *10*, 29–46. https://doi.org/10.1016/j.jcomm.2017.10.001

Headey, D. D. (2013). The Impact of the Global Food Crisis on Self-Assessed Food Security. *The World Bank Economic Review*, *27*(1), 1–27. https://doi.org/10.1093/wber/lhs033

Headey, D. d., & Martin, W. J. (2016). The Impact of Food Prices on Poverty and Food Security. *Annual Review of Resource Economics*, *8*(1), 329–351. https://doi.org/10.1146/annurev-resource-100815-095303

HLPE. (2011). *Price volatility and food security: A report by the High-Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security.* Rome. Retrieved from http://www.fao.org/fileadmin/user_upload/hlpe/hlpe_documents/HLPE-price-volatility-and-food-security-report-July-2011.pdf

Ivanic, M., & Martin, W. (2014). Implications of domestic price insulation for global food price behavior. *Journal of International Money and Finance*, *42*, 272–288. https://doi.org/10.1016/j.jimonfin.2013.08.015

Ivanic, M., Martin, W., & Zaman, H. (2012). Estimating the Short-Run Poverty Impacts of the 2010–11 Surge in Food Prices. *World Development*, *40*(11), 2302–2317. https://doi.org/10.1016/j.worlddev.2012.03.024

Jensen, H. G., & Anderson, K. (2015). Grain Price Spikes and Beggar-thy-Neighbor Policy Responses: A Global Economywide Analysis. *The World Bank Economic Review*, *29*(2), 1–23. https://doi.org/10.1093/wber/lhv047

Magrini, E., Balié, J., & Morales-Opazo, C. (2017). Cereal price shocks and volatility in sub-Saharan Africa: what really matters for farmers' welfare? *Agricultural Economics*, *48*(6), 719–729. https://doi.org/10.1111/agec.12369

Martin, W., & Anderson, K. (2012). Export Restrictions and Price Insulation During Commodity Price Booms. *American Journal of Agricultural Economics*, *94*(2), 422–427. https://doi.org/10.1093/ajae/aar105

Mitchell, R. B. (2008). *International environmental politics. Sage library of international relation.* Los Angeles, Calif.: Sage.

Naylor, R. L., & Falcon, W. P. (2010). Food Security in an Era of Economic Volatility. *Population and Development Review*, *36*(4), 693–723. https://doi.org/10.1111/j.1728-4457.2010.00354.x

Newbery, D. M. G., & Stiglitz, J. E. (1981). *The theory of commodity price stabilization: A study in the economics of risk.* Oxford: Clarendon Press.

Parkinson, M. (1980). The Extreme Value Method for Estimating the Variance of the Rate of Return. *The Journal of Business*, *53*(1), 61–65.

Pieters, H., & Swinnen, J. (2016). Trading-off volatility and distortions? Food policy during price spikes. *Food Policy*, *61*(Supplement C), 27–39. https://doi.org/10.1016/j.foodpol.2016.01.004

Rude, J., & An, H. (2015). Explaining grain and oilseed price volatility: The role of export restrictions. *Food Policy*, *57*(Supplement C), 83–92. https://doi.org/10.1016/j.foodpol.2015.09.002

Samuelson, P. A. (1971). Stochastic Speculative Price. *Proceedings of the National Academy of Sciences*, *68*(2), 335–337. https://doi.org/10.1073/pnas.68.2.335

Tadesse, G., Algieri, B., Kalkuhl, M., & Braun, J. von. (2014). Drivers and triggers of international food price spikes and volatility. *Food Policy*, *47*, 117–128. https://doi.org/10.1016/j.foodpol.2013.08.014

Timmer, C. P. (2010). Reflections on food crises past. *Food Policy*, *35*(1), 1–11. https://doi.org/10.1016/j.foodpol.2009.09.002

United Nations Conference on Trade and Development. (2015). *International Classification of Non-Tariff Measures: 2012 Version* (No. UNCTAD/DITC/TAB/2012/2/Rev.1). Geneva. Retrieved from https://unctad.org/en/PublicationsLibrary/ditctab20122_en.pdf?user=46

Transforming our world: the 2030 Agenda for Sustainable Development, United Nations General Assembly 10/21/2015.

USDA FAS. (2018). *Production, Supply and Distribution database.* Retrieved from United States Department for Agriculture - Foreign Agricultural Service website: http://apps.fas.usda.gov/psdonline/

World Trade Organization. (2018). WTO | Glossary - a guide to 'WTO speak'. Retrieved from https://www.wto.org/english/thewto_e/glossary_e/glossary_e.htm

Wossen, T., Berger, T., Haile, M. G., & Troost, C. (2018). Impacts of climate variability and food price volatility on household income and food security of farm households in East and West Africa. *Agricultural Systems*, *163*, 7–15. https://doi.org/10.1016/j.agsy.2017.02.006

Wright, B. D. (2011). The Economics of Grain Price Volatility. *Applied Economic Perspectives and Policy*, *33*(1), 32–58. https://doi.org/10.1093/aepp/ppq033

Yu, T.-H., Tokgoz, S., Wailes, E., & Chavez, E. (2011). A quantitative analysis of trade policy responses to higher world agricultural commodity prices. *Food Policy*, *36*(5), 545–561. https://doi.org/10.1016/j.foodpol.2011.07.001

5 Conclusion

This dissertation contributes to addressing critical gaps in the literature on food security, agriculture and rural development. It highlights issues that are often neglected in current research and efforts to reduce food insecurity and fluctuations of food prices, in particular improved on-farm storage. This chapter discusses the main results of this dissertation, starting with the two papers on improved on-farm storage as well as their interlinkages, followed by the third paper on the global food price volatility effects of national trade policy changes. The third section present a synthesis and policy recommendations, and the final section concludes with personal reflections.

5.1 Effects of Improved On-Farm Storage

The first and second paper analyse the effect of improved on-farm storage on seasonal food insecurity, and on local market prices, respectively. Both papers use the same study design of a matched-pair, cluster randomised control trial, implemented in two districts of Tanzania. The experimental intervention were five hermetic storage bags and training in their use, provided free-of-charge to randomly selected smallholder farmers, clustered in farmers groups.

The main outcome variable in the first paper, household food insecurity, was tracked on a quarterly basis, while the main outcome variable of the second paper, local market prices, was measured with a weekly frequency. To enable frequent data-collection in the remote and widespread rural areas in the experiment, SMS-based mobile phone surveys were used for both indicators. The effects of the intervention on these outcome variables are estimated as the average of within-pair mean differences between treatment and control groups. In the second paper, this estimation strategy is implemented through a mixed-effects model that allows to take additional explanatory variables into account (e.g. seasonal price trend).

The results from the first paper show that the experimental intervention reduced the proportion of seasonally food insecure households in the observation period. Most pronounced reductions are found for the lean season, the time shortly before the new harvest is brought in, as well as for households of female participants. The second paper presents the effects of improved on-farm storage on local market prices. The results that that the experimental intervention reduced seasonal food price gaps in the observed harvest cycle in one of the two study districts (Kondoa). More pronounced effects for the district of Kondoa are argued to reflect its more limited market integration as compared to the second study district, Kilosa.

The results of these two papers contribute to the current academic and policy discussions, which have questioned the benefits of reduced post-harvests losses (see Chapter 1). They thereby contribute to a growing literature seeking to understand the causes of seasonality in Sub-Saharan African food systems, specifically seasonal food insecurity and seasonal food price gaps. Such seasonality implies that farmers are unable to smooth their food consumption and sales throughout a harvest year, which reflects constraints to intertemporal arbitrage. The literature had so far almost exclusively focused on credit and liquidity to explain smallholder farmer's intertemporal arbitrage constraints, also based on the argument that post-harvest storage losses do not present significant limitations. In stark contrast, the here presented results suggest that it is premature to disregard post-harvest storage losses as a factor limiting intertemporal arbitrage and thereby contributing to seasonal food insecurity and seasonal price gaps.

Although these outcomes were analysed separately in the first and second paper, they have interlinkages, which have not been considered in the two papers. Specifically, seasonal food insecurity is likely influenced by the extent of seasonal food price gaps, and, similarly, the extent of seasonal food price gaps depends on the seasonal food production and consumption situation that also affects local food insecurity. Moreover, the market-level effects shown in the second paper may moderate the direct effects on food insecurity presented in the first paper. If improved on-farm storage leads to significant reductions of seasonal food price gaps, the benefits from intertemporal arbitrage for adopters of improved on-farm storage decrease. On the other hand, market-level effects can also imply indirect food security benefits for non-adopters of improved on-farm storage. Non-adopter's food insecurity may be reduced as a consequence of decreasing seasonal food price gaps. Clearly, analysing these interlinked questions should build on data from more than one harvest cycle, especially as the pattern of decreasing prices in the observed harvest cycle is not the typical case. More often, prices increase after harvest and peak in the lean season. Fortunately, the data collection for the here presented research was extended and the interlinkages between direct and indirect effects of improved on-farm storage can be considered in future papers.

An additional limitation relates to the external validity (generalizability) of the presented results. While hermetic storage technologies have been shown to be highly effective in reducing storage losses for Sub-Saharan Africa's main staple crops, namely maize and rice, their benefits for adopting household's food security may depend on the local context. Specifically, the seasonality of harvests differs across agro-ecological zones with some areas in Sub-Saharan Africa bringing in more than one harvest per year. In such a context, the benefits of improved on-farm storage may be different as the risk of losses increase with storage duration. Given the highly promising results presented in this dissertation, replicating the presented findings in further regions is a key opportunity for further research. Such further research can benefit from the results presented, for example by drawing on first evidence on stronger effects for households of female participants, but may also go beyond immediate implications on food security to consider other pertinent topics of sustainable development. Clearly, the limited attention that the academic literature has paid on improved on-farm storage leaves room for much progress to advance the understanding of food security, seasonality, and agricultural and rural development.

5.2 Effects of Trade Policy on Global Food Price Volatility

The third paper considers the question whether national trade policy interventions increase global food price volatility. The paper thereby seeks to analyse if political calls to refrain from trade policy interventions in response to volatile food prices are empirically well founded. If trade policy changes were to affect global food price volatility, their effects should appear on the day a national trade policy intervention is announced. A new dataset on announcements of national agricultural trade policy changes was hence established. The data comprises of trade policy changes affecting the world's main staple crops rice, wheat and maize, and covers the time period from 2005 until 2017. The effects on global food price volatility are analysed through a Conditional Autoregressive Range (CARR) model, extended to take additional explanatory variables into account (CARRX). The results show that the announcement of trade policy changes can lead to short-term increases in global food price volatility. Yet, these short-term effects have little persistence beyond the announcement day, and only appear when stocks are low. The results hence provide little support for political concerns that national agricultural trade policy interventions amplify global food price volatility.

Although the results show that national trade policy changes are unlikely to persistently affect global food price volatility, they do not imply an endorsement of trade policy interventions as a response to volatile or high food prices. Trade policies can still exhibit adverse effects by increasing food prices or amplifying price spikes, as a related literature indicates (e.g. Yu, Tokgoz, Wailes, & Chavez, 2011; Anderson &

Nelgen, 2012; Jensen & Anderson, 2015). The presented paper focuses on effects on global food price volatility and does not consider effects on global food price levels. Furthermore, the study is limited by its focus on the effects of trade policy changes on global markets and does not analyse whether such trade policy changes are effective in stabilizing domestic market prices. This focus is partly due to a paucity of country-level data on food prices with high frequency, which would be the basis to estimate domestic price volatility effects. In extension, the study is unable to assess the effects of trade policy changes on domestic food security or economic growth, which often are the main motivations for national governments in implementing national trade policy changes on agricultural commodities.

Taken together, extending the analysis to consider the effects of the announcement of national trade policy changes on global food price levels, as well as their domestic price, food security and income effects, are all key opportunities for future research. Such an analysis may, however, need to be focused on a limited set of countries where frequent national food price data is available. The database developed for the purpose of this analysis presents ample opportunities for future research along these lines.

5.3 Synthesis and Policy Implications

The here presented results show that improved on-farm storage can reduce seasonal food insecurity and seasonal food price gaps at local level. At global level, adequate food stocks can dampen the effects of national trade policy interventions on global food price volatility. Although these papers are based on different levels of analysis, they all highlight the role of food stocks and storage in achieving socially or politically desirable outcomes. The results of this dissertation hence point to the need to give increasing attention to improved on-farm storage and adequate food stocks to advance the aspirational goals of the 2030 Agenda for Sustainable Development. These findings have policy implications.

First, the presented results highlight that national governments and development actors should consider the promotion of improved on-farm storage as part of their agricultural and rural development strategies and policies. However, specific recommendations on ways to promote their adoption by farmers need to be tested and explored further. Currently, little is known on farmer's decisions and choices to adopt improved on-farm storage. One avenue to be explored further is extending the preferential rules commonly applied to agricultural inputs to include post-harvest technologies. For example, in Tanzania, the sales of agricultural inputs, such as improved seed varieties, fertilizer, and agricultural machinery, is exempt of Value-Added-Tax (VAT), whereas the sales post-harvest storage technologies, including hermetic storage bags and silos, is subject to VAT. An extension of such preferential rules to include post-harvest management technologies may be a feasible policy option to promote the adoption of post-harvest technologies.

Second, development actors currently focused on the promotion of agricultural practices that aim to increase agricultural production and productivity, could consider including post-harvest components in their programmes. The results of this dissertation highlight the benefits of improved on-farm storage for smallholder farmer’s food security, which are most pronounced in the lean season. Given that agricultural production interventions focus on increasing food availability at harvest time and improved on-farm storage has shown most pronounced effects in the lean season, both measures combined may provide additional direct benefits for smallholder farmers food security in addition to reduced seasonal food price gaps.

Finally, this dissertation does not provide empirical support for the concern that national government trade policy interventions exacerbate global food price volatility. However, this dissertation does not offer an assessment of the effectiveness of such interventions in stabilizing domestic food prices, which is subject to further research. Hence, the results should not be interpreted as an endorsement of national agricultural trade policy interventions.

5.4 Personal Reflection

It is my hope that the work presented in this dissertation will spur further research on these pertinent topics of post-harvest losses, improved on-farm storage, global food stocks, and the seasonality of food security and food prices. There is still much to be learned with high relevance for policy and practice. Of course, implementing the here presented research was not without challenges. I would like to highlight here the main lessons learnt, i.e. challenges encountered and success factors identified.

A critical component of this dissertation is the field experiment in Tanzania. Implementing such an experiment is challenging on many fronts. Importantly, the study design needs to be solid from the start as there is little room for changes once baseline data is collected and the experiment has started. Given that many indicators of interest have limited recall periods, it is often not possible to retrieve data points whose collection had been omitted at the beginning. For example, the research could have collected indicators to measure the effects of improved on-farm storage on smallholder farmer’s income or poverty. Yet, a choice was made to focus on food security and local markets prices in light of a relatively tight budget for a research project of this size. Hence, it was clear from the outset that the research will need to focus on a small number of outcomes, which represent the most significant gaps in the current literature. Balancing what is desirable and what is feasible was one of the critical challenges in my opinion.

In addition, I would like to highlight the importance of reliable and committed partners in the field. One of the key success factors in this research was the excellent working relationship with local partners. In the here presented field research, one local organization had a strong role in the implementation of data collection efforts, while a second organization implemented the experimental interventions. Keeping research-related and intervention-related activities separate is not only of scientific relevance, but also yields practical gains, as partners can be selected according to their respective skillsets and can focus their efforts on one area of work.

Disclosure of own Scientific Contribution and Status of Articles

According to the regulations of the D-GESS at ETH Zurich, I disclose my own (Michael Brander Wittwer) scientific contribution to co-authored papers and the status of the papers included in this dissertation. My own contribution is indicated with qualitative terms, i.e. “leading role”, “major role”, “minor role”, “no role”.

For the first paper, Brander, M., Bernauer, T., and Huss, M. (2019): Improved on-farm storage reduces seasonal food insecurity of smallholder farmer’s households – Evidence from a Randomized Control Trial in Tanzania, I overall had a major role in the analytical input. Specifically, I had a major role in the conception and design, a major role in the development and analysis of a theoretical model, a leading role in the acquisition of data, and a major role in the analysis and interpretation of data. I further had a leading role in writing, i.e. a leading role in drafting the article, and a minor role in revising it critically for important intellectual content.

For the third paper, Brander, M., Bernauer, T., and Huss, M. (2019): Do national trade policy changes increase global food price volatility?, I overall had a major role in the analytical input. Specifically, I had a major role in the conception and design, a major role in the development and analysis of a theoretical model, a leading role in the acquisition of data, a minor role in the analysis of data, and a major role in the interpretation of data. I further had a leading role in writing, i.e. a leading role in drafting the article, and a minor role in revising it critically for important intellectual content.

All papers included in this dissertation are publication manuscripts, i.e. they have not yet been submitted for journal publication. The first and second paper may be extended with data collected for an additional harvest cycle, which extends the here presented observation period, before they are submitted for journal publication.