UNDERSTANDING SMALLHOLDER FARMERS' POST-HARVEST CHOICES IN SUB-SAHARAN AFRICA: EVIDENCE FROM MALAWI

by

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A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Department of Agricultural Economics

West Lafayette, Indiana

December 2020

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This is dedicated to my husband, Taz, and to my mother, sisters and brother, thank you for being my reliable support system through this process. I would not have made it without you.

ACKNOWLEDGMENTS

I am grateful to God for being my help, strength and refuge throughout the three years I spent in this PhD program. Even in my lowest moments when I thought I would not make it, He gave me hope and reason to keep going. Thank you for taking me this far.

I would like to acknowledge and thank my committee chair Dr. Jacob Ricker-Gilbert, and the rest of my committee: Dr. Paul V. Preckel, Dr. Jonathan Bauchet and Dr. Gerald Shively. I am grateful for the countless hours and effort they committed in giving insightful comments and suggestions throughout the dissertation process. I would not have been able to complete this without their guidance and support. I really appreciate the opportunity to work and learn from them.

Lastly, to friends, colleagues and acquaintances I made through my graduate program: Nina Jovanovic, Alecia Evans, Travis Atkinson, and Hira Channa, thank you for being involved in my work and my life throughout this program. I am forever grateful for your encouragement and support.

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ABSTRACT

This dissertation has three essays that are focused on understanding smallholder farmers' choices in sub-Saharan Africa, particularly, Malawi. The first essay uses a clustered randomized control trial (RCT) to evaluate the impact of storage and commitment constraints on farmers' legume storage behavior. The second essay is motivated by the incomplete quality information problem within informal markets that undermines consumers' demand for quality and lead to lemons market. In this essay, we use a clustered RCT along with the Becker DeGroote Marshack auctions amongst 1,098 farm households to evaluate whether providing food safety (aflatoxins) information increases consumers' demand for grain quality and whether that demand for quality varies depending on food availability. The third essay uses stochastic dynamic programming to explore the role of market risk and expenditure shocks on smallholder farmers' storage and marketing behavior.

CHAPTER 1. INTRODUCTION

There are numerous contraints that smallholder farmers face in sub-Saharan Africa (SSA). This dissertation uses the case of Malawi to understand how different factors influence smallholder farmers' choices in SSA. Although the three essays in this dissertation are independent, they are related in that they are all focused on understanding how different constraints influence smallholder farmers' grain storage, sales and purchase behavior in SSA. The first essay uses a randomized control trial (RCT) among 1,739 smallholder farmers in Malawi to evaluate the impacts of storage and commitment constraints on farmers' legume storage behavior. The commitment constraints include the social and behavioral issues such as impatience, self-control and social pressure to share with one's social network that limit households' commitment to save cash. This essay makes three major contributions to the literature. First, this essay extends the concept of commitment constraints on household saving behavior to grain storage, a different form of savings, and estimates the impact of two different grain storage commitment devices in the form of group storage on farmers storage behavior. Second, while previous studies that looked into storage and commitment constraints either estimated the impact of addressing storage constraints alone (Omotilewa et al. 2018) or the joint impact of addressing storage and commitment constraints (Aggarwal, Francis, and Robinson 2018), this essay advances their work by estimating both the joint and separate effects of addressing storage and commitment constraints. Lastly, this essay also provides some insights on the effectiveness and viability of warehouse programs for smallholder farmers in developing countries as we find that providing improved storage technologies and encouraging farmers to store with others in their village may be more effective than promoting larger-scale warehouse receipt systems.

The second essay addresses the information constraints that farm households face in grain markets. For a credence food quality attribute like aflatoxins contamination, incomplete quality information within informal markets undermines consumers' demand for quality and leads to a "lemons market". This essay estimates the impact of providing quality labeling and increasing consumers' awareness about food quality and safety issues on their demand for quality. A clustered randomized control trial (RCT) along with the Becker DeGroote Marshack auctions are used with 1,098 farm households to evaluate whether providing aflatoxins information increases consumers' demand for groundnuts quality and whether that demand for quality varies depending on food availability. This paper contributes to the literature on aflatoxins and food safety in SSA by estimating and comparing consumers' demand for observable and unobservable grain quality attributes. Previous studies on consumers' WTP for grain quality in SSA have mostly focused on observable attributes such as color, grain size, and insect damage (de Groote et al. 2016; Kadjo, Ricker-Gilbert and Alexander 2016; Demont et al. 2013; Groote, Kimenju and Morawetz 2011; de Groote and Kimenju 2008). This essay contributes to this literature by estimating and comparing consumers' WTP for both observable and unobservable attributes in groundnuts.

In addition, this essay advances the literature on unobservable food safety attributes by estimating the causal impacts of providing aflatoxins information on consumers' demand for grain quality (Ordonez 2016; de Groote et al. 2016; and Hoffmann and Gatobu 2014). Empirical evidence from this paper, therefore, helps to highlight the need to raise aflatoxins awareness in SSA to increase consumers' demand for quality and eventually incentivize supply of aflatoxins-safe grain in informal markets. This essay also contributes to this literature by evaluating how rural consumers' demand for grain quality varies under different states of food availability (i.e. harvest versus lean season). This important aspect helps to highlight how conflicting food security objectives, that is, quality versus quantity concerns, affect households' food quality demand in the post-harvest period. The results from this essay help to highlight the need for policy that re-inforces the practice of aflatoxin testing and regulations in informal markets especially during the lean season. Our results also confirm the need to increase aflatoxins information campaigns for key food crops in SSA including groundnuts.

The third essay explores the role of market risk and expenditure shocks on farmers storage and marketing behsvior. This essay uses dynamic stochastic programming to evaluate how these risks and shocks influence farmers' production, storage and sales decisions. While there is extensive literature focused on explaining how liquidity constraints, imperfect credit markets and technology constraints limit farmers' ability to participate in the exploitation of intertemporal price arbitrage opportunities in sub-Saharan Africa (Burke, Bergquist, and Miguel 2019; Stephens and Barrett 2011; Channa 2019), not much has been done to explain the role of risk and shocks on this issue. This essay therefore contributes to this literature by providing another possible explanation for smallholder farmers' limited participation in grain storage for price arbitrage. The paper also helps to highlight how variations in crop market risk-hedging properties and price dynamics influence farmers' grain sales and storage patterns.

1.1 Caveat: Some Repeated Sections

The essays in this dissertation are written as separate articles with an eye towards publication in different journals. As such, some sections are repeated. These include the study area and setting as well as the sampling and experimental design. However, the research questions, data, results and policy implications from these essays are different.

CHAPTER 2. INCENTIVE MECHANISMS FOR SMALLHOLDER FARMERS TO EXPLOIT INTER-TEMPORAL ARBITRAGE OPPORTUNITIES FOR GRAIN LEGUMES: EXPERIMENTAL EVIDENCE FROM MALAWI

2.1 Abstract

Seasonal commodity price fluctuations can offer farmers potential inter-temporal arbitrage opportunities to increase their sales and profits. However, smallholder farmers in most of sub-Saharan Africa often do not exploit these opportunities to the fullest extent possible. We administered a randomized control trial (RCT) among 1,739 smallholder farmers in Malawi to evaluate the impacts of storage and commitment constraints on farmers' storage decisions for their legume (soybeans and groundnuts). The treated groups received (i) an improved storage technology in the form of two hermetic (airtight) bags (T1: technology only); (ii) the same improved storage technology under the condition that farmers store collectively with other members of their farmer club within their village, (T2: village storage program) and (iii) the improved storage technology under the condition that farmers store collectively at a centralized association warehouse (T3: warehouse storage program). We analyzed the impacts of these treatments on the following outcomes: quantity stored, number of weeks stored before largest sale, net sales quantity and net sales revenue. Our results showed that all three storage interventions helped farmers store more of their major legume at harvest, store longer, and increase revenue from legume sales compared to control households. Our results also showed that the village storage program was relatively more effective at incentivizing farmers to store legumes for exploitation of intra-seasonal price arbitrage opportunities compared to the warehouse storage program. This may have been due to several factors, including the low compliance rate with the warehouse program, higher transportation costs and farmers being less willing to store their legumes at the centralized warehouse outside their village. The finding suggests that providing improved storage technologies and encouraging farmers to store with others in their village may be more effective strategies for them to capture intra-seasonal arbitrage opportunities than promoting larger-scale warehouse receipt systems.

2.2 Introduction

In sub-Saharan Africa (SSA), agricultural commodities often exhibit large seasonal price fluctuations. For example, it is common for lean season grain prices to increase by as much as 50–100% from the peak harvest-season prices on average (Burke, Bergquist, and Miguel 2019; Gilbert, Christiaensen, and Kaminski 2017; Kaminski and Christiaensen 2014). Although these price fluctuations offer farmers potential inter-temporal price arbitrage opportunities to increase their sales and profits, smallholders in most of the region often do not exploit these opportunities to the fullest extent possible. Many farmers sell a substantial amount of their grain immediately after harvest at low harvest prices, sometimes even at the expense of buying it at a higher price later in the year when their own stocks have been drawn down (Burke, Bergquist, and Miguel 2019; Dillon 2017; Stephens and Barrett 2011). Baseline data from our study in Malawi supports what Burke, Bergquist, and Miguel 2019 considered the *"selling low and buying high"* phenomena, as close to 46 percent of farmers in our sample had their largest grain sales at harvest (i.e. largest in terms of proportion of their harvest) and also made the most grain purchases for food in the lean season (see Figure 2.1 and Figure 2.2).

Considering that smallholders in SSA generally have limited financial resources, when they do not capitalize on these potential price arbitrage opportunities it further reduces their income and undermines their food security situation. This is especially the case in the lean season when grain is scarce and prices are high. As such, the objective of the present study is to estimate how potential constraints to storing grain at harvest can be reduced. Specifically, we implemented a randomized controlled trial (RCT) with 1,739 smallholder legume (groundnut and soybean) farmers in central Malawi between 2018 and 2019 to test the effectiveness of using an improved storage technology and two grain storage commitment devices. The treatments were (i) an improved storage technology in the form of two hermetic (airtight) bags (T1: technology only); (ii) the same improved storage technology under the condition that farmers store collectively with their farmer club within their village, (T2: village storage program) and (iii) the improved storage technology under the condition that farmers store collectively at a centralized association warehouse outside-village (T3: warehouse storage program). T2 and T3 are different commitment devices and they varied in terms of (i) storage location and distance from home, (ii) group size or aggregation level, and (iii) grain deposit and withdrawal agreements or conditions.

The farmers in our sample were all members of the National Association of Smallholder Farmers in Malawi (NASFAM) cooperative, and the village storage treatment involved grain storage with other households who were members of the same farmer club (5 to 10 people) within a farmers' village. Each club identified a storage location within their village and independently agreed on grain deposit and withdraw terms and conditions. The warehouse storage program involved storage at a centralized warehouse outside the village (further away from home) with multiple farmer clubs (10 to 15 clubs, or 50 to 150 people). In that program, deposit and withdrawal conditions were agreed upon at a warehouse level, involving multiple clubs (i.e. the deposit and withdrawal conditions included for example, a minimum number of people to approve early grain withdrawal, and a minimum number of witnesses required to keep records of grain deposits or withdrawals). Through the intervention, the key research questions that we address in this article are: to what extent do improved storage technologies and two different storage commitment devices effectively incentivize smallholder farmers to store more legumes at harvest for exploitation of intra-seasonal price arbitrage opportunities? Are the village level and warehouse level commitment devices equally effective at incentivizing farmers to store legumes for sale later when prices rise?

Though still understudied, estimating the underlying factors influencing smallholder farmers' selling low and buying high behavior has been the subject of several recent studies (Burke, Bergquist, and Miguel 2019; Aggarwal, Francis, and Robinson 2018; Dillon 2017; Basu and Wong 2015; Kaminski and Christiaensen 2014; Stephens and Barrett 2011; Channa 2019). Some of the possible explanations for this behavior include challenges such as (i) lack of effective storage technologies (Aggarwal, Francis, and Robinson 2018; Omotilewa et al. 2018; Kadjo, Ricker-Gilbert, and Alexander 2016); (ii) harvest period cash and liquidity constraints that push farmers to liquidate their grain stocks in order to address urgent household expenses (Kadjo et al. 2018; Dillon 2017; Sun et al. 2013); (iii) limited access to credit markets (Channa et al. 2019; Burke, Bergquist, and Miguel 2019; Basu and Wong 2015; Stephens and Barrett 2011); (iv) limited access to better output markets due to high transaction costs (Bernard et al. 2017); as well as (v) difficulties to commit to storing grain due to behavioral and social challenges such as impatience, self-control and social pressure to share (Basu 2014; Brune et al. 2011; Baland, Guirkinger, and Mali 2011; Ashraf, Karlan, and Yin 2006).

While several studies have looked at how credit and liquidity constraints influence farmers' storage behavior, to our knowledge there is still little evidence that documents how social and behavioral issues influence farmers' commodity storage behavior. When grain is stored at home where stocks are readily available for liquidation whenever there is need, farmers are more likely to be pressured to sell their grain earlier than planned as they may be unable to deny their (extended) family's current needs in favor of storage for potentially higher future returns. This may be particularly challenging when the grain is stored in plain sight where their family can see it. The social pressure to share with ones' social network including household members, relatives or friends is considered an important cash saving constraint for the household (Brune et al. 2011; S. Anderson and Baland 2002). In this paper, we apply this result to grain storage, which is a different form saving. In addition, when farmers store their grain individually, they are likely to be tempted to liquidate their grain stocks earlier due to impatience and limited self-control. This is a common behavioral challenge that households face even when trying to save cash (Dupas and Robinson 2013; Bryan, Karlan, and Nelson 2010; Ashraf, Karlan, and Yin 2006; Thaler and Shefrin 1981). Households may also tend to be wasteful and consume more than planned when grain stocks are stored in plain sight due to limited mental accounting (Aggarwal et al. 2018). It is, therefore, important to identify effective grain storage commitment devices to help farmers deal with such commitment constraints including self-control and social pressure.

The objective of the present study is to estimate how addressing storage and commitment constraints influence farmers' legume storage behavior. Empirical evidence suggests that crop damage by pests (i.e. weevils, large grain borer or rodents) and molds significantly reduces grain market value (Kadjo, Ricker-Gilbert, and Alexander 2016). Considering that farmers who lack effective storage technologies are likely to have a high expectation of storage losses, it is possible that selling early may be a strategy for such farmers to avoid storage losses and damages. Evaluating the causal impacts of an effective storage technology intervention such as hermetic (airtight) bags on smallholders' storage behavior is important. Previous studies have evaluated the impacts of improved storage technologies, such as hermetic bags, on farmers' adoption of the bags themselves and of improve maize varieties (Aggarwal, Francis, and Robinson 2018; Omotilewa et al. 2018; Channa 2019; Omotilewa, Ricker-Gilbert, and Ainembabazi 2019; Omotilewa et al. 2018). This paper extends this literature by estimating the causal impacts of the PICS bags, along with group storage interventions, on farmers' post-harvest storage and sales behavior.

This paper, therefore, advances the literature on grain storage commitment devices by estimating the causal impacts of two variations of group storage arrangements on smallholder farmers' storage behavior. To our knowledge, the only study that evaluates the impacts of group storage on farmers' demand for grain storage in SSA is Aggarwal et al. (2018). That study implemented one treatment among Kenyan farmers, as treated farmers received the combination of hermetic bags, labels for the bags to allow for mental accounting, and the requirement that they store their maize in groups in the village.[1] The study found that the treatment increased the amount of grain stored at harvest by smallholders as well as their cash income from sales. While Aggarwal et al. (2018) estimated the joint impacts of the PICS bags, labelling and group storage; our paper advances their work by explicitly separating the causal impacts of the improved storage technology (the hermetic bags), from the group storage commitment device.

Our estimates of the aggregate treatment effects suggest that, compared to control households, all three storage interventions had a meaningful impact on farmers decisions to store more legumes at harvest (34 to 74 kg, on average), to store longer (1 to 2 weeks on average) and to also increased revenue from legume sales (MK23,000 to MK30,000; US$1=MK750). In order to tease out the marginal impacts of the two grain storage commitment devices, we compared the village storage program and the warehouse storage program to the PICS-only intervention. We found significant marginal effects on quantity stored (40 kg) of the village storage program, but not of the warehouse storage program. This is likely because over 30 percent of farmers assigned to the warehouse storage treatment groups chose not to store their legumes in the warehouse, and there were higher transportation costs and more uncertainty around storing with a larger group at a centralized warehouse outside their village. This is in line with literature suggesting that social interventions like group storage tend to be more effective within smaller groups with closer social ties, where the trust and peer effects tend to be stronger (Chandrasekhar, Kinnan, and Larreguy, n.d.; Dahl, Løken, and Mogstad 2014; Gonzalez-Mulé et al. 2014; Kandel and Lazear 1992). However, the present study is the first to inform this issue in the context of grain storage.

[1] In the Aggarwal et al. 2018 study, four bags were provided per ROSCA or group not to individual farmers while this present study provide 2 PICS bags per farmer. Unlike the Aggarwal et al. study, we do not provide labels to farmers.

2.3 Setting and Experimental Design

This section has three subsections. The first subsection provides a background on legume price seasonality, the second subsection presents the sampling strategy used in the study while the last subsection presents the experimental design for the study.

2.3.1 Background on legume price seasonality and post-harvest losses in Malawi

Legumes including soybeans, common beans, groundnuts, pigeon peas, and cowpeas are an important source of inexpensive proteins relative to animal proteins for most households in SSA and for smallholder farmers, in particular. Legumes are also an important source of income. While governments in most of SSA intervene in the maize market to stabilize maize prices, there is generally limited government interference in legume markets. This is because for most of SSA, maize is a key staple food crop with its availability and accessibility largely defining the state of food security (Minot 2011a; Sarris 2010). In Malawi for example, the Ministry of Agriculture sets price controls annually through the Control of Goods Acts and imposes export bans on maize depending on aggregate maize production each year. In this study we focused on legumes because legume prices typically exhibit relatively larger seasonal variations compared to maize. This is in line with empirical evidence from some recent studies in SSA that find limited price seasonality in maize (Burke, Bergquist, and Miguel 2019; Channa et al. 2019; Abass et al. 2014). The Ministry of Agriculture's monthly price data for Malawi from 1989 to 2017 also shows larger seasonal variations in average prices for legumes relative to maize (Figure 2.2). The historical price data also shows that the differences in average seasonal prices for legumes crops including soybeans and groundnuts are between 15 to 35 percent higher relative to maize. Legume crops, therefore, are relatively more viable for storage to exploit price arbitrage opportunities compared to maize. As such, we focus on soybeans and groundnuts in this this study.

One key issue with storing crops for later sale is Post-Harvest Losses (PHL). There are wide variations in estimates of households' PHL in SSA. For example, the reported PHL for maize range from 1.4 to 18 percent ("The African Post-Harvest Losses Information System" 2020; Kaminski and Christiaensen 2014; Hodges et al. 2014; Gustavsson, Cederberg, and Sonesson 2011). To our knowledge, very few studies have estimated PHL for specific legume crops in SSA. Mutungi and Affognon (2013) showed that about 4.2 to 9.1 percent of beans and 10 percent of groundnuts is lost during storage in Malawi, and 7.7 percent of beans is lost in Kenya. Amber et al. (2017) reported that 8 percent of soybeans and 12 percent of groundnuts is lost during and after harvest in Malawi. There is also empirical evidence to suggest significant reduction in market value due to price discounts for damaged grain (Kadjo, Ricker-Gilbert, and Alexander 2016). Though it seems that the discount for damaged grain disappear during the lean season when grain becomes scarce and people become less concerned with quality.

2.3.2 Sampling strategy

We utilized a multi-level sampling approach to select legume farmers in Malawi to participate in the study. Malawi is divided into 18 livelihood zones, which are locations that share common livelihood activities. The Kasungu-Lilongwe Livelihood zone is considered to exhibit higher potential for crop production compared to other zones. We purposively selected two districts from this zone namely Lilongwe and Mchinji (see Study Area in Figure 2.3), which are major producers of legumes in the country. We chose this region because it is more likely to have farmers who produce legume surplus that could potentially be sold and/or stored at harvest for sale later in the year. Our targeted districts have a total of 26 agricultural Extension Planning Areas (EPA) and 423 sections or communities within them.[2]

Like most sub-Saharan African countries, Malawi has an active network of smallholder farmer organizations. As mentioned in the introduction, we worked with members of the National Smallholder Farmers' Association of Malawi (NASFAM), a farmer-based organization with membership throughout the country. NASFAM has 43 Associations across Malawi. An average NASFAM Association covers an entire EPA, which typically comprises multiple communities. In each Associations, NASFAM is organized in Group Action Centers (GACs), which generally match the community or Section level. The distance between these communities or sections ranges between 10 and 35 kilometers. On average, NASFAM Associations count about 21 GACs each, and each GAC counts about 15 farmer clubs each. A club is made of about 10 farmers who reside within the same village; villages are between 1 to 8 kilometers distance from each other. Although

[2]An EPA is local administrative unit for the Ministry of Agriculture and EPAs have Sections below them as the lowest administrative level and these Sections are typically at a community level.

villages that fall within the same community are very similar, they are sufficiently far apart to limit possible treatment contamination.

Three Associations were randomly selected for the study: Chioshya, Mikundi and Mpenu. Since the clubs in each Association are grouped into GACs, we randomly selected 12 GACs in each of the targeted Associations. Then, within each of the selected GACs, we randomly selected 12 clubs. Since our main study focus was on legumes, we excluded farmers that did not plant legumes in the 2017/2018 cropping season before sampling. In total, 377 farmer clubs (i.e., villages) were randomly selected to take part in the study, comprising a total of 1,739 legume farmers (see Figure 2.4: Study Consort diagram).

All farmers in the clubs were informed about the research project and its surveys through lead farmers in their villages. We selected 5 farmers per treated club and 10 farmers per control club regardless of club size or number of farmers that showed up on the day of survey in that club. We oversampled the control group to deal with potential attrition that could have been higher for the control group. As such, it is likely that the probability of a farmer being sampled varied across clubs. In some situations, we were unable to recruit the targeted five (ten) farmers per club for the treatment (control) group due to low farmer turn-up on scheduled survey days. We used sampling weights in our regression analysis to control for the unequal probability of a household being selected to participate based on the size of the club and the number of members who attended training (Cameron and Trivedi 2005).

Power calculations

Power calculations indicated that 75 clubs per experimental arm and 5 households per club would provide a minimum detectable effect (MDE) of 0.33 standard deviations in outcomes comparison between two arms of the experiment. This is between what is generally considered small and medium effect size (Duflo, Glennerster, and Kremer 2007). Calculations were based on an intra-cluster correlation coefficient of 0.1, 80 percent power, and a 95 percent confidence level. Estimates of the intra-cluster correlation coefficient, means and standard deviations for our outcomes were based on calculations using the World Bank's 2015/16 Living Standard Measurement Survey data (agricultural survey) for Malawi. In order to account for possible attrition, we aimed to include 85 clubs or clusters per experimental arm. Appendix Table 2.1 presents details of actual ICC at baseline.

2.3.3 Experimental design

Our intervention included three treatments: a technology-only treatment consisting of hermetic storage bags (T1), a technology + village storage treatment (T2), and a technology + warehouse storage treatment (T3). Treatment assignment was random and done at the village (club) level and stratified by community (GAC) so that an equal number of clubs were randomly assigned to each of the four study groups in each community. Of the 377 clubs (1,739 farmers) sampled to be part of the study, 103 clubs (540 farmers) were randomly assigned to the control group, 85 clubs (387 farmers) were randomly assigned to the technology-only treatment, 89 clubs (389 farmers) were randomly assigned to the technology + village storage treatment, and 100 clubs (423 farmers) were randomly assigned to the technology + warehouse storage treatment. We show in the results section that the random assigned was balanced along a large number of group and farmer characteristics at baseline.

The physical storage technology (Treatment 1)

In treatment 1 (T1: PICS technology intervention), households were trained about the PICS technology and given two 100-kilogram PICS bags for free. The PICS bag is a 3-layer airtight storage bag that effectively protects grain from pests and molds without the use of chemicals, simply by hermetically sealing its contents. The PICS bags have proved to be effective at storing maize as well as legumes including cowpeas and groundnuts (Baributsa et al. 2017; Sudini et al. 2015; Williams, Baributsa, and Woloshuk 2014). The treatment was designed to help smallholder farmers overcome the storage technology constraint they face from insects and molds.

We chose to provide only two 100-kilogram bags to avoid creating an incentive for sharing bags across households, which could result in treatment spillover or contamination. However, the two 100-kilogram bags allowed farmers to effectively store a substantial share of the average harvest for legumes, which was 520 kg at baseline. The training included in this treatment informed smallholder farmers about the benefits of using PICS bags, as well as the prospects it presents for exploiting seasonal price arbitrage opportunities. This treatment was, therefore, expected to help reduce the expected quality and quantity losses for farmers and thus induce them to store more at harvest, so that they could sell good quality grain at a higher price later in the year.

The village storage program (Treatment 2)

In Treatment 2 (T2: The PICS technology + Village group storage arrangements), households received the same training and two 100-kilogram PICS bags provided in T1 and agreed to store their legumes with fellow club members within their villages. Each club selected a stock-keeper responsible for the club's stocks based on trust and storage ability (i.e. enough and secure space to store all member's grain). This treatment was designed to help farmers overcome the storage technology constraint as well as the behavioral challenge associated with individual storage of grain in homes where farmers often face social pressure to share, impatience, limited self-control and mental accounting problems (Aggarwal, Francis, and Robinson 2018; Brune et al. 2011; Baland, Guirkinger, and Mali 2011; Ashraf, Karlan, and Yin 2006).

The group storage arrangement allowed farmers to separate and deposit part of their grain stocks in a club-managed stock that was stored away from home for liquidation when prices rise. Each club independently agreed on storage length, a reservation price, and procedures for early grain withdrawal, which included getting the club's consent and/or a penalty. Farmers may have been influenced to store longer through village group storage arrangements than they would have on their own. In addition, the amount of grain deposited into the group stocks by an individual farmer is also likely to be influenced by his or her peers in the group depending on the groups' anticipated gains of storage. Given self-control and "other"-control problems that may influence farmers to liquidate stocks early, we designed this storage intervention to understand how group storage arrangements implemented locally within the village with smaller groups would induce farmers to store more grain at harvest.

The warehouse storage program (Treatment 3)

In Treatment 3 (T3: The PICS technology + Warehouse group storage arrangements), farmers received the same training and two 100-kilogram PICS bag given to households in T1, as well as an invitation to participate in a group storage arrangement. The group storage arrangements different from those in T2 in three ways. First, farmers in T3 received some information on financial management. We provided farmers information about the benefits of storing grain (a form of savings) and strategically marketing their products to exploit better prices. This intervention was initially supposed to include a loan product from a bank, by which the grain stored in the warehouses was intended to be collateral for the loan that had a maximum repayment period of up to three months. However, the bank backed out at the last minute so farmers in this group only received the financial information. Second, storage was at centralized NASFAM warehouses within Group Action Centres (i.e. at the community level) rather than within the farmers' village.[3] Unlike the village storage program, this implied that more than one club stored in each centralized warehouse. Third, clubs using the same warehouse were required to synchronize their grain deposit and withdrawal conditions, which were more stringent than the village storage program's. This requirement stemmed from the intended use of the stored crop as a guarantee for the loan and the standard loan repayment conditions. It was kept despite the lack of a loan.

The warehouse storage locations used in this treatment arm were much further away from the villages than storage locations the village storage program (i.e., 10 to 35 km versus 1 to 5 km away). However, this treatment, helped farmers assemble their legume with known quality and quantity description for easy off-taking by big traders and processors facilitating trade as well as increasing farmers' bargaining power. The cost of produce aggregation and quality control may discourage big traders, exporters and processors from engaging in direct trade with smallholder farmers. Increasing smallholders' access to improved storage technologies (PICS bags) and some form of warehousing and aggregation facilities may help increase farmers' access to better markets (i.e. exporters and processors who may offer higher prices). Poor financial management knowledge and skills may be a key driver of liquidity constraints for farm enterprises. Therefore, this treatment was designed to test how increased financial management information and access to specialized storage facilities influence farmers' storage and marketing behavior. This treatment was also designed to provide some empirical insights on the impact and viability of warehouse programs for smallholder farmers in developing countries which generally have low smallholder's participation rate.

Control group

The control group included farmers that did not receive any treatment but resided in the same area as treated farmers and were also members of NASFAM clubs. Farmers in this group were followed throughout the intervention period to keep track of all programs they were exposed to. The farmers

[3] A community is made up of multiple villages ranging of between 5 to 15 villages depending on village sizes.

in this group were also asked if they purchased PICS bags on their own or if they stored their grain in groups as a measure to determine existence of possible attenuation bias caused by the control group engaging in these activities. Only 12 households in the control group reported having bought PICS bags, with the number of bags bought per household ranging from 1 to 10 bags. However, none of the households in the control group reported storing their legumes in groups.

2.4 Data

As mentioned, the study used panel data from household-level surveys that was collected from a sample of 1,739 NASFAM farmers in Malawi. The baseline was conducted between April and May 2018. This was followed by the implementation of the interventions: training and PICS bag distribution took place just before the 2018 harvest (May-July). After implementing the interventions, supplementary data on key outcomes was collected quarterly through follow-up surveys with respondents (August 2018 and December 2018). We therefore have three waves of data on our outcome variables. The first wave, collected at baseline, and the second and third waves collected four and eight months after the 2018 harvest respectively. A timeline of the study is presented in Figure 2.5. For all surveys, a structured, pre-tested questionnaire was used to capture data on farmers' grain storage and sales behaviors. This included data on quantities of legumes stored at harvest, weeks stored before largest sale, quantity sold and bought in each quarter, average selling and purchasing prices and households' sales revenue.

2.5 Estimation of treatment effects

We follow the estimation framework in Burke et al. (2019)to estimate treatment effects of the interventions. The main outcomes of interest are households' quantity stored at harvest, number of weeks stored before the largest sale, total sales revenue, legume inventories, net quantity of legumes sold, net value of sales and average legume selling price. Legume inventories represent the total household's inventories of legumes in that quarter including legumes stored at home plus with the group. The net quantity of sales is the difference between quantity sold and quantity purchased in a given quarter. Net value of sales is the value of legume sold minus the value of legumes purchased in every quarter while the average selling price is the average price at which they sold their legume in every quarter.

We estimate both aggregate and quarterly treatment effects. Aggregate treatment effects are measured for outcome variables for which we only have an annual observation: quantity stored at harvest (kg), number of weeks stored before largest sale and total sales revenue (MK). Quarterly effects are measured for outcomes for which we have quarterly observations including grain inventories, net quantity of legumes sold, and net value of sales. We clustered our standard errors at the club level to account for possible correlation in outcomes for households within the same clubs due to the clustered experimental design and sampling.

We use Ordinary Least Squares (OLS) and Analysis of Covariance (ANCOVA) to estimate aggregate intention to treat (ITT) effects on outcomes of interest as specified below:

$$y_{ij} = \alpha + \beta T1_j + \lambda T2_j + \rho T3_j + \gamma A_j + \partial Q_{ij} + \delta yo_{ij} + \varepsilon_{ij}. \tag{2.1}$$

In equation (2.1) above, *i* indexes farmers and *j* indexes clubs; y_{ij} is the observed outcome variable; $T1_j$, $T2_j$ and $T3_j$ are binary variables equal to 1 if a household lived in a village assigned to Treatment 1, Treatment 2, and Treatment 3, respectively; $yo_{i,j}$ is the observed outcome value at baseline or before the intervention which is included for the ANCOVA specification. For robustness checks using the OLS estimation, we use equation (2.1) but do not include $yo_{i,j}$. A_j denotes a set of dummy variables controlling for the Association of which the farmer is a member, while Q_{ij} represents a dummy variable which is equal to 1 if the data come from the end line or post-intervention survey and 0 if the data are from the baseline survey. Finally, ε_{ij} is the idiosyncratic error term. Our parameters of interest are the estimated coefficients, $\hat{\beta}$, $\hat{\lambda}$, and $\hat{\rho}$, which capture the average aggregate effects (ITT) of being randomly offered treatments (T1, T2, and T3). The comparison group is the control households, who did not receive any treatments. We also run F-tests post-estimation to compare differences among the treatments themselves ($\hat{\beta} = \hat{\lambda} = \hat{\rho}$).

Quarterly treatment effects are estimated for four outcome variables: legume inventory (kg), net quantity of sales (kg), net value of legume sales (MK), and average selling price (MK/kg). We estimate quarterly intention to treat (ITT) effects on outcomes as:

$$y_{ijt} = \alpha + \sum_{d=2}^{d=3} \beta_{\mathrm{d}} Q_{d_j} * T1_j + \sum_{d=2}^{d=3} \lambda_{\mathrm{d}} Q_{d_j} * T2_j + \sum_{d=2}^{d=3} \rho_{\mathrm{d}} Q_{d_{ij}} * T3_j + \sum_{d=2}^{d=3} \partial_d Q_{d_{ij}} + \gamma A_j + \delta yo_{ij(t-1)} + \varepsilon_{ijt} \tag{2.2}$$

In equation (2.2) above unlike equation (2.1), we have quarterly observations of the outcome variables and, thus, have three waves of data including two post-intervention periods. As such, the subscript *t* represents the quarter or time period 1 to 3 and $yo_{ij(t-1)}$ is the lagged quarterly outcome variable for the ANCOVA estimation to control for quarterly initial differences in the outcome variables (i.e. lagged one quarter to control for treatment effects from the previous quarter). A_j and Q_{d_j} are dummy variables for Association and quarters respectively and ε_{ijt} is the idiosyncratic error term. Our parameter of interest includes the quarter and treatment dummy interaction coefficients, $\widehat{\beta}_d$, $\widehat{\lambda}_d$ and $\widehat{\rho_d}$, which capture the average quarterly effects (ITT) of being randomly offered the $T1_j$, $T2_j$ and $T3_j$ treatments. The comparison group in this specification is the control group in each quarter, who did not receive any treatments.

Next, to explore possible heterogeneity in aggregate treatment effects, we implement the following regression specification:

$$y_{ij} = \alpha + \sigma_0 Z_{ij} + \sigma_1 T1_j * Z_{ij} + \sigma_2 T2_j * Z_{ij} + \sigma_3 T3_j * Z_{ij} + \gamma A_j + \partial Q_{ij} + \delta yo_{ij} + \varepsilon_{ij} \qquad (2.3)$$

$Z_{i,j}$ represents a set of variables, measured at baseline, which are likely to influence heterogeneity in treatment effects: access to credit, access to grain markets and education of household head. Our treatment heterogeneity parameters of interest include σ_0 through σ_3.

All households recruited into the study agreed to participate in the treatments they were assigned to and agreed to take the PICS bags. In the follow-up survey, 89 percent of the respondents that received the PICs bags reported using the PICS bags to store legumes, and 11 percent indicated that they used the bags to store maize instead because they did not harvest enough legumes. In the village group storage treatments, 71 percent of households stored legumes with their clubs while 66 percent of households in Treatment 3 reported actually storing legumes in one or both of the PICS bags given to them in the warehouse (Figure 2.6). We had a relatively low compliance for the two group storage schemes as most farmers reported having challenges with transportation of grain for storage with the group in the village or warehouse.

For our estimates of the Local Average Treatment Effects on our aggregate outcomes, we estimate equation (2.4) below:

$$y_{ij} = \alpha + \beta T1participate_j + \lambda T2participate_j + \rho T3participate_j + \gamma A_j + \partial Q_{ij} + \delta yo_{ij} + v_{ij}. \qquad (2.4)$$

$$Xparticipate_j = \alpha + \beta T1_j + \lambda T2_j + \rho T3_j + \gamma A_j + \partial Q_{ij} + \delta yo_{ij} + \varepsilon_{ij}. \qquad (2.4.1)$$

In equation (2.4) above, $T1participate_j$, $T2participate_j$, $T3participate_j$ are binary variables equal to 1 if a household complied and participated in the PICS program (T1), Village storage program (T2), and Warehouse storage program (T3), respectively. Given that participation or compliance is endogenous, we use the random treatment indicator variables: $T1_j$, $T2_j$ and $T3_j$ to instrument for household's participation in the treatment interventions. This helps to estimate the treatment effect for households that participated. Equation 2.4.1 is the first stage specification where $Xparticipate_j$ represents the endogenous participation variables $T1participate_j$, $T2participate_j$ and $T3participate_j$.

2.5.1 Testing for potential attrition bias

Because we conducted follow-up surveys every four months during the study (August 2018 and December 2018), we generated an attrition dummy variable for each follow-up indicating the number of households that were missed in any follow-up survey. Seven percent of the households (127 households) were missed during the first follow-up, while 15 percent (236 households) were missed in the second follow-up survey (see details in Appendix Table 2.2). During the second follow-up survey, households that were missed in the previous follow-up went through multiple survey modules to collect data for the previous quarters that were missed (recall data) as well as the current quarter.

In order to determine the possibility of attrition bias, we performed a joint orthogonality test using a probit model to evaluate whether attrition was correlated with outcomes and the treatment assignment. In Appendix Table 2.3, the F-test results are F=19; p=0.025 for the first follow-up and F=16; p=0.072 for the second follow-up. These F-test results for attrition show that attrition was correlated with the treatment and outcomes variables. We, therefore, include both attrition indicator variables in our analysis to control for attrition.

2.5.2 Multiple hypothesis testing

Considering that we have multiple outcome variables, we corrected all standard errors to account for multiple hypotheses testing using Anderson' sharpened q-values (Anderson 2008). Appendix

Table 2.4 presents the adjusted sharpened q-values for our outcome variables. Our findings are robust to the adjustment for multiple hypotheses testing.

2.6 Study Results

2.6.1 Test of balance of the randomization

We start our analysis by evaluating the success of the randomization process. Table 2.1 presents results for our pre-treatment balance checks for our baseline randomization. Columns (1-3) show results of the joint orthogonality test for our three treatment groups relative to the control group using a multinomial probit model with standard errors clustered at the club level. Results suggest that the estimated coefficients for all variables are jointly equal to zero showing that the treatment variable is random and not correlated with the outcome variables of interest or household observable characteristics (F=86; p=0. 1255).[4] Farmers in the control group, therefore, are on average similar to the treated farmers *ex ante* and our estimate of treatment effects are not biased if we only use the post-intervention data to estimate treatment effect. We, however, include Association controls, in our estimation for precision.

2.6.2 Summary statistics

Table 2.2 presents baseline summary statistics. About 71 percent of the farmers in our sample reported that soybean was their major legume in the baseline year, that is, in terms of quantity harvested. About 28 percent of the sample had groundnuts while 1 percent had other legume crops including pigeon peas and common beans as their major legume. On average, farmers stored 276 kg of their major legume at harvest in the baseline year and the average number of weeks farmers stored their legumes before the largest sale in the baseline year was 10 weeks. Farmers had an average net sales revenue of about MK136,716 (US$1=MK750) from sales of their major legume with an average total sales revenue of about MK234,017, that is total value of sales only. The average reported post-harvest loss (PHL) in the previous season was about 6.7 percent of the major legume stored.

[4] For reporting purposes, we scaled up the coefficient by 1000 as majority of estimates were very small fractions.

2.6.3 Aggregate impacts on farmers' storage behavior

Table 2.3 presents the treatment effects (ITT) of the interventions on farmers' storage and sales behavior. We review each of the three main outcomes in turn in this Table. Columns (1) and (2) show the ITT estimates on legume stored at harvest, columns (3) and (4) show estimates on weeks stored before the largest sale while columns (5) and (6) show estimates on total sales. Columns (1), (3) and (5) are without Association controls while the rest have Association controls.

Estimates in Table 2.3 test whether households that are treated are subsequently more likely to store more legume at harvest. In column (2), the estimates of treatment effects on the quantity of legumes stored at harvest indicate that overall, households in all three treatment groups stored more legumes at harvest (34 to 74 kg more on average) than control households. F-tests of the difference in impacts of the PICS and village storage program show that households in the village storage treatment group stored about 40 kg more legumes at harvest, on average, than households in the PICS treatment group (F=4.34; p=0.043). However, households in the warehouse storage treatment group (T3) did not store statistically significantly more at harvest than households in the PICS group (T1). These results suggest that although all treatments helped farmers store more than the control households, the village storage program (T2) was the most effective treatment in terms of storage of legumes at harvest.

Column (4) of Table 2.3 presents estimates of treatment effects on period of storage before their largest sale. Households in all three treatment groups stored their legume longer (1 to 2 weeks longer) than control households. The F-test of difference in coefficients on PICS intervention(T1) and village storage program (T2) or the warehouse storage program (T3) show that there were no difference in storage wait time before the first largest sale for households across all three treatment groups. These results suggest that overall, the two storage commitment devices were not relatively more effective at incentivizing farmers to store their legumes longer compared to the PICS only intervention.

Column (6) of Table 2.3 presents ITT estimates on farmers' total revenue from sales of the major legume. Our estimates of treatment effects show that households in all three treatment had higher total sales (MK23,000 to MK30,000 more; US1=MK750) than control households. The F-test results for comparing treatment effects of the two storage commitment devices (i.e. the village storage program (T2) and the warehouse storage program (T3) to the PICS intervention (T1) shows that there are no differences in the total sales revenue for households in all three interventions groups. Although we find evidence that households in the village storage program stored relatively more legumes (about 40 kg) than households in the other two treatment groups, our ITT estimates show that this did not translate into a significant difference in the sales revenues. This is possibly because the differences in quantities stored are not very large given that there was no significant difference in the storage period before the first largest sale which may not have resulted in a substantial difference in price. Robustness checks results using log of the outcome variables in the analysis suggest results are consistent (see Appendix Table 2.5).

2.6.4 Quarterly impact on farmers' storage behavior

We collected three waves of data on our outcome variables. The first wave, the baseline, collected during the 2018 harvest season, and the second and third waves collected four and eight months after the 2018 harvest respectively. In order to understand the inter-year effects of the interventions on farmers' storage and sales behavior, we estimate the quarterly treatment effects on three outcome variables for which we have quarterly observations. These include (i) quantities of the major legume stored at the end of every quarter or period, (ii) net quantity of legume sales, that is, the difference between quantities sold and quantities purchased in every quarter, (iii) net value of the major legume sales, that is, the difference between value of legume sales and purchases in every quarter. Table 2.4 presents the treatment effects (ITT) of these quarterly outcome variables. Columns (1) and (2) show the ITT estimates of legume inventories, columns (3) and (4) show estimates of net quantity of legume sales, columns (5) and (6) show estimates of net value of legume sales while columns (7) and (8) show the estimates on average selling price. Columns (1), (3), (5) and (7) are without Association controls while the rest have Association controls.

Our estimates in column (2) show that households in the village storage program and the warehouse storage program had more legume inventories at the end of period 2 compared to control households (47 kg and 45 kg more, respectively). However, legume inventories for households in the PICS program are not different from control households. Households in the village storage program (T2) had about 47 kg more legumes in stock, on average, than households in the PICS program (T1; F=3.98; p=0.019). Similarly, households in the warehouse storage program (T3) had about 45 kg of legumes more than households in the PICS group (T1) in this period on average (F=2.88; p=0.044). We also find no differences in treatment effects between households in the village storage program and households in the warehouse storage program for this period (F=1.12; p=0.957). These results suggest that in the first four months after harvest, both T2 and T3 were equally effective at incentivizing households to store more legumes compared to households in the PICS only program. Although our estimates of the aggregate treatment effects show that the village storage program (T2), out-performs the other two treatment groups in general, these quarterly estimates help to highlight the variations of the treatment effects over time. We observe that in the first post-intervention period, both T2 and T3 are equally effective at incentivizing farmers to store more legumes. Similarly, we observe that households in the village storage program (T2) had significantly more legume inventories (27 kg more) than control households in period 3, that is, eight months after the interventions. Of the two commitment devices, only households in village storage program (T2) had more legume inventories (27 kg) than control households eight months after the intervention.

Column (4) presents the quarterly estimates of the treatment effects on net legume sales. Since this variable is the difference between quantities sold and quantities purchased, a negative observation indicates that a household had more legume purchases than sales. Ideally, for a "*selling-high and buying-low*" scenario, we would expect a negative observation for this variable during the harvest periods when prices are expected to be lower and some positive observation for the post-harvest periods given that prices pick up. In column (4) the results for period 2 show that households in all three treatment groups had more net legume sales (between 28 to 43 kg) compared to households in the control group. We also find that in period 3, only households in the village storage program (T2) had more net legume sales than control households (30 kg more). The quarterly treatment effect suggests that T2 influenced treated households to sell more legumes in period 3, the lean periods compared to control households.

The results in column (4) of Table 2.4 show the differences in the legume quantity sales trends between treated and control households which resulted from changes in inventories or storage behavior for treated households. In order to evaluate the monetary gains from such shifts in storage and selling trends, we evaluate the quarterly impacts of the interventions on the farmers' net value of legume sales. We define the net value of sales as the difference between the value of legume sales and purchases. In column (6), our estimates of treatment effects on net value of legume sales in period 2 show that there was no difference in net legume sales value between treated households and control group.[5] However, for period 3, we find that only households in the village storage program (T2), had higher net value of legume sales compared to control households (i.e. between MK17,000 more). This suggest that these interventions enabled households to capitalize on the higher prices faced in period 3 by storing more legumes and increasing their inventories and sales in that period compared to control households. Robustness checks results using the Ordinary Least Squares estimator suggest that our results are consistent (see Appendix Table 2.6).

2.6.5 Heterogeneity in aggregate treatment effects

Literature suggest that access to credit markets and input or output markets can influence farmers' demand for storage (Burke, Bergquist, and Miguel 2019; Stephens and Barrett 2011). The education level of the household head is also considered an important factor in households' decisions. As such, we examine how education, access to credit and markets influence heterogeneity in the aggregate treatment effects. We interact our treatment variables with the credit access variable and market access variable to determine the marginal treatment effects of a farmer having access to credit and output markets. Table 2.5 to 2.7 present our treatment effects on households' quantity of legumes stored at harvest, length of storage and total sales revenue after accounting for heterogeneity. Table 2.5 and Table 2.6 show the results when we interact our treatment variable with the dummy variable for credit access and market access, respectively. The credit access variables is a proxy for level of credit access (=1 if the farm household had access to credit in baseline year) while the market access dummy variable captures the households proximity to the closest input or output market (=1 if household <5 kms away). Table 2.7 shows results for households when we interact the treatment variables with education level of the household head (=1 if household head has no education).

In terms of credit access, we do not find evidence of heterogeneity in treatment effects for our aggregate outcomes: storage at harvest and sales revenue. However, our results indicate that households that had access to credit in the baseline year were able to wait longer before making their first largest legume sale if they were in the treatment groups compared to those that had access

[5] This is likely due to high standard error in this variable which is constructed from of four quarterly variables: sales quantities, average selling price, purchase quantities and average purchase prices.

to credit and were in the control group (i.e. the marginal storage length for credit access were was 4.1 weeks, 3.7 weeks and 3.2 weeks for T1, T2 and T3 respectively relative to -3.6 weeks marginal for those in the control group). In terms of market access, we find no evidence of heterogeneity in treatment effects. However, we find that education influenced heterogeneity in treatment effects. Our results show that households that had a household head with zero years of schooling stored more legumes if they were in the village storage program (T2) compared to those without education in the control group: households in T2 with no education stored 84 kg more legume at harvest relative to households in control with no education who stored 80 kg less at harvest. This suggest that the village storage program (T2) helped households that had household heads with zero years of schooling more, on average, compared to those with household heads that had some positive schooling years.

2.6.6 Local average treatment effects for the aggregate outcomes

We present our estimates of local average treatment effects (LATE) on our aggregate outcomes in Table 2.8. Column (2) of Table 2.8 shows that, overall, households in all three treatment groups stored more legumes at harvest (37 to 105 kg more, on average) than control households. As expected, the LATE estimates for all three treatments are higher than the ITT estimates. The LATE estimates also show that households that participated in the village storage program (T2) stored more legumes at harvest (about 68 kg), on average, than households in the PICS program (T1). Although our ITT estimates showed no difference in amount of legumes stored at harvest between T3 and T1, our LATE estimates show that households that used PICS bags to store legumes in the warehouse storage program (T3) stored about 30 kg more legumes in total at harvest than households that used the bags to store legumes in the PICS group (T1). ITT underestimates this effect due to the low compliance rate in T3 of 66%, relative to a compliance rate of 71% in T2 and 89% in T1 (see Figure 2.6).

In column (4) of Table 2.8, our estimates of LATE also show that households that participated in all three treatment groups waited for about 2 to 3 weeks longer, on average than control households before making their largest legume sale. We also find that the LATE estimates for all three treatments are relatively higher than our ITT estimates. While the ITT estimate showed that only households in the village storage program (T2) stored their legumes longer than the PICS group (T1); the LATE estimates show that households that participated in both storage commitment devices: the village storage program (T2) and the warehouse storage program (T3) stored their legumes for about a week longer than households that participated in the PICS group (T1). In column (6), the LATE estimates on farmers' total sales show that only households that participated in the PICS intervention (T1) and the village storage program (T3) had higher total sales (MK25,000 to MK43,000 more) than control households. We do not find any differences in sales revenue between households in the warehouse storage program (T3) and control households. This is possibly because the differences in quantities stored as households in the village storage program (T2) stored more, on average, than the other groups. The results for the first stage of the 2-Stage Least Squares estimator are reported in Appendix Table 2.7.

2.6.7 Cost-Benefit analysis

For policy guidance, we perform a standard economic analysis for the interventions. Our parameters including the cost of PICS bags, training costs, groundnuts prices, average marginal post-harvest price, household size, warehousing fees and charges, transportation and grain assembly costs, number of farmers trained, and estimated life of the PICS bags are based on the project data. Estimates of PHL as well as proportion of farmers that experience PHL are based on data from the African Postharvest Losses Information System (APHLIS). Since over 50 percent of the Malawi government's development project are financed by borrowing, we use the government's borrowing rate from the Central Bank as the social discount rate (13.5 percent). I also use the current income tax rates, grain consumption rates and Disability Adjusted Life Years (DALY) for Malawi in the analysis.

The Benefit-Cost analysis for the three interventions suggests that PICS only and Village Storage program had a positive Net Present Value of USD230 and US82 respectively with Internal rates of return (IRR) of 20% and 16% respectively. The transportation costs that farmers incurred in the village storage program could possibly explain why the IRR and NPV was lower for the village program compared to the PICS program. These rates of return were also greater than the interest rate of 13.5 percent. However, our analysis suggests that the third intervention, the warehouse storage program, had a negative Net Present Value of USD6703. This is likely due to high transportation and warehousing costs. See detailed of parameters used in calculations in Appendix Table 2.8.

2.7 Conclusion

The key research question addressed in this essay is: to what extent do improved storage technologies and storage commitment devices effectively incentivize smallholder farmers to store more legumes at harvest for exploitation of intra-seasonal price arbitrage opportunities? We estimate the impacts of the three storage interventions including (i) receipt of PICS bags and storage at the farmer's house (T1), (ii) receipt of PICS bags and village group storage (T2), and (iii) receipt of PICS bags, and warehouse group storage (T3) on smallholder farmers' storage behaviors in SSA. We analyze the impact of these interventions on quantity of legumes stored, number of weeks stored before the first largest sale, net sales quantity and net sales revenue. This helps to advance the literature on storage interventions that could help address the "*selling low and buying high*" phenomenon: the common behavior of selling crops at harvest at a low price and purchasing the same crops at a high price during the lean season observed amongst smallholder farmers in SSA. The results from this essay also help to extend results on the role of commitment constraints on households' savings behavior to a new era, grain storage, a different form of saving.

The key empirical findings in this study are as follows. First, we find that all three treatment interventions helped farmers store more legumes at harvest (34 to 74 kgs, on average), store longer (1 to 2 weeks on average) and also have higher total sales revenue (MK23,000 to MK30,000) compared to households in the control group. Second, using F-tests to tease out the impacts of the two grain storage commitment devices beyond the impacts of the hermetic storage solution, we find that the village group storage caused a marginal increase in the amount of legumes stored by 40 kg at harvest above the PICS only intervention. However, we do not find significant marginal effects of the warehouse group storage above the PICS-only intervention. This implies that the village group storage provides an effective grain storage commitment device, while warehouse group storage is not. However, considering the LATE estimates which show that both storage commitment devices had significant marginal effects on quantity stored at harvest, it is likely that the low take-up rate in the warehouse storage program resulted into underestimation of ITT effects for the warehouse storage program. Based on our follow-up surveys, some key explanation for the low take-up rate for this treatment include transportation costs incurred and households' limited desire to store with a larger group at the warehouses which are further away from farmers' villages. The last key finding in this essay is that there were variations in ITT effects over time, as our quarterly estimates of ITT show that in the first four months after the intervention, both grain storage commitment devices, that is, village storage program (T2) and warehouse storage program (T3), were equally effective at incentivizing households to store more legumes (had 45 to 47 kgs more legume inventories in period 2) compared to households in the control group. However, of the two commitment devices, only households in warehouse storage program (T3) had more legume inventories (27 kg more) than control households in period 3, eight months after the intervention.

In terms of policy implications, the results from this essay provide empirical evidence of the impacts of addressing the farmers' storage and commitment constraints on their legume storage behavior. This will help to inform the government, development agencies and NGOs interested in helping farmers exploit inter-temporal price arbitrage opportunities about the effectiveness of the three storage interventions implemented in this study.

In addition, the terms implemented in this study match the Village Grain Banking (VGB) and Warehouse Receipt Systems (WRS) programs that are promoted in many developing countries. VGBs are village-based farmer groups that promote grain storage and aggregation to ensure increased access to improved seeds within their villages as well as increase farmers' bargaining and access to better markets (Odhong 2018; Msaki, Regnard, and Mwenda 2015). WRS use a centralized system for recording details of commodity stored within certified warehouses. These WRS are designed to facilitate commodity trade by eliminating quality information asymmetry and reducing transaction costs for the buyers. In addition, WRS can also be used as commitment devices allowing farmers to separate and store portions of their harvest for sell later when prices rise. Although such programs have been promoted in several developing countries in SSA, participation by smallholder farmers has been low. Some possible reasons for low participation include high transaction costs, limited access to information and limited certified warehouse infrastructures in rural areas (Baulch, 2018; Coulter and Onumah 2002). To our knowledge, this paper if the first to evaluate the effectiveness of these warehouse program using an RCT. Our results help to provide some insights on the viability of warehouse programs for smallholder farmers as we learn that incentivizing smallholder farmers to store together locally within their villages is more effective than a centralized warehouse program given the limited infrastructure accessibility and transportation constraints within rural areas.

2.8 Funding Declaration

We would like to acknowledge funding support from the United States Office of Foreign Disaster Assistance under agreement AID-OFDA-G-17-00250, for the project titled "Increasing Smallholder Malawian Farmers' Access to Improved Storage Technology and Credit"

2.9 References

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2.10 Tables and Figures

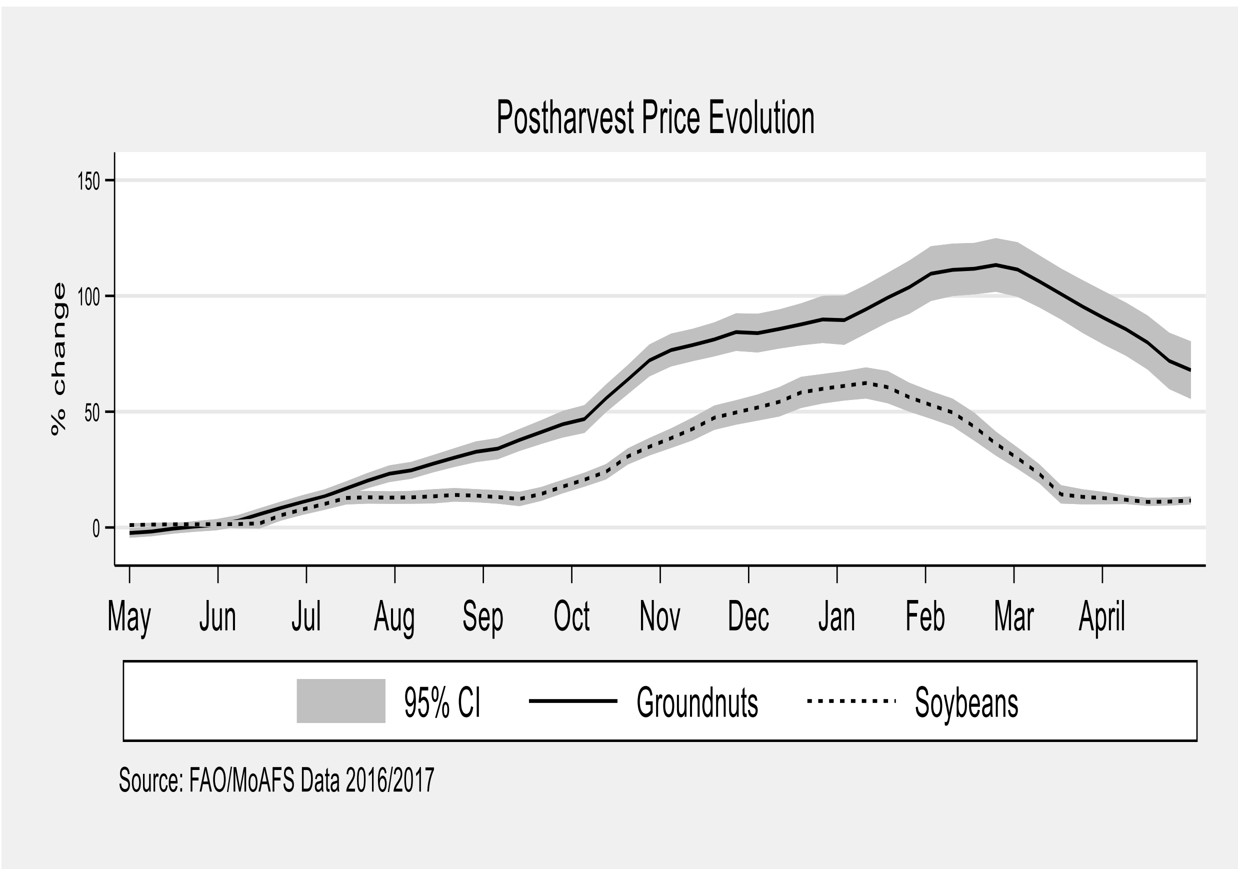

Figure 2.1: Baseline Legume Price Trends

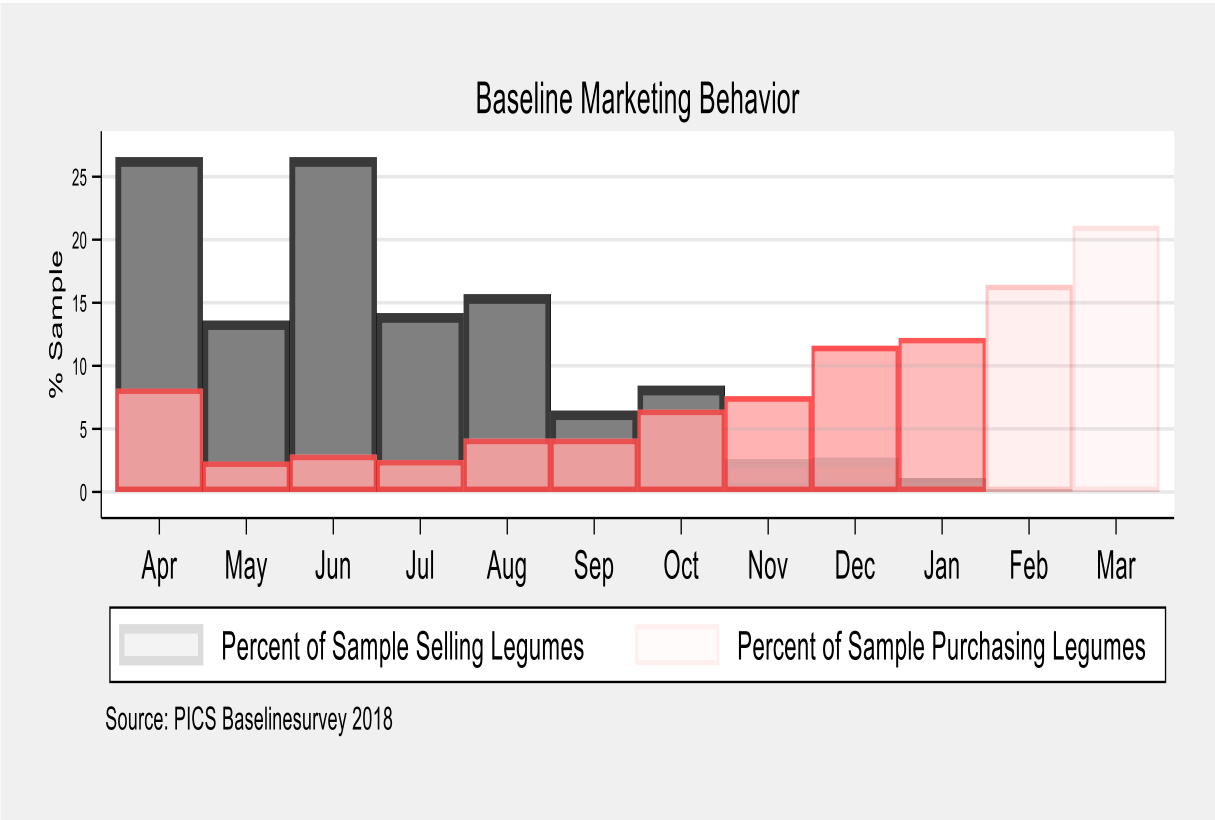

Figure 2.2: Baseline Grain Marketing Trends

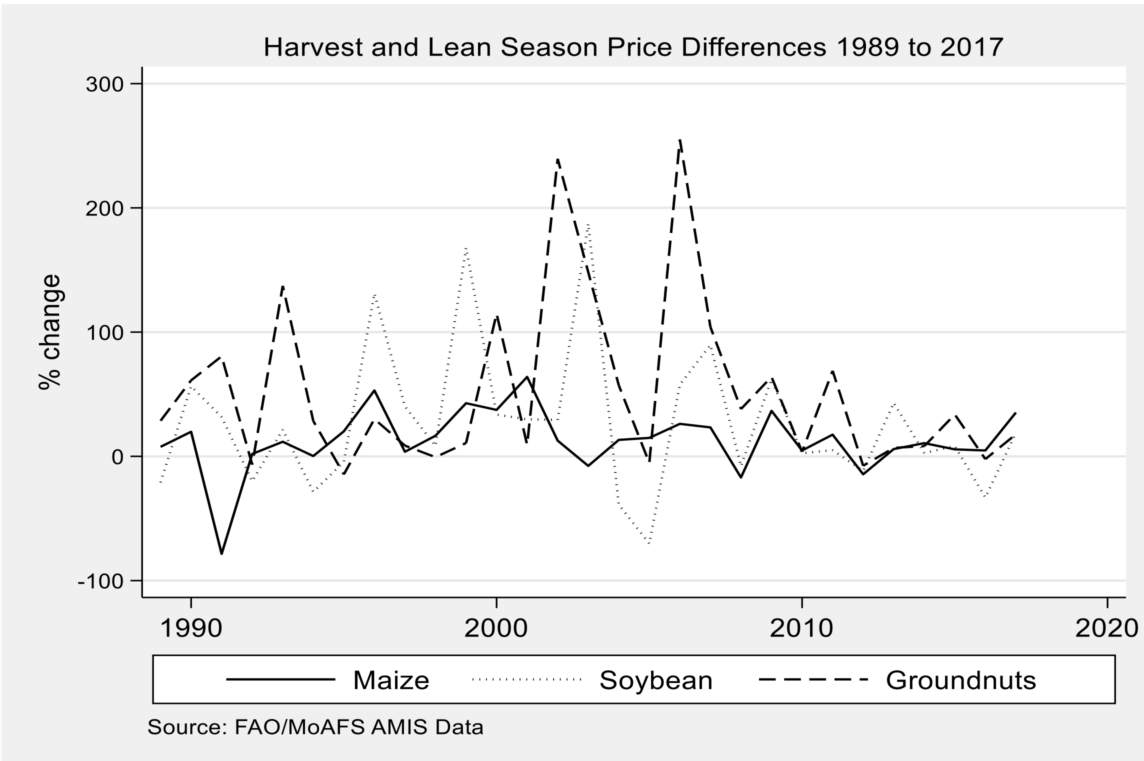

Figure 2.3: Seasonal Price Variations for Crops in Malawi (1989 to 2017)

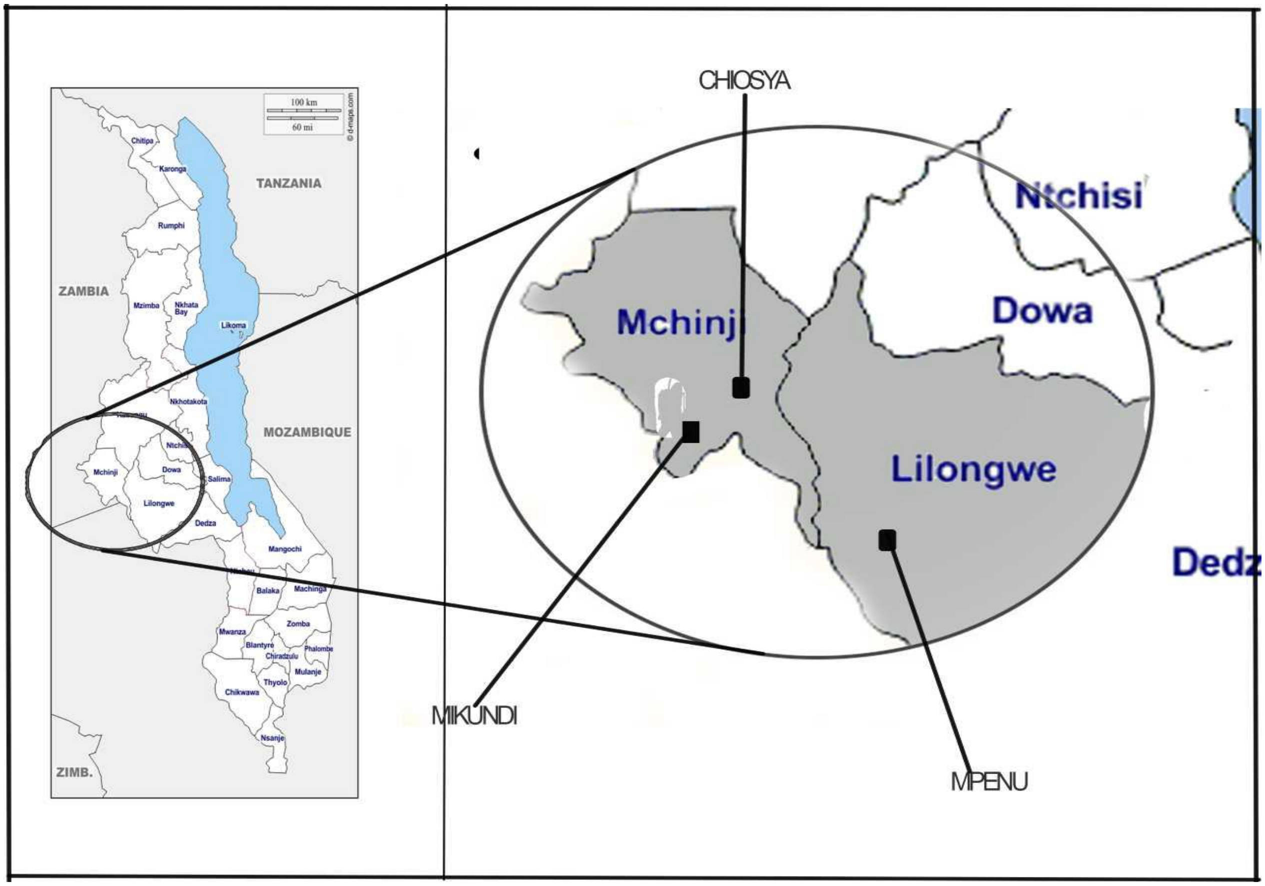

Figure 2.4: Study Area

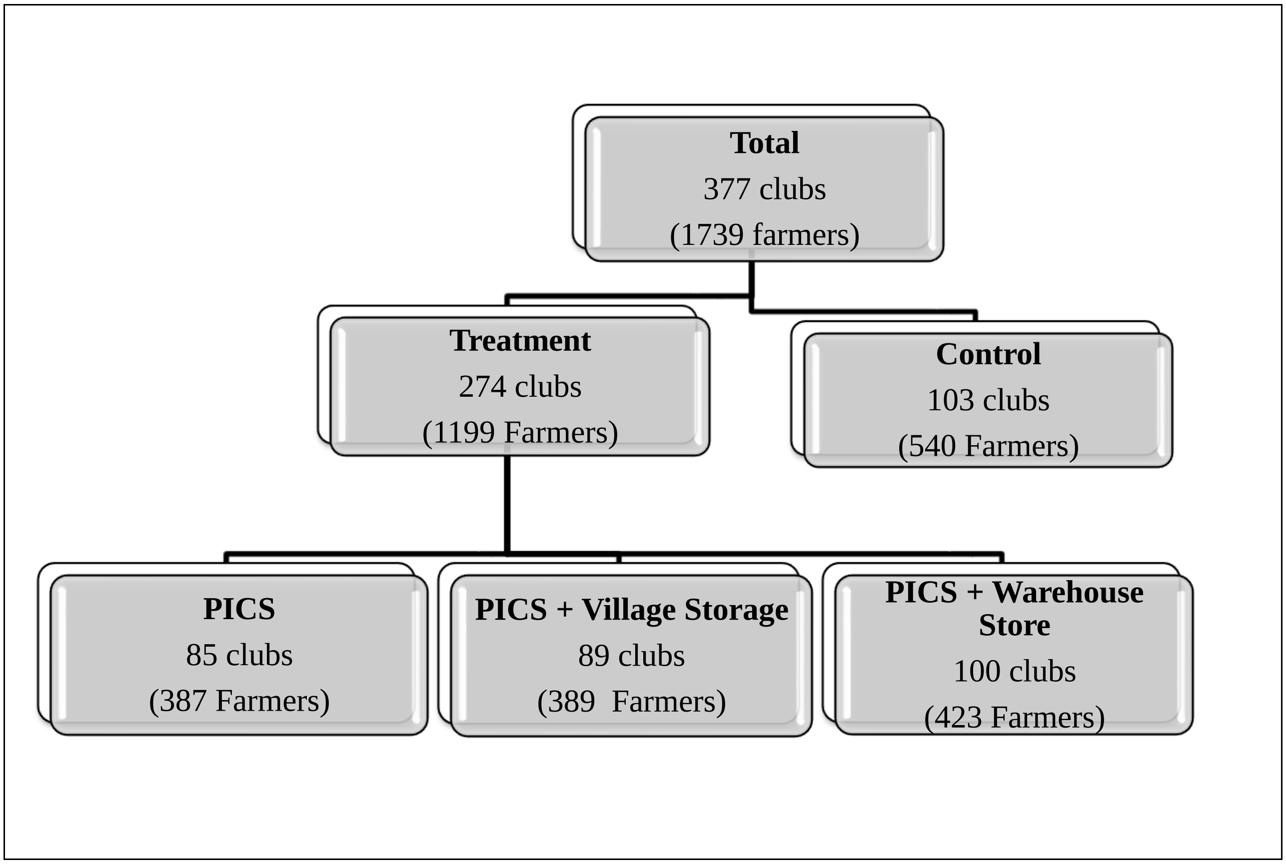

Figure 2.5: Study Consort Diagram

2017/18 Planting season	**December 2017**	**Study Design & Preparations**
2017/18 Harvest season	**April 2018**	**Baseline Study** ✓ 1739 farmers recruited in the study ✓ 377 clubs of which 274 are treated & 103 in control ✓ Detailed survey (Demographics, agricultural production, storage and marketing activities, assets, consumption, expenditures, credit & saving use)
	April 2018	**Treatment Assignment** ✓ 103 clubs in control ✓ 85 clubs PICs only ✓ 89 clubs PICS + Village Group storage ✓ 100 clubs PICS + Warehouse Group storage
2017/18 Post- Harvest season	**August 2018**	**Follow up Round 1** ✓ Outcome variables of interest only
2018/2019 Planting season	**December 2018**	**Follow up Round 2** ✓ Outcome variables of interest only
2018/2019 Harvest season	**April 2019**	**End line study** ✓ Detailed survey

Figure 2.6: Study Timeline

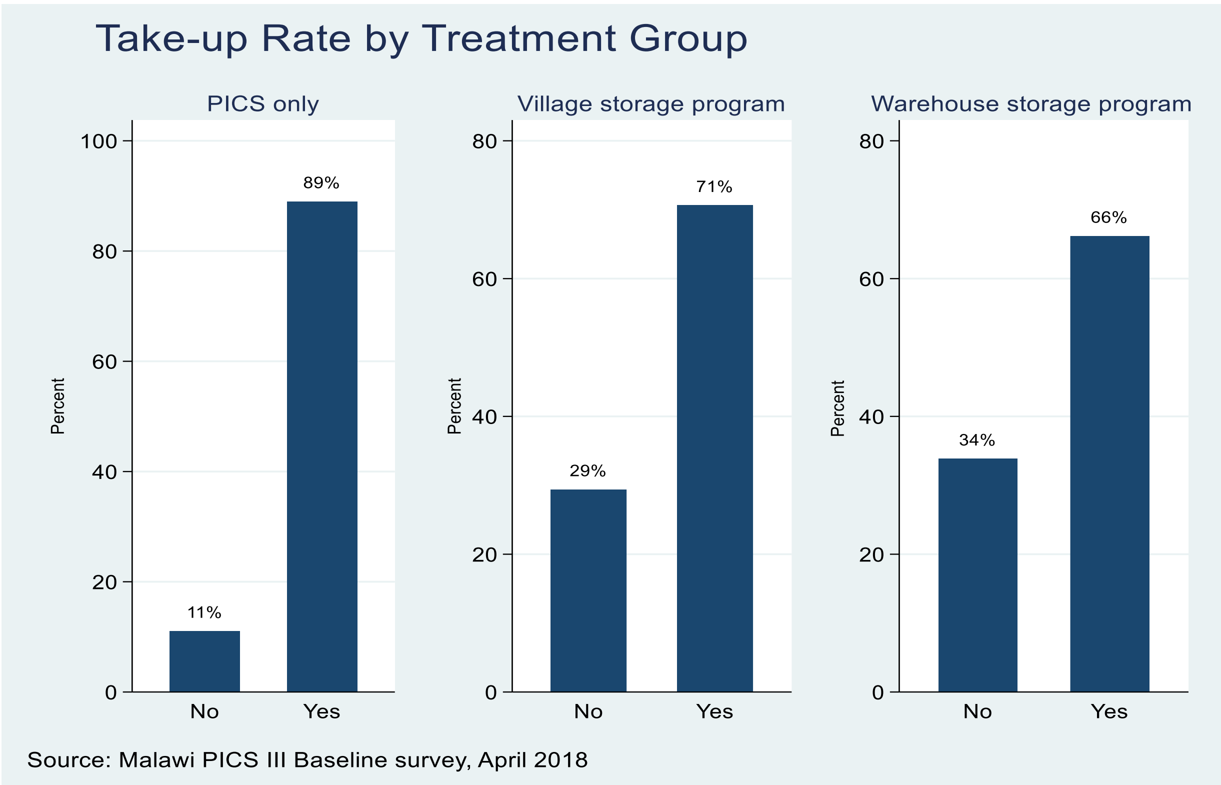

Figure 2.7: Treatment Take-up Rate

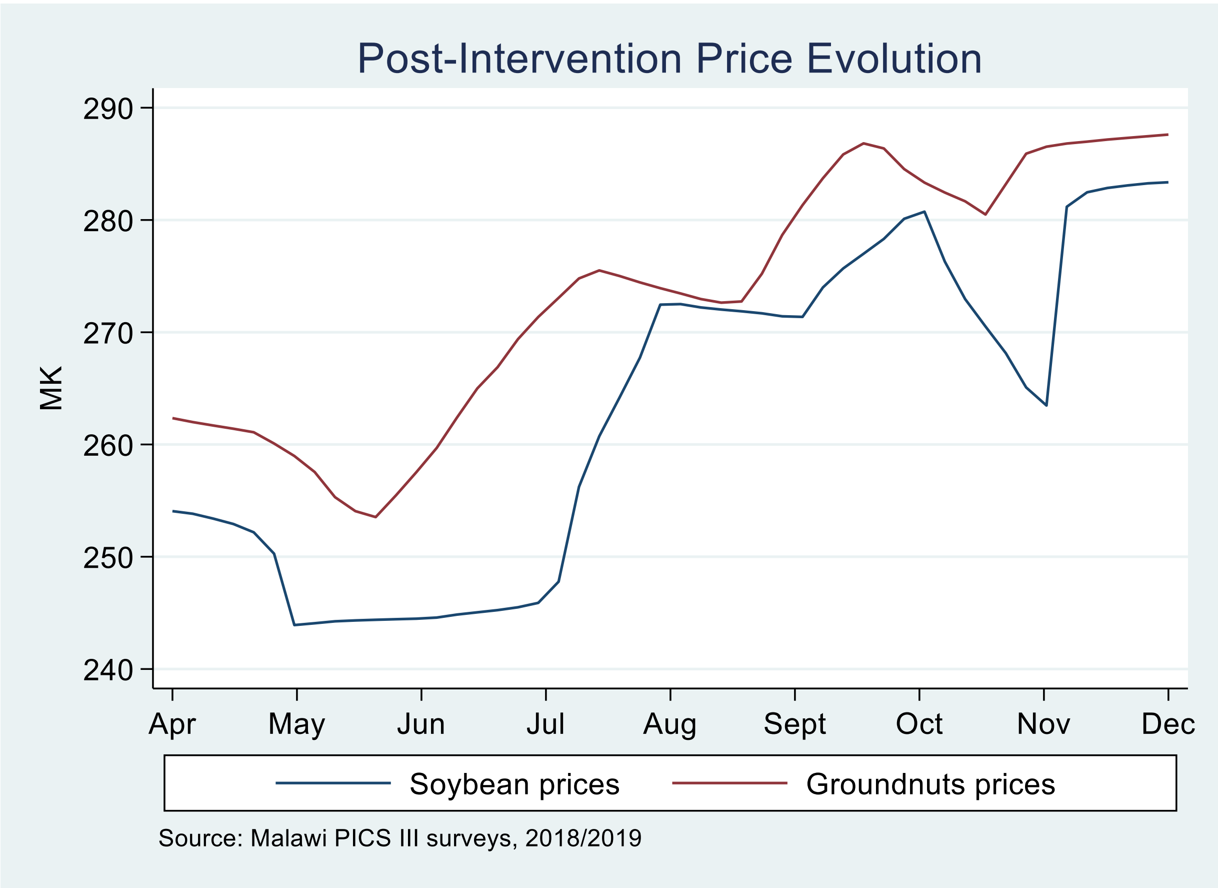

Figure 2.8: Price Trends Post-Intervention

Table 2.1: Baseline Balance Checks using a Multinomial Probit Model

VARIABLES	(1) T1	(2) T2	(3) T3
Total legume stored at harvest in baseline year (kg)	0.5153*	0.2669	0.3245
	(0.2681)	(0.2602)	(0.2698)
Weeks legume stored before largest sale in baseline year	10.4375	16.5107*	17.2731*
	(9.2854)	(8.6267)	(9.1336)
Total legume sales revenue in baseline year (MK)	0.0015**	0.0019**	0.0013*
	(0.0007)	(0.0007)	(0.0007)
Baseline major legume inventory (kgs)	-0.0071	0.0349	-0.0760
	(0.1655)	(0.1530)	(0.1585)
Baseline net legume sales (kgs)	-3.1103	-3.1060	5.0981*
	(2.8065)	(2.7707)	(2.8055)
Baseline net value of legume sales (MK)	0.0056	0.0061	-0.0210**
	(0.0096)	(0.0095)	(0.0097)
Baseline legume PHL % out of inventory	-3.1235	-4.7873	-5.0386
	(4.7706)	(4.7419)	(4.4872)
Baseline legume harvest (kg)	-0.0374	0.0012	-0.0640
	(0.2172)	(0.2009)	(0.2053)
Baseline total income from all sources in (MK)	-0.0001	-0.0000	-0.0002
	(0.0002)	(0.0002)	(0.0002)
Number of people in household	-79.4458	-29.6102	-4.8584
	(50.2282)	(45.4452)	(50.6428)
Age of household head	2.4557	-0.1563	-2.5976
	(4.5114)	(4.7227)	(4.5261)
=1 if household head is female	-0.1162	-0.1764	-0.1066
	(0.1651)	(0.1533)	(0.1598)
Landholding in acres	30.5063	-25.3837	29.0410
	(40.4615)	(40.2645)	(40.0446)
Loans outstanding in baseline year (MK)	-0.0036	-0.0001	-0.0002
	(0.0030)	(0.0013)	(0.0015)
=1 if household head has no education	-0.1357	0.1312	-0.0305
	(0.1588)	(0.1632)	(0.1598)
number of school goers in household	-24.9046	-19.2898	-20.0895
	(54.6342)	(50.0075)	(52.8117)
years NASFAM Experience	1.7233	11.9087	12.3852
	(21.7583)	(21.0154)	(21.4748)
Baseline Cash savings (MK)	-0.0015	0.0006	-0.0011
	(0.0032)	(0.0033)	(0.0033)
Distance to the closest market (km)	-5.8104	0.8329	0.3466
	(6.6080)	(6.0565)	(5.8505)
Amount spent on fertilizer (MK)	0.0012	0.0004	0.0009
	(0.0019)	(0.0020)	(0.0020)
=1 if harvested soybean in baseline year	0.1031	0.0749	0.2099
	(0.1387)	(0.1341)	(0.1419)
=1 if used actellic in baseline year	0.0606	-0.0548	-0.0996
	(0.2191)	(0.2242)	(0.2421)
=1 if there is a bicycle in household	0.1761	-0.0850	0.0870
	(0.1177)	(0.1183)	(0.1163)
Association = 2, Mikundi	-0.2791	-0.1604	-0.1585
	(0.2569)	(0.2532)	(0.2489)
Association = 3, Mpenu	0.3236	0.1613	0.5676*
	(0.3380)	(0.3300)	(0.3266)
Constant	0.0051	-0.0925	-0.4818
	(0.3608)	(0.3533)	(0.3730)
Observations	1,739	1,739	1,739

Note: Standard errors clustered at club level in parentheses, *** p<0.01, ** p<0.05, * p<0.1 and (F=86; p=0.1255; Coefficients scaled up by 1000).

Table 2.2: Baseline Summary Statistics

Panel A: Outcome variables	**Count**	**Mean**	**Std Dev.**	**Min**	**Max**
Legume stored at harvest (kg)	1739	275.77	271.18	0.00	1,135.00
Weeks stored before largest sale	1739	10.35	6.42	0.00	28.00
Legume total sales revenue (MK)	1739	234,017.00	133,408.00	27,808.00	920,548.00
Legume inventory at end of quarter (kg)	1739	188.66	349.74	0.00	1095.00
Net legumes sales (kgs)	1739	389.93	213.56	-3.00	639.07
Net legume sales value (MK)	1739	136,717.00	86,267.00	-11,000.00	656,463.00
Panel B: Household variables					
Legume PHL out of inventory (%)	1739	6.72	11.54	0.00	50.00
Legume harvest (kg)	1739	519.93	390.21	0.00	1770.00
Total baseline income (MK)	1739	280,798.00	392,456.00	0.00	2,400,000.00
Household size	1739	5.03	1.81	1.00	10.00
Household head's age	1739	41.13	12.54	20.00	68.00
=1 if household head female	1739	0.14	0.35	0.00	1.00
Landholding (acres)	1739	3.54	1.94	0.45	11.75
=1 if borrowed in past year	1739	0.31	0.46	0.00	1.00
Loans outstanding (MK)	1739	9,639.00	33,914.00	0.00	1,050,000.00
=1 if household head has no education	1739	0.13	0.33	0.00	1.00
Number of students in household	1739	2.21	1.70	0.00	7.00
Years of NASFAM experience	1739	3.50	2.72	0.00	25.00
Baseline cash savings (MK)	1739	6,085.00	17,832.00	0.00	120,000.00
Distance to market (km)	1739	11.81	11.05	0.00	45.00
Fertilizer Expenditure (MK)	1739	38,108.00	38,585.00	0.00	211,000.00
=1 if Major legume is Soybeans	1739	0.71	0.45	0.00	1.00
=1 if use actellic	1739	0.05	0.22	0.00	1.00
=1 if have bicycle	1739	0.59	0.49	0.00	1.00

Note: Actellic is the most common storage chemical used in Malawi.

Table 2.3: Treatment Effects on Annual Outcomes (ANCOVA)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Storage at harvest (kg)		Weeks stored until largest sale		Sales revenue (MK)	
=1 for PICS only (T1)	32*	34*	1.7*	1.5*	20,919*	23,161**
	(19)	(19)	(0.9)	(0.9)	(11,806)	(11,528)
=1 for PICS + Village group store (T2)	73***	74***	2.5***	2.4***	28,442**	30,073***
	(20)	(19)	(0.9)	(0.9)	(11,671)	(11,440)
=1 for PICS + Warehouse group store (T3)	42**	42**	1.8*	1.8*	23,849*	23,763*
	(18)	(18)	(1.0)	(1.0)	(13,632)	(13,280)
Constant	78	62	10.0***	10.4***	107,218***	120,080***
	(51)	(56)	(1.9)	(1.9)	(15,872)	(17,016)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association fixed effects	No	Yes	No	Yes	No	Yes
Observations	1,358	1,358	1,358	1,358	1,358	1,358
R-squared	0.01	0.01	0.10	0.13	0.06	0.06
P-values from F-tests:						
Treatment 1=Treatment 2	0.041	0.042	0.391	0.350	0.526	0.537
Treatment 1=Treatment 3	0.593	0.638	0.966	0.881	0.827	0.963
Treatment 2=Treatment 3	0.093	0.090	0.434	0.457	0.734	0.626

Note: Standard errors clustered at the club level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. We include association dummies because randomization was stratified by association. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Table 2.4: Treatment Effects on Quarterly Outcome (ANCOVA)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Legume storage at the end of quarter (kg)		Net legume sales in the quarter (kg)		Net value of sales in the quarter (MK)	
Panel A: Four months after harvest season, August 2018 (Period 2)						
=1 for PICS only (T1)	0.32	2.11	27.24***	28.33***	6,460	6,510
	(18.98)	(18.51)	(3.58)	(3.76)	(6,833)	(6,795)
=1 for PICS + Village group store (T2)	45.47**	47.37**	42.03***	42.97***	10,196	10,257
	(21.39)	(21.01)	(1.70)	(1.95)	(6,855)	(6,921)
=1 for PICS + Warehouse group store (T3)	42.63*	45.27*	32.43***	33.50***	8,218	8,353
	(23.69)	(23.72)	(2.55)	(2.72)	(6,571)	(6,612)
Constant	60.65***	31.18*	5.69*	-2.09	-42,915***	-44,753***
	(15.51)	(16.93)	(3.13)	(5.13)	(5,872)	(7,193)
P-values from F-tests:						
Treatment 1=Treatment 2	0.0177	0.0191	<0.001	0.0001	0.8304	0.001
Treatment 1=Treatment 3	0.0476	0.0437	0.2000	0.2067	0.7537	0.163
Treatment 2=Treatment 3	0.9203	0.9557	0.0001	0.0001	0.9349	0.006
Panel B: Eight months after harvest season, December 2018 (Period 3)						
=1 for PICS only (T1)	17.53	19.09	16.48	17.65	6,299	6,314
	(14.73)	(14.52)	(13.84)	(13.74)	(5,761)	(5,740)
=1 for PICS + Village group store (T2)	25.63*	26.95**	29.65*	30.53*	17,299***	17,297***
	(13.17)	(13.03)	(16.43)	(16.54)	(6,281)	(6,361)
=1 for PICS + Warehouse group store (T3)	0.30	2.45	-1.31	-0.32	2,566	2,642
	(10.32)	(10.10)	(13.02)	(12.99)	(5,604)	(5,679)
Constant	60.65***	31.18*	5.69*	-2.09	-42,915***	-44,753***
	(15.51)	(16.93)	(3.13)	(5.13)	(5,872)	(7,193)
P-values from F-tests:						
Treatment 1=Treatment 2	0.5464	0.6290	0.4140	0.4167	0.3276	0.659
Treatment 1=Treatment 3	0.2565	0.2355	0.1643	0.1606	0.7928	0.524
Treatment 2=Treatment 3	0.0402	0.0506	0.0461	0.0464	0.2279	0.321
Baseline outcome and attrition control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	3,114	3,114	3,114	3,114	3,114	3,114
R-squared	0.01	0.01	0.10	0.11	0.09	0.09

Note: Standard errors clustered at club level in parentheses and *** $p<0.01$, ** $p<0.05$, * $p<0.1$. US$1=MK750. We include association dummies because randomization was stratified by association. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Table 2.5: Heterogeneity in Annual Outcome Treatment Effects by Credit Access (ANCOVA)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Storage at harvest (kg)		Weeks stored until largest sale		Sales revenue (MK)	
=1 for PICS only (T1)	37*	39**	0.3	0.2	25,471*	26,710*
	(20)	(20)	(1.1)	(1.1)	(14,260)	(13,856)
=1 for PICS + Village group store (T2)	79**	83**	1.3	1.1	28,383	27,171
	(32)	(33)	(1.8)	(1.8)	(18,185)	(18,087)
=1 for PICS + Warehouse group store (T3)	19	21	0.8	0.7	22,529	22,120
	(18)	(18)	(1.2)	(1.2)	(15,901)	(15,479)
=1 if had credit access in past year	-6	-4	-3.5***	-3.6***	15,950	14,232
	(26)	(26)	(1.0)	(1.0)	(13,614)	(13,424)
=1 if T1 * credit access	-18	-20	4.1***	4.1***	-12,728	-9,684
	(39)	(38)	(1.6)	(1.6)	(20,268)	(19,712)
=1 if T2 * credit access	-4	-9	3.5*	3.7*	-9,246	-4,795
	(41)	(40)	(1.9)	(1.9)	(21,187)	(21,246)
=1 if T3 * credit access	62	58	3.1*	3.2*	2,669	3,655
	(43)	(42)	(1.7)	(1.8)	(29,275)	(28,217)
Constant	83	66	11.0***	11.5***	102,934***	116,567***
	(54)	(58)	(1.9)	(2.0)	(16,285)	(17,321)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	1,358	1,358	1,358	1,358	1,358	1,358
R-squared	0.02	0.03	0.02	0.02	0.05	0.06
P-values from F-tests:						
T1 * credit access = T2 * credit access	0.051	0.053	0.347	0.310	0.399	0.398
T1 * credit access = T3 * credit access	0.855	0.896	0.892	0.968	0.738	0.846
T2 * credit access = T3 * credit access	0.055	0.054	0.305	0.322	0.716	0.609

Note: Standard errors clustered at club level in parentheses and *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. Credit Access is a dummy variable which is 1 if household borrowed money in baseline year. We include association dummies because randomization was stratified by association. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Table 2.6: Heterogeneity in Annual Outcome Treatment Effects by Market Access (ANCOVA)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Storage at harvest(kg)		Weeks stored before largest sale		Sales revenue (MK)	
=1 for PICS only (T1)	38*	40*	1.6	1.4	13,268	17,065
	(22)	(22)	(1.1)	(1.1)	(12,824)	(12,570)
=1 for PICS + Village group store (T2)	77***	78***	2.4**	2.3**	27,515**	30,148**
	(23)	(23)	(1.1)	(1.1)	(13,216)	(13,043)
=1 for PICS + Warehouse group store (T3)	44**	44**	1.8*	1.8*	30,214*	30,978**
	(21)	(21)	(1.1)	(1.1)	(15,772)	(15,514)
=1 if Market access	12	7	-0.5	-0.5	-4,968	2,599
	(20)	(20)	(1.6)	(1.6)	(17,124)	(17,031)
=1 if T1*Market access	-24	-24	0.3	0.5	29,334	22,201
	(33)	(32)	(2.1)	(2.1)	(25,428)	(25,818)
=1 if T2 *Market access	-15	-15	0.3	0.5	3,908	-543
	(35)	(34)	(2.2)	(2.2)	(27,085)	(26,895)
=1 if T3 *Market access	-9	-6	0.1	0.0	-26,537	-30,096
	(31)	(30)	(2.3)	(2.3)	(25,441)	(25,142)
Constant	76	61	10.0***	10.4***	106,873***	119,022***
	(52)	(56)	(1.9)	(2.0)	(15,516)	(16,659)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	1,358	1,358	1,358	1,358	1,358	1,358
R-squared	0.06	0.06	0.01	0.01	0.01	0.01
P-values from F-tests:						
T1 * Market access= T2 * Market access	0.108	0.107	0.445	0.400	0.295	0.326
T1 * Market access = T3 * Market access	0.792	0.869	0.882	0.765	0.283	0.365
T2 * Market access = T3 * Market access	0.141	0.125	0.527	0.574	0.855	0.942

Note: Standard errors clustered at club level in parentheses and *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. Market access is a dummy variable which is 1 if household is less than 5 km away from the closest market. We include association dummies because randomization was stratified by association. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Table 2.7: Heterogeneity in Annual Outcome Treatment Effects by Education (ANCOVA)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Storage at harvest(kg)		Weeks stored before largest sale		Sales revenue (MK)	
=1 for PICS only (T1)	25	27	1.5	1.4	22,987*	25,863**
	(21)	(20)	(0.9)	(0.9)	(12,566)	(12,210)
=1 for PICS + Village group store (T2)	64***	64***	2.1**	2.1**	29,713**	32,280***
	(22)	(21)	(1.0)	(1.0)	(12,101)	(11,945)
=1 for PICS + Warehouse group store (T3)	35*	36*	1.7*	1.7	27,555*	27,765*
	(19)	(19)	(1.0)	(1.0)	(14,648)	(14,307)
=1 1 if head has No Education	-80***	-79***	-0.6	-0.7	1,933	5,962
	(24)	(23)	(1.3)	(1.3)	(18,993)	(18,811)
=1 if T1* No Education	49	46	1.5	1.8	-23,470	-28,166
	(42)	(42)	(2.7)	(2.7)	(24,062)	(23,539)
=1 if T2 * No Education	84*	85*	2.7	2.8	-12,424	-18,325
	(45)	(45)	(2.4)	(2.4)	(31,325)	(30,657)
=1 if T3 * No Education	46	45	1.0	1.1	-35,197	-36,864
	(38)	(37)	(2.4)	(2.4)	(24,880)	(25,233)
Constant	88*	72	9.9***	10.3***	110,075***	121,892***
	(53)	(57)	(1.9)	(2.0)	(15,765)	(16,836)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	3,053	3,053	3,053	3,053	3,053	3,053
R-squared	0.02	0.03	0.01	0.01	0.05	0.06
P-values from F-tests :						
T1 * No Education = T2 * No Education	0.086	0.093	0.507	0.453	0.591	0.605
T1 * No Education = T3 * No Education	0.592	0.634	0.959	0.866	0.753	0.892
T2 * No Education = T3 * No Education	0.178	0.181	0.568	0.596	0.892	0.758

Note: Standard errors clustered at club level in parentheses and *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. No Education is a dummy variable which is 1 if household head has never been to school before. We include association dummies because randomization was stratified by association. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Table 2.8: Local Average Treatment Effects on Annual Outcome (ANCOVA)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Storage at harvest(kg)		Weeks stored until largest sale		Sales revenue (MK)	
=1 for participation in T1	36*	37*	1.9*	1.7*	23,156*	25,250**
	(21)	(20)	(1.0)	(1.0)	(12,870)	(12,461)
=1 for participation in T2	105***	105***	3.5***	3.4**	40,594**	42,690***
	(27)	(27)	(1.3)	(1.3)	(16,520)	(16,058)
=1 for participation in T3	67**	67**	2.9*	2.9*	38,114*	37,925*
	(28)	(28)	(1.5)	(1.5)	(21,732)	(21,199)
Constant	116**	101**	11.3***	11.8***	123,146***	137,094***
	(47)	(50)	(1.7)	(1.7)	(12,690)	(14,721)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	1,358	1,358	1,358	1,358	1,358	1,358
R-squared	0.06	0.07	0.01	0.01	0	0
P-values from F-tests:						
T1 participation = T2 participation	0.006	0.006	0.180	0.160	0.244	0.233
T1 participation = T3 participation	0.204	0.212	0.534	0.473	0.453	0.520
T2 participation = T3 participation	0.164	0.168	0.590	0.621	0.912	0.822

Note: Standard errors clustered at club level in parentheses and *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. We use the treatment indicators as instrumental variables for actual participation or compliance to the treatment groups to estimate the local average treatment effects. We include association dummies because randomization was stratified by association. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Appendix: Supplementary Results Tables

Appendix Table 2.1: Actual Intra-Cluster Correlation Coefficient at Baseline

Outcome Variable	ICC	SE	N
Quantity stored at harvest (Kg)	0.12	0.023	1739
Weeks stored before largest sell (Weeks)	0.08	0.021	1739
Total sales revenue (MK)	0.12	0.023	1739
Inventory (kg)	0.08	0.022	1739
Net sales quantity(kg)	0.06	0.024	1739
Net Sales Value (MK)	0.07	0.026	1739
Average Realized legume selling price (Mk/kg)	0.04	0.019	1739

Notes: An ICC value closer to 1, implies less variations in farmers within a club hence no power gain in having more farmers within each club. However, a value closer to zero shows a bigger variation in farmers within clusters, which is beneficial in terms of efficiency as more observations within the cluster implies more power gain.

Appendix Table 2.2: Attrition Rate

Variables	**Overall Rate**	Control	PICS Only	Village program	Warehouse program	p-values
Follow-up 1 Attrition	**7% (127 households)**	50 households	15 households	35 households	27 households	0.0057
Follow-up 2 Attrition	**14% (236 households)**	96 households	34 households	54 households	52 households	0.4111

Note: The attrition rate represents the final attrition rate without accounting for those that were missed first follow up and tracked in the second follow-up

Appendix Table 2.3: Attrition Bias Checks using Joint Orthogonality Test

VARIABLES	Follow-up 1	Follow-up 2
=1 for PICS only(T1)	-0.4538**	-0.4311***
	(0.1920)	(0.1589)
=1 for PICS+ Group store at village(T2)	0.0006	-0.1621
	(0.1703)	(0.1531)
=1 for PICS+ Group store at warehouse (T3)	-0.1919	-0.2505*
	(0.1653)	(0.1463)
Total legume stored at harvest in baseline year (kg)	0.2438	0.2290
	(0.2145)	(0.1884)
Weeks legume stored before largest sale in baseline year	10.9733	7.0586
	(7.3823)	(5.8410)
Total legume sales revenue in baseline year (MK)	-0.0018*	-0.0009
	(0.0010)	(0.0006)
Baseline major legume inventory (kgs)	-0.1822	0.1812
	(0.1334)	(0.1108)
Baseline net legume sales (kgs)	1.4423	1.9701
	(2.4584)	(1.9112)
Baseline net value of legume sales (MK)	-0.0029	-0.0059
	(0.0085)	(0.0066)
Baseline legume PHL % out of inventory	5.7443	1.2994
	(3.9423)	(3.4502)
Baseline legume harvest (kg)	-0.1381	-0.0231
	(0.1823)	(0.1562)
Baseline total income from all sources in (MK)	0.0002	0.0001
	(0.0001)	(0.0001)
Number of people in household	17.2265	-20.5181
	(40.5984)	(34.8051)
Age of household head	-1.9799	1.6541
	(4.9630)	(3.4432)
=1 if household head is female	0.0666	-0.0136
	(0.1400)	(0.1097)
Landholding in acres	35.8497	-6.7166
	(29.7365)	(28.8762)
Loans outstanding in baseline year (MK)	-0.0052*	0.0011
	(0.0029)	(0.0008)
=1 if household head has no education	0.2596**	0.1252
	(0.1261)	(0.1065)
number of school goers in household	-27.6983	15.9500
	(43.2515)	(35.1377)
years NASFAM Experience	-17.8085	-27.9877*
	(18.0712)	(15.9397)
Baseline Cash savings (MK)	0.0017	0.0025
	(0.0029)	(0.0024)
Distance to the closest market (km)	2.2291	0.5254
	(4.5817)	(3.7574)
Amount spent on fertilizer (MK)	0.0020	0.0002
	(0.0014)	(0.0013)
=1 if harvested soybean in baseline year	-0.0846	-0.1515*
	(0.0979)	(0.0893)
=1 if used actellic in baseline year	-0.0564	0.0249
	(0.2002)	(0.1726)
=1 if there is a bicycle in household	-0.0601	0.0147
	(0.1067)	(0.0867)
Association = 2, Mikundi	0.0197	0.1945
	(0.1426)	(0.1295)
Association = 3, Mpenu	-0.2120	0.2347
	(0.1866)	(0.1541)
Constant	-1.3523***	-0.9799***
	(0.2838)	(0.2704)
	1739	1739
F-Test for treatment and outcome variables	(F=19; p=0.025)	(F=16; p=0.072)

Note: Standard errors clustered at club level in parentheses & *** p<0.01, ** p<0.05, * p<0.1; attrition is regressed on baseline variables including Quarter 1 or Period 1 Outcome variables and Coefficients are scaled up by 1000.

Appendix Table 2.4: Comparing of p-values and Andersons' Sharpened q-values for Multiple Hypothesis Testing

Panel A: Multiple Hypothesis Test for Table 2.3 Results ANCOVA Estimates of ITT on Key Aggregate Outcomes

	Legumes stored at harvest(kg)				Weeks stored before the first largest sale				Sales Revenue (MK)			
	(1)		(2)		(3)		(4)		(5)		(6)	
VARIABLES	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values
Treatment 1	0.0993	0.035	0.0735	0.031	0.0686	0.054	0.0911	0.065	0.0880	0.067	0.0539	0.057
Treatment 2	0.0002	0.001	0.0002	0.001	0.0076	0.024	0.0092	0.029	0.0177	0.057	0.0109	0.034
Treatment 3	0.0216	0.023	0.0196	0.02	0.0763	0.054	0.0806	0.065	0.0929	0.067	0.0875	0.062

Panel B: Multiple Hypothesis Test for Table 2.4 Results ANCOVA Estimates of ITT on Key Aggregate Outcomes

	Inventories at the end of the quarter(kg)				Legume Sales (kg)				Legume Sales value			
	(1)		(2)		(3)		(4)		(5)		(6)	
VARIABLES	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values	p-values	Anderson q-values
Treatment 1 # Quarter 2	0.9849	0.490	0.68	0.433	<0.001	0.001	<0.001	0.001	0.6137	0.400	0.5828	0.396
Treatment 2 # Quarter 2	0.0314	0.059	0.01	0.028	<0.001	0.001	<0.001	0.001	0.4952	0.340	0.4681	0.326
Treatment 3 # Quarter 2	0.0660	0.088	0.03	0.059	<0.001	0.001	<0.001	0.001	0.4215	0.300	0.3803	0.293
Treatment 1 # Quarter 3	0.2259	0.197	0.09	0.104	0.2251	0.197	0.2069	0.191	0.1913	0.181	0.1824	0.178
Treatment 2 # Quarter 3	0.0390	0.064	0.01	0.028	0.0673	0.088	0.0648	0.088	0.0336	0.059	0.0334	0.059
Treatment 3 # Quarter 3	0.8416	0.472	0.41	0.300	0.9327	0.490	0.9640	0.490	0.2971	0.230	0.2850	0.227

Note: Standard errors clustered at club level computed following Anderson (2008); US$1=MK750.

Appendix Table 2.5: Robustness checks for Treatment Effects on Annual Outcome in Table 2.3 using Logs of Outcome Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Storage at harvest (kg)		Weeks stored until largest sale		Sales revenue (MK)	
=1 for PICS only (T1)	0.95***	0.96***	0.39***	0.38***	0.26***	0.27***
	(0.18)	(0.18)	(0.07)	(0.08)	(0.07)	(0.07)
=1 for PICS + Village group store (T2)	1.15***	1.15***	0.43***	0.43***	0.28***	0.28***
	(0.17)	(0.17)	(0.08)	(0.08)	(0.07)	(0.06)
=1 for PICS + Warehouse group store (T3)	0.95***	0.95***	0.26***	0.26***	0.16**	0.15**
	(0.17)	(0.17)	(0.09)	(0.09)	(0.07)	(0.07)
Constant	2.90***	2.72***	2.14***	2.18***	11.17***	11.16***
	(0.39)	(0.44)	(0.17)	(0.18)	(0.42)	(0.41)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association fixed effects	No	Yes	No	Yes	No	Yes
Observations	1,358	1,358	1,358	1,358	1,358	1,358
R-squared	0.01	0.01	0.10	0.13	0.06	0.06
P-values from F-tests:						
Treatment 1=Treatment 2	0.575	0.51	0.358	0.306	0.983	0.905
Treatment 1=Treatment 3	0.502	0.418	0.447	0.368	0.823	0.962
Treatment 2=Treatment 3	0.946	0.906	0.914	0.949	0.820	0.877

Note: Standard errors clustered at the club level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. We include association dummies because randomization was stratified by association. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Appendix Table 2.6: Robustness checks for Treatment Effects on Quarterly Outcome in Table 2.4 using OLS estimator

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Legume storage at the end of quarter (kg)		Net legume sales in the quarter (kg)		Net value of sales in the quarter (MK)	
Panel A: Four months after harvest season, August 2018 (Period 2)						
=1 for PICS only (T1)	1.52	9.42	27.11***	29.01***	11,761**	12,632**
	(19.04)	(19.16)	(3.61)	(4.04)	(5,464)	(5,479)
=1 for PICS + Village group store (T2)	46.37**	53.58**	41.69***	43.44***	7,999	8,876
	(21.46)	(21.29)	(1.70)	(2.34)	(5,858)	(5,894)
=1 for PICS + Warehouse group store (T3)	44.00*	52.30**	32.19***	34.23***	12,978**	14,157**
	(23.82)	(23.75)	(2.59)	(3.01)	(5,559)	(5,601)
Constant	192.36***	128.64***	393.54***	377.38***	140,065***	128,113***
	(11.20)	(11.62)	(6.53)	(9.45)	(2,779)	(4,609)
P-values from F-tests:						
Treatment 1=Treatment 2	0.021	0.023	<0.001	<0.001	0.515	0.519
Treatment 1=Treatment 3	0.053	0.049	0.202	0.237	0.824	0.778
Treatment 2=Treatment 3	0.922	0.957	0.001	0.001	0.396	0.334
Panel B: Eight months after harvest season, December 2018 (Period 3)						
=1 for PICS only (T1)	18.07	26.23*	16.73	18.67	11,375	12,161
	(14.92)	(14.99)	(13.82)	(13.74)	(8,741)	(8,685)
=1 for PICS + Village group store (T2)	27.97**	33.93**	30.03*	31.44*	20,674**	21,207**
	(13.51)	(13.42)	(16.38)	(16.35)	(9,715)	(9,721)
=1 for PICS + Warehouse group store (T3)	2.12	9.31	-1.07	0.67	9,214	10,089
	(10.56)	(10.89)	(13.01)	(12.98)	(8,795)	(8,810)
Constant	192.36***	128.64***	393.54***	377.38***	140,065***	128,113***
	(11.20)	(11.62)	(6.53)	(9.45)	(2,779)	(4,609)
P-values from F-tests:						
Treatment 1=Treatment 2	0.546	0.635	0.414	0.428	0.328	0.339
Treatment 1=Treatment 3	0.257	0.235	0.166	0.157	0.800	0.806
Treatment 2=Treatment 3	0.040	0.052	0.047	0.047	0.231	0.242
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	No	Yes	No	Yes	No	Yes
Observations	4,849	4,849	4,849	4,849	4,849	4,849
R-squared	0.04	0.05	0.51	0.51	0.20	0.20

Note: Standard errors clustered at club level in parentheses and *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. We include association dummies because randomization was stratified by association.

Appendix Table 2.7: First Stage Results for LATE Estimates on Annual Outcomes in Table 2.8 (ANCOVA)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Storage at harvest(kg)			Weeks stored before largest sale			Sales revenue (MK)		
Compliance in:	T1	T2	T3	T1	T2	T3	T1	T2	T3
=1 for PICS only (T1)	0.91***	-0.00	-0.00	0.91***	-0.00	-0.00	0.91***	-0.00	-0.00
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
=1 for PICS+ Village group store (T2)	0.00	0.71***	0.01	0.00	0.71***	0.01	0.00	0.71***	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
=1 for PICS+ Warehouse group store (T3)	0.00	-0.00	0.61***	0.00	0.00	0.61***	0.00	-0.00	0.61***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
QUARTER	0.01	0.27***	0.12**	0.01	0.27***	0.12**	0.01	0.26***	0.11**
	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
=1 if Household missed in first follow-up survey	0.00	-0.01	-0.06**	0.00	-0.01	-0.06**	0.00	-0.01	-0.06**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
=1 if Household missed in second follow-up survey	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.03
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Constant	-0.01	-0.27***	-0.12**	-0.01	-0.27***	-0.12**	-0.01	-0.27***	-0.12**
	(0.03)	(0.04)	(0.05)	(0.03)	(0.05)	(0.05)	(0.03)	(0.04)	(0.05)
Baseline outcome control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Association controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,361	1,361	1,361	1,361	1,361	1,361	1,361	1,361	1,361
R-squared	0.89	0.66	0.55	0.89	0.66	0.55	0.89	0.66	0.55

Note: Standard errors clustered at club level in parentheses and *** p<0.01, ** p<0.05, * p<0.1. US$1=MK750. We use the treatment indicators as instrumental variables for actual participation or compliance to the treatment groups to estimate the local average treatment effects. The baseline outcome variable is included in the ANCOVA analysis to increase efficiency (McKenzie 2012).

Appendix Table 2.8: Cost-Benefit Analysis Parameters

Parameters			**Units**
Social discount rate-Nominal		0.135	%
Number of households in PICS		387	People
Number of households in PICS +Village Group store		389	People
Number of households in PICS +Warehouse Group store		423	People
Number of households trained		1199	People
Estimated life of a PICS bag (years)		3	years
Wholesale costs of bags in Malawi		1.95	$
Annual equivalent cost of a PICS bag		0.83	$
Training cost per household		8.80	$
Training costs (SACCO personnel + transportation)		10550.00	$
Annual equivalent cost of training (perpetuity)		1.19	$
GDP per capita Malawi in 2018 (PPP adjusted, 2018 dollars)		1165.5	$
% of PICS users who "averted" at Malawi level out of those that at baseline likely to have high levels above 10 ppt		0.29	%
Malawi's median disability adjusted life years per 100,000 people		35	DALY
Averted DALY per person (maize + groundnuts)		0.00035	DALY
Maize consumption proportion of aflatoxin prone foods (maize and groundnuts)		0.73	%
Maize consumption / day Malawi		353	g
Groundnut consumption/ day Malawi		133	g
Total consumption maize and groundnut in grams/day		486	g
Average Post harvest Loss in ordinary storage (APHLIS Estimates)		4.2%	%
Lean Groundnuts Price per Kg		$0.65	$
Number of 100-kg PICS bag per household		2	bags
Bag Capacity		100	kgs
Grain assembling and Transportation costs per 100 kg bag PICS + VGS		$0.67	$
Grain assembling and Transportation costs per 100 kg bag PICS + WGS		0.98	$
Warehousing Fees and Charges per bag		$1.94	$
Average Marginal Post Harvest Price (2 weeks after harvest)		$0.10	$
Income tax		0.25	%
Percent that report losses		50%	%
Percent that Complied with PICS only intervention		0.89	%
Percent that Complied with PICS + VGS intervention		0.72	%
Percent that Complied with PICS +WGS intervention		0.68	%
Estimated Aggregate TE on storage for PICS only		30	kgs
Estimated Aggregate TE on storage for PICS + VGS		$ 68.00	kgs
Estimated Aggregate TE on storage for PICS + WGS		$42.00	kgs
Average household size		4.3	people
Average annual household expenses on Storage chemical		$6.16	$
Inflation Rate		0.115	%
Total Intervention Benefits and Costs Parameters			
Benefits	Food Safety Benefits Using Malawi Guideline (≤ 10 ppb) PICS only	0.034959645	
	Food Safety Benefits Using Malawi Guideline (≤ 10 ppb) PICS + VGS intervention	0.02842812	
	Food Safety Benefits Using Malawi Guideline (≤ 10 ppb) PICS+ WGS intervention	0.02919546	
	Food Security Benefits Using APHLIS Estimates (4.2%)		
	Value of abated PHL Through PICS only intervention	$2,113.02	
	Value of abated PHL Through PICS + VGS intervention	$2,123.94	
	Value of abated PHL Through PICS+ WGS intervention	$2,309.58	

CHAPTER 3. CAN INFORMATION INCREASE RURAL CONSUMERS' FOOD QUALITY VALUATION? EXPERIMENTAL EVIDENCE FROM MALAWI

3.1 Abstract

For a credence food quality attribute like aflatoxins contamination, incomplete quality information within informal markets undermines consumers' demand for quality and lead to a "lemons market." We seek to understand if quality labeling and increasing consumers' awareness about food quality and safety issues help to solve this problem for rural grain markets in Sub-Saharan Africa. To do so, we use a clustered randomized control trial (RCT) with 1,098 farm households in Malawi to evaluate whether providing aflatoxins information increases consumers' demand for grain quality and whether that demand for quality varies depending on food availability. For our outcome variable, we use the Becker DeGroote Marshack auctions to elicit consumers' willingness to pay (WTP) for three quality grades of groundnuts:(i) visibly unsorted grade ("*the unsorted grade*"); (ii) visibly sorted grade without aflatoxins information label ("*the sorted grade*"); and (iii) visibly sorted and labeled "aflatoxins-safe"*("the labeled grade")*. Our results show that consumers that received the aflatoxins information treatment were willing to pay higher quality premiums for both sorting and aflatoxins safety labeling compared to consumers in the control group. We also find that consumers had significant quality premiums for both sorting and labeling during the harvest season. However, relative to their quality premiums in harvest season, the informed (uninformed) households had higher (lower) quality premiums for labeling in the lean season. This may be due to scarcity in the lean season which may have diminished demand for labeling from consumers whowere not informed about its benefits. Our results highlight the need for policy that re-enforces aflatoxin testing and regulations in informal markets especially during the lean season. Our results also confirm the need to increase aflatoxins information campaigns for key food crops in SSA including groundnuts.

3.2 Introduction

Informal food markets in sub-Saharan Africa (SSA) are dominated by numerous small-scale producers and traders who typically operate without formal business registration. This makes enforcement and monitoring of quality standards in these markets difficult and expensive (Hoffmann, Moser, and Saak 2019; Roesel and Grace 2014; Grace 2015), with important negative consequences on human health (WHO, 2015). Given the unobservability of many food quality attributes (for example, presence of contaminants), producers and traders have little or no incentive to invest in grain quality, giving rise to “lemon markets” in which low quality dominates (Akerlof, 1970).

In this paper we use a randomized control trial (RCT) among of 1,098 farm households in Malawi to estimate the impact of providing information about unobservable food contaminants, aflatoxins, on consumers’ demand for grain quality. Aflatoxins are poisons produced by fungi present in the soil that affect staple and cash crops such as maize, rice, sorghum, cassava, groundnuts and millet. Fungi thrive in the field, and in storage if grains are not dried and stored properly. These toxins pose a serious health risk globally, including liver and esophagus cancers, stunting, malnutrition and immunodeficiency (Khlangwiset, Shephard, and Wu 2011).

We estimate the impact of this information intervention on their willingness to pay for quality. Using the Becker-Degroot-Marschak auctions, we elicited households’ WTP for three quality grades of groundnuts: (i) visibly unsorted groundnuts (“unsorted grade”) which is the lowest quality grade with the presence of some broken, moldy, immature, and foreign materials; (ii) visibly sorted groundnuts without aflatoxins information label (“sorted grade”); and (iii) visibly sorted and labeled “aflatoxins-safe” groundnuts (“labeled grade”), which is the highest quality grade. The willingness to pay auction was conducted in the harvest and in the lean seasons to measure the impact of grain scarcity on willingness to pay for quality given various food quality observability regimes.

Our main research objective is to evaluate whether filling the aflatoxins information gap increases consumers’ demand for higher-quality grain and induces a separating equilibrium, where people pay different prices for groundnuts with different levels of observable and unobservable quality. We specifically measure the premium that consumers place on the unobservable grain quality (the aflatoxins-safe label) beyond that on observable grain quality (the sorting of good grains from visibly broken grains and foreign materials). Information campaigns are also a key policy lever, so testing their effectiveness in redressing a market imperfection provides critical information to address both economic and health aspects of this food safety issue. Furthermore, increasing awareness of aflatoxins makes a latent, unobservable food quality issue salient, which could create an incentive for producers and consumers to transact higher-quality grain at a premium price if they value the unobservable attribute.

This paper contributes to the literature on aflatoxins and food safety in SSA in three main ways. First, by estimating and comparing consumers' demand for observable and unobservable grain quality attributes. To our knowledge, previous studies on consumers' WTP for grain quality in SSA have either focused on observable attributes such as color, grain size, and insect damage (de Groote et al. 2016; Kadjo, Ricker-Gilbert and Alexander 2016; Demont et al. 2013; Groote, Kimenju and Morawetz 2011; de Groote and Kimenju 2008), or unobservable quality attributes in in (Ordonez 2016; de Groote et al. 2016; and Hoffmann and Gatobu 2014; Prieto et al. 2021). We contribute to this literature by estimating and comparing consumers' WTP for both observable and unobservable attributes in groundnuts.

Second, this paper advances the literature on unobservable food safety attributes by estimating the causal impacts of providing aflatoxins information on consumers' demand for grain quality. To our knowledge, the studies that looked at unobservable quality attributes in SSA include Ordonez (2016); de Groote et al. (2016); and Hoffmann and Gatobu 2014. Empirical evidence from this paper, therefore, highlights the need to raise aflatoxins awareness in SSA to increase consumers' demand for quality and eventually incentivize supply of aflatoxins-safe grain in informal markets. Ordonez (2016) evaluated the impacts of providing different food safety information on consumers' maize flour purchase behavior in Kenya. Using a choice experiment (on market site), she found that consumers who were given information prior to shopping decided to purchase aflatoxin-tested maize flour at a 20% price premium. However, there were no significant variation in behavior due to variation in the type of information provided. Hoffmann and Gatobu (2014) used a framed field experiment in Kenya and found that farmers cared and understood the prevailing information asymmetry in unobservable attributes between traders and buyers such that they placed higher quality premiums on maize produced by themselves relative to maize sourced from somewhere. Using experimental auction, de Groote et al. (2016) measured consumers' WTP for aflatoxins-safe maize in Kenya and found that providing aflatoxins information did not increase WTP for tested and aflatoxins-safe labeled maize.

Third, we contribute to the literature by further evaluating how rural consumers' demand for grain quality varies under different states of food availability (i.e. harvest versus lean season). This important aspect helps to highlight how conflicting food security objectives, that is, quality versus quantity concerns, affect households' food quality demand in the post-harvest period. Our paper provides empirical evidence of the effect of scarcity on consumers' demand for quality, highlighting the need for policy that re-enforces aflatoxin testing and regulations in informal markets especially during the lean season. Lastly, previous studies focused on maize, a staple crop. This paper advances their work by estimating the impacts of providing aflatoxins information on consumers' demand for quality in groundnuts, which is mostly considered a cash crop for smallholder farmers in SSA.

Our results show that without the information intervention, consumers(uninformed) have significant quality premium for both observable and unobservable quality attributes on average (MK82; $p<0.001$ and MK7; $p=0.093$, respectively). However, their quality premium for sorting, the observable attribute, is higher than that for aflatoxin labeling, the unobservable attribute. When we factor in the information treatment, we find that the informed consumers (treated) were willing to pay about MK34 ($p<0.001$) more for the sorting than uninformed consumers, and about MK55 ($p<0.001$) more for aflatoxin safety than uninformed consumers. These results show that the aflatoxin information treatment helped to increase consumers' demand for both observable and unobservable grain quality attributes.

In terms of the scarcity effects, we calculate the quality premiums as a percent of the unsorted grade margin in each season and compare these across season. We find that scarcity influenced uninformed consumers to compromise their quality demand for the unobservable attribute (aflatoxin safety) in the lean season relative to the harvest season (i.e. 5% in harvest vs 1% in the lean season). However, we observe an increase in demand for aflatoxin safety in the lean season relative to harvest season amongst the informed consumers (i.e. 14% in the harvest season vs. 27 % in the lean season). Our results suggest that raising awareness about aflatoxins and its health risk helped to increase consumers' demand for aflatoxin safety, the unobservable attribute.

The rest of the paper is organized as follows: Section 3.3 presents the study setting and experimental design and procedures, Section 3.4 provides the empirical model as well as the estimation methods, Section 3.5 presents the study results and discussions while Section 3.5 presents the study conclusions.

3.3 Study Setting, Experimental Design and Auction Procedures

This section has four subsections: the background on groundnuts production and consumption, the experimental design, auction procedures and power calculations sections.

3.3.1 Background on groundnut production, consumption and food safety issues in Malawi.

Groundnuts is an important crop in Malawi accounting for an average of about 10 percent of the average total cultivated area between 2007 and 2017 (FAOSTAT 2020). The crop is particularly important to smallholder farmers who account for about 90 percent of its total production (Derlagen and Phiri 2012). In the past 10 years, Malawi has been among the top 14 producers of groundnuts in Africa (ranked number 2 in Southern and Eastern Africa) producing an average of about 311,912 tonnes of shelled groundnuts (FAOSTAT 2018). Groundnuts also contributes over 20 percent of smallholder farmers' agricultural income (Beghin et al. 2004). The crop is also valuable to farmers because of its nitrogen fixing properties, which help with soil improvement.

For Malawi, about 60 percent of the total production of groundnuts is sold and consumed locally (Derlagen and Phiri 2012). This means that the crop is also an important source of dietary protein, fats and vitamins for farm households. A study by Gelli et al. (2020) finds that legumes including groundnuts contribute about 8 percent of the average equivalent daily food consumption per adult in Malawi.

Although export markets continue to be important target markets for Malawi's groundnuts (i.e. 40 percent of the groundnuts produced in Malawi is exported), the export quantities for Malawi have significantly declined compared to 20 to 50 year ago (FAOSTAT 2018). This is due to the introduction of aflatoxins regulations in several countries (Njoroge 2018). These regulations have limited Malawi's access to some key export markets such as the European markets which have a maximum aflatoxin requirement of 4μg/kg for groundnuts (European trade helpdesk, 2020). Domestic markets, especially the under-regulated informal grain markets, are becoming important target markets for groundnuts that fail to meet the restrictive export markets requirements (Edelman and Aberman 2015). Informal grain markets, therefore, are likely to be characterized by the undersupply of aflatoxins-safe grain.

Results from several studies that tested samples of groundnuts and groundnuts products collected from various markets show that aflatoxins contamination remains a major problem in most of SSA (Seetha et al. 2018; Njoroge et al. 2017; 2016; Matumba et al. 2015; Soko et al. 2014; Matumba et al. 2014). Considering the ineffective aflatoxins regulatory systems and low market demand for aflatoxins-safe grain due to the information gap, producers and traders are likely to have no incentives to bear the cost of aflatoxins control. However, given that consumers' quality preferences or demand (i.e. demand for labels/shunning unlabeled goods) can play a significant role in incentivizing producers and traders to invest in quality, it is important to understand factors that may influence consumers' demand for grain quality.

3.3.2 Experimental setting and design

We targeted farm households in Malawi to assess rural consumers' demand for grain quality and safety. A total of 1098 farmers from Mchinji district, the major producer of groundnuts in the country, were randomly selected to participate in the study (see Study area in Figure 3.1). These farmers are members of the National Smallholder Farmers' Association of Malawi (NASFAM), a farmer-based organization that has over 43 associations across the country. Each NASFAM Association has sub-units at community level which are called Group Action Centers (GACs). The GACs are typically about 10 to 35 kilometers apart on average. A single NASFAM Association has an average of about 21 GACs (or communities) with each GAC having an average of about 15 farmer clubs. A club is made of 10 farmers who reside within the same village and these village are typically about 1 to 5 kilometers apart.

We targeted two Associations for the study namely, Chioshya and Mlonyeni and we randomly selected 16 GACs from each Association. Out of the 16 GACs selected within each Association, 8 were randomly assigned to each of the two study groups (control and treatment). A total of 32 GACs were sampled and half of these GACs received the aflatoxins information treatment while the other half were in the control group (see Study Consort diagram and timeline in Figure 3.2). Within each of the selected GACs, we randomly selected 25 farmers and at least 2 (at most 5) farmers were selected per club. Our treatment assignment was, therefore, at GAC level. We assigned treatment at the GAC level to avoid potential information spillover across clubs (or villages) within the same GAC (or community). This arrangement also ensured cost-effective administration of the study activities (aflatoxins training and auction). Although GACs are far apart enough to limit possible information contamination, GACs that fall within the same Association are generally similar.

3.3.3 Auction procedures

We worked with farm households in Malawi and implemented experimental auctions in order to elicit their WTP for grain quality. The objective was to evaluate how factors including providing aflatoxins information and the state of food availability influence WTP for three different quality grades of groundnuts: (1) visibly unsorted grade ("*the unsorted grade*") is the lowest quality grade with the presence of some broken, moldy, immature, and foreign materials; (2) visibly sorted grade without aflatoxins information label ("*the sorted grade*"); and (3) visibly sorted, tested and labeled "aflatoxins-safe"*("the labeled grade")*, the highest quality grade (see auction samples in Figure 3.3).[6] We implemented an incentive-compatible auction using the Becker-Degroot-Marschak mechanism, which is commonly applied in field experiments in developing countries (Becker, Degroot, and Marschak 1964; Channa et al. 2019; Prieto et al. 2020). We managed to elicit revealed preferences from the study because participants were involved in bidding real money for real grain where one of their three bids was randomly selected as a binding bid.

Participants were first oriented about the Becker-Degroot-Marschak exercise and procedures, then went through practice rounds using sweets to ensure they understood the process as well as understood that strategic behavior was not beneficial. Once this was done, participants completed the auction. All the three grades were auctioned in one-kilogram units and the participants were allowed to inspect the groundnuts before bidding. Following a random order, participants bid for the three grades of groundnuts. Once they bid for all the grades, the enumerator then rolled a die in the presence of the participant to determine a binding bid. The participants then drew a paper from a bag that had uniformly distributed numbers which were used as "offer prices" at which the binding bid was offered.[7] The participant bought the selected groundnuts grade if their bid was higher than the randomly drawn "offer price" from the bag. Participants were given a fixed participation fee to eliminate liquidity constraints that would limit participation and bias the elicited WTP.

[6] All three grades of groundnuts were tested and complied with Malawi's aflatoxin safety requirement of 10ppb. See attached laboratory results in Appendix 3.1.

[7] The median of the prevailing market prices is based on price information reported by NASFAM lead farmers. The lead farmers visited NASFAM members for study schedule sensitization some days prior to the experiments and they reported selling prices in their villages to the study team. The median prices from the provided price information were also used as the median prices in the auctions' uniform distribution of "offer prices".

The field auction was implemented twice, first during the 2019/2020 harvest season when farmers have abundant stocks of grains, and then again targeting the same participants during the 2019/2020 lean season (see Study consort diagram and timeline in Figure 3.2). This helped to evaluate how consumers' demand for grain quality may vary depending on the state of food availability. We also recruited an additional sample of 268 farmers (155 in control and 113 treated group) during the second auction to tease out possible learning effects from the repeated experimental auction games.[8]

We implemented the information treatment to measure the impact of providing food safety information on consumers' demand for quality. The information treatment was randomly assigned to GACs (pre-assigned by a computer) such that half of our participants randomly received the treatment (treatment group) while the other half were in the control group. The information included food safety issues related to aflatoxins such as prevalence of aflatoxins in different food crops, its indicators, the health risks posed by aflatoxins as well as practices that prevent aflatoxins contamination (see Aflatoxins Information script for the training in Appendix 3.2). Participants randomly assigned to the treatment group were trained about the food safety issues related to aflatoxins using the aflatoxins information script. After the information training, participants went through the auction. In the lean season auction (i.e. the second or repeated auction), participants in the treatment group were not given the aflatoxin information again. However, new participants assigned to the treatment group in the added sample were given aflatoxin information. In order to ensure fair information dissemination as per IRB requirements, we provided the aflatoxins information to participants in control group at the end of the study.

We purchased all the grain from a single source during the 2019 harvest in order to reduce heterogeneity in other grain attributes. The grain was then used to simulate the different grain quality grades prevalent in local markets (i.e. sorted and unsorted grain) for both auctions. For the second auction which was implemented in the lean season, we used the same grain which we purchased during the harvest season and stored in PICS bags to ensure minimal variation in grain quality (Baributsa et al. 2017; Sudini et al. 2015; Williams, Baributsa, and Woloshuk 2014).

[8] For the treatment(informed) and control (uninformed) in the added sample, a minimum of 10 farmers in 10 clusters of each study group with at least 10 farmers per cluster would ensure a minimum detectable effect (MDE) of 0.32 standard deviations.

3.3.4 Power calculations

Since our outcome variable is WTP for groundnuts, we use baseline data from the PICS III pilot project implemented in 2018 to get an estimate of mean and standard deviation of groundnuts purchase prices for the harvest and lean season. We use the same data to get an average intra-cluster correlation coefficient within GAC of 0.02 and based our power calculations on 80 percent power and 95 percent confidence intervals. Our calculations suggested that a minimum of 368 farmers in 16 clusters of each study group with at least 23 farmers per cluster would ensure a minimum detectable effect (MDE) of 0.32 standard deviations between treated and control households. This is generally considered a small-to-medium effect size (Cohen, 1988; Duflo, Glennerster, and Kremer 2007). Appendix Table 3.1 presents the actual intra-cluster correlation within GAC at baseline.

3.4 Empirical Model

In order to compare consumers' quality premiums for the observable quality attribute (sorting) and the unobservable quality attribute (aflatoxins safety) in groundnuts given the status quo where there are no information intervention, we test our first hypothesis which is: the uninformed consumers' quality premium for sorting is not different from their quality premium for aflatoxin safety labeling in groundnuts.[9] Limited awareness and/or understanding of aflatoxins and the health risk posed by aflatoxins may influence consumers to value the observable attribute more than the unobservable attribute.

Our second hypothesis is: treated (informed) consumers' demand for the observable and unobservable attributes is not different from control (uninformed) consumers' demand for these attributes. It is likely that consumers who are informed may have higher (lower) quality premiums for aflatoxins-safety labeling (sorting) in groundnuts than consumers that are uninformed. This is because when consumers are informed about the prevalence and health risks of aflatoxins, they are likely to place a lower (higher) probability of risk on groundnuts that has (does not have) aflatoxins-safety labeling compared to consumers who are uninformed about the potential risk.

Our last hypothesis is to evaluate if demand for food quality varies depending on the state of food availability or scarcity. Considering that food quality concerns in the face of scarcity may

[9] Sorting in this case implies removal of broken, moldy, immature, and foreign materials in the grain.

be compromised, we test if demand for quality is influenced by scarcity by comparing WTP elicited during harvest season to WTP elicited during the lean season. We hypothesize that consumers' food quality concerns may be more profound when they have more grain available compared to when they have limited stocks and our hypothesis is: consumers WTP for sorting and aflatoxins-safety labeling in groundnuts is higher in the harvest season compared to the lean season.

Given that aflatoxins contamination is a credence attribute, the lack of reliable testing methods available in rural areas implies that consumers are unable to determine its presence (or lack thereof) in food. Provision of aflatoxins safety labeling as well as ensuring that participants are able to trust this information can help avoid market failure. We elicit WTP for three quality grades of groundnuts, the unsorted grade, the sorted grade and the labeled grade (labeled "aflatoxins-safe") and estimate uninformed consumers' demand for groundnuts quality using equation 1 below:

$$WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 X_{it} + \sigma_i + \varepsilon_{ijt} \qquad (1)$$

where WTP is the bid value in Malawi Kwacha per kg for individual i for groundnuts grade j in period *t* and S_{it}, L_{it} are binary variables equal to one if the grade of groundnut on which individual *i* bid are sorted and labeled grade respectively, and zero otherwise. The unsorted groundnut grade is the omitted binary variable; $\widehat{\beta_1}$ is the estimated average difference in WTP between the unsorted and sorted grades, and $\widehat{\beta_2}$ is the estimated average difference in WTP between the labeled and unsorted grades.

In order to address our first hypothesis, that is, evaluating if consumers have significant quality premium for observable (sorting) and unobservable (aflatoxins safety) quality attributes in groundnuts, we evaluate the significance and compare our parameters of interest $\widehat{\beta_1}$ and $\widehat{\beta_2}$. The parameter $\widehat{\beta_1}$ presents the quality premium for the observable(sorting) while β_2 comprises both the sorting and labeling premium. The difference between $\widehat{\beta_2}$ and $\widehat{\beta_1}$ present the quality premium for the unobservable attribute (aflatoxins safety). For our second hypothesis, which is to evaluate the treatment effects (ITT) of the aflatoxins information on consumers' demand for observable and unobservable quality attributes, we estimate a modified version of equation 2 below which include variable I_{it}, a binary variable indicating the information treatment (=1 if the individual was assigned to receiving aflatoxins information), In this equation, we also interact the information variable I_{it} with the two quality grade variables S_{it} and L_{it}:

$$WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 I_{it} + \beta_4 X_{it} + \delta_1 I_{it} * S_{it} + \delta_2 I_{it} * L_{it} + \sigma_i + \varepsilon_{ijt.} \quad (2)$$

The parameters of interest are $\hat{\delta}_1$, and $\hat{\delta}_2$, which present the impact of the information treatment on consumers' quality premium. The estimate $\hat{\delta}_1$, presents the marginal impact of the information treatment on consumers' quality premium for the observable attribute (sorting) while the difference between $\hat{\delta}_1$, and $\hat{\delta}_2$, presents the marginal impact of the information treatment on consumes' quality premium for the unobservable attributes (aflatoxin safety). Appendix Table 3.2 shows the details of how the effects of interest for our hypothesis are derived.

For our last hypothesis, which is to evaluate the effect of the food scarcity or availability on consumers' demand for quality, we include the seasonality indicator variable T_{it} (=1 if auction was conducted in the lean season) and interact it with the quality grade variables S_{it} and L_{it}:

$$WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 T_{it} + \beta_4 X_{it} + \alpha_1 S_{it} * T_{it} + \alpha_2 L_{it} * T_{it} + \sigma_i + \varepsilon_{ijt}. \quad (3)$$

The parameters of interest $\hat{\alpha}_1$ and $\hat{\alpha}_2$, present the average effect of "scarcity" on consumers' quality premiums. The estimate $\hat{\alpha}_1$ presents the marginal effect of scarcity on consumers quality premium for the observable attribute (sorting) while the difference between $\hat{\alpha}_1$ and $\widehat{\alpha}_2$, presents the marginal effect of scarcity on consumers quality premium for the unobservable attributes (aflatoxin safety). The estimates from equation 3 help to tease out the average scarcity effects for all participants regardless of their treatment group. In order to separate out the scarcity effect by information treatment group and given that the average prices are different across seasons, we estimate equation 2 twice: first in the harvest season and then in the lean season, and calculate and compare the quality premiums as percentages of the unsorted grade means across seasons..

3.4.1 Sampling weights

NASFAM lead farmers responsible for the GACs were used to inform farmers about our research surveys program. During study recruitment, we sampled 25 farmers per GAC where between 2 to 5 farmers per club were randomly selected regardless of club size or number of farmers that showed up on the day of survey in that club. It is, therefore, likely that the probability of a farmer being sampled varied across GACs as well as clubs. To deal with this issue, we used sampling weights based on the inverse proportionality to probability of being sampled based on the number of farmers per GACs who showed up on the day of training (Cameron and Trivedi 2005).

3.5 Results and Discussion

3.5.1 Baseline randomization balance checks

We start our analysis by evaluating the success of the randomization process. We used a probit model to evaluate if the outcome variables and household demographic variables are balanced across the treatment and control group. Table 3.1 present baseline randomization balance results for the information treatment with standard errors clustered at GAC level. Although our F-test results ($F=64$, $p<0.001$) suggest that our covariates are not jointly equal to zero, individual significance test suggests that all variables are not different from zero. This shows that none of the variables are individually correlated with the treatment indicator. Given the nature of our experiment which had, WTP as the outcome variable, we also evaluated balance with standard errors clustered at household level as it is likely that the bids for different quality grades for an individual household are correlated. Our results show that only six out of 24 variables are individually significant (See Appendix Table 3.3). These include baseline aflatoxin awareness score, landholding (acres), number of years in NASFAM, distance from home to the closest market (in km), a dummy variable for repeated auction participation, and an association dummy variable. These results also suggest that, on average, our treatment variable was not correlated with the covariates at baseline except for the six variables that showed some significant baseline differences across the treatment and control groups. We, therefore, take a conservative approach and control for these six variables in our estimation.

3.5.2 Summary statistics

Table 3.2 presents baseline summary statistics. The average WTP in Malawi Kwacha per kg for unsorted, sorted and labeled groundnuts grades were MK233, MK313 and MK334 respectively (US$1=MK750). At baseline (before the aflatoxins information treatment), participants were asked questions about aflatoxins and a baseline aflatoxins awareness score (0 to 10) was constructed based on participants' response to 10 key aflatoxins awareness questions (i.e. questions asked about aflatoxins indicators, crops affected, practices that proliferate aflatoxins in grain, its health effects and prevention). Participants got a score of 1 for each of the 10 questions that they got right. Only 43 percent of our sample scored above 50 percent in this baseline aflatoxins awareness survey.

3.5.3 Attrition bias

We conducted the baseline study during the 2019 harvest season (June) and this was followed by provision of aflatoxins information training and our first experimental auction. A total of 830 farmers participated in the first auction. In the lean season, which peaks six months (January) after harvest, we went back and conducted a follow-up survey with the same farmers. Ten percent of the households (85 households) from the first auction could not be located for the follow-up survey, either because they moved or changed location and contact details. Of the 85 households, 50 were in the treatment group and 35 in the control group.

In order to determine the possibility for attrition bias, we regressed the attrition binary indicator (1=could not be found for the lean season survey; 0=completed the lean season survey) on the treatment indicator, the WTP at baseline, and the baseline household characteristics.[10] Although the F-test shown in Table 3.3 ($F=274$, $p<0.001$) indicates that attrition was not random, individual significance test suggest that it was not correlated with the outcome or treatment indicator (i.e. satisfies Missingness Independent of Potential Outcomes condition but not

[10] Baseline aflatoxins knowledge score (0 to 10), age of respondent (years), years of schooling for respondent (years) Respondent' gender, Household size, Landholding (acres),number of years in NASFAM, number of school goers in household, number of females in household, number of adults in household (Age>18 years), distance from home to the closest market (in km), number of extension officer visits per year, television ownership, radio ownership, cash savings availability at the beginning harvest, storage expenditure (MK), number of months food insecure (0 to 12), long-term illness in the past 2 years, deaths in past two years, respondents' anchor price (MK), Association, and quality grade variables.

treatment).[11] We, therefore, control for attrition and the variable that was correlated with attrition in our analysis.

3.5.4 Main results

We report estimates from an Ordinary Least Squares (OLS) estimator, and columns (1) and (2) present estimates with standard errors clustered at household level where column (1) has baseline controls and (2) is does not have controls.

WTP for observable and unobservable quality attributes

Our results from Table 3.4 suggest that consumers have a significant quality premium for observable attributes as uninformed consumers were willing to pay about MK82 more for the sorted grade, on average, than for the unsorted grade ($p<0.001$). We also observe a significant quality premium for the unobservable quality attribute, aflatoxins safety. uninformed consumers were willing to pay about MK7 more for the labeled grade, on average, than for the sorted grade ($p=0.093$). These results show that the quality premium for the observable attribute (sorting) is higher than the quality premium for the unobservable attribute (aflatoxins safety). This suggests that in the status quo, consumers place a higher WTP value on observable quality attributes than on unobservable quality attributes on average. This is possibly due to limited awareness and/or understanding of the aflatoxin information and health risk posed by aflatoxins.

The impact of information treatment on WTP for quality

In order to tease out the causal impact of providing aflatoxins information on consumers' demand for quality, we interact the information treatment indicator with our quality grades variables. Our results in Table 3.5 suggest that informed consumers (treated) had a higher quality premium for both the observable and unobservable attribute compared to the uninformed consumers (control). We find significant marginal quality premiums for sorting and aflatoxin safety of about MK34 ($p<0.001$) and (MK55, $p<0.001$) respectively for the informed consumers (treated). Our results also show that consumers in the control group had a significant quality premium for sorting

[11] We report results for attrition bias checks with standard errors clustered at household level in Appendix Table 3.4 which suggest that the number of years worked with NASFAM and treatment may be correlated by attrition.

(MK82, $p<0.001$) but not for aflatoxin safety labelling (MK7, $p=0.093$). These results suggest that consumers do see the problem with unsorted grain (the observables attribute) but do not value unobservable attributes like aflatoxin safety. This finding corresponds with what Hoffmann et al. (2020) finds in Kenya where observable maize attributes had a significant effect on price, but not unobservable attributes, such as aflatoxin contamination. However, we learn from our results that providing aflatoxins information to consumers may increase their demand for aflatoxins safety, the unobservable quality attributes. Figure 3.4 below shows how WTP for the different grades varies by information treatment. Our comparison of the cost of testing in Table 3.8 shows that the marginal WTP for aflatoxin is higher than the cost of testing when consumers are informed about aflatoxins and its health risks. These results provide evidence that confirms the need to increase food quality or safety information campaigns for key food crops in Malawi, including groundnuts.

The impact of food scarcity on WTP for quality (i.e. food quantity versus quality)

In order to estimate the effect of scarcity on consumers' demand for quality, we compare their WTP in the harvest season to their WTP in lean season. Table 3.6 shows that respondents were willing to pay a quality premium of about MK80 ($p<0.001$) for sorting; the observable attribute during the harvest season. We also observe that consumers were willing to pay a quality premium of MK21 ($p<0.001$) for aflatoxin safety during the harvest season. Overall, we observe that marginal lean season quality premium for sorting was MK31 ($p=<0.001$) while that for aflatoxin safety was MK20 ($p<0.001$). This shows that when pooled together, the average willingness to pay for both sorting and labeling was relatively higher than their WTP in the harvest season. This is likely because of the price differences across the season.

In our further analysis of scarcity effects, we estimate equation (2) for each season separately and then calculate the sorting and labeling quality premiums as percentages of the unsorted grade mean. We then, compare these quality premium percentages across season to evaluate the effect of scarcity. Our results in Table 3.7 show that the informed consumers' quality premium for sorting was higher in the harvest season compared to the lean season: their quality premiums as a percent of the unsorted grade margin were 55% and 35% in harvest and lean season respectively. However, for labeling we observe that their quality premium was higher in the lean season compared to the harvest season (14% and 27% for the harvest and lean season respectively). This shows that the informed consumers cared more about labeling than sorting in the lean season.

This suggests that the information treatment increased their demand for labeling in the lean season when quality is likely to be scarce. It is also possible that due to scarcity, their demand for sorting diminished in the lean season as they may have considered conducting the sorting task themselves at home as long as the grain is safe.

However, for the uninformed consumers, we find that their quality premium for aflatoxin labeling decreased in the lean season relative to the harvest season (20% vs. 32% in harvest and lean season respectively), while their premium for sorting increased in the lean season relative to the harvest season (5% vs. 1% for harvest and lean season respectively). Our results help to show the impact of scarcity and information treatment on consumers demand for aflatoxin safety labeling. We find that relative to their quality premiums in harvest season, the informed (uninformed) households had higher (lower) quality premiums for labeling in the lean season. This may be due to scarcity in the lean season which may have diminished uninformed consumers' demand for labeling.

We learn from our results, therefore, that respondent's quality demand (observables) are more profound in the harvest season when grain is readily available compared to the lean season when scarcity strikes. Our findings highlight how the conflicting food quantity and quality objectives that households face during the lean season may push them to trade-off food quality for food quantity. These results highlight the need to identify and support initiatives or policy interventions that could help rural households achieve both food quality and security objectives. In addition, these results also expose the need for policy that would target increasing quality enforcement and monitoring (e.g. regular random checks like livestock informal markets) in the informal grain market during the lean season. Figure 3.5 and 3.6 shows the impact of food scarcity on WTP for different grades. Appendix Table 3.5 report results considering triple interaction between the information and seasonality dummy variables.

Economic Analysis

Table 3.8 presents results from our economic analysis which compares the cost of aflatoxin testing and labeling to the consumers ‘quality premium for aflatoxin labeling. We use the average testing and labeling cost incurred per 100-kg bag during the experiment to proxy the cost of aflatoxin testing and labeling per bag (MK5,462/ 100-kg bag). This is also close to the estimated cost of an average testing kit (e.g. AgraStrip kit at MK5,775 per test). Similarly, the estimated cost of aflatoxin information training is also proxied using the average cost incurred to train a household (i.e. MK2,400 per household). Our analysis using the estimates of quality premium for the uninformed group suggests that given the status quo, where there are no aflatoxin information interventions, the cost of testing and labeling exceeds the consumers' quality premium for aflatoxin testing and labeling. This result gives an explanation for the prevalence of the pooling equilibrium within informal grain markets as there is no incentive for producers and sellers to invest in aflatoxin testing and labeling.

However, when we consider the quality premiums for the informed consumers, we find that there is value in investing in aflatoxin testing and labeling for producers or sellers as the quality premium that informed consumers are willing to pay is higher than the cost of testing. This results helps to show the power of information as we observe that providing information alone can help to solve the market failure problem within the informal grain markets by creating an incentive for producers to differentiate their grain even without government enforcement of testing and labeling. These results, therefore, help to show the importance of increasing aflatoxin awareness s among consumers in rural markets. In addition, these results also help to bring to light the need for cheaper testing and labeling technologies as this could help reduce the cost and increase incentive for testing even when WTP for the label is relatively lower.

Effects of learning in repeated auction games (learning effects)

We carried out the experimental auction twice with the same households: 745 households (68 percent of the total sample) participated in both rounds of our experimental auctions.[12] It is possible that these households' bidding in the second auction may have been influenced by learning from the first auction's experience. To tease out possible learning effects, we randomly selected an additional sample in the lean season that included 268 (24 percent of total sample) households who only participated in the lean auction. We also considered households that attrited and only participated in the harvest auction as part of the households that are not affected by learning. As such, we created a dummy variable which equals one if the household participated in both rounds and zero if they did not participate in both auctions (i.e. are in the new sample or

[12] The total sample has 1098 farmers and the harvest auction had 830 of whom 85 attrited and the lean auction had 1013 farmers of whom 268 farmers were in the new sample.

attrited). This variable is used as a control variable in our analysis and we also estimate and report the effect of learning on households' demand for groundnuts quality by interacting the learning dummy variable with quality grade variables. Our results from all analyses suggest that there were no significant learning effects on demand for quality. Appendix Table 3.6 presents the specific results from our analysis of the impact of learning on quality demand. The estimates of marginal learning effect on quality premium for sorting was -MK6.25 (p=0.397) while the marginal learning effect on quality premium for aflatoxin safety was MK0.7 (p=0.713). These results suggest that learning did not have significant effect on households' quality valuations (see Figure 3.7).

3.6 Conclusion

For a credence food quality attribute like aflatoxins contamination, incomplete quality information within informal markets undermines consumers' demand for quality and lead to a lemons market. Literature shows that providing information can help improve farmers' grain post-harvest management practices (Magnan et al. 2019); help reduce aflatoxin proliferation (Pretari, Hoffmann, and Tian 2019) ; increase demand for technology to control and prevent aflatoxins (Channa 2019; Magnan et al. 2019); as well as influence consumers' purchase choices (Ordonez 2016). We also learn that when aware and faced with unobservable attributes like aflatoxins, farmers prefer self-provision than purchasing grain from the market(Hoffmann and Gatobu 2014). While these previous studies helped to show the how information affects adoption of post-harvest management practices, increases demand for aflatoxin managing technologies as well as reduce aflatoxin levels in grain, this present paper advances this literature by estimating the causal impact of providing aflatoxin information on consumers demand for grain quality.

We evaluate how quality labeling and increasing consumers' awareness about food quality and safety issues influence consumers' demand for observable and unobservable grain quality attributes in rural grain markets. A clustered randomized control trial (RCT) with 1098 farm households is used to evaluate whether providing aflatoxins information increases consumers' demand for grain quality and whether that demand for quality varies depending on food availability. For the outcome variable, Becker DeGroote Marshack auctions were used to elicit consumers' willingness to pay(WTP) for three quality grades of groundnuts:(i) visibly unsorted grade ("*the unsorted grade*"); (ii) visibly sorted grade without aflatoxins information label ("*the sorted grade*"); and (iii) visibly sorted and labeled "aflatoxins-safe"*("the labeled grade")*. The difference between the unsorted grade and sorted grade is considered a quality premium for sorting, the observable food quality attribute , while the difference between the sorted grade and the labeled grade is considered a quality premium for aflatoxins safety, the unobservable food quality attribute.

This study has three main research findings. First, we find that overall, consumers have significant quality premium for both the observable and unobservable quality attributes (MK96 and MK32 respectively). However, the estimated quality premium for the observable attribute (sorting) is significantly higher compared to the premium for the unobservable attribute (aflatoxins safety). This may be due to limited awareness and/or understanding of the aflatoxin information and health risk posed by aflatoxins also likely influenced consumers' valuation processes. This finding supports what Hoffmann et al. (2020; 2013) finds in Kenya where observable maize attributes had significant effect on price, but not unobservable attributes, such as aflatoxin contamination. Second, our results show that consumers that received the aflatoxins information treatment had higher quality premiums for both sorting (MK34 higher) and aflatoxins safety labeling (MK55 higher) compared to consumers in the control group. Lastly, we also find that consumers had significant quality premiums for both sorting and labeling during the harvest season. However, relative to their quality premiums in harvest season, the uninformed (informed) households had lower (higher) quality premiums for aflatoxin-safety labeling in the lean season: 5 percent (20 percent) premium for labeling in harvest season versus 1 percent (32 percent) premium in the lean season. This may be due to scarcity in the lean season which may have diminished uninformed consumers' demand for labeling.

Our analysis of the impact of providing aflatoxins information on consumers' demand for quality suggest that giving consumers information about aflatoxins and its health risks significantly increases their demand for quality especially aflatoxins safety, the unobservable grain quality attributes. It is likely that the new information about health risk associated by aflatoxins may have influenced consumers' beliefs and increased their quality demand. Our results suggest that raising awareness about aflatoxins and the health risk posed by it may help to increase consumers' demand for grain quality especially for unobservable attributes like aflatoxins safety. Therefore, in terms of policy, our results highlight the need to increase aflatoxins information campaigns for key food crops in Malawi including groundnuts. Our comparison of the cost of testing shows that the marginal WTP for aflatoxin is higher than the cost of testing when consumers are informed about aflatoxins and its health risks. In addition, our results suggest that consumers' quality demand is more profound in the harvest season when grain is readily available compared to the lean season when they face scarcity. Conflicting food security objectives (i.e. to achieving both desired food quantities and quality) that households face during the lean season likely influence them to trade-off food quality for quantity. These results expose the need for policy that re-enforces aflatoxin testing and regulations in informal markets especially during the lean season when consumers' own quality demand is compromised.

3.7 Funding Declaration

We would like to acknowledge funding support from the United States Office of Foreign Disaster Assistance under agreement AID-OFDA-G-17-00250, for the project titled "Increasing Smallholder Malawian Farmers' Access to Improved Storage Technology and Credit" and The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) and the Global Alliance on Agricultural Green Gases (GRA) through their CLIFF-GRADS research fellowship programme.

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3.9 Figures and Tables

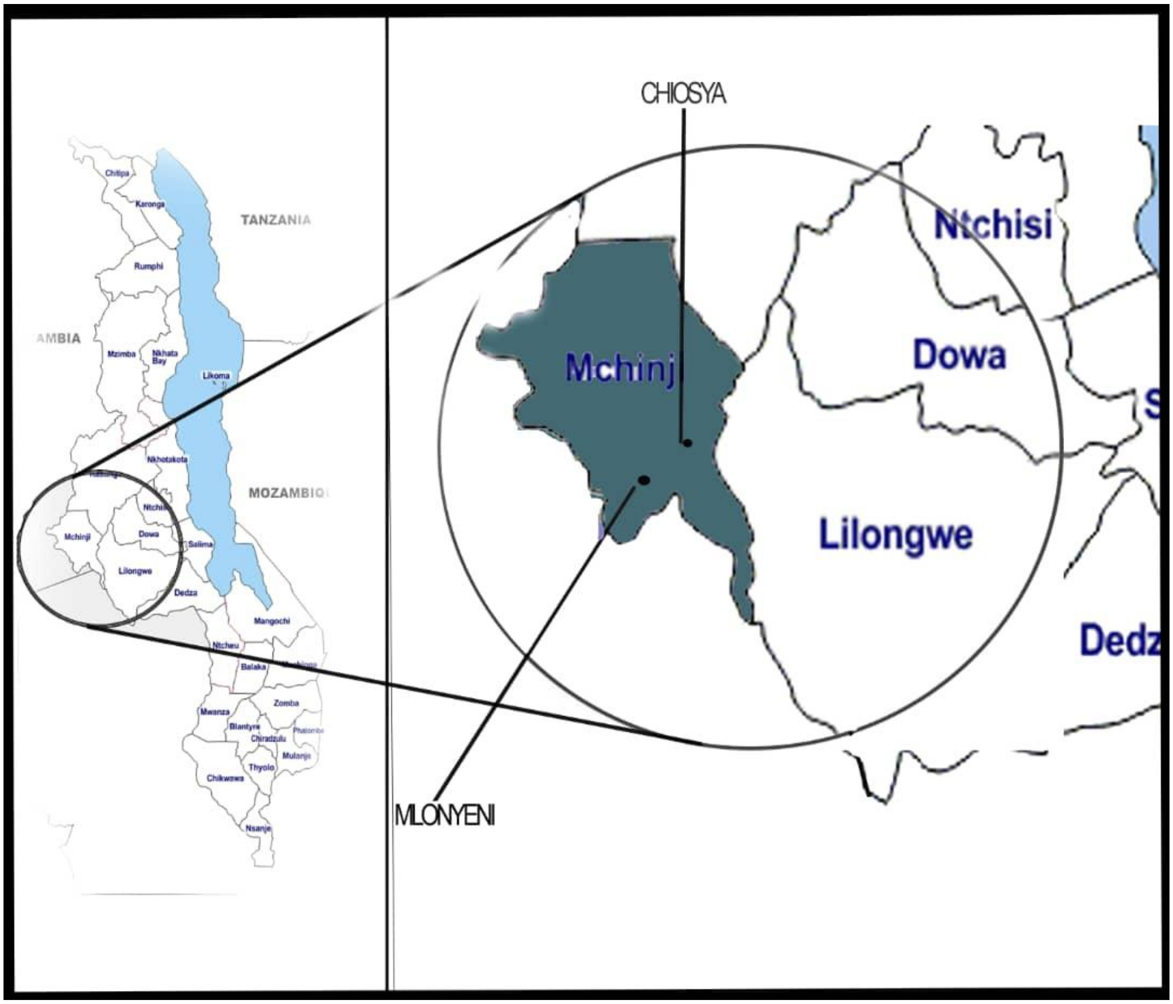

Figure 3.1: Study Area

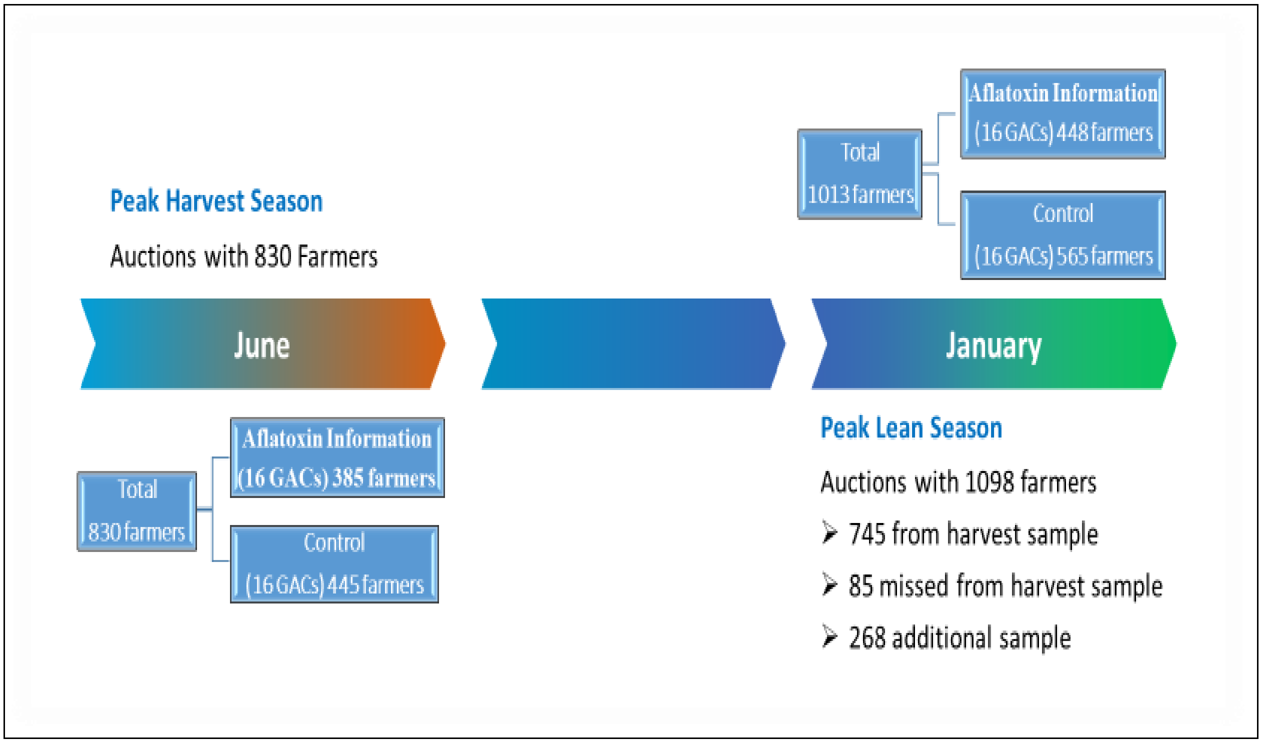

Figure 3.2: Study consort diagram and timeline

Figure 3.3: Auction Samples

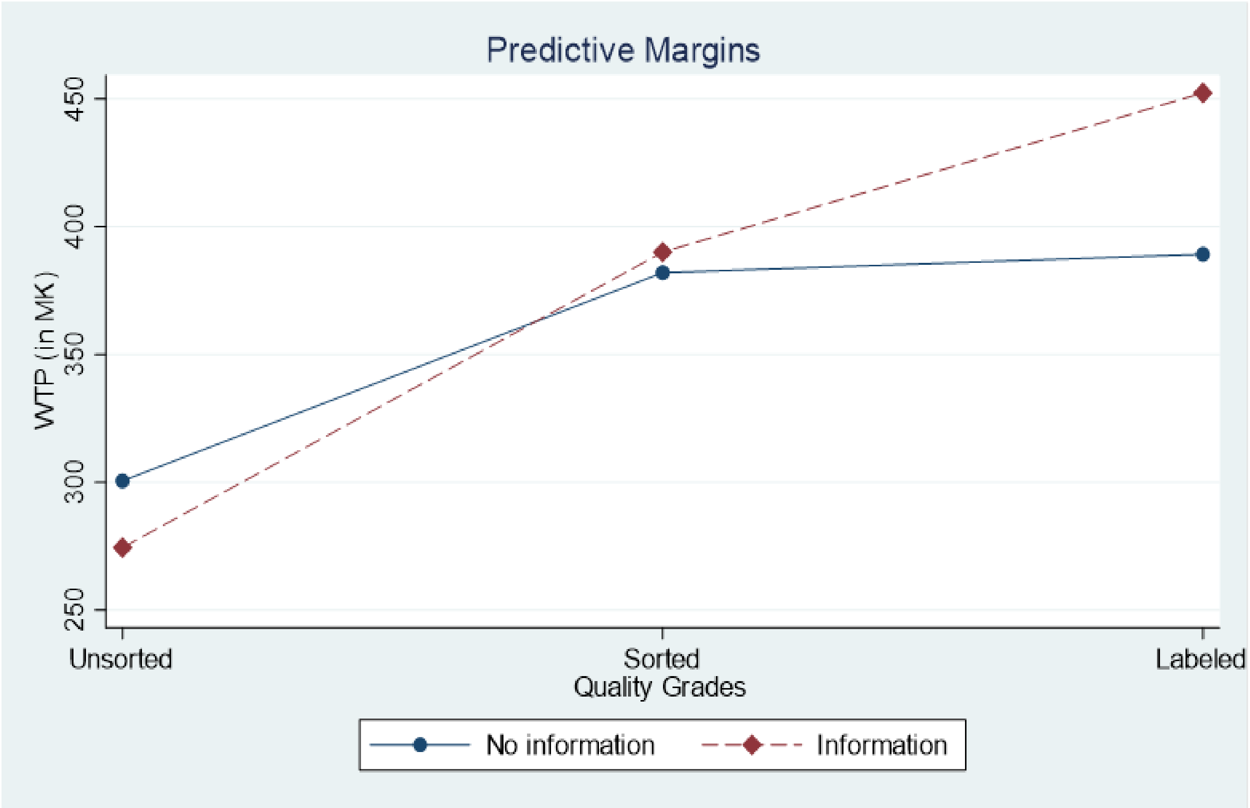

Figure 3.4: Effect of Information Treatment on WTP for Different Groundnuts Quality Grades

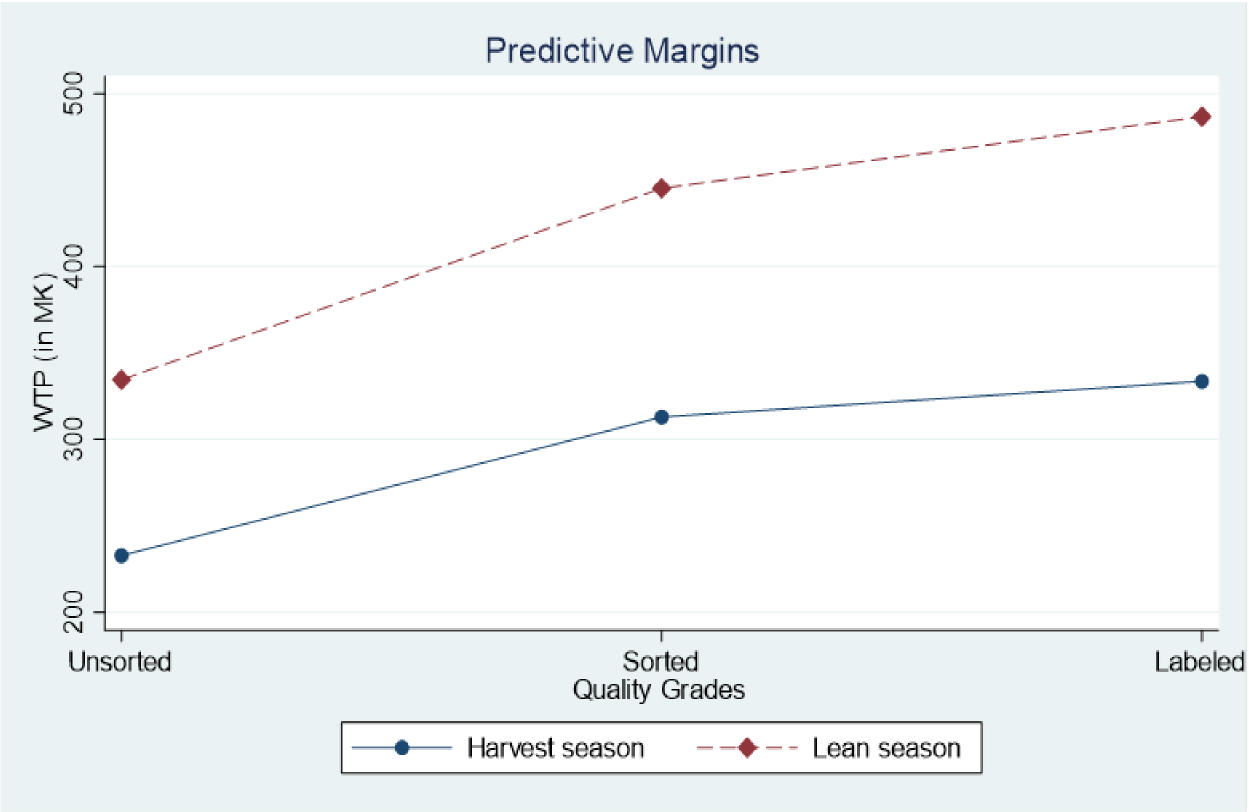

Figure 3.5: Effect of Scarcity or Seasonality on WTP for Different Groundnuts Quality Grades

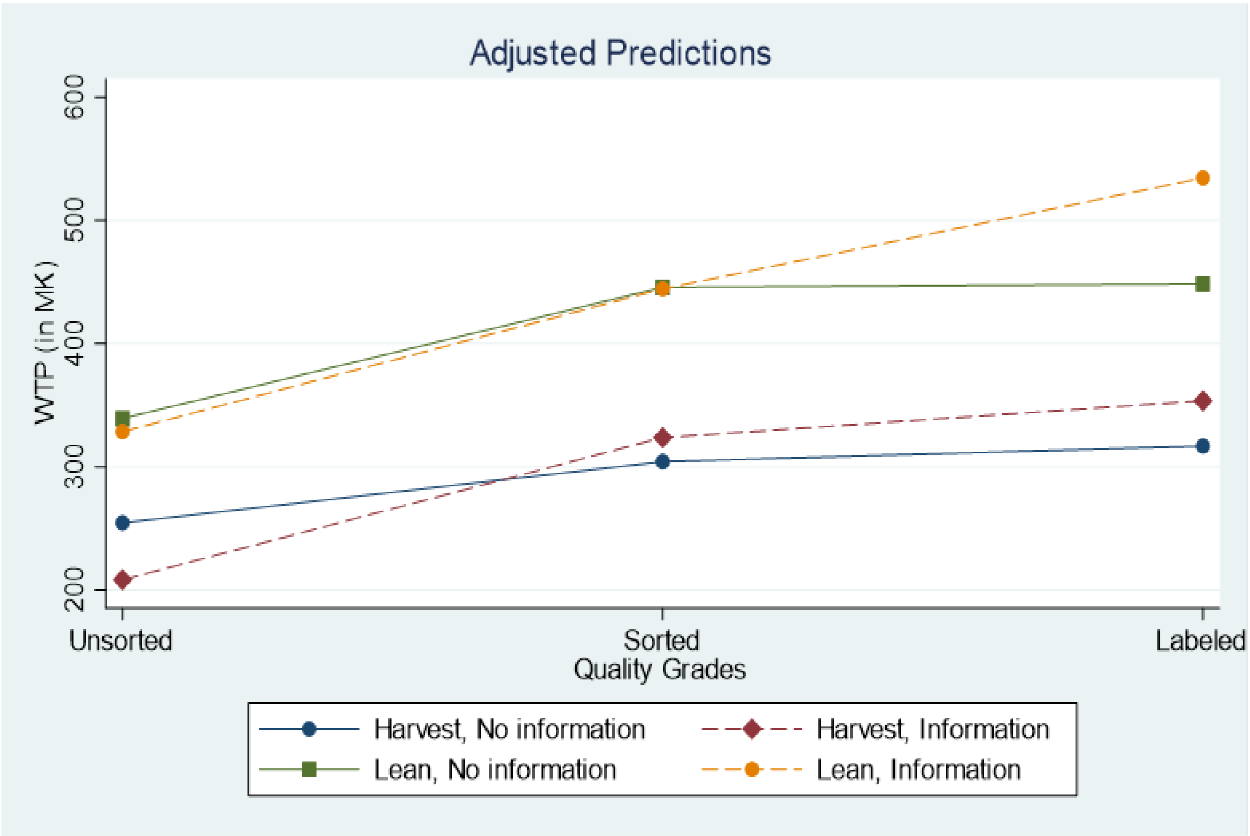

Figure 3.6: Effect of Information and Scarcity on WTP for Groundnuts Quality Grades

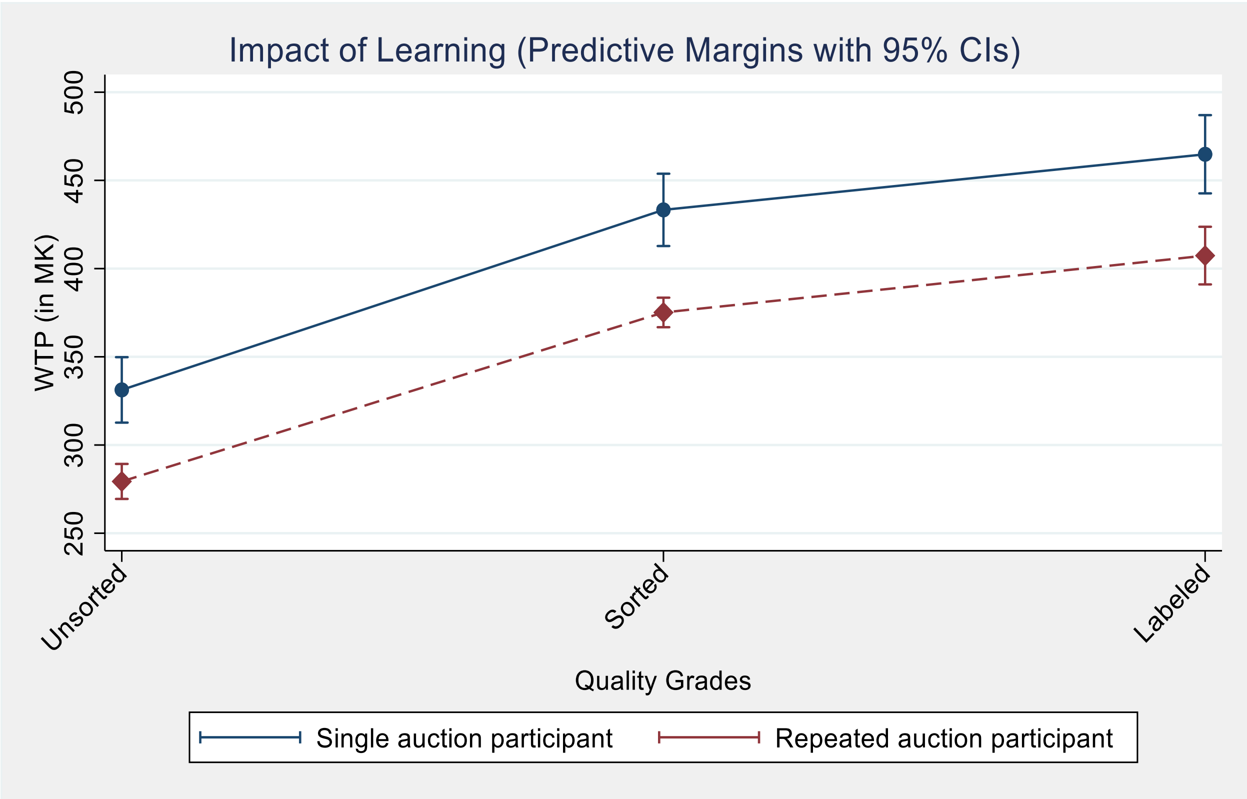

Figure 3.7: Effect of Learning on WTP for Different Groundnuts Quality Grades

Table 3.1: Baseline Balance Checks using Joint Orthogonality test

Outcome variable:	Information Treatment: 1= informed about aflatoxins (treatment), 0=not informed (control)
Standard errors clustered at:	GAC level
Willing to Pay in Malawi Kwacha (MK)	0.0002
	(0.0004)
Baseline aflatoxins knowledge score (0 to 10)	0.0337
	(0.0216)
Age of respondent (years)	0.0027
	(0.0042)
Years of schooling for respondent (years)	0.0114
	(0.0160)
=1 if Respondent is Male	0.0354
	(0.1324)
Household size	-0.0276
	(0.0486)
Landholding (Acres)	-0.0808
	(0.1060)
Number of years in NASFAM	-0.0280
	(0.0203)
Number of school goers in household	0.0315
	(0.0518)
Number of females in household	0.0184
	(0.0505)
Number of adults in household (Age>18 years)	-0.0322
	(0.0469)
Distance from your home is the closest market (in km)	-0.0102
	(0.0072)
No of Extension officer visits per year	0.0057
	(0.0070)
=1 if Household owns a television set	0.0908
	(0.2151)
=1 if Household owns radio set	0.0800
	(0.1059)
=1 Had cash savings at the beginning harvest	-0.0730
	(0.1320)
Storage Expenditure (Malawi Kwacha)	-0.0000
	(0.0000)
Number of months Food insecure (0 to 12)	-0.0453
	(0.0318)
=1 if member too ill to farm for >2 months in past 2 years	0.0860
	(0.1017)
=1 if had deaths in past two years	0.2756
	(0.1800)
=1 if representative of original participant	0.0730
	(0.2034)
Respondents' Anchor price (MK)	0.0014
	(0.0020)
=1 if repeated auction participant (Learning effects)	-0.3127
	(0.2361)
=1 if Assoc. is Chioshya	0.1697
	(0.5391)
Constant	-0.0964
	(0.9754)
Observations	2,490
Number of Households	830
F-Test	F=64, p<0.001

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1; The GAC is community level cluster at which treatment was assigned; Balance checks results with household level clustering are in the appendix with 6 out of 24 variables statistically significant. We control for these in our analysis to be conservative. The exchange rate is 1 US$=750 Malawi Kwacha. Baseline aflatoxins knowledge score (0 to 10) is constructed based on participants' response to 10 aflatoxins awareness questions (i.e. questions ask about aflatoxins indicators, causes, health effects and prevention). Participants got a score of 1 for each of the 10 questions that they got right.

Table 3.2: Baseline Summary Statistics

Panel A: Outcome Variables	Count	Mean	Std. Dev.	Min	Max
WTP Unsorted Groundnuts (MK)	830	233	104	70	740
WTP Sorted Groundnuts (MK)	830	313	104	50	760
WTP Labeled Groundnuts (MK)	830	334	103	70	870
Panel B: Household Observables					
Baseline aflatoxins knowledge score (0 to 10)	830	4.14	10.65	0	10
=1 if baseline aflatoxins awareness score >median	830	0.43	0.49	0	1
Age of respondent (years)	830	39.00	11.97	17	69
years of schooling for respondent (years)	830	5.69	3.69	0	38
=1 if Respondent is Male	830	0.48	0.49	0	1
Household size	830	5.42	1.84	1	12
Landholding (Acres)	830	3.50	1.65	.4	10
Number of years in NASFAM	830	4.35	3.52	0	30
Number of school goers in household	830	2.46	1.56	0	9
Number of females in household	830	2.69	1.27	0	9
Number of adults in household (Age>18 years)	830	2.55	1.12	0	9
Distance from your home is the closest market (in km)	830	12.14	16.57	0	300
No of Extension officer visits per year	830	5.17	7.62	0	28
=1 if Household owns a television set	830	0.04	0.20	0	1
=1 if Household owns radio set	830	0.49	0.49	0	1
=1 Had cash savings at the beginning harvest	830	0.26	0.44	0	1
Storage Expenditure (MK)	830	2,075.00	5,263.00	0	91,000
Number of months Food insecure (0 to 12)	830	1.57	1.45	0	10
=1 if member too ill to farm for >2 months in past 2 years	830	0.21	0.40	0	1
=1 if had deaths in past two years	830	0.07	0.25	0	1
=1 if representative of original participant	830	0.20	0.40	0	1
Respondents' Anchor price (MK)	830	299.00	30.00	0	450
=1 if repeated auction participant (learning effects)	830	0.89	0.30	0	1
=1 if Association is Chioshya	830	0.52	0.49	0	1

Note: MK is Malawi Kwacha where 1 US$=750 Malawi Kwacha; Baseline aflatoxins knowledge score (0 to 10) is constructed based on participants' response to 10 aflatoxins awareness questions (i.e. questions ask about aflatoxins indicators, causes, health effects and prevention). Participants got a score of 1 for each of the 10 questions that they got right.

Table 3.3: Attrition Bias checks using Joint Orthogonality Test

Outcome variable:	Attrition: 1= Participant Attrited 0=if did not attrite)
Standard errors clustered at:	GAC level
Information Treatment	0.2330
	(0.1892)
Willing to Pay (MK)	0.0001
	(0.0004)
Baseline Aflatoxins Knowledge Score (0 to 10)	0.0047
	(0.0143)
Age of respondent (years)	-0.0040
	(0.0053)
Years of schooling for respondent (years)	-0.0045
	(0.0191)
=1 if Respondent is Male	0.0456
	(0.0983)
Household size	0.0675
	(0.0503)
Landholding (Acres)	-0.0543
	(0.0479)
Number of years in NASFAM	-0.0951***
	(0.0322)
Number of school goers in household	-0.0254
	(0.0597)
Number of females in household	-0.0099
	(0.0604)
Number of adults in household (Age>18 years)	-0.0528
	(0.0683)
Distance from your home is the closest market (in km)	-0.0018
	(0.0036)
No of Extension officer visits per year	-0.0127
	(0.0106)
=1 if Household owns a television set	-0.4087
	(0.3313)
=1 if Household owns radio set	-0.1093
	(0.1108)
=1 Had cash savings at the beginning harvest	-0.2167
	(0.1744)
Storage Expenditure (MK)	-0.0000
	(0.0000)
Number of months Food insecure (0 to 12)	-0.0107
	(0.0422)
=1 if member too ill to farm for >2 months in past 2 years	-0.0468
	(0.1126)
=1 if had deaths in past two years	0.1507
	(0.2034)
Respondents' Anchor price (MK)	-0.0004
	(0.0015)
=1 if Assoc. is Chioshya	0.1327
	(0.2134)
Constant	-0.6157
	(0.8348)
Observations	2,490
Number of Households	830
F-test	F=274, p<0.001

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1; The GAC is community level cluster at which treatment was assigned; Balance checks results with household level clustering are in the appendix with 6 out of 24 variables statistically significant. We control for these in our analysis to be conservative. The exchange rate is 1 US$=750 Malawi Kwacha. Baseline aflatoxins knowledge score (0 to 10) is constructed based on participants' response to 10 aflatoxins awareness questions (i.e. questions ask about aflatoxins indicators, causes, health effects and prevention). Participants got a score of 1 for each of the 10 questions that they got right.

Table 3.4: WTP for Observable and Unobservable Groundnuts Quality Attributes

Panel A: Coefficient Estimates	**Uninformed respondents**	**All Respondents**
=1 if sorted grade	82***	97***
	(4)	(3)
=1 if labeled grade	89***	129***
	(4)	(3)
Constant	353***	342***
	(15)	(11)
Observations	3,030	5,529
R-squared	0.11	0.15
Number of unique respondents	600	1,098
Mean WTP for unsorted grade	302	289
Labeling premium (labeled grade-sorted grade)	7*	32*
Test of H1: Sorting premium = Labeling premium		
F statistic	123	163
Prob > F	p<0.001	p<0.001
Panel B: Premiums as percent of unsorted grade Mean	**Uninformed respondents**	**All respondents**
Variable	Unsorted grade margin=302	Unsorted grade margin=289
Sorting premium as % of margin for unsorted grade	27%	34%
Labeling premium as % of margin for unsorted grade	2%	11%

Note: Standard errors clustered at GAC level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The GAC is community level cluster at which treatment was assigned; WTP is in Malawi Kwacha per kg (US$1=MK750). The sorting premium is the coefficient on the sorted grade variable; the labeling premium is the difference (labeled grade coefficient – sorted grade coefficient).

Table 3.5: Effect of information treatment on WTP for groundnuts quality

Panel A: Coefficient Estimates		**All Respondents**
=1 if sorted grade		82***
		(3)
=1 if labeled grade		89***
		(5)
=1 if respondent was informed		-26***
		(7)
Sorted grade * Informed		34***
		(6)
Labeled grade * Informed		89***
		(7)
Constant		352***
		(12)
Observations		5,529
R-squared		0.17
Number of unique respondents		1,098
Mean WTP for unsorted grade and uninformed respondents		300
Labeling premium for uninformed respondents		7*
Labeling premium for informed respondents		62***
Test of H2a: Sorting premium for informed = Sorting premium for uninformed		
F statistic		31
Prob > F		p<0.001
Test of H2b: Labeling premium for informed = Labeling premium for uninformed		
F statistic		97
Prob > F		p<0.001
Panel B: Premium as percent of mean WTP for unsorted grade and uninformed respondents		
	Uninformed Respondents	**Informed Respondents**
Sorting premium (%)	27%	39%
Labeling premium (%)	2%	21%

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1 and WTP in Malawi Kwacha per kg (US$1=MK750); The GAC is community level cluster at which treatment was assigned; See Appendix Table 3.2 which shows that the impact of the information treatment on the sorting premium is the coefficient on Sorted grade *Information while the impact of the information treatment on the labeling premium is the difference (Labeled grade * Information – Sorted grade * Information).

Table 3.6: Effect of seasonality on WTP for groundnuts quality

Panel A: Coefficient Estimates		**All Respondents**
=1 if Sorted grade		80***
		(8)
=1 if Labeled grade		101***
		(10)
=1 if Lean season		104***
		(10)
Sorted grade * Lean		31***
		(8)
Labeled grade * Lean		51***
		(6)
Constant		226***
		(12)
Observations		5,529
R-squared		0.31
Number of unique respondents		1098
Mean WTP for unsorted grade in the harvest season		232
Labeling premium in harvest season		21***
Labeling premium in lean season		41***
Test of H3a: Sorting premium for harvest = Sorting premium for lean		
F statistic		23
Prob > F		p<0.0001
Test of H3b: Labeling premium for harvest = Labeling premium for lean		
F statistic		13
Prob > F		P=0.0002
Panel B: Premium as percent of mean WTP for unsorted grade and uninformed respondents		
	Harvest season	**Lean season**
Sorting premium (%)	35%	48%
Labeling premium (%)	9%	18%

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1 and WTP in Malawi Kwacha per kg (US$1=MK750); The GAC is community level cluster at which treatment was assigned; See Appendix Table 3.2 which shows that the impact of the seasonality on the sorting premium is the coefficient on Sorted grade * Lean while the impact of the seasonality on the labeling premium is the difference (Labeled grade * Lean – Sorted grade * Lean).

Table 3.7: Effect of information on WTP for groundnuts quality, by season

Panel A: Coefficient Estimates	**(1)**	**(2)**
Season:	**Harvest**	**Lean**
=1 if Sorted grade	50***	107***
	(5)	(3)
=1 if Labeled grade	62***	109***
	(6)	(5)
=1 if respondent was informed	-46***	-8
	(9)	(10)
Sorted grade * Informed	66***	9
	(8)	(8)
Labeled grade * Informed	83***	97***
	(9)	(10)
Constant	246***	345***
	(14)	(17)
Observations	2,490	3,039
R-squared	0.18	0.20
Number of respondents	830	1013
Labeling premium for uninformed	12**	2
Labeling premium for the informed	29***	88***
Test of H2a: Sorting premium for informed = Sorting premium for uninformed		
F statistic	49	1.3
Prob > F	p<0.0001	p=2540
Test of H2b: Labeling premium for informed = Labeling premium for uninformed		
F statistic	3.75	159
Prob > F	P=0.053	p<0.0001

Panel B: Comparing premiums as percent of unsorted mean in each season.				
Premium as % of unsorted grade mean	**Harvest Informed**	**Harvest Uninformed**	**Lean Informed**	**Lean Uninformed**
Mean WTP for unsorted grade by group	**208**	**255**	**330**	**338**
Sorting Premium (%):	56%	20%	35%	32%
Labeling Premium (%)	14%	5%	27%	1%

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1 and WTP in Malawi Kwacha per kg (US$1=MK750); The GAC is community level cluster at which treatment was assigned; See Appendix Table 3.2 which shows that the impact of the information treatment on the sorting premium is the coefficient on Sorted grade *Information while the impact of the information treatment on the labeling premium is the difference (Labeled grade * Information – Sorted grade * Information).

Table 3.8: Aflatoxin Testing Cost compared to WTP for Aflatoxin Safety Labeling

	Aflatoxins-safety labelling premium per 100 kg bag	Estimated cost of testing per 100 kg bag	Estimated cost of Information Treatment per household
Uninformed households	MK700 (Estimate is (MK7/kg)	MK5,472	0[13]
Informed households	MK 6,200 (Estimate is MK62/kg)	MK5,472	MK2,400

Note: Aflatoxin testing costed MK16,416 per test of a batch and it costed a total of MK 65,664 for all our experimental tests for a total of 1,200 kg of groundnuts. This is equivalate to about MK54,72/100-kg bag which is equivalent to about $7.3 (1US$=MK750). This cost estimate is close to the average test strip cost of about $7.7 (e.g. Seedburo's Agra Strip kit costs $186 per kit for 24 test). The cost of information treatment per household is estimated by dividing the total training cost incurred during experiment by the number of households trained. This estimate is higher than what it would be if we consider interventions by government which already has agricultural extension staff in every agricultural extension planning area.

[13] The cost of training was also MK2,400 per household for the uninformed group during the end of study training as per IRB requirement.

Appendix: Supplementary Information, Tables And Figures

Appendix 3.1: Aflatoxins testing procedures, results and labeling

Samples of each crop were collected from two traders (i.e. traders samples were labeled A and B) for testing before purchasing. This was done to ensure purchase and use of grain that was safe for consumption by the MBS quality standards of 10ppb or less for the experiments. Considering the opportunity to sell 1200 kg of grain, both traders allowed us to take (buy) samples for testing and report results. We thus, purchased grain that was safe (from trader A) and then sorted half of the grain (removed any broken or foreign materials) to create the visible or observable differences between the unsorted grade and the other two sorted quality grade: sorted and unlabeled grade as well as the sorted and labeled “aflatoxins tested and safe” grade. In order to distiguish the sorted grade and the labeled grade a sticker which was labeled aflatoxins tested and safe was added to the labeled grade and copies of results from our aflatoxins analysis were displayed during the experimental auctions to assure respondents of aflatoxins test and label validity. Below is the aflatoxins test certificate from the laboratory in Lilongwe that tested our grain.

VALID NUTRITION

Valid Nutrition, Box 202, Lilongwe, Malawi
+265 (0)1 712 488 malawi@validnutrition.org www.validnutrition.org

DATE: 15/05/2019

Sample type: Raw nut and Maize
Sample ID: Grade A & B
Test required: Total aflatoxin
Date analysis started: 15/05/2019

CERTIFICATE OF ANALYSIS

1. Mycotoxin test

SAMPLE	TEST	RESULT	UNITS	METHOD	LAB REFERENCE NUMBER
Maize (A)	Total aflatoxin	1.7	ppb	Fluorometry	CHE/19/AO/17
Maize (B)	Total aflatoxin	0.71	ppb	Fluorometry	CHE/19/AO/17
Raw nut (A)	Total aflatoxin	2.1	ppb	Fluorometry	CHE/19/AO/17
Raw nut (B)	Total aflatoxin	41	ppb	Fluorometry	CHE/19/AO/17

Declaration

The undersigned hereby certify that the data is true to the specification of the obtained results of tests

Emmanuel Mawanga
Quality Assurance and Control Supervisor

Chikondi Matiki
Quality Assurance Manager

Appendix 3.2: Aflatoxins Training Script for the Food Safety Study

We will now take you through a training session to inform you about Aflatoxins prevalence, its health effects as well as how to control or prevent contamination.

What are aflatoxins?

Aflatoxins are carcinogenic poisons produced by molds or fungus such as *Aspergillus flavus* and *Aspergillus parasiticus* which are usually found in improperly stored food. These toxins are invisible and tasteless such that it is hard for a consumer to detect them in their food without use of some lab equipment.

Which crops and foods are affected by Aflatoxins?

As pointed out earlier aflatoxins are found in improperly stored food including maize, rice, sorghum, cassava, groundnuts and millet amongst other staple foods. Molds are a key indicator of aflatoxins and these can also grow in flour or spices that are not stored properly and contaminate them with aflatoxins. Feeding animals grain contaminated with molds can also affect the products we get from them such as milk as these toxins can be carried over and are difficult to neutralize. Aflatoxins cannot be neutralized by cooking or processing. Some traditional food processing procedures especially those that increase moisture content can also increase aflatoxins infestation in food.

Health Effects and Economic Costs

Consumption of aflatoxins in large quantities can cause aflatoxicosis. This condition involves abdominal pain, vomiting, fever, diarrhea and convulsions. There has been several publicized epidemics in other countries like Kenya and Tanzania, but it is likely that people in Malawi experience this but few reports it.

Chronic consumption of aflatoxins in small quantities which is more prevalent in Malawi is also dangerous. This is because it can suppress the immune system, cause stunting, malnutrition, especially in children. There extensive research evidence that suggest a strong correlation between chronic aflatoxins exposure and liver diseases and cancers. Besides, because maize is a staple food crop in Malawi, taking up to about 60 percent of the daily caloric intake, it is likely that Malawians may be at high risk of chronic exposure to aflatoxins. For children who are mostly feed grain-processed products like porridges and puddings (*"Phala")* as weaning foods, this may also be a serious health threat.

Aflatoxins contamination in grain can also pose economic threat by limiting farmers access to high value markets. For example, for export markets and local processing sectors, there are limitation in terms of aflatoxins contents for grain, as such farmers that have contaminated grain with aflatoxins level beyond the allowable levels can fail to access such markets and this can have significant effects on the economy as well as reduce incomes for farmers. There has been limited awareness about aflatoxins in Malawi with the few initiatives focused on Groundnuts mostly because of the need to deal with such barrier to markets. However, not much has been done to raise consumer awareness about aflatoxins prevalence in different food crops especially those sold/purchased from informal grain markets such as groundnuts and maize. Our purpose is to raise awareness about aflatoxins prevalence and its health effects

How to Avoid Contaminations (Dealing with Practices that Proliferate aflatoxins)?

Aflatoxins contamination can be avoided in many ways in the different stages of production.

- ***During production***, farmers can use some bio pesticides like Afla-safe to control aflatoxins while the crops are still in the fields.
- ***During harvest***, farmers can avoid contamination by avoiding direct grain contact with soils i.e. not piling grain on the ground before and during harvesting.
- ***After harvest***, farmers can avoid aflatoxins contamination by ensuring that their grain is properly dried before packing as well as avoiding drying grain directly on the ground. This is because high moisture content promotes aflatoxins growth.
- ***During storage***, farmers can also further control aflatoxins by using effective storage technologies like hermetic bags (PICS bags) which have proven to be more effective at controlling molds.

Appendix Table 3.1: Information for Actual Power Calculations

Baseline Actual Means and ICC (GAC-Community level)					
Outcome Variable	**Count**	**Mean**	**SE**	**ICC**	**SE (4 ICC)**
Groundnuts WTP (MK)	830	293	112	0.016	0.0077
Groundnuts Anchor price (MK)	830	298	31.94	0.051	0.0174
Baseline Actual Means and ICC (CLUB-village level)					
Outcome Variable	**Count**	**Mean**	**SE**	**ICC**	**SE (4 ICC)**
Groundnuts WTP (MK)	830	293	112	0.088	0.0156
Groundnuts Anchor price (MK)	830	298	31.94	0.245	0.0252

Appendix Table 3.2: Details of Hypothesis Test by Equation Parameters

	Impact of information: Equation 2 $WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 I_{it} + \beta_4 T_{it} + \beta_7 X_{it} + \delta_1 I_{it} * S_{it} + \delta_2 I_{it} * L_{it} + \sigma_i + \varepsilon_{ijt.}$	
	Observable quality premium: WTP for sorted grade – WTP for unsorted grade	
1.	WTP for unsorted grade, uninformed participant	β_0
2.	WTP for unsorted grade, informed participant	$\beta_0 + \beta_3$
3.	WTP for sorted grade, uninformed participant	$\beta_0 + \beta_1$
4.	WTP for sorted grade, informed participant	$\beta_0 + \beta_1 + \beta_3 + \delta_1$
5.	Observable quality premium for uninformed participant = (3)-(1)	$\beta_0 + \beta_1 - \beta_0 = \boldsymbol{\beta_1}$
6.	Observable quality premium for informed participant =(4)-(2)	$\beta_0 + \beta_1 + \beta_3 + \delta_1 - \beta_0 - \beta_3 = \boldsymbol{\beta_1 + \delta_1}$
7.	**Impact of information on observable quality premium (H2a)** = (6)-(5)	$\beta_1 + \delta_1 - \beta_1 = \boldsymbol{\delta_1}$
	Unobservable quality premium: WTP for labeled grade – WTP for sorted grade	
1.	WTP for sorted grade, uninformed participant	$\beta_0 + \beta_1$
2.	WTP for sorted grade, informed participant	$\beta_0 + \beta_1 + \beta_3 + \delta_1$
3.	WTP for labeled grade, uninformed participant	$\beta_0 + \beta_2$
4.	WTP for labeled grade, informed participant	$\beta_0 + \beta_2 + \beta_3 + \delta_2$

5.	Unobservable quality premium for uninformed participant = (3)-(1)	$\beta_0 + \beta_2 - \beta_0 - \beta_1 = \boldsymbol{\beta_2 - \beta_1}$
6.	Unobservable quality premium for informed participant = (4)-(2)	$\beta_0 + \beta_2 + \beta_3 + \delta_2 - \beta_0 - \beta_1 - \beta_3 - \delta_1 = \boldsymbol{\beta_2 + \delta_2 - \beta_1 - \delta_1}$
7.	**Impact of information on unobservable quality premium (H2b)** = (6)-(5)	$\beta_2 + \delta_2 - \beta_1 - \delta_1 - \beta_2 + \beta_1 = \boldsymbol{\delta_2 - \delta_1}$

Impact of food scarcity: Equation 3

$$WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 I_{it} + \beta_4 T_{it} + \beta_7 X_{it} + \alpha_1 S_{it} * T_{it} + \alpha_2 L_{it} * T_{it} + \sigma_i + \varepsilon_{ijt}$$

According to the same logic as Equation 2:

The average impact of food scarcity on the observable quality premium (H3a)	$\boldsymbol{\alpha_1}$
The average impact of food scarcity on the unobservable quality premium (H3b)	$\boldsymbol{\alpha_2 - \alpha_1}$.

Equation 4 in Appendix 3.9: Impact of food scarcity for informed vs. uninformed consumers (Triple effects)

$$WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 I_{it} + \beta_4 T_{it} + \beta_5 X_{it} + \delta_1 I_{it} * S_{it} + \delta_2 I_{it} * L_{it} + \alpha_1 T_{it} * S_{it} + \alpha_2 T_{it} * L_{it} + \alpha_3 T_{it} * I_{it} + \gamma_1 I_{it} * S_{it} * T_{it} + \gamma_2 I_{it} * L_{it} * T_{it} + \sigma_i + \varepsilon_{ijt.}$$

Harvest Observable quality premium: WTP for sorted grade – WTP for unsorted grade

	Observable quality premium: WTP for sorted grade – WTP for unsorted grade	
1.	WTP for unsorted grade, uninformed participant, harvest	β_0
2.	WTP for unsorted grade, informed participant, harvest	$\beta_0 + \beta_3$
3.	WTP for sorted grade, uninformed participant, harvest	$\beta_0 + \beta_1$
4.	WTP for sorted grade, informed participant, harvest	$\beta_0 + \beta_1 + \beta_3 + \delta_1$
5.	Observable quality premium for uninformed participant = (3)-(1)	$\beta_0 + \beta_1 - \beta_0 = \boldsymbol{\beta_1}$
6.	Observable quality premium for informed participant (4)-(2)	$\beta_0 + \beta_1 + \beta_3 + \delta_1 - \beta_0 - \beta_3 = \boldsymbol{\beta_1 + \delta_1}$
7.	**Harvest Impact of information on observable quality premium (H3a)** = (6)-(5)	$\beta_1 + \delta_1 - \beta_1 = \boldsymbol{\delta_1}$

	Harvest Unobservable quality premium: WTP for labeled grade – WTP for sorted grade	
1.	WTP for sorted grade, uninformed participant, harvest	$\beta_0 + \beta_1$
2.	WTP for sorted grade, informed participant, harvest	$\beta_0 + \beta_1 + \beta_3 + \delta_1$
3.	WTP for labeled grade, uninformed participant, harvest	$\beta_0 + \beta_2$
4.	WTP for labeled grade, informed participant, harvest	$\beta_0 + \beta_2 + \beta_3 + \delta_2$
5.	Unobservable quality premium for uninformed participant = (3)-(1)	$\beta_0 + \beta_2 - \beta_0 - \beta_1 = \boldsymbol{\beta_2 - \beta_1}$
6.	Unobservable quality premium for informed participant = (4)-(2)	$\beta_0 + \beta_2 + \beta_3 + \delta_2 - \beta_0 - \beta_1 - \beta_3 - \delta_1 = \boldsymbol{\beta_2 + \delta_2 - \beta_1 - \delta_1}$
7.	**Impact of information on unobservable quality premium (H3b)** = (6)-(5)	$\beta_2 + \delta_2 - \beta_1 - \delta_1 - \beta_2 + \beta_1 = \boldsymbol{\delta_2 - \delta_1}$

$$WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 I_{it} + \beta_4 T_{it} + \beta_5 X_{it} + \delta_1 I_{it} * S_{it} + \delta_2 I_{it} * L_{it} + \alpha_1 T_{it} * S_{it} + \alpha_2 T_{it} * L_{it} + \alpha_3 T_{it} * I_{it} + \gamma_1 I_{it} * S_{it} * T_{it} + \gamma_2 I_{it} * L_{it} * T_{it} + \sigma_i + \varepsilon_{ijt.}$$

Lean Observable quality premium: WTP for sorted grade – WTP for unsorted grade

Observable quality premium: WTP for sorted grade – WTP for unsorted grade		
1.	WTP for unsorted grade, uninformed participant, lean	$\beta_0 + \beta_4$
2.	WTP for unsorted grade, informed participant, lean	$\beta_0 + \beta_3 + \beta_4 + \alpha_3$
3.	WTP for sorted grade, uninformed participant, lean	$\beta_0 + \beta_1 + \beta_4 + \alpha_1$
4.	WTP for sorted grade, informed participant, lean	$\beta_0 + \beta_1 + \beta_3 + \beta_4 + \delta_1 + \alpha_1 + \alpha_3 + \gamma_1$
5.	Observable quality premium for uninformed participant = (3)-(1)	$\beta_0 + \beta_1 + \beta_4 + \alpha_1 - \beta_0 - \beta_4 = \boldsymbol{\beta_1} + \boldsymbol{\alpha_1}$
6.	Observable quality premium for informed participant =(4)-(2)	$\beta_0 + \beta_1 + \beta_3 + \beta_4 + \delta_1 + \alpha_1 + \alpha_3 + \gamma_1 - \beta_0 - \beta_3 - \beta_4 - +\alpha_3 = \boldsymbol{\beta_1 + \delta_1 + \alpha_1 + \gamma_1}$
7.	**Lean Impact of information on observable quality premium (H4a)** = (6)-(5)	$\beta_1 + \delta_1 + \alpha_1 + \gamma_1 - \beta_1 + \alpha_1 = \boldsymbol{\delta_1} + \boldsymbol{\gamma_1}$

Lean Unobservable quality premium: WTP for labeled grade – WTP for sorted grade		
1.	WTP for sorted grade, uninformed participant, lean	$\beta_0 + \beta_1 + \beta_4 + \alpha_1$
2.	WTP for sorted grade, informed participant, lean	$\beta_0 + \beta_1 + \beta_3 + \beta_4 + \delta_1 + \alpha_1 + \alpha_3 + \gamma_1$
3.	WTP for labeled grade, uninformed participant, lean	$\beta_0 + \beta_2 + \beta_4 + \alpha_2$
4.	WTP for labeled grade, informed participant, lean	$\beta_0 + \beta_2 + \beta_3 + \beta_4 + \delta_2 + \alpha_2 + \alpha_3 + \gamma_2$
5.	Unobservable quality premium for uninformed participant = (3)-(1)	$\beta_0 + \beta_2 + \beta_4 + \alpha_2 - \beta_0 - \beta_1 - \beta_4 - \alpha_1 = \boldsymbol{\beta_2 + \alpha_2 - \beta_1 - \alpha_1}$
6.	Unobservable quality premium for informed participant = (4)-(2)	$\beta_0 + \beta_2 + \beta_3 + \beta_4 + \delta_2 + \alpha_2 + \alpha_3 + \gamma_2 - \beta_0 - \beta_1 - \beta_3 - \beta_4 - \delta_1 - \alpha_1 - \alpha_3 - \gamma_1 = \boldsymbol{\beta_2 + \delta_2 + \alpha_2 + \gamma_2 - \beta_1 - \delta_1 - \alpha_1 - \gamma_1}$
7.	**Lean Impact of information on unobservable quality premium (H4b)** = (6)-(5)	$= \boldsymbol{\delta_2 + \gamma_2 - \delta_1 - \gamma_1}$

Appendix Table 3.3: Baseline Balance using Joint Orthogonality test to evaluate differences between treatment and control households.

Outcome variable:	Information Treatment: 1= informed about aflatoxins (treatment), 0=not informed (control)
Standard errors clustered at:	Household level
Willing to Pay in Malawi Kwacha (MK)	0.000153
	(0.000242)
Baseline aflatoxins knowledge score (0 to 10)	0.033717**
	(0.014387)
Age of respondent (years)	0.002656
	(0.004225)
Years of schooling for respondent (years)	0.011391
	(0.014008)
=1 if Respondent is Male	0.035417
	(0.097677)
Household size	-0.027593
	(0.048777)
Landholding (Acres)	-0.080849***
	(0.028500)
Number of years in NASFAM	-0.028038**
	(0.013946)
Number of school goers in household	0.031542
	(0.046234)
Number of females in household	0.018377
	(0.046476)
Number of adults in household (Age>18 years)	-0.032216
	(0.050779)
Distance from your home is the closest market (in km)	-0.010188**
	(0.004444)
No of Extension officer visits per year	0.005693
	(0.006114)
=1 if Household owns a television set	0.090849
	(0.222162)
=1 if Household owns radio set	0.079975
	(0.097086)
=1 Had cash savings at the beginning harvest	-0.073039
	(0.110431)
Storage Expenditure (Malawi Kwacha)	-0.000000
	(0.000009)
Number of months Food insecure (0 to 12)	-0.045293
	(0.031970)
=1 if member too ill to farm for >2 months in past 2 years	0.085994
	(0.116426)
=1 if had deaths in past two years	0.275640
	(0.182894)
=1 if representative of original participant	0.073043
	(0.121650)
Respondents' Anchor price (MK)	0.001414
	(0.001412)
=1 if repeated auction participant (Learning effects)	-0.312720**
	(0.153119)
=1 if Assoc. is Chioshya	0.169715*
	(0.098702)
Constant	-0.096434
	(0.535868)
Observations	2,490
Number of Households	830
F-Test	F=49, p=0.0017

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1; The GAC is community level cluster at which treatment was assigned; Balance checks results with household level clustering are in the appendix with 6 out of 24 variables statistically significant. We control for these in our analysis to be conservative. The exchange rate is 1 US$=750 Malawi Kwacha. Baseline aflatoxins knowledge score (0 to 10) is constructed based on participants' response to 10 aflatoxins awareness questions (i.e. questions ask about aflatoxins indicators, causes, health effects and prevention). Participants got a score of 1 for each of the 10 questions that they got right.

Appendix Table 3.4: Attrition Bias checks using Joint Orthogonality Test to evaluate differences between attritors and non-attritors.

Outcome variable:	Attrition: 1= Participant Attrited 0=if did not attrite)
Standard errors clustered at:	Household level
Information Treatment	0.2330*
	(0.1240)
Willing to Pay (MK)	0.0001
	(0.0003)
Baseline Aflatoxins Knowledge Score (0 to 10)	0.0047
	(0.0194)
Age of respondent (years)	-0.0040
	(0.0059)
Years of schooling for respondent (years)	-0.0045
	(0.0171)
=1 if Respondent is Male	0.0456
	(0.1263)
Household size	0.0675
	(0.0608)
Landholding (Acres)	-0.0543
	(0.0362)
Number of years in NASFAM	-0.0951***
	(0.0295)
Number of school goers in household	-0.0254
	(0.0601)
Number of females in household	-0.0099
	(0.0602)
Number of adults in household (Age>18 years)	-0.0528
	(0.0662)
Distance from your home is the closest market (in km)	-0.0018
	(0.0040)
No of Extension officer visits per year	-0.0127
	(0.0095)
=1 if Household owns a television set	-0.4087
	(0.3395)
=1 if Household owns radio set	-0.1093
	(0.1290)
=1 Had cash savings at the beginning harvest	-0.2167
	(0.1660)
Storage Expenditure (MK)	-0.0000
	(0.0000)
Number of months Food insecure (0 to 12)	-0.0107
	(0.0422)
=1 if member too ill to farm for >2 months in past 2 years	-0.0468
	(0.1608)
=1 if had deaths in past two years	0.1507
	(0.2261)
Respondents' Anchor price (MK)	-0.0004
	(0.0018)
=1 if Assoc. is Chioshya	0.1327
	(0.1312)
Constant	-0.6157
	(0.6301)
Observations	2,490
Number of Households	830
F-test	F=274, p<0.001

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1; The GAC is community level cluster at which treatment was assigned; Balance checks results with household level clustering are in the appendix with 6 out of 24 variables statistically significant. We control for these in our analysis to be conservative. The exchange rate is 1 US$=750 Malawi Kwacha. Baseline aflatoxins knowledge score (0 to 10) is constructed based on participants' response to 10 aflatoxins awareness questions (i.e. questions ask about aflatoxins indicators, causes, health effects and prevention). Participants got a score of 1 for each of the 10 questions that they got right.

For further analysis, we valuate the effect of triple interaction of quality grades, information treatment and seasonality to address possible questions including: do the consumers' quality premiums for observable and unobservable attributes differ in the harvest season when food is plentiful compared to the lean season when it is scarce? If yes, when are the effects of providing information (quality labels and /or information treatment) more pronounced? The following specification is used to estimate these effects:

$$WTP_{ijt} = \beta_0 + \beta_1 S_{it} + \beta_2 L_{it} + \beta_3 I_{it} + \beta_4 T_{it} + \beta_7 X_{it} + \delta_1 I_{it} * S_{it} + \delta_2 I_{it} * L_{it} + \alpha_1 T_{it} * S_{it} + \alpha_2 T_{it} * L_{it} + \alpha_3 T_{it} * I_{it} + \gamma_1 I_{it} * S_{it} * T_{it} + \gamma_2 I_{it} * L_{it} * T_{it} + \sigma_i + \varepsilon_{ijt.} \quad (4)$$

Appendix Table 3.5: Effect of Information and Scarcity Treatment on WTP for Groundnuts Quality

Standard errors clustered at:	Household level	
	(1)	**(2)**
VARIABLES	OLS	OLS
=1 if Sorted grade	49.73***	49.73***
	(5.94)	(5.94)
=1 if Labeled grade	62.34***	62.34***
	(5.70)	(5.70)
=1 if Lean season	85.78***	85.78***
	(7.25)	(7.25)
Sorted grade #. Lean	56.80***	56.80***
	(8.03)	(8.03)
Labeled grade # Lean	47.06***	47.06***
	(7.82)	(7.82)
=1 if Information treatment	-45.83***	-45.83***
	(7.09)	(7.09)
Sorted grade #. Information	65.63***	65.63***
	(9.37)	(9.37)
Labeled grade # Information	82.95***	82.95***
	(8.87)	(8.87)
Lean # Information	34.92***	34.92***
	(11.16)	(11.16)
Sorted grade #Lean # Information	-56.27***	-56.27***
	(12.59)	(12.59)
Labeled grade #Lean # Information	13.74	13.74
	(11.95)	(11.95)
=1 if repeated auction participant (learning effects)	5.61	5.61
	(6.66)	(6.66)
Baseline controls	No	Yes
Constant	249.26***	249.26***
	(7.53)	(7.53)
Observations	5,529	5,529
R-squared	0.33	0.33
Number of HHH_ID	1,098	1,098
Contrasts: Aggregate Scarcity effect (double interaction)	**Contrast**	Standard Errors
Unsorted grade # Lean = Unsorted grade # Harvest:	101.56***	5.61
Sorted grade # Lean = Sorted grade # Harvest:	132.94***	5.74
Labeled grade # Lean = Labeled grade # Harvest:	154.84**	5.92
Contrasts: Aggregate information effect (double interaction)		
Unsorted grade # Information= Unsorted grade # No information:	-26.84***	5.87
Sorted grade # Information = Sorted grade # No information:	9.07	5.92
Labeled grade # Information= Labeled grade #No information:	63.86***	5.96
Contrasts: Marginal effect of information in the harvest season(triple)		
Unsorted grade # Harvest #Informed=Unsorted grade # Harvest #Not Informed	-45.83***	8.81
Sorted grade # Harvest #Informed= Sorted grade # Harvest #Not Informed	19.80***	7.27
Labeled grade # Harvest #Informed= Labeled grade # Harvest #Not Informed	37.12***	6.99
Contrasts: Marginal effect of information in the lean season(triple)		
Unsorted grade #Lean #Informed=Unsorted grade #Lean #Not Informed	-10.90	8.81
Sorted grade #Lean #Informed= Sorted grade #Lean #Not Informed	-1.54	8.92
Labeled grade #Lean #Informed= Labeled grade #Lean #Not Informed	85.78***	6.32
Contrasts: Marginal effect of scarcity for the Uninformed (triple)		
Unsorted grade #Lean # Not Informed =Unsorted grade #Harvest # Not Informed	85.78***	7.25
Sorted grade #Lean # Not Informed = Sorted grade # Harvest # Not Informed	142.58***	7.49
Labeled grade #Lean # Not Informed = Labeled grade # Harvest # Not Informed	132.84***	7.96
Contrasts: Marginal effect of scarcity for the informed (triple)		
Unsorted grade #Lean #Informed=Unsorted grade #Harvest #Informed	120.70***	8.62
Sorted grade #Lean #Informed= Sorted grade # Harvest # Informed	121.24***	8.77
Labeled grade #Lean #Informed= Labeled grade # Harvest #Informed	181.50***	8.71

Note: Clustered standard errors in parentheses & *** p<0.01, ** p<0.05, * p<0.1 and WTP in Malawi Kwacha (US$1 =MK750).

Appendix Table 3.6: Effect of Learning on WTP for Groundnuts quality

Standard errors clustered at:	Household level	
	(1)	**(2)**
VARIABLES	OLS	OLS
=1 if Sorted grade	102.05***	102.05***
	(7.70)	(7.70)
=1 if Labeled grade	133.57***	133.57***
	(7.81)	(7.81)
=1 if Information treatment	15.06***	16.36***
	(4.86)	(4.87)
=1 if Lean season	129.93***	131.48***
	(4.66)	(5.16)
=1 if repeated auction participant (learning effects)	10.34	11.63
	(8.12)	(10.08)
Sorted grade #. Repeated auction Participant	-6.25	-6.25
	(8.40)	(8.40)
Labeled grade #. Repeated auction Participant	-5.55	-5.55
	(8.55)	(8.56)
Baseline controls	No	Yes
Constant	202.09***	199.32***
	(8.17)	(13.01)
Observations	5,529	5,529
R-squared	0.31	0.31
Number of respondents	1,098	1,098
Labeling premium if not repeated auction participant	**32*** **	**32*** **
Labeling premium if repeated auction participant	33**	33**
Test of H2a: Sorting premium for informed = Sorting premium for uninformed		
F statistic	6	6
Prob > F	p<0.011	p<0.011
Test of H2b: Labeling premium for informed = Labeling premium for uninformed		
F statistic	1.3	1.3
Prob > F	p=713	p=713

Note: Standard errors clustered at GAC level in parentheses & *** p<0.01, ** p<0.05, * p<0.1 and WTP in Malawi Kwacha per kg (US$1=MK750); The GAC is community level cluster at which treatment was assigned.

Appendix Table 3.7: T-test of Means for Three Quality Grades by Season

Variable	Means			Grade Mean Comparison		
	(1) Unsorted grade	(2) Sorted grade	(3) Labeled grade	(1) vs. (2)	(1) vs. (3)	(2) vs. (3)
Lean Season (n=1013)				Difference	Difference	Difference
WTP (MK)	334.44	445.12	486.59	-110.676***	-152.154***	-41.478***
	(4.38)	(4.41)	(4.78)			
Harvest Season (n=830)						
WTP (MK)	233.04	313.21	333.85	-80.173***	-100.812***	-20.639***
	(3.59)	(3.62)	(3.56)			

Note: The value displayed for t-tests are the differences in the means across the groups; Standard errors in parenthesis; ***, **, and * indicate significance at the 1, 5, and 10 percent critical level. US$1=MK750

Appendix Table 3.8: T-test of Means for the Quality Grades for by Information Treatment and Season

Variable	Means			Grade Mean Comparison		
	(1) Unsorted grade	(2) Sorted grade	(3) Labeled grade	(1) vs. (2)	(1) vs. (3)	(2) vs. (3)
Lean Season Informed (n=448)				Difference	Difference	Difference
WTP (MK)	328.478	444.377	534.556	-115.900***	-206.078***	-90.179***
	[6.576]	[6.695]	[7.081]			
Lean Season Uninformed(n=565)						
WTP (MK)	339.166	445.701	448.563	-106.535***	-109.396***	-2.862
	[5.865]	[5.873]	[6.015]			
Harvest Season Informed (n=385)						
WTP (MK)	208.312	323.672	353.594	-115.361***	-145.283***	-29.922***
	[5.419]	[5.525]	[4.913]			
Harvest Season Uninformed (n=445)						
WTP (MK)	254.427	304.157	316.764	-49.730***	-62.337***	-12.607*
	[4.561]	[4.729]	[4.973]			

Note: The value displayed for t-tests are the differences in the means across the groups; Standard errors in parenthesis; ***, **, and * indicate significance at the 1, 5, and 10 percent critical level. US$1=MK750

CHAPTER 4. ROLE OF MARKET RISK AND EXPENDITURE SHOCKS IN SMALLHOLDERS' MARKETING BEHAVIOR IN SSA

4.1 Abstract

While there is extensive literature focused on explaining how liquidity constraints, imperfect credit markets and storage technology constraints limit farmers' ability to participate in the exploitation of intertemporal price arbitrage opportunities in sub-Saharan Africa, not much has been done to explain the role of risk and shocks on this issue. Considering that most smallholder farmers generally do not insure against production and market risks as well as household expenditure shocks, we use dynamic stochastic programming to evaluate how these risks and shocks influence their production, storage and sales decisions. We compare the farm households' optimal plans across four scenarios: Scenario 1-farm households do not face any expenditure shocks; Scenario 2-farm households face expenditure shocks; Scenario 3-farm households face expenditure shocks and they have access to government relief aid program in response to yield shocks; and Scenario 4-the farm households face expenditure shocks and they have access to microinsurance. We find that expenditure shocks influence the farm household to alter its optimal crop mix by increasing land allocated to the less profitable food crop, maize. This is likely due to food security motivation and also because the expected net revenue for maize have relatively lower volatility compared to groundnuts. We also observe that risks and shocks significantly influence the farm household's optimal storage and sales at harvest. Results from this model illustrate how market risk and shocks can influence farmers to forgo potential gains of grain storage.

4.2 Introduction

Risk is a key part of smallholder farmers' experiences in sub-Saharan Africa (SSA). The risks include production yield risk due to random weather and market risk due to uncertain prices, as well as idiosyncratic household expenditure shocks emanating from ill health, injuries, funerals or pest and disease expenses (Komarek, De Pinto, and Smith 2020). However relative to other sectors, the smallholder agricultural sub-sector is the least insured sector in SSA, and literature shows that limited access to formal insurance is a key issue for farmers (Jensen and Barrett 2016; Smith 2016). There is extensive literature focused on understanding how rural households manage risk and shocks in this context. Some of the key findings from this literature suggest that in the presence of incomplete insurance markets, farm households use crop diversification, share cropping, capital asset (livestock) holding and precautionary labor supply (off-farm employment) to manage production risk (Smith 2016; Carter 1997; Alderman and Paxson 1994; Rosenzweig and Wolpin 1993; Rosenzweig and Binswanger 1993).

Several studies have also looked at how market risks and idiosyncratic household income shocks affect saving behavior (Paxson 1992; Rosenzweig and Stark 1989). Current assets, including grain stock and cash savings, are considered to play a significant role in risk management for rural households (Park 2006; Chaudhuri and Paxson 2002; Saha 1994; Saha and Stroud 1994; Renkow 1990). Risk sharing or risk pooling are also considered key coping strategies for rural households facing idiosyncratic shocks given limited access to formal insurance (Townsend 1995; Robert, Townsend 1994). However, there is empirical evidence to suggest that full risk sharing is generally nonexistent (Ravallion and Chaudhuri 1997; Townsend 1995; Udry 1994; Deaton 1991). As such, expenditure shocks remain an important factor to consider when evaluating household behavior especially the puzzling "*sell low and buy high*" behavior observed in SSA where farmers engage in distress sales of grain at harvest, forgoing potential gains of storage, even if they have to buy grain back later in the year at a higher price (Burke, Bergquist, and Miguel 2019; Stephens and Barrett 2011).

Although the existing literature suggests that on average commodity prices in SSA trend upward after harvest, there is substantial evidence that suggest wide variability in expected returns of grain storage (Cardell and Michelson n.d.; Gilbert, Christiaensen and Kaminski 2017; Kaminski, Christiaensen and Gilbert 2016). In addition, farmers in most of rural SSA face high and varying transaction costs that exacerbate the foregone return to storage associated with harvest sales (Bernard et al. 2017; Coulter and Onumah 2002). About 70 to 85 percent of smallholder farmers sell their produce to middlemen or traders who buy grain at farm gate for assembling and resale to processors, exporters and urban consumers (Bernard et al. 2017; Nyirenda, n.d.; Nzima 2014; Jayne et al. 2010). These traders mostly set up grain aggregation depots within the villages during harvest season when prices are low to capitalize on seasonal price flactuations. However, not much of such grain assembling activities occur in the lean season as the cost of aggregation increases due to grain scarcity. This implies relatively lower search and transportation costs for farmers during harvest season compared to the lean season. As a result, smallholder farmers living in rural areas are likely to sell to traders at harvest for convenience to avoid the the transaction costs associated with market search and transportation of grain in the post-harvest period. Imperfect commodity markets and the existence of high transaction costs for the grain market are, therefore, also possible issues that may be influencing the farmers to sell low and buy high.

In the recent past, development economists have been increasingly interested in understanding smallholder farmers' commodity storage and marketing behavior in SSA due to this observed sell low and buy high behavior (Burke, Bergquist, and Miguel 2019; Channa 2019; Aggarwal, Francis, and Robinson 2018; Dillon 2017; Basu and Wong 2015; Stephens and Barrett 2011). There is growing literature exploring how (i) lack of effective storage technology; (ii) liquidity and credit constraints as well as (iii) lack of effective grain storage commitment devices possibly explain this phenomena. However, not much has been done to assess the effects of market risk and household expenditure shocks on smallholder farmers' grain storage and marketing behavior.

In the present study, we estimate the role of market risk and expenditure shocks on smallholder farmers' grain storage and marketing behavior. In the absence of formal insurance markets and perfect risk sharing mechanisms, self-insurance from risks and shocks may be fundamental in the households' grain storage and marketing processes. We assume the farm household grows two types of crops, a food crop (maize) and a cash crop (groundnuts) and use dynamic stochastic programming to evaluate how self-insurance motives influence farm households' grain production and marketing decisions. Our paper addresses two research questions related to these risks: (i) How do farm households' random future expenses due to ill health, injuries, funerals or pest and disease expenses influence their grain storage and marketing decisions in the post-harvest period given imperfect commodity markets? (ii) How do uncertainty in gross returns from grain storage and uncertainity in market availability (i. e. high transaction costs) influence farm households' grain storage and marketing decisions? Identifying how these sources of uncertainty influence farmers' decisions provides new insights on how risk and shocks limit smallholder farmers' participation in exploitation of the intertemporal price arbitrage opportunities in sub-Saharan Africa. This paper helps to higlight the impact of imperfect insurance and commodity markets on smallholder farmers' behavior.

To our knowledge some of the previous studies that have looked at how risk affects smallholder storage and marketing decisions include Cardell and Michelson (2020) Park (2006)

Saha and Stroud (1994) Saha (1994) and Renkow (1990). Saha and Stroud (1994) show that risk may significantly influence households to engage in staple grain storage even when there are no significant return to storage as stocks may be used as a buffer in the face of market uncertainty (price and grain availability). Park (2006) also reports interesting effects of risk on households' grain storage behavior. Using Chinese data, he finds that grain consumption objectives influence households to engage in precautionary grain storage as a price hedge even when there are no credit constraints. His findings highlight the importance of accounting for risk-hedging properties of specific assets when evaluating how credit and insurance influence households' behavior. A more recent study by Cardell and Michelson (n.d.) also evaluates how risk and risk preferences affect smallholders' marketing behavior in SSA. Using a two-period model, they find that wide variability in storage rate of return with significant existence of negative returns may influence smallholders to forgo the potential gains grain storage.

This paper makes three major contributions to the literature on risk and commodity marketing behavior in SSA. While previous studies generally used a simplified 2-period model that only accounts for the lean and harvest periods price dynamics, we explore quarterly price dynamics using a 4-period dynamic model. In addition, we also contribute to this literature by exploring and comparing price dynamics across crops and evaluating how farmers' storage and marketing choices may vary across crops depending on each crops' price dynamics and specific risk-hedging properties. For most of SSA, maize is a key staple crop while legume crops like groundnuts are an important cash crop for smallholder farmers. As such, the market dynamics for these two type of crops are very different. Besides, food security policies in most of SSA are largely influenced by the availability and affordability of staples like maize. As a result, there are predominantly more government interventions in the maize market relative to legume markets. This adds a layer of complication and uncertainity for the maize price dynamics. Lastly, while most extant studies evaluate the impact of price risk alone on farmers' post-harvest marketing behavior, we advance their work by evaluating the impact of household expenditure shocks along with price risk given high time-varying transaction costs.

We compare a representative farm household's optimal plans across four scenarios: Scenario 1-farm households face yield and price risk, but do not face any expenditure shocks; Scenario 2-farm households face yield and price risk as well as expenditure shocks; Scenario 3-farm households face yield and price risk as well as expenditure shocks and they have access to government relief aid program in response to yield shocks; and Scenario 4-the farm households face yield and price risk as well as expenditure shocks and they have access to microinsurance to fully offset the impact of expenditure shocks. We find that expenditure shocks influence the farm household to alter its optimal crop mix by increasing land allocated to maize, the food crop which is less profitable on average but has lower variability of net revenue. This is likely due to food security motives and the need for liquidity in the case where both prices are low and expenditure shocks occur. In addition, the expected prices for maize are relatively less variable compared to groundnuts and this gives maize some market risk-hedging properties. These results provide a possible explanation for the prevalence of subsistence farming amongst smallholder farmers. We also observe that risks and shocks significantly influence the farm households' optimal storage at harvest and sales in the post-harvest seasons. Therefore, the results of this model help to highlight the impact of imperfect insurance and grain markets on smallholder farmers' production, grain storage and marketing behavior.

The rest of the paper is organized as follows: Section 2 presents the background on smallholder commodity markets and motivation behind our model; Section 3 provides the methodology, including the set-up of our stochastic dynamic model, the stochastic process and the scenarios used in the analysis; Section 4 presents the details of the data used and its sources; Section 5 presents the study results and discussions; while Section 6 concludes.

4.3 Background on rural grain markets and price trends

While most previous analysis on the sell-low and buy-high behaviour has focused only on liquidity, credit and technology contraints. We advance this literature by exploring the role of market risk and expenditure shocks on household marketing decisions. We argue that, while agricultural commodities exhibit a positive price trend on average, the distributions of these price trends vary across crops, with existence of significant price risk (i.e. a substantial probability of negative returns). Using price data from Malawi, we show that the prices for the two crops, maize and groundnuts, exhibit a higher probability of negative returns across seasons (i.e. seasons are mirrored by the stages in our Discrete Stochastic Programming (DSP) model). Hence, there is a need to account for seasonal price dynamics in modeling agricultural household marketing behavior. The Malawi data also shows substantial variations in prices for the two crops across seasons, and this is likely to also influence households' production and marketing patterns. When households face substantial expenditure shocks and market risks, their knowledge of the possibility of expenditure shocks may play a significant role in their storage and sales decisions especially when there are no insurance markets and other risk sharing mechanisms. If farm households are aware of the possibility of expenditure shocks, the farmer may prefer to have sufficient liquidity (i.e. a rainy-day fund or convenience fund) compared to having grain stocks given price risk, high transaction costs, and inefficient risk sharing mechanisms within the farm's social network.

4.3.1 Commodity price risk

We use monthly market-year observations from 1989 to 2016 for 74 markets in Malawi to explore the seasonal price dynamics and variability. In order to highlight the prevalence of price risk, we evaluate how prices evolve across time periods and evaluate the distributions of gains from grain storage. That is, looking at evolution of prices across periods and compare the expected price and coefficient of variations across crops in the different time periods. Using the 1050-market-year observations of maize and groundnuts quarterly prices in Malawi, we observe that the expected prices for the groundnuts are relatively higher than maize on average for all quarters.[14] However, the coefficients of variation for the expected prices of maize are lower relative to groundnuts. Similarly, the expected net returns per hectare for groundnuts are also higher and with higher variability compared to maize. Table 4.1 summarizes the price dynamics reflected by both the historical and empirical distribution of prices as well as the expected net returns per hectare at harvest.

The low seasonality in maize prices emanating from the widespread government interventions in the maize market aimed at regulating food prices is one of the possible explaination for the variations in price dynamics across crops. This is in line with what other previous studies also find in Kenya and Tanzania (Chapoto and Jayne 2009.; Minot 2011; Minot 2010; Abass et al. 2014; Burke et al. 2019; Channa 2019). This data highlights the importance of considering seasonal price dynamics and variability when evaluating farmers' storage and marketing behavior. In addition, given the differences in price dynamics across crops, it is also important to explore how farmers' storage and marketing decisions may vary across crops.

[14] We have missing data in some markets and years.

4.3.2 Transaction costs

We use data from the PICS pilot project conducted in central Malawi between 2018 and 2019 to explore the variations in transaction costs across seasons. Transaction costs resulting from market search costs and transportation costs vary across seasons for smallholder farmers in rural areas. This is because during the harvest season when volumes are higher within villages, middlemen or traders set up grain market depots within villages to aggregate grain for storage or reselling to urban consumers, exporters, or processors. However, due to scarcity and limited grain availability, the cost of grain aggregation increases in the post-harvest seasons such that very few traders are incentivized to set up grain market depots within villages. In addition, the higher average prices during the lean season also erodes the middlemen's margins. As such, the transaction costs for cash crops like soybean and groundnuts are higher for farmers during the lean season due to increased market search and transportation costs. This is because farmers have fewer market options for cash crops in the post-harvest periods. However, for staple crops like maize, markets are always available due to food demand from local consumers within the village. As such, farmers are likely to sell their cash crops at harvest when grain purchasing depots are widely accessible within villages for convenience to avoid transaction costs.

In order to obtain estimates of the magnitudes of transaction costs across periods, we evaluate the spread between selling prices and purchase prices for maize and groundnuts. Figure 4.1 below shows the spread between the purchase and selling prices for the two crops. That is, the difference between groundnuts (maize) purchase and selling prices as a percentage of selling price for the four periods including harvest, early lean, lean and planting are 9 (9.5), 6 (11), 16 (9.5) and 15 (9) percent, respectively. We notice from the survey data that transaction costs for groundnuts vary more widely across periods compared to maize. This is because, unlike maize, over 60 percent of the groundnuts produced by smallholder farmers is produced for sale to traders or export markets (Beghin et al. 2004). The wedge between purchase and selling prices is tighter during the harvest season and wider in the post-harvest periods for groundnuts. This reflects the variations in market search and transaction costs across seasons. As such, farmers that expect higher marginal transaction costs in the post-harvest periods are likely to sell early for convenience. The motivation to sell early may be even higher if the farmer anticipates the possibility of facing urgent cash needs due to expenditure shocks. Exploring how expenditure shocks along with uncertainty in returns of grain storage and market availability (i.e. high and varying market search and transaction costs) influence farmers' storage and sales behavior is, therefore, important.

4.4 Methodology

The objective of this section is to present our stochastic dynamic model and how it is set up. We begin the section with a presentation of the motivation behind the farm model to show how self-insurance motives may influence the farm households' grain production and management in SSA. Our model follows the traditional household models (Chetty, Sándor, and Szeidl 2017; Stephens and Barrett 2011; Park 2006; Fafchamps, Udry, and Czukas 1998; Saha and Stroud 1994; Deaton 1991), but builds upon them by adding the role of liquid assets (grain and cash) in managing market risk and household idiosyncratic shocks. We consider grain storage and cash in hand as our two key assets for the optimal portfolio choice model where the cash in hand is the risk free asset, i.e. a liquid rainy day fund, while stored grain is a risky asset with uncertainty in returns to storage. The key result from the optimal portifolio choice model under risk shows that a positive correlation in the rate of return for grain storage and potential future alternative sources of cash or remitances to cover idiosyncratic shocks, may reduce the optimal allocation devoted to grain storage, the risky asset(Chetty, Sándor, and Szeidl 2017). As such, when the household's social network faces common market risks and expenditure shocks, households may not depend on risk sharing mechanisms but rather commit to total liquid asset accumulation with a higher allocation to a risk-free asset. Given that the farm household in this case makes two choices simultaneously, first, how much total liquid wealth to hold and second, what proportion of that to hold in grain inventories, the result from the optimal portfolio model under risk helps to intuitively show how market risk and expenditure shocks may influence households grain storage and sales decisions: sell early or liquidate grain stocks early to ensure robust liquidity to deal with expenditure shocks.

From literature on household's response to risk and shocks, we also learn that there are a number of factors that may influence the household's grain storage and sales decisions. For example, high variability in expected returns is likely to have a negative effect on grain inventories (Park 2006; Saha and Stroud 1994). In addition, the physical cost of storage including storage losses may also have a negative effect on grain storage and influence the household to forgo the gains of storage (Kadjo et al. 2018). The objective for the present model is to show that in the presence of imperfect commodity markets where the marginal transaction cost of liquidating grain in future periods is high, the self-insurance motivation to maintaining sufficient liquidity to deal with expenditure shocks may likely influence households to sell their grain early.

While Stephens and Barrett (2011) show that liquidity is one of the key factors that influence households' commodity marketing behavior, this essay helps to advance their work by showing that uninsured risks and shocks can exacerbate household's liquidity constraints by pushing the liquidity threshold at which to liquidate investment assets (grain storage) upwards. This may be prevalent in the absence of insurance where the household's liquidity has two roles: sustaining regular predictable expenses and maintaining a contingency fund for shocks and risks. Of particular interest in our model are the self-insurance motives in the face of random future expenses given that the household's social network, which is the source of the household's remittances and casual employment, is also facing similar market risk and uncertainty (i.e. price risk and high transaction costs) as the household. Our model therefore advances previous work on farm household modeling by adding expenditure shocks to the typical set of random variables included in farm models to illustrate the role of risk and shocks on households' grain production and marketing behavior.

4.4.1 Set-up of our discrete sequential stochastic programming model

We develop a dynamic stochastic model of household grain production and marketing management using Discrete Stochastic Programming (Rae 1971). For modeling purposes, the cropping year is divided into four periods where the farmer makes decisions at the beginning of each period: Planting (January), Harvest (April), Early Lean (July) and Lean (October).[15] The focus of the analysis is on the household's intra-cropping year grain production and especially inventory management behavior considering seasonal price dynamics. We consider a finite horizon model with 6 periods spanning two cropping years from planting in year 1 through harvest in year 2 to account for the impact of cash requirements throughout the year (see Figure 4.2 for a detailed time line for the DSP model).

We consider a representative farm household that maximizes expected total wealth at the end of the planning horizon, (W_t).

[15] The Early Lean and Lean periods are considered our post-harvest period 1 and 2, respectively.

$$E[W] = \sum_{t=1}^{T} W_t s_t \tag{1}$$

Ending wealth is a random variable distributed over states of nature indexed by t and occurring with probability s_t, due to the risks associated with yields at harvest, prices at each decision point through the planning horizon, and expenditure shocks beyond normal expenditures, representing unexpected expenses (e.g., medical expenses due to illness or accident, funeral expenses for family members, etc.). We chose expected end of horizon wealth maximization instead of expected utility as we assume separability of production from consumption in our model (i.e. consumption is fixed and not a choice variable). This approach also allows us to account for the role of self-consumption of grain as well as required household expenses (e.g. groceries, clothing, utilities, school fees etc.). For simplicity, the farm household produces just two types of crops, a cash crop (i.e. groundnuts) and a staple crop (i.e. maize). The farm household is endowed with three resources land *(K)*, family labor *(L_F)*, and cash, which are allocated to the production of the crops such that production depends on random weather shocks and the household's resource constraints. We assume that the household labor demand may exceed its own labor supply during the harvest period and consider the existence of a labor market where the household can hire labor *(L_H)*, at a prevailing market wage during the harvest season.

For this model, we assume the household faces three key sets of random variables with known distributions. These include yields, prices and expenditure shocks. The household's choice variables of interest at each decision point include: how much of each crop to sell, how much to buy, how much to store, and how much cash to hold for self-sustenance and self-insurance (i.e. liquidity to cover both regular household expenses plus a liquid rainy-day fund in case of expenditure shocks). The farm household has no control over these random variables but can use the knowledge of their distributions in the initial decision period and knowledge of conditional distributions in subsequent periods to inform grain inventory and marketing decisions, as well as decisions regarding cash management. We also assume that between the decision points, the random variables evolve. The household is assumed to make its decisions sequentially from the planting season in year 1 to harvest season in year 2 with a goal of maximizing the expected utility of end of model horizon wealth. This is done subject to accounting constraints for the household's resources, including cash and grain inventories, to ensure equality of sources and uses for each period and state of nature.

In Figure 4.2 above, the rectangles show the decision stages and corresponding decisions that the farmer makes in the given decision stages. The ovals show the random variables and their evolution across stages. The polygon at the bottom of the diagram shows the end period when the wealth random variable is realized and whose expectation the farmer aims to maximize. Some key nonrandom parameters include initial endowments of resources including cash, maize and groundnuts stocks in planting period 1, as well as some cash remittances or income in each given period for typical expenses including school fees, groceries, clothing and utilities.

4.4.2 Model variables and constraints

This section describes the model variables and the relationships between these variables and the parameters that define the constraints. The full model is displayed in Appendix A in GAMS notation (Brooke et al. 1997).

4.4.3 Resource endowments

In the planting period of each year, there is a limit on the allocation of land to the cash and staple crop to be no more than the endowment of household land. This is a single constraint for year one. For year two, there is a set of land constraints – one for each realization of the sequence of random variables that occurs during year one. Similarly, in each planting period (year one and year two) and harvest period, there are constraints that limit the use of labor to be no greater than the endowment of family labor plus hired labor. Beyond the year one planting period, these will be sets of constraints that are conditional on the sequence of random variables that have been realized up to that point in time.

4.4.4 Inventory constraints

There are three principle commodities to be tracked in this model: maize, groundnuts, and cash. These are handled through inventory or "sources and uses" constraints by decision period that are conditional on the random variables that have been realized up to that decision period. For the crop products, that is maize and groundnuts, these constraints are denominated in kilograms, and the sources are: initial inventory (if it is the first year planting period) plus purchases plus production (realized yields times area planted if it is a harvest period) plus storage from the previous decision period (if it is beyond the first planting period). Uses for each crop in a given period are household consumption plus sales plus storage for future use. For each crop, the purchases, sales, and storage at each decision period are all conditional on the sequence of realizations of random variables up to that decision period. Thus, these constraints, which are conditional on the outcomes of the random variables that have been realized up to that decision period, require that uses are less than or equal to sources. An additional constraint relates to grain storage in each period and serves to limit the smallholder farmer's storage capacity to the total quantity of maize and groundnuts that the farmer can hold to reflect the smallholder farmer's secure storage space. Thus, these constraints, which are conditional on the outcomes of the random variables that have been realized up to that decision period, require that uses are less than or equal to sources.

In each decision period, we also have cash constraints that are measured in Malawi Kwacha (MK) where US$1=MK750. The sources of cash include income from crop sales, cash savings from previous periods, including the initial cash endowment for the planting period in year 1, and cash remittances where the farmer's remittances are an aggregation of all other income sources for the farm household including wages, income from other non-crop enterprises and cash transfers from their social circle. For crop sales in each decision period, we account for transaction costs such that the farmer's crop sales are valued at that period's realized levels of prices minus transaction cost. The uses of cash include expenses on crop purchases, savings for future periods and household living expenditures as well as random expenses due to ill health, injuries or funerals. In addition, we also have variable production costs for typical production expenses such as seed and fertilizer costs in the planting periods, and for transportation, packaging, storage pesticides and wages for hired labor in the harvest periods. For crop purchases in each period, the farmer's crop purchases are valued at that period's realized level of prices. Although purchase and sales prices move together in response to market forces, there remains a wedge that varies over time and causes purchase prices to exceed sales prices due to a variety of sources of transactions costs. We approximate transaction costs using the estimated gap between selling and purchase prices for each period based on household survey data in Malawi.

4.4.5 The stochastic processes for random variables

In this section, we present the assumptions and stochastic processes governing the random variables in our model. Literature shows that there is a long history of using Discrete Stochastic Programming (DSP) to analyze and model farmers' decisions in a dynamic, stochastic setting (Rae 1971; Featherstone, Preckel, and Baker 1990; Krause et al. 1990; Etyang et al. 1998; Ahmed et al. 2000; Coulibaly et al. 2015; Robert, Bergez, and Thomas 2018; Boussios et al. 2019). The stochastic processes used in our model extends the typical set of random variables in the farm modeling literature, i.e., yields and prices, by also accounting for idiosyncratic expenditure shocks as another key source of uncertainty potentially influencing farmers' post-harvest decisions. In this model, we consider six stages where the farm household makes decisions conditional on the outcomes of random variables and prior decisions up to the given decision point in time. Our goal is to understand how production and market risk as well as expenditure shocks influence smallholders' marketing decisions over time. Although the goal is to understand farmers' decisions in the harvest and post-harvest periods; we also consider the decisions made at planting because farmers' harvest realizations are a function of the production choices (i.e. the amount of land allocated to each crop). Random weather is considered to influence the evolution of yields between the planting stage and harvest stage, and this occurs once a year as the farmer depends on rain-fed production with one cropping season per year. We also assume that the household may experience expenditure shocks. Expenditure shocks are modelled as occurring only between harvest and the next, early lean, period in year one. While the timing of expenditure shocks is not so restricted, this sequencing serves to illustrate the impact of random shocks to household expenditure.

Prices evolve across periods to account for random price fluctuations across time. We assume that there is spatial integration of grain market where prices and yields are jointly distributed to account for the effect of weather on both maize and ground nut yields and aggregate regional supply on local prices. This is in line with empirical evidence from spatial integration studies that suggest grain markets in Malawi are reasonably integrated and becoming more efficient over time (Golletti and Babu 1994; Chirwa 1999; Abdulai 2007; mapila et al. 2013; Myers 2013). However, to reflect the market search and transportation costs for smallholders in rural areas where information asymmetry between farmers and middlemen is common, we consider the existence of high transaction costs that vary across periods for farm households. These are considered to have a negative impact on the household's realized selling price.

Random variables for yields, prices and expenditure shocks are empirically approximated based on historical data. Expenditure shocks are assumed to be independent of yields and prices. For the planting period in year 1, which is our initial stage, we use average prices from our historical price data as realized prices, and price distributions for future periods are approximated using Gaussian Quadrature (GQ) to produce discrete approximations to the distributions of realizations of prices beyond the year one planting period. GQ is a numerical approximation method that can be used to construct a discrete empirical distribution that mirrors an actual distribution based on its moments (see DeVuyst and Preckel 2007 for details). The GQ method produces a discrete distribution that is consistent with the moments (mean and covariance matrix in this case) of the joint distribution of these prices using a limited number of possible outcomes.

We assume three states of nature for each of the three variables, namely: good, roughly average and bad for yields; high, medium and low for prices; and severe, minor and none for expenditure shocks. Using our historical data from 1989 to 2016, we used averages of the top quartiles to approximate the values for the highest state of nature for prices and yields (i.e. good for yields and high for prices). The averages of the middle two quartiles are used to approximate the middle state of nature while the averages of the lower quartiles are used to approximate the worst state of nature, that is, bad for yields or low for prices. In order to capture price seasonality, we chose months that are considered the peak of the seasons such that for harvest, early lean, lean and planting (peak or late lean) period we used average April, July, October, and January prices, respectively. April coincides with harvest for most crops (e.g. maize, rice, soybeans, beans) and on average. July is considered a recovery period (early lean) for most commodity prices though prices for some legumes including groundnuts can decrease because of their late harvest calendar which ends in July. On average commodity prices are considered to have a general positive trend from July (early lean) through to October (lean) and October to December and they peak in January (peak/late lean) (MoA AMIS data 1989 to 2016). These planting and harvest months are also in line with the cropping patterns in Malawi as reported by FEWSNET.

At harvest periods, the distributions of realized prices and yields are jointly approximated using GQ based on a set of vectors defining the lattice of the quartile-based conditional means of prices and yields' states of nature. This approximated distribution presents the states of nature and corresponding probability mass function that are consistent with the empirical means and covariance matrices of these random variables. Similarly, for the other post-harvest periods – early lean and lean – the joint distributions of prices are also approximated using GQ. The vectors of prices and yields assigned positive probabilities are used as the realizations of these random variables.[16]

For expenditure shocks, we use the 2016 LSMS data for Malawi with 12,444 household observations to generate an aggregate variable for households' reported expenditure shocks (i.e. medical expenses, funeral expenses, and asset replacement expenses due to theft). To limit model size, we use our data to select three states of nature. The lowest state of nature is based on observations that do not report any shocks – thus the level of shock is zero. For our upper states of nature, that is, severe and minor, conditional averages from our sample are used to define states. We consider MK35,000 per month (equivalent to about $50) as the cutoff point between severe and minor where any reported positive shocks below this cutoff are considered minor, while those above are considered severe shocks. We used the minimum wage for casual labor in Malawi as reference to guide our choice for cutoff point as any expenditure shock below the monthly minimum wage rate may be considered minor and manageable. The empirical distribution of expenditure shocks is then approximated using GQ to obtain probabilities associated with these three states. This distribution is used in our model as stochastic disturbances to the cash uses in the early lean season. We assume shocks are realized between harvest and early lean and hence may influence the household to sell at harvest. If farm households are aware of the possibility of expenditure shocks, the farmer may prefer to have sufficient liquidity compared to having grain stocks given price risk, high time-varying transaction costs, and imperfect risk sharing mechanisms within the farm's social network.

4.4.6 Model scenarios

We use model scenarios to motivate why farmers appear to pursue marketing strategies that appear to be at odds with their best interests and to assess the impacts of policy alternatives relative to credit and insurance programs. We evaluate four scenarios based on the possible combination of the two policies to evaluate the effect of uninsured risk/shocks and limited access to credit. These scenarios include: (i) farm households do not face any expenditure shocks and high time-varying transaction costs; (ii) farm households face expenditure shocks and high time-varying transaction

[16] We assume independence of yields/prices across time periods for convenience as using the VAR with our data gives negative returns.

costs; (iii) farm households face expenditure shocks and variations in transaction costs plus households have access to relief aid program (i.e. government cash transfer in response to systematic shocks); and lastly (iv) farm households face expenditure shocks and variations in transaction costs plus have access to "microinsurance" when they face idiosyncratic household expenditure shocks. For the microinsurance program, we consider an insurance scheme that fully covers idiosyncratic household expenditure shocks. We assume the household has access to this scheme when they face severe shocks only if they pay a premium at the beginning of that year (planting period). We price the premium at the actuarially fair rate plus 5 percent to allow for administrative costs, and the insurance pays an indemnity when severe expenditure shocks occur (Goovaerts et al. 1984; Goovaerts et al. 2012). Administratively, we envision offering of the insurance via microcredit cooperatives such as village saving and loans associations (VSLAs) which already exist in most rural areas (Ksoll et al. 2016).

4.5 Data and Sources

We use annual yield data for Malawi as reported by Food and Agricultural Organization (FAO) statistics (FAOSTAT) from 1989 to 2016. Our monthly historical prices are from the Ministry of Agriculture's Agricultural Markets Information Systems (AMIS), a data collection system that is generated to help inform food security policies in collaboration with FAO's Global Information and Early Warning System (GIEWS), the FEWSNET initiative and The World Food Program (WFP) food price monitoring system. The Ministry collects daily commodity prices for key food crops in major commodity markets, and these are used to derive weekly and monthly average prices reported by the Ministry. We use the reported monthly price data from 74 markets in Malawi from 1989 to 2016, and we have a total of 1,050 market-year observations and these are adjusted to account for inflation using CPI index from World Bank with January 2016 as the base year. For expenditure shocks we use the 2016 LSMS data for Malawi which has data for 12,444 households and we generate an aggregate variable for household's reported expenditure shocks including medical expenses, funeral expenses and theft.

Other key data used in the model are household demographic parameters including average household size, and endowments of labor and land, production inputs and costs, minimum grain consumption requirements, average monthly household expenditure, average planting and harvest labor use per acre, average monthly income and average grain inventory capacity. These are based on estimates from literature or calculation from the 2016 LSMS data by World Bank and the PICS pilot project baseline survey data from Malawi (see Table 4.2 for details of parameters used in the model).

4.6 Results and Discussion

In our analysis, the states of nature at harvest in the order: X1.X2.X3.X4, represent the most likely combinations of the possible outcomes for maize yields (X1 = G for good, A for average, or B for bad), groundnuts yields (X2 = G, A, or B), harvest maize prices (X3 = H for high, M for medium, or L for low) and harvest groundnuts prices (X4 = H, M, or L), respectively. Similarly, in the early lean season, the representative post-harvest period discussed in our results, the state of nature in the order: X1.X2.X3.X4.X5.X6.X7, represent the most likely combinations of possible outcomes X1 to X4 as presented above for harvest period plus: early lean maize prices (X5=H, M, or L), early lean groundnuts prices (X6= H, M, or L), and expenditure shocks (X7=S for Severe, M for Minor and N for none). This means that in terms of realized outcomes, we move from best to worst possible outcomes as we move from the top the bottom of Tables 4.3 to 4.7. The probabilities for each state of nature are presented in parentheses on the horizontal axis.

Figure 4.3 shows that the optimal crop mix at the planting stage across scenarios, Table 4.3 reports the grain inventory and sales patterns at harvest, Table 4.4 presents the monetary values of grain sales, purchases and inventory at harvest based on the realized prices in each given state of nature, while Table 4.5 presents the total net sales value (the difference in the total value of grain sales and grain purchases at harvest). Table 4.6 reports the optimal cash savings at harvest. Given that the total number of states of nature in the post-harvest periods is larger (i.e. 270 and 4,878 state of nature for early lean and lean respectively), instead of reporting the specific results for each state of nature in the post-harvest periods, we only report the expected purchases, sales, and inventory for grains conditional on the realization of each period’s state of nature (see Table 4.7). The full details of the optimal marketing plans are presented in supplementary Tables 4.A.1 and 4.A.2. Panel A and B of Tables 4.7 present the expected value of sales, purchases and inventories for the early lean and lean period, respectively.

4.7 Optimal production and marketing strategies for scenario 1: farm households do not face any expenditure shocks

Our model results show that in the scenario where farm households do not face expenditure shocks (Scenario 1), the farm household will allocate 64 percent of its total landholding to maize, the food crop, and 36 percent to the cash crop. In terms of the optimal grain sales and purchases at harvest, Table 4.3 shows that in this scenario, the expected maize sales and inventories at harvest are 458 kg and 529 kg, respectively, while the expected groundnut sales and inventories are 65 kg and 451 kg, respectively. In terms of purchases at harvest, we observe that the expected maize purchase at harvest is 144 kg while the expected purchases for groundnuts is 313 kg. In this reference scenario, the expected total net sales value for this scenario is MK 3,686 and this suggests that the farm household is likely to have more sales than purchases at harvest. For scenario 1 particularly, the model shows that the farm household is likely to sell more maize at harvest than groundnuts and also purchase and store more groundnuts than maize at harvest. This may be due to the higher expected returns of storage for groundnuts relative to maize (see Table 4.1). In terms of liquid wealth accumulation, we observe that when households do not anticipate the possibility of experiencing expenditure shocks, the household's optimal expected cash savings at harvest is MK139,728 (US1=MK750).

In the post-harvest period, we observe that the farm household's expected maize sales and purchases are 478 kg and 964 kg, respectively, while the expected sales and purchase of groundnuts, the cash crop are 742 kg and 714 kg, respectively. In general, the results for the post-harvest period show that the farm household expected total value of purchases (MK476,256; US1=MK750) are higher than total expected value of sales (MK323,616; US1=MK750) at harvest. Overall, these expected values reflect the "buy-high" patterns prevalent among smallholder farmers. In this scenario, however, this is more pronounced for maize than groundnuts likely because of the optimal crop mix which implies lower production of maize than groundnuts. In addition, based on the price dynamics in Table 4.1, when we look at the purchase patterns in appendix Table 4.A.1, the farm household purchases maize in the early lean season in states of nature that have a combination of "bad" yields and "low" prices realizations. This is because the household expects to gain from storing maize in the early lean season and selling in the lean season with the worst realization in the lean season (i.e. "Low" price) still guaranteeing some gains from storage.

4.8 Optimal production and marketing strategies for Scenario 2: farm households face expenditure shocks

In order to evaluate the impact of expenditure shocks, we compare scenario 1 to scenario 2, the scenario where farm households face expenditure shocks. Our model results show that when farm households face the possibility of expenditure shocks (Scenario 2), the farm household allocates 68 percent of its total landholding to maize, the staple crop, and 32 percent is allocated to the groundnut cash crop. When we compare the optimal crop mix of this scenarios with scenario 1, we observe that households allocate a little more land to maize (68 percent) compared to the state of the world where household expenditure shocks are ignored (64 percent). Intuitively, in the face of expenditure shocks, one would expect the farm household to allocate more land to the crop which has higher expected returns with the motivation to increase agricultural incomes to manage the expected future expenditure shocks. However, given the constraints that the farm households must be solvent, we observe that in a world where there may be unexpected future expenses, it is optimal for the farm household to allocate more land to the food crop even though it has lower expected returns. This is because of the market risk-hedging properties associated with the staple crop. That is, relatively lower variability in expected net returns per acre and lower maize price variability compared to the cash crop. Maize also has limited variations in the transaction costs over time compared to the cash crop. As such, the farmer allocates more land to maize as a form of self-insurance against risks associated with market prices and expenditure shocks. The households' food security motives (self-reliance or self-provision) could also explain this result such that in a scenario where the household anticipates random future expenditure shocks, the farmer may allocate more land to the food crop even when the relative expected returns are higher for the cash crop. The model results from this essay provide a possible explanation for the observed prevalence of subsistence farming behavior amongst smallholder farmers where production of staples dominates cash crops.

For scenario 2, the grain sales and purchase plan at harvest in Table 4.3 show that the farmer's expected maize sales and inventories at harvest are 394 kg and 685 kg, respectively, while the expected groundnut sales and inventories are 73 kg and 326 kg respectively. In terms of purchases at harvest, we observe that the expected purchase of maize at harvest is 185 kg while the expected purchases for groundnuts is 236 kg. When we compare this scenario to the reference scenario 1, the model shows that the farm household would sell relatively less maize at harvest in scenario 2 compared to the reference scenario. However, in terms of the cash crop, the farm household's expected sales are relatively higher in scenario 2 compared to scenario 1. We also observe that the farm household's expected inventory of maize at harvest in scenario 2 is higher than in scenario 1 while the expected inventory of the cash crop is lower than in scenario 1. This may be due to the household's self-insurance motives as anticipation of expenditure shocks may influence the household to produce and store more of a crop that has lower variability in expected price forgoing the gains from producing and storing a relatively high value cash crop.

Our model results provides a possible explanation for "*the sell-low*" behavior as we observe that when farm households experience expenditure shocks, the farmer's optimal marketing plan is to sell relatively higher quantities of the cash crop at harvest compared to scenarios where there are no expenditure shocks. The sales value results in Table 4.5 also support this as we observe that the farm household's total net sales values are higher in scenario 2 than scenario 1. Our results in terms of liquid wealth accumulation also show that when households anticipate the possibility of experiencing expenditure shocks, the household's optimal cash savings at harvest are higher compared to scenario 1 (i.e. MK144,241 vs. MK139,728; (US1=MK750). These results illustrate how the household's motive to ensure sufficient liquidity given the possibility of experiencing expenditure shocks may influence them to liquidate their grain stocks at harvest (i.e. high value crops with higher variability in expected returns due to a combination of price risk and transaction cost dynamics). This helps to highlight the importance of expenditure shocks in explaining smallholder farmers' marketing and inventory behavior.

4.9 Optimal production and marketing plans for scenario 3: relief aid policy to address yields shocks

We develop two policy frameworks relevant for addressing shocks faced by smallholder farmers. (i) Scenario 3: the relief aid program which addresses yield shocks and (ii) Scenario 4: the microinsurance program which addresses expenditure shocks. The relief program in the model provides a cash pay-out to farmers at harvest when their realized yields have a combination of "bad" yields for both crops. The expected amount of money paid out to farmers is equivalent to the net payment farmers get in scenario 4 (i.e. expected indemnity minus premium). Our results for scenario 3 which provides farmers relief from yields shocks show that the farmer's optimal crop mix in Scenario 3 is to allocate 68 percent of land to maize and 32 percent to the cash crop. This is similar to what we observe in Scenario 2. Likewise, the optimal grain sales, purchase and inventory plans in the harvest and post-harvest periods for this scenario are very similar to what is observed in scenario 2 (see Tables 4.3 through 4.6). These results highlight the need for specific policies that address household expenditure shocks, as we observe that addressing yields shocks through government safety net programs like the relief aid program modeled in this paper does not have much of an impact on the household's optimal production and marketing plans relative to what is observed in scenario 2.

4.10 Optimal production and marketing plans for scenario 4: microinsurance policy to address expenditure shocks

When we consider policy scenario 4, where the policy is focused on ameliorating the household's expenditure shocks, we find that the farm household's optimal crop mix at planting is to allocate 66 percent of the land to maize and 34 percent to groundnuts. In this scenario, we observe that the proportion of land allocated to the cash crop increases relative to scenario 2 where the household faces shocks, but there are no policies or institutions to provide them with relief. However, this is still lower than the observed optimal crop mix in scenario 1, the scenario 1 where there are no expenditure shocks. These model results help to illustrate how expenditure shocks affect smallholder farmers' production choices with implications for their marketing patterns. Our model results for scenario 4 show the role of microinsurance programs in helping farmers cope with market risk and expenditure shocks. This suggest that for the commercialization of smallholder agriculture in SSA, there is a need for microinsurance policies to help farmers deal with the risks and shocks that they face, particularly, expenditure shocks, which may limit their ability to specialize in the production of high value crops like groundnuts instead of the staple crops and for exploiting favorable price dynamics more fully.

Table 4.3 shows that if households have access to microinsurance programs when they face the possibility of expenditure shocks (scenario 4), the expected maize sales at harvest is 379 kg while the expected sales of groundnut is 51 kg. The expected purchases of maize and groundnut at harvest are 144 kg and 203 kg respectively, while the expected inventories are 646 kg and 332 kg for maize and groundnuts, respectively. The optimal sales, purchases and inventory for this scenario, are closer to what we observe in scenario 1, the base scenario, relative to scenario 2 and

3, indicating that microinsurance can ameliorate much of the negative impacts of expenditure shocks on production and marketing behavior. In terms of the total net sales value, we also observe that the farm household has lower expected total net sales value in this scenario compared to scenario 2 and that the liquid wealth accumulated at harvest in this scenario is lower compared to scenario 2. Our model results also show that the optimal marketing plan for the farm household in this scenario is to sell relatively less of both crops at harvest compared to the other scenarios. In general, our model results show that *"the sell-low"* pattern varies across crops and these are generally more profound when households face expenditure shocks.

4.11 Conclusions and Policy Recommendations

We use dynamic stochastic programming to evaluate how production and market risks as well as household expenditure shocks influence smallholder farmers' production, storage and sales decisions in SSA. We compare the farm households' optimal production and marketing plans across four scenarios: Scenario 1: farm households do not face any expenditure shocks; Scenario 2: farm households face expenditure shocks; Scenario 3: farm households face expenditure shocks and they have access to a government relief aid program in response to yield shocks; and Scenario 4: the farm households face expenditure shocks and they have access to microinsurance. We find that expenditure shocks alter the farm household's optimal crop mix influencing the farmer to scale down the production of the high value crop, groundnut, in favor of the staple crop, maize, because of the market risk-hedging properties associated with the staple. We also observe that risks and shocks also influence the farm household's optimal storage and sales at harvest. Our results show that when households face shocks, the farm household's optimal plan is to sell more and store less of the cash crop at harvest compared to when there are no expenditure shocks. However, we also observe that the household sells less and stores more of the staple crop at harvest in scenario 2 relative to scenario 1. These model results illustrate the impact of market risks and expenditure shocks on smallholder farmer's production and marketing behavior.

In terms of policy, we find that social safety net programs that only address yield shocks like the relief aid programs in scenario 3 may not help to address the constraints farmers face from production and market risks, as well as risks of expenditure shocks. However, for farmers to participate in the production and storage of cash crops which are associated with market risk (i.e. higher price variability and dynamics of market search and transportation costs), there is a need for microinsurance programs that address households expenditure shocks, allowing their participation in more cash crop oriented production and exploitation of price arbitrage opportunities.

4.12 References

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4.13 Tables and Figures

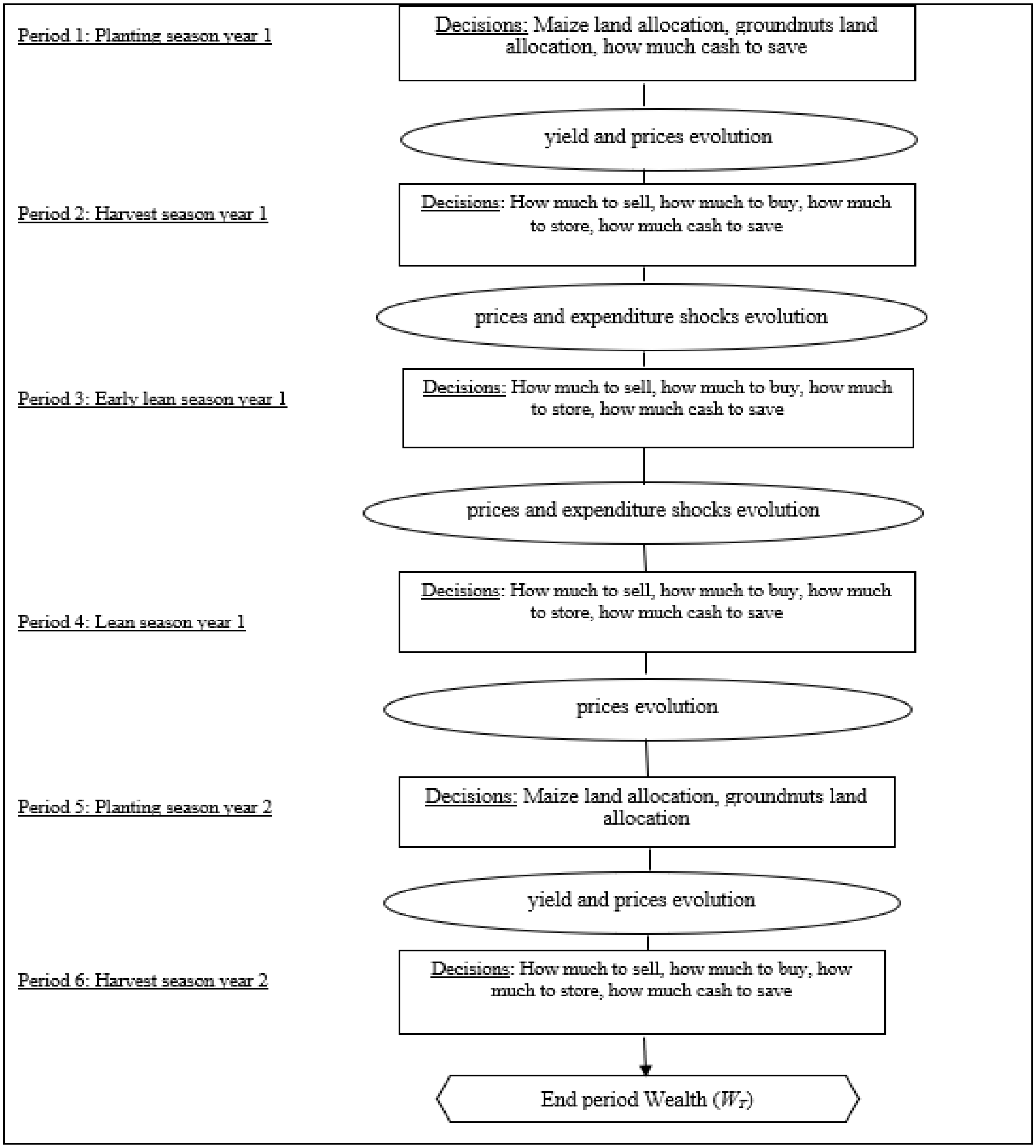

Figure 4.1: Event Schedule for the Discrete Stochastic Programming Model

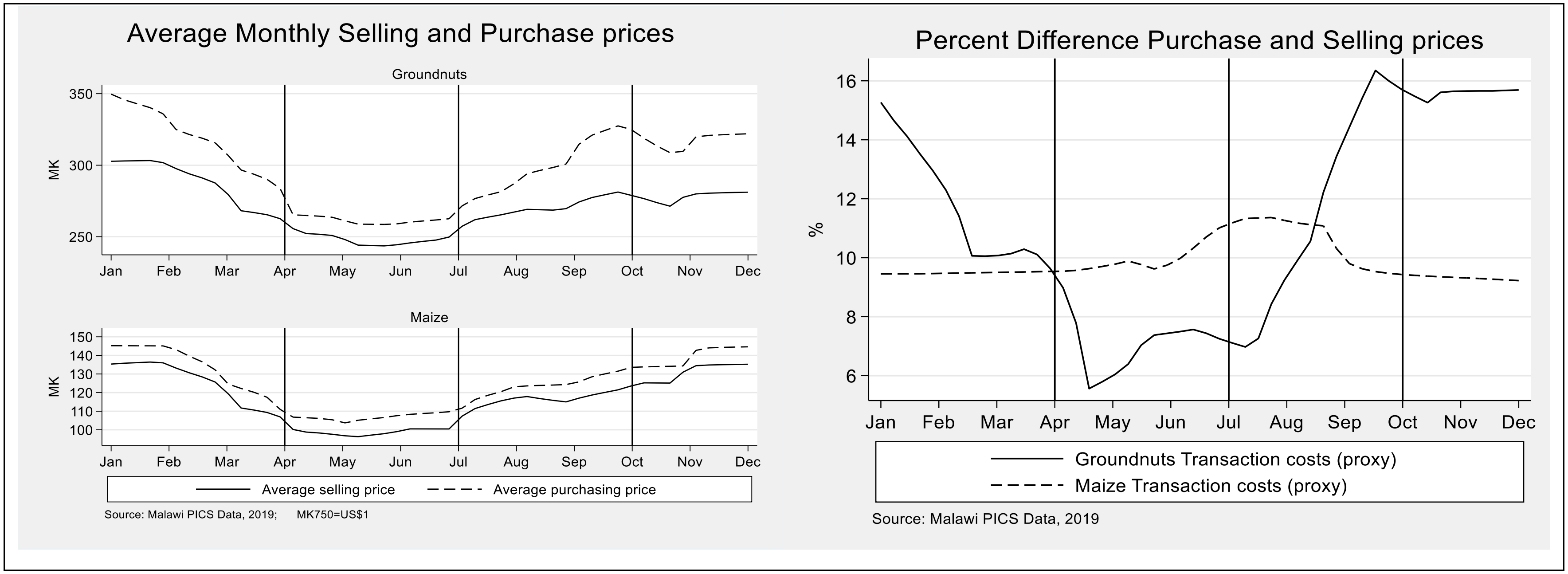

Figure 4.2: Transaction costs variations across seasons

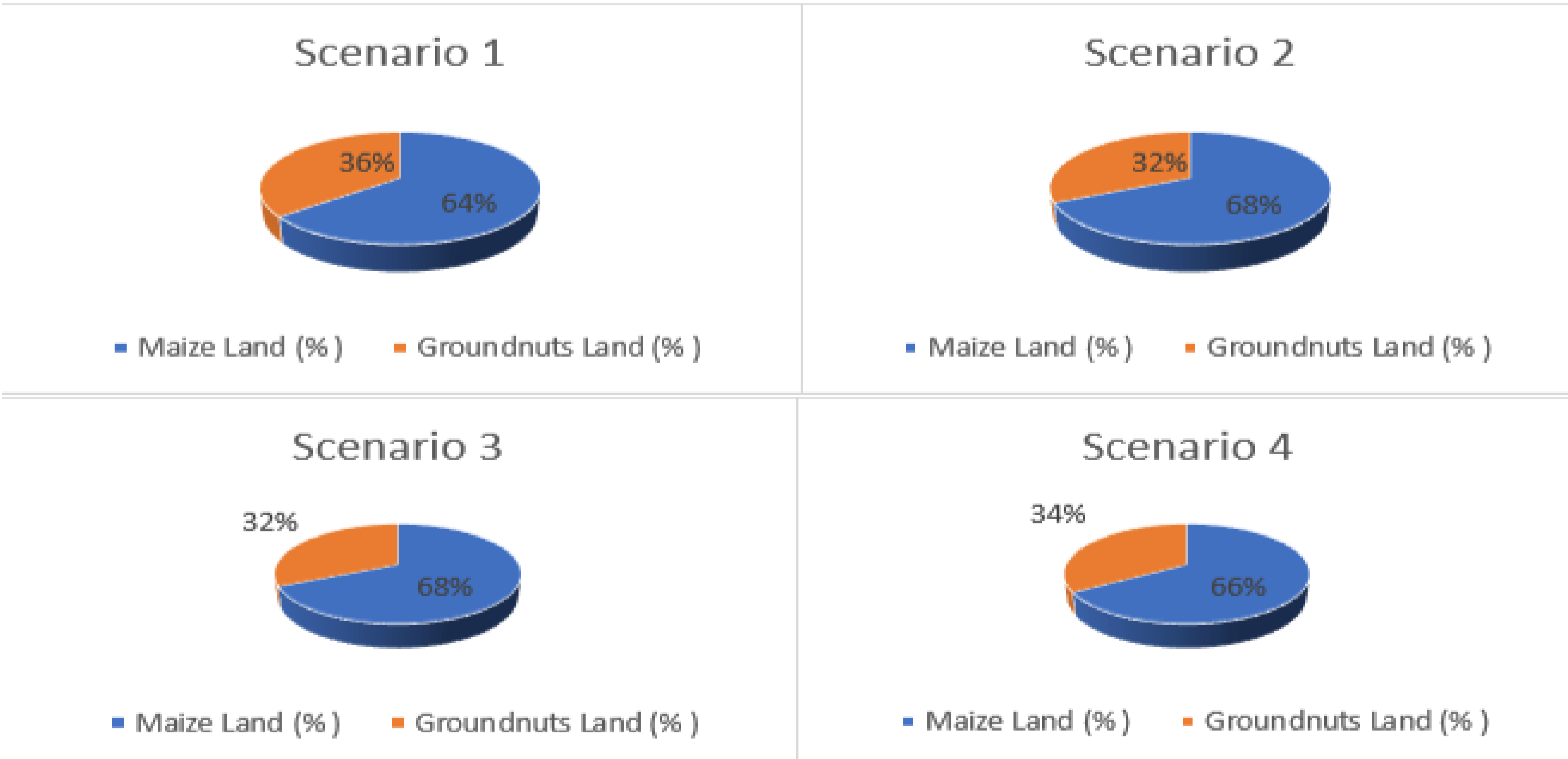

Figure 4.3: Optimal crop mix at planting period year 1

Table 4.1: Summary of the model price dynamics by period

MAIZE	Price type	Expected Value	Std. Dev.	CV	High	Prob	Medium	Prob	Low	Prob
Planting year 1	Purchase price	186.000	0	0.00			186	1		
	Selling price (TC=0.095)	168.000	0	0.00			168	1		
Harvest Year 1	Purchase price	173.464	75	0.43	277	0.292	166	0.4	85	0.308
	Selling price (TC=0.095)	**157.008**	**68**	**0.43**	**251**		**150**		**77**	
Early lean year 1	Purchase price	180.816	74	0.41	285	0.292	172	0.398	94	0.31
	Selling price (TC=0.095)	**163.774**	**67**	**0.41**	**258**		**156**		**85**	
Lean year 1	Purchase price	188.032	69	0.37	284	0.294	181	0.396	106	0.31
	Selling price (TC=0.095)	**170.262**	**63**	**0.37**	**257**		**164**		**96**	
Planting year 2	Purchase price	186.742	72	0.39	287	0.296	178	0.389	103	0.316
	Selling price (TC=0.095)	**168.977**	**66**	**0.39**	**260**		**161**		**93**	
Harvest year 2	Purchase price	173.464	75	0.43	277	0.292	166	0.4	85	0.308
	Selling price (TC=0.095)	**157.008**	**68**	**0.43**	**251**		**150**		**77**	
GROUNDNUTS	**Price type**	**Expected Value**			**High**	**Prob**	**Medium**	**Prob**	**Low**	**Prob**
Planting year 1	Purchase price	417.000	0	0.00			417	1		
	Selling price (TC=0.15)	**355.000**	**0**	**0.00**			**355**	**1**		
Harvest Year 1	Purchase price	352.743	190	0.54	664	0.248	372	0.376	157	0.307
	Selling price (TC=0.05)	**334.959**	**180**	**0.54**	**631**		**353**		**149**	
Early lean year 1	Purchase price	423.676	210	0.50	709	0.298	407	0.39	172	0.312
	Selling price (TC=0.09)	**385.494**	**191**	**0.50**	**645**		**370**		**157**	
Lean year 1	Purchase price	426.295	208	0.49	712	0.295	407	0.395	179	0.31
	Selling price (TC=0.16)	**358.000**	**175**	**0.49**	**598**		**342**		**150**	
Planting year 2	Purchase price	417.083	212	0.51	707	0.296	399	0.393	164	0.311
	Selling price (TC=0.15)	354.352	180	0.51	601		339		139	
Harvest year 2	Purchase price	352.743	190	0.54	664	0.248	372	0.376	157	0.307
	Selling price (TC=0.05)	334.959	180	0.54	631		353		149	

Note: Std. Dev is standard deviation, CV is coefficient of variation, prob is probability while TC is transaction cost parameter estimate used in the model.

Table 4.2 : Model parameters details

State of Nature	Price	Yields	Net returns per acre	Prob	Net returns per acre*Prob	Price	Yields	Net returns per acre	Prob	Net returns per acre*Prob
	GROUNDNUTS					**MAIZE**				
G.G.H.M(0.060)	372	425	54,208	0.060	3230	277	949	174,335	0.06	10386
G.G.M.H(0.101)	664	425	178,310	0.101	17937	166	949	69,383	0.101	6980
G.G.L.L(0.110)	157	425	-37,206	0.110	-4087	85	949	-7,439	0.11	-817
G.A.H.H(0.042)	664	357	133,138	0.042	5599	277	949	174,335	0.042	7331
G.B.L.H(0.002)	664	238	54,088	0.002	104	85	949	-7,439	0.002	-14
A.G.H.H(0.044)	664	425	178,310	0.044	7927	277	702	105,954	0.044	4710
A.G.M.L(0.023)	157	425	-37,206	0.023	-852	166	702	28,318	0.023	649
A.G.L.M(0.040)	372	425	54,208	0.040	2145	85	702	-28,509	0.04	-1128
A.A.M.M(0.235)	372	357	28,893	0.235	6800	166	702	28,318	0.235	6665
A.B.M.M(0.041)	372	238	-15,409	0.041	-633	166	702	28,318	0.041	1164
B.A.H.M(0.023)	372	357	28,893	0.023	664	277	401	22,622	0.023	520
B.B.H.M(0.002)	372	238	-15,409	0.002	-36	277	401	22,622	0.002	53
B.B.H.L(0.121)	157	238	-66,601	0.121	-8052	277	401	22,622	0.121	2735
B.B.L.H(0.103)	664	238	54,088	0.103	5571	85	401	-54,186	0.103	-5581
B.B.L.L(0.053)	157	238	-66,601	0.053	-3558	85	401	-54,186	0.053	-2895
				Expected Net returns per acre	**32,759**				**Expected Net returns per acre**	**30,757**
				Variance	**6,065,330,950**				**Variance**	**3,942,707,413**
				Std. Dev	**77,880**				**Std. Dev**	**62,791**
				CV	**2**				**CV**	**2**

Table 4.3: Model parameters details

Parameter	Value	Units	Source
Landholding	2.3	acres	IHS4 Data: Agriculture Module B1
Household expenditure	18,386	MK	IHS4 WB Household Module G1 to G3
Maize consumption	109.1	Kgs per month	IHS4 Data: Household Module G1 to G3
Groundnuts consumption	39.5	Kgs per month	IHS4 Data: Household Module G1 to G3
Household size	4.3	persons	IHS4 WB aggregate consumption per capita
PHL maize	4.1	percent	APHLIS website
PHL groundnuts	12	percent	Ambler et al. 2018
Inventory capacity	1,500	kg	PICS Baseline Survey for RCT 1 Module F1
Trade capacity	250	kgs per month	PICS Baseline Survey for RCT 1 Module F1
Required maize planting labor	461.75	hours per season per acre	IHS4 Data: Agricultural Module D
Required groundnuts planting labor	350.7	hours per season per acre	IHS4 Data: Agricultural Module D
Required maize harvesting labor (by yield: G, A, B)	182, 142, 102	hours per season per acre	IHS4 Data: Agricultural Module D
Required groundnuts harvesting labor (by yield: G, A, B)	445., 371, 287	hours per season per acre	IHS4 Data: Agricultural Module D
Wage per hour	163.75	Mk per hour	IHS4 Data: Household Module E waged jobs
Hired labor hours	13.7	hours per week per person	IHS4 HH Module E Casual labor hours
Available hired labor harvest period	1,972.8	Hours available harvest season	Imputed IHS4 Data: Agriculture Module D & E
Family agricultural labor	12.5	hours per week per person	Malawi IHS4 Report (Page 112)
Available family labor	860	Hours available per season	Imputed IHS4 report (page 112) & Household size
Enterprise revenue	20,821.4	MK per month	IHS4 Data: Household Module E enterprises
Other cash sources	3275	MK per month	IHS4 Data: Household Module E other sources
Cash remittances (Wages + other transfers)	44,296.4	MK per Month	PICS Baseline Survey for RCT 1 Module D1
Cash transfer	50,150	MK per quarter	IHS4 Data: Household Module R Social Safety nets
Cash savings (Initial cash endowments)	85,501	Malawi Kwacha (2016)	IHS4 Data: Household Module P Incomes
Maize stocks (Initial endowments)	295	Kgs	IHS4 Data: Agricultural Module I Sales and Storage
Groundnuts stocks (Initial endowments)	58.25	Kgs	IHS4 Data: Agricultural Module I Sales and Storage
Transportation cost associated with sales	4,271	MK per 500 kgs	IHS4 Data: Agricultural Module I Sales and Storage
Groundnuts planting transaction cost estimate	15	Wedge as percent of selling price	PICS survey baseline Module G2
Groundnuts harvest transaction cost estimate	5	Wedge as percent of selling price	PICS survey data marketing module
Groundnuts early lean transaction cost estimate	9	Wedge as percent of selling price	PICS survey data marketing module
Groundnuts lean transaction cost estimate	16	Wedge as percent of selling price	PICS survey data marketing module
Maize planting (Peak lean) transaction cost estimate	9.5	Wedge as percent of selling price	PICS survey baseline Module G2
Maize harvest transaction cost estimate	9.5	Wedge as percent of selling price	PICS survey data marketing module
Maize early lean transaction cost estimate	9.5	Wedge as percent of selling price	PICS survey data marketing module
Maize lean transaction cost estimate	9.5	Wedge as percent of selling price	PICS survey data marketing module
Maize variable cost per ac planting	43,204	MK per ac	PICS survey baseline Module B2
Groundnuts variable cost per ac planting	21,500	MK per ac	PICS survey baseline Module B2
Maize variable cost per ac harvesting	26,100	MK per ac	PICS survey baseline Module B2
Groundnuts variable cost per ac harvesting	46,206	MK per ac	PICS survey baseline Module B2

Table 4.4: Harvest period inventory and marketing strategy

CROP	MAIZE											
States of Nature	**Optimal sales plan**				**Optimal purchase plan**				**Optimal storage plan**			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
G.G.H.M(0.060)	1000	1000	1000	1000	0	0	0	0	245	327	327	288
G.G.M.H(0.101)	9	91	91	52	0	0	0	0	1236	1236	1236	1236
G.G.L.L(0.110)	842	715	715	986	0	0	0	0	403	611	611	302
G.A.H.H(0.042)	1000	1000	1000	1000	0	0	0	0	245	327	327	288
G.B.L.H(0.002)	0	0	0	0	755	673	673	712	2000	2000	2000	2000
A.G.H.H(0.044)	878	939	939	910	0	0	0	0	0	0	0	0
A.G.M.L(0.023)	563	550	550	910	0	0	0	0	315	388	388	
A.G.L.M(0.040)	0	0	0	0	1000	1000	1000	1000	1878	1939	1939	1910
A.A.M.M(0.235)	444	287	287	0	0	0	0	0	434	652	652	910
A.B.M.M(0.041)	490	638	638	0	0	0	0	0	0	0	0	0
B.A.H.M(0.023)	432	467	467	450	0	0	0	0	0	0	0	0
B.B.H.M(0.002)	432	467	467	450	0	0	0	0	0	0	0	0
B.B.H.L(0.121)	432	467	467	450	0	0	0	0	0	0	0	0
B.B.L.H(0.103)	0	0	0	0	1000	1000	1000	1000	1432	1467	1467	1450
B.B.L.L(0.053)	432	0	0	149		769	769	0	0	1236	1236	302
Expected Value	**458**	**394**	**394**	**379**	**144**	**185**	**185**	**144**	**529**	**685**	**685**	**646**
Standard Deviation	**324**	**329**	**329**	**1495**	**351**	**1501**	**375**	**350**	**567**	**2742**	**548**	**569**
CROP	GROUNDNUTS											
States of Nature	**Optimal sales plan**				**Optimal purchase plan**				**Optimal storage plan**			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
G.G.H.M(0.060)	278	229	229	252	520	0	0	0	798	229	229	252
G.G.M.H(0.101)	0	0	0	0	0	0	0	0	0	0	0	0
G.G.L.L(0.110)	0	0	0	0	918	842	842	613	1196	1072	1072	866
G.A.H.H(0.042)	224	183	183	202	0	0	0	0	0	0	0	0
G.B.L.H(0.002)	130	103	103	115	0	0	0	0	0	0	0	0
A.G.H.H(0.044)	278	229	229	252	0	0	0	0	0	0	0	0
A.G.M.L(0.023)	0	168	168	188	1000	1000	1000	1000	1278	1229	1229	1252
A.G.L.M(0.040)	156	0	0	0	0	0	0	0	122	61	61	64
A.A.M.M(0.235)	23	106	106	0	0	0	0	0	201	77	77	202
A.B.M.M(0.041)	38	36	36	0	0	0	0	0	91	67	67	115
B.A.H.M(0.023)	0	18	18	0	7	0	0	0	231	166	166	202
B.B.H.M(0.002)	0	18	18	0	121	0	0	0	251	85	85	115
B.B.H.L(0.121)	0	0	0	0	1000	1000	1000	846	1130	1103	1103	962
B.B.L.H(0.103)	130	103	103	115	0	0	0	0	0	0	0	0
B.B.L.L(0.053)	0	0	0	0	698	0	0	202	827	103	103	317
Expected Value	**65**	**73**	**73**	**51**	**313**	**236**	**236**	**203**	**451**	**326**	**326**	**332**
Standard Deviation	**94**	**77**	**77**	**89**	**425**	**407**	**407**	**334**	**612**	**473**	**456**	**375**

Note: Scenario 1 is without expenditure shocks; Scenario 2 is with expenditure shocks; Scenario 3 is with expenditure shocks + relief aid while Scenario 4 is with expenditure shocks + microinsurance

Table 4.5: Monetary value of sales, purchases and inventories

TOTAL MONETARY VALUE (in MK; US1=MK750)														
States of Nature	**Realized Prices**		**Total sales revenue**				**Total purchase value**				**Total inventory value**			
	Maize	Groundnuts	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
G.G.H.M(0.060)	277	372	380242	362215	362215	370741	193512	0	0	0	364733	175896	175896	173625
G.G.M.H(0.101)	166	664	1496	15129	15129	8645	0	0	0	0	205493	205493	205493	205493
G.G.L.L(0.110)	85	157	71828	60994	60994	84112	144305	132401	132401	96418	222340	220567	220567	161826
G.A.H.H(0.042)	277	664	425542	398519	398519	411301	0	0	0	0	67828	90529	90529	79732
G.B.L.H(0.002)	85	664	86151	68115	68115	76646	209021	186319	186319	197116	553697	553697	553697	553697
A.G.H.H(0.044)	277	664	427564	412284	412284	419471	0	0	0	0	0	0	0	0
A.G.M.L(0.023)	166	157	93602	117852	117852	180818	157191	157191	157191	157191	253218	257743	257743	196836
A.G.L.M(0.040)	85	372	57952	0	0	0	85306	85306	85306	85306	205645	188224	188224	186902
A.A.M.M(0.235)	166	372	82429	87125	87125	0	0	0	0	0	146876	137177	137177	226644
A.B.M.M(0.041)	166	372	95742	119345	119345	0	0	0	0	0	34005	24900	24900	42954
B.A.H.M(0.023)	277	372	119598	135861	135861	124582	2640	0	0	0	85972	61614	61614	75351
B.B.H.M(0.002)	277	372	119598	135861	135861	124582	45080	0	0	0	93361	31600	31600	42954
B.B.H.L(0.121)	277	157	119598	129288	129288	124582	157191	157191	157191	133052	177577	173309	173309	151189
B.B.L.H(0.103)	85	664	86151	68115	68115	76646	85306	85306	85306	85306	122158	125144	125144	123694
B.B.L.L(0.053)	85	157	36852	0	0	12711	109655	65600	65600	31743	130041	121556	121556	75642
Expected Value	**174**	**392**	**123863**	**119214**	**119214**	**99219**	**68573**	**53174**	**53174**	**44516**	**163838**	**148740**	**148740**	**157114**

Note: Scenario 1 is without expenditure shocks; Scenario 2 is with expenditure shocks; Scenario 3 is with expenditure shocks + relief aid while Scenario 4 is with expenditure shocks + microinsurance

Table 4.6: Total Net Sales Values (Total sales value -Total purchase value)

States of Nature	Total Sales Value in MK; US1=MK750)			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4
G.G.H.M(0.060)	11125	21579	21579	22087
G.G.M.H(0.101)	151	1522	1522	870
G.G.L.L(0.110)	-7961	-7844	-7844	-1352
G.A.H.H(0.042)	17896	16759	16759	17297
G.B.L.H(0.002)	-237	-228	-228	-232
A.G.H.H(0.044)	19008	18329	18329	18648
A.G.M.L(0.023)	-1457	-901	-901	541
A.G.L.M(0.040)	-1082	-3376	-3376	-3376
A.A.M.M(0.235)	19400	20505	20505	0
A.B.M.M(0.041)	3934	4904	4904	0
B.A.H.M(0.023)	2687	3122	3122	2862
B.B.H.M(0.002)	173	316	316	290
B.B.H.L(0.121)	-4545	-3373	-3373	-1024
B.B.L.H(0.103)	87	-1771	-1771	-892
B.B.L.L(0.053)	-3889	-3504	-3504	-1017
Expected Value	3686	4403	4403	3647

Note: Scenario 1 is without expenditure shocks; Scenario 2 is with expenditure shocks; Scenario 3 is with expenditure shocks + relief aid while Scenario 4 is with expenditure shocks + microinsurance

Table 4.7: Harvest period liquid wealth accumulation plan

States of Nature	Optimal cash savings plan (in MK; US1=MK750)			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4
G.G.H.M(0.060)	153876	327714	327714	270823
G.G.M.H(0.101)	257032	232505	232505	183916
G.G.L.L(0.110)	0	0	0	0
G.A.H.H(0.042)	494416	440868	440868	395864
G.B.L.H(0.002)	93924	83092	83092	30820
A.G.H.H(0.044)	496340	454020	454020	404077
A.G.M.L(0.023)	8734	2786	2786	0
A.G.L.M(0.040)	45166	50032	50032	0
A.A.M.M(0.235)	154723	156998	156998	20275
A.B.M.M(0.041)	167912	185569	185569	20275
B.A.H.M(0.023)	188939	200173	200173	133052
B.B.H.M(0.002)	146500	200173	200173	133052
B.B.H.L(0.121)	34389	36869	36869	0
B.B.L.H(0.103)	73049	55207	55207	6250
B.B.L.L(0.053)	0	11529	11529	0
Expected Cash Savings	**139,728**	**144,241**	**144,241**	**78,922**

Note: Scenario 1 is without expenditure shocks; Scenario 2 is with expenditure shocks; Scenario 3 is with expenditure shocks + relief aid while Scenario 4 is with expenditure shocks + microinsurance

Table 4.7: Panel A: Early Lean period inventory and marketing strategy

CROP	MAIZE											
States of Nature	**Optimal sales plan**				**Optimal purchase plan**				**Optimal storage plan**			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Expected Value	478	755	755	457	964	508	508	774	1391	1154	1154	1322
Standard Deviation	348	387	387	311	360	330	330	375	400	393	393	436
CROP	GROUNDNUTS											
States of Nature	**Optimal sales plan**				**Optimal purchase plan**				**Optimal storage plan**			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Expected Value	742	633	633	326	714	695	695	1092	904	675	675	783
Standard Deviation	357	333	333	235	386	368	368	410	460	371	371	414

Note: Scenario 1 is without expenditure shocks; Scenario 2 is with expenditure shocks; Scenario 3 is with expenditure shocks + relief aid while Scenario 4 is with expenditure shocks + microinsurance

Table 7 Panel B Lean period inventory and marketing strategy

CROP	MAIZE											
States of Nature	**Optimal sales plan**				**Optimal purchase plan**				**Optimal storage plan**			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Expected Value	458	394	394	379	144	185	185	144	529	685	685	646
Standard Deviation	324	329	329	1495	351	1501	375	350	567	2742	548	569
CROP	GROUNDNUTS											
States of Nature	**Optimal sales plan**				**Optimal purchase plan**				**Optimal storage plan**			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Expected Value	292	268	307	329	302	275	362	351	382	323	414	402
Standard Deviation	307	240	283	278	356	333	374	368	450	398	446	449

Note: Scenario 1 is without expenditure shocks; Scenario 2 is with expenditure shocks; Scenario 3 is with expenditure shocks + relief aid while Scenario 4 is with expenditure shocks + microinsurance

Appendix : Stochastic Farm Planning Model In Gams Notation

```
$title Malawi Stochastic Farm Planning Model LP/NLP
*#################################################################################################
*#################################################################################################

*1. Empirical approximation of distributions for the random variables using GQ
option decimals=2;
*option limrow=0, limcol=0;

SETS
crops   Crops in the model /maize, gnuts /
Time    Time periods in years /t1*t27/
labor   Sources of labor /family, hired/
y       market-year observations /1*1050 /
*y     Years of Historical Data /1989*2016 /
ps    State of Crop Prices / H, M, L /
ys        State of crop yields / Good, Avg, Bad /

*es    State of expenditure shocks / yes, No /
es    State of expenditure shocks / Sev, Min, No /
i     Moments /zero, one, two /
h     households in IHS 4 data / h1*h12447 /
hss   harvest / YieldsM,YieldsG,PRICES1HM,PRICES1HG /
h2ss   harvest / YieldsM,YieldsG,PRICES2HM,PRICES2HG /
states1 States after first transition /ym1,yg1,pm1,pg1/
states2 States after second transition /elpm,elpg/
states3 States after third transition / lpm,lpg /
states4 States after fourth transition /p2pm,p2pg /
states5 States after firth transition /ym2,yg2,pm2,pg2/ ;
Alias (ys,ym1,yg1),(ps,pm1,pg1) ;
Alias (ys,ym2,yg2),(ps,pm2,pg2) ;
Alias (i,j,i1,j1) ;
```

```
SCALARS
LANDT   Total landholding (acres) /2.3/
TOTCAPI Total Inventory capacity /2000/
TRADECAP maximum trade volumes for farmer /1000/
MAIZE0I Initial Maize stocks (Kilograms) /195/
GNUTS0I Initial Groundnuts stocks (Kilograms) /38.25/
CASH0S Initial cash endowments (Malawi Kwacha) /85500/
LABORF1P Family labor available in year 1 planting period (hours) /963.2/
LABORF1H Family labor available in year 1 harvest period (hours) /860/
LABORF2P Family labor available in year 2 planting period (hours) /963.2/
LABORF2H Family labor available in year 2 harvest period (hours) /860/
CLABORH1H Hired labor available in year 1 harvest period (hours) /1172.8/
CLABORH2H Hired labor available in year 1 harvest period (hours) /1172.8/

***##################################################################################
*#Proxy for Transaction costs by crop using % difference between selling & purchase
*either add to purchase price if AMIS Prices r selling prices
*or subtract from selling price if AMIS prices r purchase prices
*either would mean cheaper (less TC) to trade at harvest than lean
**##################################################################################

*$ontext
**SHOCK TCs
TRANSCSTMP Maize Transaction Cost planting period % /0.095/
TRANSCSTMH Maize Transaction Cost planting period % /0.095/
TRANSCSTME Maize Transaction Cost planting period % /0.095/
TRANSCSTML Maize Transaction Cost planting period % /0.095/

*Varying Transaction costs for cash crop
TRANSCSTGP Gnuts Transaction Cost planting period %  /0.15/
TRANSCSTGH Gnuts Transaction Cost planting period % /0.05/
TRANSCSTGE Gnuts Transaction Cost planting period % /0.09/
TRANSCSTGL Gnuts Transaction Cost planting period % /0.16/
*$offtext
```

```
$ontext
**NO SHOCK TCs
TRANSCSTMP Maize Transaction Cost planting period % /0.0095/
TRANSCSTMH Maize Transaction Cost planting period % /0.0095/
TRANSCSTME Maize Transaction Cost planting period % /0.0095/
TRANSCSTML Maize Transaction Cost planting period % /0.0095/

**Non varying Transaction costs for cash crop
TRANSCSTGP Gnuts Transaction Cost planting period % /0.0112/
TRANSCSTGH Gnuts Transaction Cost planting period % /0.0112/
TRANSCSTGE Gnuts Transaction Cost planting period % /0.0112/
TRANSCSTGL Gnuts Transaction Cost planting period % /0.0112/
$offtext

**##################################################################################
*PHL standard wooven bag
M1HSF Maize survivor factor in year 1 harvest period
G1HSF Groundnuts survivor factor in year 1 harvest period
M1ESF Maize survivor factor in year 1 early lean period
G1ESF Groundnuts survivor factor in year 1 early lean period
M1LSF Maize survivor factor in year 1 lean period
G1LSF Groundnuts survivor factor in year 1 lean period
M2PSF Maize survivor factor in year 2 Planting period
G2PSF Groundnuts survivor factor in year 2 Planting period
M2HSF Maize survivor factor in year 2 harvest period
G2HSF Groundnuts survivor factor in year 2 harvest period;
M1HSF =POWER(0.959,3);
G1HSF =POWER(0.88,3) ;
M1ESF =POWER(0.959,6);
G1ESF =POWER(0.88,6) ;
M1LSF =POWER(0.959,8) ;
G1LSF =POWER(0.88,8) ;
M2PSF =POWER(0.959,12) ;
G2PSF =POWER(0.88,12) ;
```

```
M2HSF =POWER(0.959,4);
G2HSF =POWER(0.88,4) ;
*###############################################################################################################
**PICS Technology
M1HSF =POWER(0.99,3);
G1HSF =POWER(0.98,3) ;
M1ESF =POWER(0.99,6);
G1ESF =POWER(0.98,6) ;
M1LSF =POWER(0.99,8) ;
G1LSF =POWER(0.98,8) ;
M2PSF =POWER(0.99,12) ;
G2PSF =POWER(0.98,12) ;
M2HSF =POWER(0.99,4) ;
G2HSF =POWER(0.98,4) ;

*###############################################################################################################
scalars
*Micro credit and insurance program parameters
CASHAID   Governement Cash tranfer in case of shock MK /91000/
FOODAID   Government Food aid (kgs) /92 /
MCREDIT   Maximum credit available for farmer MK /500000/
INTEREST  Cost of Money per Kwacha credit rate /0.05 /
PREMIUM   Microinsurance premium for idiosyncratic shocks /55000/
INSURANCE Insurance payment received in event of severe shocks /140000/

*Planting year 1
MAIZE1PC Maize consumption in year 1 planting period (kg) /218.2/
GNUTS1PC Groundnuts consumption in year 1 planting period(kg) / 79 /
CASH1PM Variable cost of maize per acres in year 1 planting period (MKperha) /43204/
CASH1PG Variable cost of maize per acres in year 1 planting period (MKperha) /21500/
CASH1PR Cash remittances in year 1 planting period (MK) /177185.6/
CASH1PHE Money spend on households' expenditures in year 1 planting period (MK) / 73547/
LABOR1PM Labor required per acres of maize in year 1 planting period (hours per ac) /461.75 /
LABOR1PG Labor required per acres of groundnuts (hours per ac) /350.7/
```

```
*Harvest year 1
MAIZE1HC Maize consumers in year 1 harvest period (kg) /163.65/
GNUTS1HC Groundnuts consumers in year 1 harvest period (kg) /59.25 /
CASH1HHE Money spend on households expenditures in year 1 harvest period (MK) /55160.25 /
CASH1HR Cash remittances in year 1 harvest period (MK) /132889.2/
CASHH1WG Wage paid for hired labor in year 1 harvest period (MK per hour) /173.75/
CASH1HM Variable cost of maize per acre in year 1 harvest period (MK per ac) /26100/
CASH1HG Variable cost of gnuts per acre in year 1 harvest period (MK per ac) /66206/

*Early Lean year 1
MAIZE1EC Maize consumers in year 1 early lean period (kg) /163.65/
GNUTS1EC Groundnuts consumers in year 1 early lean period (kg)/59.25/
CASH1ER Cash remittances in year 1 early lean period (MK) /132889.2/
CASH1EHE Money spend on households' expenditures in year 1 early lean period (MK) /55160.25/

*Lean year 1
MAIZE1LC Maize consumers in year 1 lean period (kg) /109.1/
GNUTS1LC Groundnuts consumers in year 1 lean period (kg)/39.5/
CASH1LR Cash remittances in year 1 lean period (MK) /88592.8/
CASH1LHE Money spent on households' expenditures in year 1 lean period (MK) /66773.5/

*Planting year 2
MAIZE2PC Maize consumers in year 2 Planting period (kg) /218.2/
GNUTS2PC Groundnuts consumers in year 2 Planting period (kg) /79/
CASH2PR Cash remittances in year 2 Planting period (MK) /177185.6/
CASH2PHE Money spend on households' expenditures in year 2 planting period (MK) /73547/
CASH2PM Maize VC per ac in year 2 Planting period (MKperac) /43204 /
CASH2PG Gnuts VC per ac in year 2 Planting period (MKperac) /21500/
LABOR2PM Labor required per acre of maize in year 2 Planting (hrs per ac) /461.75/
LABOR2PG Labor required per acre of gnuts in year 2 Planting (hrs per ac)/350.7/

*Harvest year 2
MAIZE2HC Maize consumers in year 2 harvest period (kg) /163.65/
```

```
GNUTS2HC Groundnuts consumers in year 2 harvest period (kg)/59.25/
CASH2HR Cash remittances in year 2 harvest period (MK) /132889.2/
CASH2HHE Money spent on households' expenditures in year 2 harvest period (MK)/ 55160.25 /
CASHH2WG Wage paid for hired labor in year 2 harvest period (MK per hour) /173.75/
CASH2HM Maize VC per ac in year 2 harvest period (MK per ac) /26100 /
CASH2HG Gnuts VC per ac in year 2 harvest period (MK per ac) /66206 /   ;

Parameters
**Harvest year 1
LABOR1HM(ym1) Maize labor requirement year 1 harvest(hours per ac) / Good 282.23,Avg 162.23,Bad 102.23/
LABOR1HG(yg1) Gnuts Labor requirement year 1 harvest(hours per ac) / Good 556.38,Avg 471.38,Bad 287.38/
LABOR2HM(ym2) Maize labor requirement year 2 harvest (hours per ac) /Good 282.23,Avg 162.23,Bad 102.23/
LABOR2HG(yg2) Gnuts Labor requirement year 2 harvest (hours per ac)/ Good 556.38,Avg 471.38,Bad 287.38/;

parameter
HHSHOCK1H(es) household expenditure shocks harvest 1
HHSHOCK1E(es) household expenditure shocks harvest 2
HHSHOCK1L(es) household expenditure shocks Lean 1;

*##Mean and Variance for Shocks GQ
*HHSHOCK1H(es)= EShocks(es) ;
*HHSHOCK1E(es)= EShocks(es)  ;

*##Mean and standard Deviation for Shocks actual historical distribution
HHSHOCK1H(es)= EShocks2(es) ;
HHSHOCK1E(es)= EShocks2(es)  ;

Parameters
 lscale Labor scaling factor / 24 /
 cscale Cash scaling factor  / 1000 /
 Scalar scale scaling factor for ending wealth /0.000001/
 r risk coefficient /0.5/

Variable
```

```
EH2CASH ending period wealth or Utility? (MK)

POSITIVE VARIABLES
LAND1M land allocated to maize in year 1 (acres)
LAND1G land allocated to maize in year 1 (acres)
LAND2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) land allocated to maize in year 2 (acres)
LAND2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) land allocated to maize in year 2 (acres)

*Planting year 1
MAIZE1PS maize sold in year 1 planting period (kg)
GNUTS1PS groundnuts sold in year 1 planting period (kg)
MAIZE1PB maize bought in year 1 planting period (kg)
GNUTS1PB groundnuts bought in year 1 planting period(kg)
MAIZE1PI maize stored in year 1 planting period (kg)
GNUTS1PI groundnuts stored in year 1 planting period(kg)
CASH1PI Money saved in year 1 planting period(MK)
CREDIT1P  Money borrowed during planting 1  in MK

*Harvest year 1
MAIZE1HS(ym1,yg1,pm1,pg1) maize sold in year 1 harvest period (kg)
GNUTS1HS(ym1,yg1,pm1,pg1) groundnuts sold in year 1 harvest period(kg)
MAIZE1HB(ym1,yg1,pm1,pg1) maize bought in year 1 harvest period(kg)
GNUTS1HB(ym1,yg1,pm1,pg1) groundnuts bought in year 1 harvest period(kg)
MAIZE1HI(ym1,yg1,pm1,pg1) maize stored in year 1 harvest period (kg)
GNUTS1HI(ym1,yg1,pm1,pg1) groundnuts stored in year 1 harvest period(kg)
CASH1HI (ym1,yg1,pm1,pg1) Money saved in year 1 harvest period(MK)
CREDIT1H(ym1,yg1,pm1,pg1) Money borrowed during harvest 1  in MK
LABORH1H(ym1,yg1,pm1,pg1) Hired labor used in year 1 harvest (hours)

*Early Lean year 1
MAIZE1ES(ym1,yg1,pm1,pg1,elpm,elpg,es) maize sold in year 1 early lean period(kg)
GNUTS1ES(ym1,yg1,pm1,pg1,elpm,elpg,es) groundnuts sold in year 1 early lean period(kg)
MAIZE1EB(ym1,yg1,pm1,pg1,elpm,elpg,es) maize bought in year 1 early lean period(kg)
GNUTS1EB(ym1,yg1,pm1,pg1,elpm,elpg,es) groundnuts bought in year 1 early lean period(kg)
```

```
MAIZE1EI(ym1,yg1,pm1,pg1,elpm,elpg,es) maize stored in year 1 early lean period(kg)
GNUTS1EI(ym1,yg1,pm1,pg1,elpm,elpg,es) groundnuts stored in year 1 early lean period(kg)
CASH1EI (ym1,yg1,pm1,pg1,elpm,elpg,es) Money saved in year 1 early lean period(MK)

*Lean year 1
MAIZE1LS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) maize sold in year 1 lean period (kg)
GNUTS1LS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) groundnuts sold in year 1 lean period (kg)
MAIZE1LB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) maize bought in year 1 lean period (kg)
GNUTS1LB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) groundnuts bought in year 1 lean period(kg)
MAIZE1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) maize stored in year 1 lean period (kg)
GNUTS1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) groundnuts stored in year 1 lean period(kg)
CASH1LI (ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) money saved in year 1 lean period(MK)

*Planting year 2
MAIZE2PS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) maize sold in year 2 planting period (kg)
GNUTS2PS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) groundnuts sold in year 2 planting period (kg)
MAIZE2PB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) maize bought in year 2 planting period (kg)
GNUTS2PB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) groundnuts bought in year 2 planting period(kg)
MAIZE2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) maize stored in year 2 planting period (kg)
GNUTS2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) groundnuts stored in year 2 planting period(kg)
CASH2PI (ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) money saved in year 2 planting period (MK)

*Harvest year 2
MAIZE2HS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) maize sold in year 2 harvest period(kg)
GNUTS2HS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) groundnuts sold in year 2 harvest period(kg)
MAIZE2HB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) maize bought in year 2 harvest period(kg)
GNUTS2HB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) groundnuts bought in year 2 harvest period(kg)
MAIZE2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) maize stored in year 2 harvest period(kg)
GNUTS2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) groundnuts stored in year 2 harvest period(kg)
LABORH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) Hired labor used in year 2 harvest (hours)
CASH2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) money saved in year 2 harvest period(MK);

*Setting Bounds on Variables  to Limit unboundedness
scalar growfactor / 1/ ;
```

```
LAND1M.up = 2.3*growfactor ;
LAND1G.up = 2.3*growfactor ;
LAND2M.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) = 2.3*growfactor ;
LAND2G.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) = 2.3*growfactor ;

*Planting year 1
MAIZE1PS.up=TRADECAP*growfactor;
GNUTS1PS.up=TRADECAP*growfactor;
MAIZE1PB.up=TRADECAP*growfactor;
GNUTS1PB.up=TRADECAP*growfactor;

*Harvest year 1
MAIZE1HS.up(ym1,yg1,pm1,pg1)=TRADECAP*growfactor;
GNUTS1HS.up(ym1,yg1,pm1,pg1)=TRADECAP*growfactor;
MAIZE1HB.up(ym1,yg1,pm1,pg1)=TRADECAP*growfactor;
GNUTS1HB.up(ym1,yg1,pm1,pg1)=TRADECAP*growfactor;

*Early Lean year 1
MAIZE1ES.up(ym1,yg1,pm1,pg1,elpm,elpg,es)=TRADECAP*growfactor;
GNUTS1ES.up(ym1,yg1,pm1,pg1,elpm,elpg,es)=TRADECAP*growfactor;
MAIZE1EB.up(ym1,yg1,pm1,pg1,elpm,elpg,es)=TRADECAP*growfactor;
GNUTS1EB.up(ym1,yg1,pm1,pg1,elpm,elpg,es)=TRADECAP*growfactor;

*Lean year 1
MAIZE1LS.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)=TRADECAP*growfactor;
GNUTS1LS.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)=TRADECAP*growfactor;
MAIZE1LB.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)=TRADECAP*growfactor;
GNUTS1LB.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)=TRADECAP*growfactor;

*Planting year 2
MAIZE2PS.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=TRADECAP*growfactor;
GNUTS2PS.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=TRADECAP*growfactor;
MAIZE2PB.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=TRADECAP*growfactor;
GNUTS2PB.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=TRADECAP*growfactor;
```

```
*Harvest year 2
MAIZE2HS.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=1750*growfactor;
GNUTS2HS.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=1750*growfactor;
MAIZE2HB.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=TRADECAP*growfactor;
GNUTS2HB.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=TRADECAP*growfactor;

*ARTIFICIAL VARIABLES TO IDENTIFY CAUSE OF INFEASIBILITY
POSITIVE VARIABLES
PENCASH1P  Artificial for cash Planting 1 accounting cosntraint
PENCASH1H(ym1,yg1,pm1,pg1) Artificial for cash harvest  1 accounting cosntraint
PENCASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es) Artificial for cash Elean 1 accounting cosntraint
PENCASH1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) Artificial for cash Lean 1 accounting cosntraint
PENCASH2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) Artificial for cash Planting 2 accounting cosntraint
PENCASH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) Artificial for cash Planting 2 accounting cosntraint

EQUATIONS
OBJECTIVE1  Net cash savings objective definition(MK) lp risk neutral
OBJECTIVE2  Net cash savings objective definition(MK) nlp risk neutral
OBJECTIVE3  Net cash savings objective definition(MK) nlp risk averse
LAND1  Year 1 land constraint(acres)
LAND2  Year 1 land constraint(acres)

PLANT1M  Year 1 Planting maize grain accounting constraint(kg)
PLANT1G  Year 1 Planting gnuts grain accounting constraint(kg)
LABOR1P  Year 1 Planting labor constraint(hours)
CASH1P   Year 1 Planting cash constraints(MK)
CASH1PS4   Year 1 Planting cash constraints(MK)
INVENT1P Year 1 Planting Inventory capacity constraints(kg)

HARV1M(ym1,yg1,pm1,pg1) Year 1 Harvest maize grain accounting constraint(kg)
HARV1G(ym1,yg1,pm1,pg1) Year 1 Harvest gnuts grain accounting constraint(kg)
LABOR1H(ym1,yg1,pm1,pg1) Year 1 Harvest labor constraint(hours)
CASH1H(ym1,yg1,pm1,pg1) Year 1 Harvest cash constraints(MK)
```

```
CASH1HS3(ym1,yg1,pm1,pg1) Year 1 Harvest cash constraints(MK)
INVENT1H(ym1,yg1,pm1,pg1) Year 1 Harvest Inventory capacity constraints(kg)

ELEAN1M(ym1,yg1,pm1,pg1,elpm,elpg,es) Year 1 Early lean maize grain accounting constraint(kg)
ELEAN1G(ym1,yg1,pm1,pg1,elpm,elpg,es) Year 1 Early lean gnuts grain accounting constraint(kg)
CASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es)  Year 1 Early lean cash constraints(MK)
CASH1ES4(ym1,yg1,pm1,pg1,elpm,elpg,es)  Year 1 Early lean cash constraints(MK)
INVENT1E(ym1,yg1,pm1,pg1,elpm,elpg,es) Year 1 Early lean Inventory capacity constraints(kg)

LEAN1M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) Year 1 Lean maize grain accounting constraint(kg)
LEAN1G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) Year 1 Lean gnuts grain accounting constraint(kg)
CASH1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) Year 1 Lean cash constraints (MK)
INVENT1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) Year 1 lean Inventory capacity constraints(kg)

PLANT2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) Year 2 Planting maize grain accounting constraint(kg)
PLANT2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) Year 2 Planting gnuts grain accounting constraint(kg)
LABOR2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) Year 2 Planting labor constraint(hours)
CASH2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) Year 2 Planting cash constraints(MK)
INVENT2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es) Year 2 Planting Inventory capacity constraints(kg)

HARV2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) Year 2 Harvest maize grain accounting constraint(kg)
HARV2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) Year 2 Harvest gnuts grain accounting constraint(kg)
LABOR2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) Year 2 Harvest labor constraint(hours)
CASH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) Year 2 Harvest cash constraints(MK)
INVENT2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es) Year 2 Harvest Inventory capacity constraints(kg);

;
*##########################################################################################################################
*Equations
*##########################################################################################################################
*Year 1 Planting Period
PLANT1M..MAIZE1PS+ MAIZE1PI + MAIZE1PC =l= MAIZE1PB+ MAIZE0I;
PLANT1G..GNUTS1PS +GNUTS1PI + GNUTS1PC =l= GNUTS1PB + GNUTS0I;
INVENT1P.. MAIZE1PI+ GNUTS1PI =l= TOTCAPI;
```

```
LAND1.. LAND1M+LAND1G =l= LANDT;
LABOR1P..(LAND1M*LABOR1PM + LAND1G*LABOR1PG)/lscale =l= LABORF1P/lscale;
CASH1P..(LAND1M*CASH1PM + LAND1G*CASH1PG + PRICE1PM*MAIZE1PB
      + PRICE1PG*GNUTS1PB+ CASH1PI
      +CASH1PHE)/cscale
      =l= (PRICE1PM*MAIZE1PS*(1-TRANSCSTMP) +PRICE1PG*GNUTS1PS*(1-TRANSCSTGP) +CASH0S+ CASH1PR
      -PENCASH1P)/cscale ;

CASH1PS4..(LAND1M*CASH1PM + LAND1G*CASH1PG + PRICE1PM*MAIZE1PB
      + PRICE1PG*GNUTS1PB+ CASH1PI
      + PREMIUM
      +CASH1PHE)/cscale
      =l= (PRICE1PM*MAIZE1PS*(1-TRANSCSTMP) +PRICE1PG*GNUTS1PS*(1-TRANSCSTGP) +CASH0S+ CASH1PR
      -PENCASH1P)/cscale ;

*Year 1 Harvest Period
*##############################################################################################################################
HARV1M(ym1,yg1,pm1,pg1)$HStates(ym1,yg1,pm1,pg1,'probh1')
     ..MAIZE1HS(ym1,yg1,pm1,pg1)+MAIZE1HI(ym1,yg1,pm1,pg1)+MAIZE1HC=l=LAND1M*MMYields(ym1)
     +MAIZE1HB(ym1,yg1,pm1,pg1)+MAIZE1PI*M1HSF;

HARV1G(ym1,yg1,pm1,pg1)$HStates(ym1,yg1,pm1,pg1,'probh1')
    ..GNUTS1HS(ym1,yg1,pm1,pg1)+GNUTS1HI(ym1,yg1,pm1,pg1)+GNUTS1HC=l=LAND1G*MGYields(yg1)
    +GNUTS1HB(ym1,yg1,pm1,pg1)+GNUTS1PI*G1HSF;

INVENT1H(ym1,yg1,pm1,pg1)$HStates(ym1,yg1,pm1,pg1,'probh1')
    .. MAIZE1HI(ym1,yg1,pm1,pg1)+GNUTS1HI(ym1,yg1,pm1,pg1)=l=TOTCAPI;

LABOR1H(ym1,yg1,pm1,pg1)$HStates(ym1,yg1,pm1,pg1,'probh1')
    ..(LAND1M*LABOR1HM(ym1)+ LAND1G *LABOR1HG(yg1))/lscale=l=(LABORF1H+LABORH1H(ym1,yg1,pm1,pg1))/lscale;

CASH1H(ym1,yg1,pm1,pg1)$HStates(ym1,yg1,pm1,pg1,'probh1')..(LAND1M*CASH1HM
  +LAND1G*CASH1HG+RPRICES1HM(ym1,yg1,pm1,pg1)*MAIZE1HB(ym1,yg1,pm1,pg1)
  +RPRICES1HG(ym1,yg1,pm1,pg1)*GNUTS1HB(ym1,yg1,pm1,pg1)+CASH1HI(ym1,yg1,pm1,pg1)
```

```
  +CASH1HHE + LABORH1H(ym1,yg1,pm1,pg1)*CASHH1WG)/cscale
  =l= (RPRICES1HM(ym1,yg1,pm1,pg1)*MAIZE1HS(ym1,yg1,pm1,pg1)*(1-TRANSCSTMH)
  + RPRICES1HG(ym1,yg1,pm1,pg1)*GNUTS1HS(ym1,yg1,pm1,pg1)*(1-TRANSCSTGH)+CASH1PI + CASH1HR
  -PENCASH1H(ym1,yg1,pm1,pg1))/cscale;

CASH1HS3(ym1,yg1,pm1,pg1)$HStates(ym1,yg1,pm1,pg1,'probh1')..(LAND1M*CASH1HM
  +LAND1G*CASH1HG+RPRICES1HM(ym1,yg1,pm1,pg1)*MAIZE1HB(ym1,yg1,pm1,pg1)
  +RPRICES1HG(ym1,yg1,pm1,pg1)*GNUTS1HB(ym1,yg1,pm1,pg1)+CASH1HI(ym1,yg1,pm1,pg1)
  +CASH1HHE + LABORH1H(ym1,yg1,pm1,pg1)*CASHH1WG)/cscale
  =l= (RPRICES1HM(ym1,yg1,pm1,pg1)*MAIZE1HS(ym1,yg1,pm1,pg1)*(1-TRANSCSTMH)
  + RPRICES1HG(ym1,yg1,pm1,pg1)*GNUTS1HS(ym1,yg1,pm1,pg1)*(1-TRANSCSTGH)+CASH1PI + CASH1HR
  + CASHAID$(MMYields('Bad')and MGYields('Bad'))
  -PENCASH1H(ym1,yg1,pm1,pg1))/cscale;

*Year 1 Early Lean Period
*###########################################################################################################################
ELEAN1M(ym1,yg1,pm1,pg1,elpm,elpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
    ELStates(elpm,elpg,'probel'))..MAIZE1ES(ym1,yg1,pm1,pg1,elpm,elpg,es)+MAIZE1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)
    +MAIZE1EC=l=MAIZE1EB(ym1,yg1,pm1,pg1,elpm,elpg,es)+MAIZE1HI(ym1,yg1,pm1,pg1)*M1ESF ;

ELEAN1G(ym1,yg1,pm1,pg1,elpm,elpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
   ELStates(elpm,elpg,'probel'))..GNUTS1ES(ym1,yg1,pm1,pg1,elpm,elpg,es)+GNUTS1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)
   +GNUTS1EC =l=GNUTS1EB(ym1,yg1,pm1,pg1,elpm,elpg,es)+GNUTS1HI(ym1,yg1,pm1,pg1)*G1ESF ;

INVENT1E(ym1,yg1,pm1,pg1,elpm,elpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
   ELStates(elpm,elpg,'probel'))..MAIZE1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)+ GNUTS1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)
   =l= TOTCAPI ;

CASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
    ELStates(elpm, elpg,'probel'))..(RPRICES1EM(ym1,yg1,pm1,pg1,elpm,elpg)*
    MAIZE1EB(ym1,yg1,pm1,pg1,elpm,elpg,es) + RPRICES1EG(ym1,yg1,pm1,pg1,elpm,elpg)*
    GNUTS1EB(ym1,yg1,pm1,pg1,elpm,elpg,es) + CASH1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)
  + HHSHOCK1E(es)
  + CASH1EHE )/cscale
```

```
    =l=(RPRICES1EM(ym1,yg1,pm1,pg1,elpm,elpg)*MAIZE1ES(ym1,yg1,pm1,pg1,elpm,elpg,es)*(1-TRANSCSTME)
  + RPRICES1EG(ym1,yg1,pm1,pg1,elpm,elpg)*GNUTS1ES(ym1,yg1,pm1,pg1,elpm,elpg,es)*(1-TRANSCSTGE)
  + CASH1HI(ym1,yg1,pm1,pg1)+CASH1ER
  - PENCASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es))/cscale;

CASH1ES4(ym1,yg1,pm1,pg1,elpm,elpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
    ELStates(elpm, elpg,'probel'))..(RPRICES1EM(ym1,yg1,pm1,pg1,elpm,elpg)*
    MAIZE1EB(ym1,yg1,pm1,pg1,elpm,elpg,es) + RPRICES1EG(ym1,yg1,pm1,pg1,elpm,elpg)*
    GNUTS1EB(ym1,yg1,pm1,pg1,elpm,elpg,es) + CASH1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)
  + HHSHOCK1E(es)
  + CASH1EHE )/cscale
    =l=(RPRICES1EM(ym1,yg1,pm1,pg1,elpm,elpg)*MAIZE1ES(ym1,yg1,pm1,pg1,elpm,elpg,es)*(1-TRANSCSTME)
  + RPRICES1EG(ym1,yg1,pm1,pg1,elpm,elpg)*GNUTS1ES(ym1,yg1,pm1,pg1,elpm,elpg,es)*(1-TRANSCSTGE)
  + CASH1HI(ym1,yg1,pm1,pg1)+CASH1ER
  +INSURANCE$(HHSHOCK1E('Sev'))
  - PENCASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es))/cscale
;
*Year 1 Lean Period
*##########################################################################################################################
LEAN1M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
     ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))
     ..MAIZE1LS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) +MAIZE1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+ MAIZE1LC
     =l= MAIZE1LB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+ MAIZE1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)*M1LSF ;

LEAN1G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
     ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))
     ..GNUTS1LS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+ GNUTS1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+ GNUTS1LC
     =l= GNUTS1LB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+GNUTS1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)*G1LSF   ;

INVENT1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
     ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))
     ..MAIZE1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+ GNUTS1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)=l=TOTCAPI  ;

CASH1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
```

```
    ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))
    ..(RPRICES1LM(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg)*MAIZE1LB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)
    +RPRICES1LG(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg)*GNUTS1LB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)
    +CASH1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+CASH1LHE)/cscale
    =l= (RPRICES1LM(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg)*MAIZE1LS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)*(1-TRANSCSTML)
    +RPRICES1LG(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg)*GNUTS1LS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)*(1-TRANSCSTGL)
    +CASH1EI(ym1,yg1,pm1,pg1,elpm,elpg,es)+ CASH1LR
   -PENCASH1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es))/cscale
;
*Year 2 Planting Period
*###########################################################################################################################
PLANT2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
    ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP'))
    ..MAIZE2PS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)+MAIZE2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
    + MAIZE2PC=l= MAIZE2PB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)+ MAIZE1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)* M2PSF ;

PLANT2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
    ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP'))
    ..GNUTS2PS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)+GNUTS2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)+GNUTS2PC
    =l= GNUTS2PB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)+GNUTS1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)*G2PSF  ;

INVENT2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
   ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP'))
   ..MAIZE2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   + GNUTS2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=l= TOTCAPI ;

LAND2(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
   ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP'))
   ..LAND2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   +LAND2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=l= LANDT ;

LABOR2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
   ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP'))
   ..(LAND2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*LABOR2PM
```

```
   + LAND2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*LABOR2PG)/lscale =l= LABORF2P/lscale ;

CASH2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)$(HStates(ym1,yg1,pm1,pg1,'probh1')*
    ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP'))
    ..(LAND2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*CASH2PM
    +  LAND2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*CASH2PG
    +RPRICESP2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg)*MAIZE2PB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
    +RPRICESP2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg)*GNUTS2PB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
    + CASH2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)+CASH2PHE)/cscale
    =l= (RPRICESP2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg)*
    MAIZE2PS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*(1-TRANSCSTMP)
    + RPRICESP2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg)*
    GNUTS2PS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*(1-TRANSCSTGP)
    + CASH1LI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+CASH2PR
    -PENCASH2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es))/cscale
;

*Year 2 Harvest Period
*###########################################################################################################################
HARV2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*
     LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2'))..
     MAIZE2HS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
     +MAIZE2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)+MAIZE2HC =l=
        LAND2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*MMYields(ym2)
     + MAIZE2HB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
     +MAIZE2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*M2HSF ;

HARV2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*
    LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2'))
    ..GNUTS2HS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
      +GNUTS2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
    + GNUTS2HC =l= LAND2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*MGYields(yg2)
```

```
    + GNUTS2HB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
    + GNUTS2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*G2HSF;

INVENT2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm, elpg,'probel')*
    LStates(lpm,lpg,'probl')*P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2'))..
    MAIZE2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
    + GNUTS2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=l= TOTCAPI ;

LABOR2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2'))
    ..(LAND2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*LABOR2HM(ym2)
   + LAND2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*LABOR2HG(yg2)
   -LABORH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))/lscale=l= LABORF2H /lscale;

CASH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm, elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')* H2States(ym2,yg2,pm2,pg2,'probh2'))
    ..(LAND2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*CASH2HM
    +  LAND2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)*CASH2HG
    + RPRICESH2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2)*
        MAIZE2HB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
    + RPRICESH2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2)*
        GNUTS2HB(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)
    +  CASH2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)+ CASH2HHE
    + LABORH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)*CASHH2WG)/cscale
    =l= (RPRICESH2M(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2)*
    MAIZE2HS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)*(1-TRANSCSTMH)
    + RPRICESH2G(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2)*
    GNUTS2HS(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)*(1-TRANSCSTGH)
    + CASH2PI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)+ CASH2HR
    -PENCASH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))/cscale
;
```

```
*############################################################################################################################

OBJECTIVE1..EH2CASH=e=Sum{(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*HStates(ym2,yg2,pm2,pg2,'probh1')),
    ((scale*CASH2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)))*
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm, elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2')*ProbEShocks(es))
    -10*(PENCASH1P+ PENCASH1H(ym1,yg1,pm1,pg1)+PENCASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es)
   +PENCASH1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+ PENCASH2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   +PENCASH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))} ;

OBJECTIVE2..EH2CASH=e=Sum{(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*HStates(ym2,yg2,pm2,pg2,'probh1')),
    ((scale*CASH2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))**1)*
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm, elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2')*ProbEShocks(es))
    -10*(PENCASH1P+ PENCASH1H(ym1,yg1,pm1,pg1)+PENCASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es)
   +PENCASH1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)
   + PENCASH2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   +PENCASH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))} ;

OBJECTIVE3..EH2CASH=e=Sum{(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*HStates(ym2,yg2,pm2,pg2,'probh1')),
    ({scale*CASH2HI(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)}**5)/5*
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2')*ProbEShocks(es))
   -10*(PENCASH1P+PENCASH1H(ym1,yg1,pm1,pg1)+PENCASH1E(ym1,yg1,pm1,pg1,elpm,elpg,es)
   +PENCASH1L(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)+PENCASH2P(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   +PENCASH2H(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))} ;

Model
```

```
*SCENARIO 2 MODELS: A=LP, B,C=NLP
*################################################################################################################################
MLWFPLANS2a / OBJECTIVE1,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1P,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1H,ELEAN1M,ELEAN1G,INVENT1E,CASH1E,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

 MLWFPLANS2b / OBJECTIVE2,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1P,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1H,ELEAN1M,ELEAN1G,INVENT1E,CASH1E,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

 MLWFPLANS2c / OBJECTIVE3,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1P,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1H,ELEAN1M,ELEAN1G,INVENT1E,CASH1E,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

*SCENARIO 3 MODELS: CASH EQUATIONS AT HARVEST YEAR 1 INCLUDE RELIEF AID & A=LP, B,C=NLP
*################################################################################################################################
MLWFPLANS3a / OBJECTIVE1,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1P,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1HS3,ELEAN1M,ELEAN1G,INVENT1E,CASH1E,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

 MLWFPLANS3b / OBJECTIVE2,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1P,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1HS3,ELEAN1M,ELEAN1G,INVENT1E,CASH1E,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

 MLWFPLANS3c / OBJECTIVE3,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1P,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1HS3,ELEAN1M,ELEAN1G,INVENT1E,CASH1E,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /
```

```
*SCENARIO 4 MODELS:CASH EQUATIONS AT PLANTING & HARVEST YEAR 1 INCLUDE INSURANCE SCHEME ONLY, & A=LP, B,C=NLP
*############################################################################################################################
MLWFPLANS4a / OBJECTIVE1,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1PS4,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1H,ELEAN1M,ELEAN1G,INVENT1E,CASH1ES4,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

 MLWFPLANS4b / OBJECTIVE2,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1PS4,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1H,ELEAN1M,ELEAN1G,INVENT1E,CASH1ES4,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

 MLWFPLANS4c / OBJECTIVE3,LAND1,PLANT1M,PLANT1G,INVENT1P,LABOR1P,CASH1PS4,HARV1M ,
                  HARV1G,INVENT1H,LABOR1H,CASH1H,ELEAN1M,ELEAN1G,INVENT1E,CASH1ES4,LEAN1M,
                  LEAN1G,INVENT1L,CASH1L,LAND2,PLANT2M,PLANT2G,INVENT2P,LABOR2P,
                  CASH2P,HARV2M,HARV2G,INVENT2H,LABOR2H,CASH2H /

;
Option lp=cplex,reslim=10000000,iterlim=10000000 ;
*option lp=conopt;

*############################################################################################################################
*############################################################################################################################
*## SCENARIO 2 SOLVE STATEMENTS AND REPORTS
*############################################################################################################################
*############################################################################################################################
LABORH1H.up(ym1,yg1,pm1,pg1)=CLABORH1H ;
LABORH2H.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=CLABORH2H ;
*Fixing Pen variables to equal zero
PENCASH1P.l =0 ;
PENCASH1H.l(ym1,yg1,pm1,pg1)=0 ;
PENCASH1E.l(ym1,yg1,pm1,pg1,elpm,elpg,es) =0 ;
PENCASH1L.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) =0 ;
PENCASH2P.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=0 ;
```

```
PENCASH2H.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=0 ;
scale=0.0001;
*scale=1;
*$ontext
CASH2HI.lo(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=5000;
option limrow=4,limcol=0 ;
Solve MLWFPLANS2a using lp maximizing EH2CASH ;
*$exit;
$ontext;
Solve MLWFPLANS2b using nlp maximizing EH2CASH ;
*$exit;

EH2CASH.l=Sum{(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*HStates(ym2,yg2,pm2,pg2,'probh1')),
    ({scale*CASH2HI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)}**5)/5*
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2')*ProbEShocks(es))
   -10*(PENCASH1P.l+PENCASH1H.l(ym1,yg1,pm1,pg1)+PENCASH1E.l(ym1,yg1,pm1,pg1,elpm,elpg,es)
   +PENCASH1L.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)
   +PENCASH2P.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   +PENCASH2H.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))} ;

Solve MLWFPLANS2c using nlp maximizing EH2CASH ;
$offtext
*###########################################################################################################################
*## SCENARIO 2 SOLVE STATEMENTS AND REPORTS
*###########################################################################################################################
$onExternalOutput
*##SCENARIO 2 : All planting 1
parameter CropMixReport(*,*) Planting Year 1 Report ;
CropMixReport('CASH_1P',"Scenario 2" )= CASH1PI.l ;
CropMixReport( 'lAND1M',"Scenario 2" )= LAND1M.l ;
CropMixReport( 'PROPlAND1M',"Scenario 2" )= LAND1M.l/LANDT ;
```

```
CropMixReport( 'PROPlAND1G',"Scenario 2" )= LAND1G.l/LANDT ;
CropMixReport('EH2CASH',"Scenario 2" )= EH2CASH.l;

*##SCENARIO 2 :All Harvest year 1
*############################################################################################################################
parameter HarvestReport(ym1,yg1,pm1,pg1, *) Harvest Prices plan  ;
HarvestReport(ym1,yg1,pm1,pg1, 'Prob'  )$(HStates(ym1,yg1,pm1,pg1,'probh1'))= HStates(ym1,yg1,pm1,pg1,'probh1') ;
HarvestReport(ym1,yg1,pm1,pg1, 'RPrice1HM')$(HStates(ym1,yg1,pm1,pg1,'probh1'))=  MM4Prices(pm1);
HarvestReport(ym1,yg1,pm1,pg1, 'RPrice1HG' )$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MG4Prices(pg1);

parameter HarvestMaizeSales(ym1,yg1,pm1,pg1, *, *) Harvest Maize Sales plan  ;
HarvestMaizeSales(ym1,yg1,pm1,pg1,'M1H_sell' ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HS.l(ym1,yg1,pm1,pg1) ;

parameter HarvestMaizePurchases(ym1,yg1,pm1,pg1, *, *) Harvest Maize Purchase plan  ;
HarvestMaizePurchases(ym1,yg1,pm1,pg1,'M1H_Buy'  ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HB.l(ym1,yg1,pm1,pg1);

parameter HarvestMaizeInventory(ym1,yg1,pm1,pg1, *, *) Harvest Maize Inventory plan  ;
HarvestMaizeInventory(ym1,yg1,pm1,pg1,'M1H_store',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutSales(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Sales plan  ;
HarvestGnutSales(ym1,yg1,pm1,pg1,'G1H_sell', "Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HS.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutPurchases(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Purchase plan  ;
HarvestGnutPurchases(ym1,yg1,pm1,pg1,'G1H_Buy'  ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HB.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutInventory(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Inventory plan  ;
HarvestGnutInventory(ym1,yg1,pm1,pg1,'G1H_store',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestSavings(ym1,yg1,pm1,pg1, *, *) Harvest Savings plan  ;
HarvestSavings(ym1,yg1,pm1,pg1,'CASH_1H',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= CASH1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestMaizeProduction(ym1,yg1,pm1,pg1, *, *) Harvest Maize Production  ;
HarvestMaizeProduction(ym1,yg1,pm1,pg1,'PRODUCT1M',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= LAND1M.l*MMYields(ym1) ;
```

```
parameter HarvestGnutProduction(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Production  ;
HarvestGnutProduction(ym1,yg1,pm1,pg1,'PRODUCT1G',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= LAND1G.l*MGYields(yg1) ;

*###########################################################################################################################
*#SCENARIO 2 : All Early lean year 1
*###########################################################################################################################
parameter EarlyLeanReport(ym1,yg1,pm1,pg1,elpm,elpg,es, *) Early lean Farm Plan ;
EarlyLeanReport(ym1,yg1,pm1,pg1,elpm,elpg,es,'Prob' )$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel') ;
EarlyLeanReport(ym1,yg1,pm1,pg1,elpm,elpg,es,'RPrice1EM')$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))=RPRICES1EM(ym1,yg1,pm1,pg1,elpm,elpg) ;
EarlyLeanReport(ym1,yg1,pm1,pg1,elpm,elpg,es,'RPrice1EG')$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))=RPRICES1EG(ym1,yg1,pm1,pg1,elpm,elpg);

parameter EleanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Sales plan  ;
EleanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,es, 'M1E_sell',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1ES.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Purchase plan  ;
EleanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, 'M1E_Buy' ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1EB.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Inventory plan  ;
EleanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,es,'M1E_store',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Sales plan  ;
EleanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_sell' ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1ES.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Purchase plan  ;
EleanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_Buy'  ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1EB.l(ym1,yg1,pm1,pg1,elpm,elpg,es);
```

```
parameter EleanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Inventory plan  ;
EleanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_store',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanSavings(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Savings plan  ;
EleanSavings(ym1,yg1,pm1,pg1,elpm,elpg,es,'CASH_1E' ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= CASH1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es) ;

*###########################################################################################################################
*#SCENARIO 2 : Lean year 1
*###########################################################################################################################
parameter LeanReport(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *)  lean Farm Plan ;
LeanReport(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'Prob' )$(HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*
    LStates(lpm,lpg,'probl'))= HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl') ;
LeanReport(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'RPrice1LM')$(HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*
    LStates(lpm,lpg,'probl'))=RPRICES1LM(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg);
LeanReport(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'RPrice1LG')$(HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*
    LStates(lpm,lpg,'probl'))=RPRICES1LG(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg);

parameter     LeanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Sales plan  ;
              LeanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, 'M1L_sell',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
              ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LS.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter LeanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Purchase plan  ;
          LeanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, 'M1L_Buy' ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
          ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LB.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter LeanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Inventory plan  ;
          LeanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'M1L_store',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
          ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter      LeanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Sales plan  ;
               LeanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_sell' ,"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
               ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LS.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter  LeanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Purchase plan  ;
           LeanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_Buy',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
           ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LB.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
```

```
parameter  LeanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Inventory plan  ;
           LeanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_store',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
           ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter        LeanSavings(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) lean Savings plan  ;
                 LeanSavings(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'CASH_1L',"Scenario 2")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
                 ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= CASH1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) ;

*##SCENARIO 2 Harvest Statistics
*############################################################################################################################
$ontext
*set control tricks for means across SoN
parameter HarvestStatistics(*, *) Harvest Statistics Report ;
HarvestStatistics('ExpectedMSales',"Scenario 2" )$(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum((ym1,yg1,pm1,pg1), MAIZE1HS.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1'));

HarvestStatistics('VarMSales',"Scenario 2" )$(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum{(ym1,yg1,pm1,pg1), power(MAIZE1HS.l(ym1,yg1,pm1,pg1)-sum{(ym1,yg1,pm1,pg1),
         MAIZE1HS.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1')},2)};

HarvestStatistics( 'ExpectedGSales',"Scenario 2" )= $(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum((ym1,yg1,pm1,pg1), GNUTS1HS.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1'));

HarvestStatistics('VarGSales',"Scenario 2" )$(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum{(ym1,yg1,pm1,pg1), power(GNUTS1HS.l(ym1,yg1,pm1,pg1)-sum{(ym1,yg1,pm1,pg1),
         GNUTS1HS.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1')},2)};

HarvestStatistics( 'ExpectedMPurchases',"Scenario 2" )= $(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum((ym1,yg1,pm1,pg1), MAIZE1HB.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1'));

HarvestStatistics('VarMPurchases',"Scenario 2" )$(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum{(ym1,yg1,pm1,pg1), power(MAIZE1HB.l(ym1,yg1,pm1,pg1)-sum{(ym1,yg1,pm1,pg1),
         MAIZE1HB.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1')},2)};

HarvestStatistics( 'ExpectedGPurchases',"Scenario 2" )= $(HStates(ym1,yg1,pm1,pg1,'probh1'))=
```

```
      sum((ym1,yg1,pm1,pg1), GNUTS1HB.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1'));

HarvestStatistics('VarGPurchases',"Scenario 2" )$(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum{(ym1,yg1,pm1,pg1), power(GNUTS1HB.l(ym1,yg1,pm1,pg1)-sum{(ym1,yg1,pm1,pg1),
         GNUTS1HB.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1')},2)};

HarvestStatistics('ExpectedMInventories',"Scenario 2" )= $(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum((ym1,yg1,pm1,pg1), MAIZE1HI.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1'));

HarvestStatistics('VarMInventory',"Scenario 2" )$(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum{(ym1,yg1,pm1,pg1), power(MAIZE1HI.l(ym1,yg1,pm1,pg1)-sum{(ym1,yg1,pm1,pg1),
         MAIZE1HI.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1')},2)};

HarvestStatistics('ExpectedGInventories',"Scenario 2" )= $(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum((ym1,yg1,pm1,pg1), GNUTS1HI.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1'));

HarvestStatistics('VarMInventory',"Scenario 2" )$(HStates(ym1,yg1,pm1,pg1,'probh1'))=
      sum{(ym1,yg1,pm1,pg1), power(GNUTS1HI.l(ym1,yg1,pm1,pg1)-sum{(ym1,yg1,pm1,pg1),
         GNUTS1HI.l(ym1,yg1,pm1,pg1)*HStates(ym1,yg1,pm1,pg1,'probh1')},2)};
$offtext
*############################################################################################################################

*############################################################################################################################
*############################################################################################################################
*############################################################################################################################
*############################################################################################################################
*## SCENARIO 3 SOLVE STATEMENTS AND REPORTS
*############################################################################################################################
*############################################################################################################################
LABORH1H.up(ym1,yg1,pm1,pg1)=CLABORH1H ;
LABORH2H.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=CLABORH2H ;
*Fixing Pen variables to equal zero
PENCASH1P.l =0 ;
PENCASH1H.l(ym1,yg1,pm1,pg1)=0 ;
```

```
PENCASH1E.l(ym1,yg1,pm1,pg1,elpm,elpg,es) =0 ;
PENCASH1L.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) =0 ;
PENCASH2P.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=0 ;
PENCASH2H.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=0 ;
scale=0.0001;
*scale=1;
*$ontext
CASH2HI.lo(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=5000;
option limrow=4,limcol=0 ;
Solve MLWFPLANS3a using lp maximizing EH2CASH ;
*$exit;
$ontext;
Solve MLWFPLANS3b using nlp maximizing EH2CASH ;
*$exit;

EH2CASH.l=Sum{(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*HStates(ym2,yg2,pm2,pg2,'probh1')),
    ({scale*CASH2HI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)}**5)/5*
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2')*ProbEShocks(es))
   -10*(PENCASH1P.l+PENCASH1H.l(ym1,yg1,pm1,pg1)+PENCASH1E.l(ym1,yg1,pm1,pg1,elpm,elpg,es)
   +PENCASH1L.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)
   +PENCASH2P.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   +PENCASH2H.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))} ;

Solve MLWFPLANS3c using nlp maximizing EH2CASH ;
$offtext
*##########################################################################################################################
*## SCENARIO 3 SOLVE STATEMENTS AND REPORTS
*##########################################################################################################################

*##SCENARIO 3 All planting 1
parameter CropMixReport(*,*) Planting Year 1 Report ;
```

```
CropMixReport('CASH_1P',"Scenario 3" )= CASH1PI.l ;
CropMixReport( 'lAND1M',"Scenario 3" )= LAND1M.l ;
CropMixReport( 'PROPlAND1M',"Scenario 3" )= LAND1M.l/LANDT ;
CropMixReport( 'PROPlAND1G',"Scenario 3" )= LAND1G.l/LANDT ;
CropMixReport('EH2CASH',"Scenario 3" )= EH2CASH.l;

*##SCENARIO 3 All Harvest year 1
*#############################################################################################################################
parameter HarvestMaizeSales(ym1,yg1,pm1,pg1, *, *) Harvest Maize Sales plan  ;
HarvestMaizeSales(ym1,yg1,pm1,pg1,'M1H_sell' ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HS.l(ym1,yg1,pm1,pg1) ;

parameter HarvestMaizePurchases(ym1,yg1,pm1,pg1, *, *) Harvest Maize Purchase plan  ;
HarvestMaizePurchases(ym1,yg1,pm1,pg1,'M1H_Buy'  ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HB.l(ym1,yg1,pm1,pg1);

parameter HarvestMaizeInventory(ym1,yg1,pm1,pg1, *, *) Harvest Maize Inventory plan  ;
HarvestMaizeInventory(ym1,yg1,pm1,pg1,'M1H_store',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutSales(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Sales plan  ;
HarvestGnutSales(ym1,yg1,pm1,pg1,'G1H_sell',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HS.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutPurchases(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Purchase plan  ;
HarvestGnutPurchases(ym1,yg1,pm1,pg1,'G1H_Buy'  ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HB.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutInventory(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Inventory plan  ;
HarvestGnutInventory(ym1,yg1,pm1,pg1,'G1H_store',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestSavings(ym1,yg1,pm1,pg1, *, *) Harvest Savings plan  ;
HarvestSavings(ym1,yg1,pm1,pg1,'CASH_1H',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= CASH1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestMaizeProduction(ym1,yg1,pm1,pg1, *, *) Harvest Maize Production  ;
HarvestMaizeProduction(ym1,yg1,pm1,pg1, 'PRODUCT1M',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= LAND1M.l*MMYields(ym1) ;

parameter HarvestGnutProduction(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Production  ;
HarvestGnutProduction(ym1,yg1,pm1,pg1,'PRODUCT1G',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= LAND1G.l*MGYields(yg1) ;
```

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*############################################################################################################################
*#SCENARIO 3 All Early lean year 1
*############################################################################################################################
parameter EleanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Sales plan  ;
EleanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,es, 'M1E_sell',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1ES.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Purchase plan  ;
EleanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, 'M1E_Buy' ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1EB.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Inventory plan  ;
EleanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,es,'M1E_store',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Sales plan  ;
EleanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_sell' ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1ES.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Purchase plan  ;
EleanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_Buy'  ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1EB.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Inventory plan  ;
EleanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_store',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanSavings(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Savings plan  ;
EleanSavings(ym1,yg1,pm1,pg1,elpm,elpg,es,'CASH_1E' ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= CASH1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es) ;

*############################################################################################################################
*#SCENARIO 3 : Lean year 1
*############################################################################################################################
```

```
parameter     LeanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Sales plan  ;
              LeanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, 'M1L_sell',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
              ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LS.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter LeanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Purchase plan  ;
          LeanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, 'M1L_Buy' ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
          ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LB.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter LeanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Inventory plan  ;
          LeanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'M1L_store',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
          ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter      LeanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Sales plan  ;
               LeanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_sell' ,"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
               ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LS.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter  LeanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Purchase plan  ;
           LeanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_Buy',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
           ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LB.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter  LeanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Inventory plan  ;
           LeanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_store',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
           ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter        LeanSavings(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) lean Savings plan  ;
                 LeanSavings(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'CASH_1L',"Scenario 3")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
                 ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= CASH1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) ;

*#############################################################################################################################
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*## SCENARIO 4 SOLVE STATEMENTS AND REPORTS
*#############################################################################################################################
*#############################################################################################################################
LABORH1H.up(ym1,yg1,pm1,pg1)=CLABORH1H ;
LABORH2H.up(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=CLABORH2H ;
*Fixing Pen variables to equal zero
PENCASH1P.l =0 ;
PENCASH1H.l(ym1,yg1,pm1,pg1)=0 ;
```

```
PENCASH1E.l(ym1,yg1,pm1,pg1,elpm,elpg,es) =0 ;
PENCASH1L.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) =0 ;
PENCASH2P.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)=0 ;
PENCASH2H.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=0 ;
scale=0.0001;
*scale=1;
*$ontext
CASH2HI.lo(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)=5000;
option limrow=4,limcol=0 ;
Solve MLWFPLANS4a using lp maximizing EH2CASH ;
*$exit;
$ontext;
Solve MLWFPLANS4b using nlp maximizing EH2CASH ;
*$exit;

EH2CASH.l=Sum{(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)$
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*HStates(ym2,yg2,pm2,pg2,'probh1')),
    ({scale*CASH2HI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es)}**5)/5*
    (HStates(ym1,yg1,pm1,pg1,'probh1')*ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl')*
    P2States(p2pm,p2pg,'probP')*H2States(ym2,yg2,pm2,pg2,'probh2')*ProbEShocks(es))
   -10*(PENCASH1P.l+PENCASH1H.l(ym1,yg1,pm1,pg1)+PENCASH1E.l(ym1,yg1,pm1,pg1,elpm,elpg,es)
   +PENCASH1L.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es)
   +PENCASH2P.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,es)
   +PENCASH2H.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,p2pm,p2pg,ym2,yg2,pm2,pg2,es))} ;

Solve MLWFPLANS4c using nlp maximizing EH2CASH ;
$offtext
*#########################################################################################################################
*## SCENARIO 4 SOLVE STATEMENTS AND REPORTS
*#########################################################################################################################

*##SCENARIO 4 All planting 1
parameter CropMixReport(*,*) Planting Year 1 Report ;
```

```
CropMixReport('CASH_1P',"Scenario 4" )= CASH1PI.l ;
CropMixReport( 'lAND1M',"Scenario 4" )= LAND1M.l ;
CropMixReport( 'PROPlAND1M',"Scenario 4" )= LAND1M.l/LANDT ;
CropMixReport( 'PROPlAND1G',"Scenario 4" )= LAND1G.l/LANDT ;
CropMixReport('EH2CASH',"Scenario 4" )= EH2CASH.l;

*##SCENARIO 4 All Harvest year 1
*#########################################################################################################################
parameter HarvestMaizeSales(ym1,yg1,pm1,pg1, *, *) Harvest Maize Sales plan  ;
HarvestMaizeSales(ym1,yg1,pm1,pg1,'M1H_sell' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HS.l(ym1,yg1,pm1,pg1) ;

parameter HarvestMaizePurchases(ym1,yg1,pm1,pg1, *, *) Harvest Maize Purchase plan  ;
HarvestMaizePurchases(ym1,yg1,pm1,pg1,'M1H_Buy'  ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HB.l(ym1,yg1,pm1,pg1);

parameter HarvestMaizeInventory(ym1,yg1,pm1,pg1, *, *) Harvest Maize Inventory plan  ;
HarvestMaizeInventory(ym1,yg1,pm1,pg1,'M1H_store',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= MAIZE1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutSales(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Sales plan  ;
HarvestGnutSales(ym1,yg1,pm1,pg1,'G1H_sell' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HS.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutPurchases(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Purchase plan  ;
HarvestGnutPurchases(ym1,yg1,pm1,pg1,'G1H_Buy' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HB.l(ym1,yg1,pm1,pg1);

parameter HarvestGnutInventory(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Inventory plan  ;
HarvestGnutInventory(ym1,yg1,pm1,pg1,'G1H_store',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= GNUTS1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestSavings(ym1,yg1,pm1,pg1, *, *) Harvest Savings plan  ;
HarvestSavings(ym1,yg1,pm1,pg1,'CASH_1H',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= CASH1HI.l(ym1,yg1,pm1,pg1);

parameter HarvestMaizeProduction(ym1,yg1,pm1,pg1, *, *) Harvest Maize Production  ;
HarvestMaizeProduction(ym1,yg1,pm1,pg1,'PRODUCT1M',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= LAND1M.l*MMYields(ym1) ;

parameter HarvestGnutProduction(ym1,yg1,pm1,pg1, *, *) Harvest Groundnuts Production  ;
HarvestGnutProduction(ym1,yg1,pm1,pg1,'PRODUCT1G',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1'))= LAND1G.l*MGYields(yg1) ;
```

```
*################################################################################################################################
*#SCENARIO 4 All Early lean year 1
*################################################################################################################################
parameter EleanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Sales plan  ;
EleanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,es, 'M1E_sell',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1ES.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Purchase plan  ;
EleanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, 'M1E_Buy' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1EB.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Maize Inventory plan  ;
EleanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,es,'M1E_store',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= MAIZE1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Sales plan  ;
EleanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_sell' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1ES.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Purchase plan  ;
EleanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_Buy'  ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1EB.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Groundnut Inventory plan  ;
EleanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,es,'G1E_store',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= GNUTS1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es);

parameter EleanSavings(ym1,yg1,pm1,pg1,elpm,elpg,es, *, *) Elean Savings plan  ;
EleanSavings(ym1,yg1,pm1,pg1,elpm,elpg,es,'CASH_1E' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
ELStates(elpm,elpg,'probel'))= CASH1EI.l(ym1,yg1,pm1,pg1,elpm,elpg,es) ;

*################################################################################################################################
*#SCENARIO 4: Lean year 1
*################################################################################################################################
```

```
parameter     LeanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Sales plan  ;
              LeanMaizeSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, 'M1L_sell',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
              ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LS.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter LeanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Purchase plan  ;
          LeanMaizePurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, 'M1L_Buy' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
          ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LB.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter LeanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Maize Inventory plan  ;
          LeanMaizeInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'M1L_store',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
          ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= MAIZE1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter      LeanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Sales plan  ;
               LeanGnutSales(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_sell' ,"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
               ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LS.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter  LeanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Purchase plan  ;
           LeanGnutPurchases(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_Buy',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
           ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LB.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter  LeanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) Lean Groundnut Inventory plan  ;
           LeanGnutInventory(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'G1L_store',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
           ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= GNUTS1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es);
parameter        LeanSavings(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es, *, *) lean Savings plan  ;
                 LeanSavings(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es,'CASH_1L',"Scenario 4")$(HStates(ym1,yg1,pm1,pg1,'probh1')*
                 ELStates(elpm,elpg,'probel')*LStates(lpm,lpg,'probl'))= CASH1LI.l(ym1,yg1,pm1,pg1,elpm,elpg,lpm,lpg,es) ;

*##########################################################################################################################
*##########################################################################################################################

display CropMixReport ;
*Option  CropMixReport:2:1:1 ;
execute_unload 'CropMixReport.gdx', CropMixReport  ;
execute 'gdxxrw.exe CropMixReport.gdx o=CropMixReport.xlsx par=CropMixReport rng=flow!A1:bU886020';
*#########################################################################################################################
display HarvestReport;
*Option  HarvestReport:2:1:1 ;
execute_unload 'HarvestReport.gdx', HarvestReport  ;
execute 'gdxxrw.exe HarvestReport.gdx o=HarvestReport.xlsx par=HarvestReport rng=flow!A1:bU886020';
```

```
display HarvestMaizeSales ;
execute_unload 'HarvestMaizeSales.gdx', HarvestMaizeSales  ;
execute 'gdxxrw.exe HarvestMaizeSales.gdx o=HarvestMaizeSales.xlsx par=HarvestMaizeSales rng=flow!A1:bU886020';

display HarvestMaizePurchases ;
execute_unload 'HarvestMaizePurchases.gdx', HarvestMaizePurchases  ;
execute 'gdxxrw.exe HarvestMaizePurchases.gdx o=HarvestMaizePurchases.xlsx par=HarvestMaizePurchases rng=flow!A1:bU886020';

display HarvestMaizeInventory;
execute_unload 'HarvestMaizeInventory.gdx', HarvestMaizeInventory  ;
execute 'gdxxrw.exe HarvestMaizeInventory.gdx o=HarvestMaizeInventory.xlsx par=HarvestMaizeInventory rng=flow!A1:bU886020';

display HarvestGnutSales;
execute_unload 'HarvestGnutSales.gdx', HarvestGnutSales  ;
execute 'gdxxrw.exe HarvestGnutSales.gdx o=HarvestGnutSales.xlsx par=HarvestGnutSales rng=flow!A1:bU886020';

display HarvestGnutPurchases;
execute_unload 'HarvestGnutPurchases.gdx', HarvestGnutPurchases  ;
execute 'gdxxrw.exe HarvestGnutPurchases.gdx o=HarvestGnutPurchases.xlsx par=HarvestGnutPurchases rng=flow!A1:bU886020';

display HarvestGnutInventory ;
execute_unload 'HarvestGnutInventory.gdx', HarvestGnutInventory  ;
execute 'gdxxrw.exe HarvestGnutInventory.gdx o=HarvestGnutInventory.xlsx par=HarvestGnutInventory rng=flow!A1:bU886020';

display HarvestSavings;
execute_unload 'HarvestSavings.gdx', HarvestSavings  ;
execute 'gdxxrw.exe HarvestSavings.gdx o=HarvestSavings.xlsx par=HarvestSavings rng=flow!A1:bU886020';

display HarvestMaizeProduction;
execute_unload 'HarvestMaizeProduction.gdx', HarvestMaizeProduction  ;
execute 'gdxxrw.exe HarvestMaizeProduction.gdx o=HarvestMaizeProduction.xlsx par=HarvestMaizeProduction rng=flow!A1:bU886020';

display HarvestGnutProduction;
```

```
execute_unload 'HarvestGnutProduction.gdx', HarvestGnutProduction  ;
execute 'gdxxrw.exe HarvestGnutProduction.gdx o=HarvestGnutProduction.xlsx par=HarvestGnutProduction rng=flow!A1:bU886020';

*###########################################################################################################################
display EarlyLeanReport ;
*Option  EarlyLeanReport:2:1:1 ;
execute_unload 'EarlyLeanReport.gdx', EarlyLeanReport  ;
execute 'gdxxrw.exe EarlyLeanReport.gdx o=EarlyLeanReport.xlsx par=EarlyLeanReport rng=flow!A1:bU886020';

display EleanMaizeSales ;
execute_unload 'EleanMaizeSales.gdx', EleanMaizeSales  ;
execute 'gdxxrw.exe EleanMaizeSales.gdx o=EleanMaizeSales.xlsx par=EleanMaizeSales rng=flow!A1:bU886020';

display EleanMaizePurchases ;
execute_unload 'EleanMaizePurchases.gdx', EleanMaizePurchases  ;
execute 'gdxxrw.exe EleanMaizePurchases.gdx o=EleanMaizePurchases.xlsx par=EleanMaizePurchases rng=flow!A1:bU886020';

display EleanMaizeInventory;
execute_unload 'EleanMaizeInventory.gdx', EleanMaizeInventory  ;
execute 'gdxxrw.exe EleanMaizeInventory.gdx o=EleanMaizeInventory.xlsx par=EleanMaizeInventory rng=flow!A1:bU886020';

display EleanGnutSales;
execute_unload 'EleanGnutSales.gdx', EleanGnutSales  ;
execute 'gdxxrw.exe EleanGnutSales.gdx o=EleanGnutSales.xlsx par=EleanGnutSales rng=flow!A1:bU886020';

display EleanGnutPurchases;
execute_unload 'EleanGnutPurchases.gdx', EleanGnutPurchases  ;
execute 'gdxxrw.exe EleanGnutPurchases.gdx o=EleanGnutPurchases.xlsx par=EleanGnutPurchases rng=flow!A1:bU886020';

display EleanGnutInventory ;
execute_unload 'EleanGnutInventory.gdx', EleanGnutInventory  ;
execute 'gdxxrw.exe EleanGnutInventory.gdx o=EleanGnutInventory.xlsx par=EleanGnutInventory rng=flow!A1:bU886020';

display EleanSavings;
```

```
execute_unload 'EleanSavings.gdx', EleanSavings  ;
execute 'gdxxrw.exe EleanSavings.gdx o=EleanSavings.xlsx par=EleanSavings rng=flow!A1:bU886020';

*###########################################################################################################################
display LeanReport ;
*Option  LeanReport:2:1:1 ;
execute_unload 'LeanReport.gdx', LeanReport  ;
execute 'gdxxrw.exe LeanReport.gdx o=LeanReport.xlsx par=LeanReport rng=flow!A1:bU886020';

display LeanMaizeSales ;
execute_unload 'LeanMaizeSales.gdx', LeanMaizeSales  ;
execute 'gdxxrw.exe LeanMaizeSales.gdx o=LeanMaizeSales.xlsx par=LeanMaizeSales rng=flow!A1:bU886020';

display LeanMaizePurchases ;
execute_unload 'LeanMaizePurchases.gdx', LeanMaizePurchases  ;
execute 'gdxxrw.exe LeanMaizePurchases.gdx o=LeanMaizePurchases.xlsx par=LeanMaizePurchases rng=flow!A1:bU886020';

display LeanMaizeInventory;
execute_unload 'LeanMaizeInventory.gdx', LeanMaizeInventory  ;
execute 'gdxxrw.exe LeanMaizeInventory.gdx o=LeanMaizeInventory.xlsx par=LeanMaizeInventory rng=flow!A1:bU886020';

display LeanGnutSales;
execute_unload 'LeanGnutSales.gdx', LeanGnutSales  ;
execute 'gdxxrw.exe LeanGnutSales.gdx o=LeanGnutSales.xlsx par=LeanGnutSales rng=flow!A1:bU886020';

display LeanGnutPurchases;
execute_unload 'LeanGnutPurchases.gdx', LeanGnutPurchases  ;
execute 'gdxxrw.exe LeanGnutPurchases.gdx o=LeanGnutPurchases.xlsx par=LeanGnutPurchases rng=flow!A1:bU886020';

display LeanGnutInventory ;
execute_unload 'LeanGnutInventory.gdx', LeanGnutInventory  ;
execute 'gdxxrw.exe LeanGnutInventory.gdx o=LeanGnutInventory.xlsx par=LeanGnutInventory rng=flow!A1:bU886020';

display LeanSavings;
```

```
execute_unload 'LeanSavings.gdx', LeanSavings  ;
execute 'gdxxrw.exe LeanSavings.gdx o=LeanSavings.xlsx par=LeanSavings rng=flow!A1:bU886020';

*############################################################################################################################
$offExternalOutput
```