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# Expecting Too Much, Foreseeing Too Little? Behavioral Explanations for the Sell Low-Buy High Puzzle in Smallholder Market Participation

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**Abstract**

It is often observed that smallholder farmers sell most of their marketable surplus immediately after the harvest when seasonal price movements reach their lowest point, instead of waiting just a few more months until prices recover. Most explanations for this seemingly sub-optimal behavior focus on economic or infrastructural issues, such as credit constraints or lack of storage facilities. In this study, we take a closer look at two potential behavioral explanations. One explanation focuses on household expenditure and assumes that households face challenges in accurately predicting future expenditures, systematically underestimating future needs. A second potential explanation focuses on household income, where motivated reasoning leads farmers to sell too early and/or at low prices. To test these hypotheses, we conduct two planning-based interventions among a sample of Malawian smallholder farmers: (1) a detailed expense budget and (2) a sales plan with explicit commitment to timing of sales, quantities and prices. The treatments were administered at harvest time in May 2022 and April 2023.

# Introduction

It is often observed that smallholder farmers sell most of their marketable surplus or cash crops immediately after the harvest to itinerant traders at the farm gate. Selling immediately after the harvest is not optimal: thin and poorly integrated markets often mean that immediately post-harvest prices in excess supply areas drop to their seasonal low. Additionally, agricultural commodities are often not yet in optimal condition. For instance, in the case of maize, fresh grains are generally not dry enough, requiring further processing and leading to increased risk of rot by the trader. Often, this is used by buyers as an additional reason to further drive down the price paid to the farmer.

Over time, prices gradually recover, reaching their seasonal high just before the next harvest. At this time, many farmers have run out of stock and need to turn to the market to buy back maize at prices that are often much higher than they received, a phenomenon known as the "sell low-buy high" puzzle (Stephens and Barrett, 2011; Burke, Bergquist, and Miguel, 2018). Van Campenhout, Lecoutere, and D'Exelle (2015) further show how farmers lose out twice—traders pass transaction costs on to farmers when traders buy commodities from farmers in rural areas immediately after the harvest and store in warehouses in towns, and farmers incur transaction costs when they have to go to town to buy back maize from the same traders.

The literature suggests many possible reasons why farmers choose to sell early at low prices instead of waiting a few months until prices recover. For example, farmers may simply not have the space and infrastructure available to safely store large quantities of maize for extended periods of time (Omotilewa et al., 2018), or they may be in urgent need of cash after the lean season (Burke, Bergquist, and Miguel, 2018; Dillon, 2021). Alternatively, farmers may be too risk averse to engage in inter-temporal arbitrage if price movements are unpredictable (Cardell and Michelson, 2023). It could also be the case that traders only visit villages immediately after harvest, and farmers do not have the means to transport maize to markets themselves. Furthermore, issues related to social taxation may mean farmers convert maize to cash, which is easier to hide from friends and family (Jakiela and Ozier, 2015).

Most of the explanations above focus on neoclassical constraints to farmers' exploiting inter-temporal arbitrage. In this study, we take a closer look at two potential behavioral explanations for farmers' seemingly sub-optimal selling. One potential explanation focuses on household expenditure and assumes that households face challenges in accurately predicting future expenditures. In particular, farmers are constrained in their cognitive capacity leading them to underestimate future needs. Such "budget neglect" leads farmers to sell earlier on and save too little for later in the year (Augenblick et al., 2021). A second potential explanation focuses on household income. Here the assumption is that "sell low-buy high" behavior is caused by the fact that impatient farmers are prone to motivated reasoning, with farmers spending more than they should because they use reasoning to justify discretionary expenditures.

The above hypotheses are tested with a field experiment among smallholder farmers in Malawi. These farmers produce (a mix of) maize, groundnuts, and soybean from which at least some are destined for the market. Our experiment takes the form of a simple parallel design with two treatment arms and one control group. A first treatment arm tests for the role of budget neglect in explaining the sell low-buy high paradox. Farmers that are randomly assigned to the first treatment arm are taken through a detailed budgeting exercise immediately after harvest. In particular, in this intervention a trained enumerator sits with the household head and fills in a budget matrix of projected expenses for each month in the coming year. The second treatment arm uses commitment as a way to test the motivated reason hypothesis. Farmers that are randomly allocated to the second treatment arm receive a sales planning intervention where a trained enumerator sits with the household head and works out how much they plan to sell of which crop in which month during in the coming year. For each planned sale, the household head is also asked to commit to a minimum price. Impact of the interventions on a variety of outcomes is compared against outcomes of a control group that did not get any intervention.

We also decided to repeat treatment after one season, allowing us to test if repeated treatments are more effective than one-off treatments. As such, in the second year we have seven parallel treatment arms: farmers who were in the control group in both years, farmers that received a treatment in the first year (either the first or the second) but not in the second year, farmers who received the treatment only in the second year (either the first or the second), and those who received treatment in both years (the same treatment was administered in both years; we do not switch treatments).

This document presents the main findings of the project. It is based on the pre-analysis planand the mock report, and compares outcomes of households in the different treatment groups at particular points in time during the course of the two agricultural seasons the project was implemented during. It combines findings of different interim reports that were created after each survey round (September 2022, January 2023, April 2023, September 2023, January 2024, and April 2024).

In the next section, we provide a selective overview of related studies. We then outline the main research hypothesis we test, and describe the interventions used to do so. We then turn to the data with subsections that present descriptives for the study population and balance between treatment and control groups. We then turn to the endline data and report attrition and impact on primary and secondary outcomes. The final section concludes.

# Related Research

Why do farmers "sell low and buy high"? One of the most obvious neo-classical explanations is related to credit constraints. Using observational data, Stephens and Barrett (2011) find that many farmers end up buying back grain from the market a few months after selling it in order to meet consumption needs later in the year, effectively using the maize market as a high-interest lender of last resort. Burke, Bergquist, and Miguel (2018) show that, in a field experiment in Kenya, credit market imperfections limit farmers' abilities to move grain inter-temporally. Providing timely access to credit allows farmers to buy at lower prices and sell at higher prices, increasing farm revenues and generating a return on investment of almost 30 percent. Dillon (2021) notes that because primary school began 3 months earlier in 2010 than in 2009, households with children were prompted to sell maize when prices are particularly low. To identify the impacts of liquidity constraints during the lean season, Fink, Jack, and Masiye (2020) offered subsidized loans in randomly selected villages in rural Zambia. They find that relaxing liquidity constraints not only changed marketing behavior, but also increased labor allocated to agricultural production (as opposed to day laboring as a coping strategy) and conclude that liquidity constraints thus contribute to inequality in rural economies in the longer run. While credit constraints seem to be an important reason why farmers sell immediately post harvest at low prices, we feel this is not the entire story. If farmers need urgent cash, it would make more sense to only sell part of the harvest to cover most urgent expenses, or to sell commodities, such as small livestock, that are less affected by price seasonality. However, farmers often seem to sell all of their marketable surplus immediately post harvest in a single transaction.

Risk averse farmers may also fail to delay sales if there is considerable uncertainty about the future price. A recent article by Cardell and Michelson (2023) argues that the "sell low-buy high" puzzle is not a puzzle at all. Using 20 years of data from 787 markets in 26 countries, they argue that in many cases the price increase seems insufficient and too uncertain for farmers to engage in inter-temporal arbitrage (Cardell and Michelson, 2023). However, their analysis uses prices obtained from market centers, which may be a poor proxy for the farm-gate prices that farmers face: markets in main towns are generally much better integrated in the wider national, regional, and even global economies and are less prone to the extreme spikes and slumps that smallholder farmers in more remote areas experience.

A third reason may be that because farmers have nowhere to safely store crops, they simply sell. This could be due to either a lack of space—the average smallholder often harvest 20-40 bags (50kg/bag) of maize—or risks related to pests and diseases affecting the stored maize. If lack of safe storage is the primary reason why farmers do not engage in inter-temporal arbitrage, then providing storage technology should delay sales. Omotilewa et al. (2018) indeed find that households that received PICS bags, a type of hermetically sealed bag of two layers of polyethylene liners and a third layer made from woven polypropylene, stored maize for a longer period and reported a substantial drop in storage losses. Although the availability of safe storage can explain why farmers sell early, we feel it does not explain everything. For instance, this explanation is at odds with the fact that the Agricultural Commodities Exchange (ACE) in Malawi consistently fails to fill its warehouses.

Social taxation may also explain why farmers "sell low and buy high". If a farmer stores a lot of maize in their house, this is visible for family and neighbors, which may make it difficult to deny neighbors should they ask for help during the hunger season. Therefore, farmers may choose to convert their harvest to money, which is easier to hide, even though this comes at a cost. Social taxation has been found to be important in a similar marketing decisions where households seem to forgo the benefits of buying in bulk (Dillon, De Weerdt, and O'Donoghue, 2020).

Related research on the behaviors and psychology of the "sell low-buy high" puzzle is ongoing. Augenblick et al. (2021) study recurrent seasonal hunger in Zambia, which could be a direct consequence of sub-optimal marketing behaviour, and speculate that individuals tend to overestimate their available resources and thus under-save. They test this hypothesis through an intervention that induces individuals to think through their budget set and formulate a spending plan. They find that treated households enter the hunger season with one additional month of savings, leading to a smoother spending profile over the year.

Our research is also related to literature on lack of self-control in cases where individuals have to make complex inter-temporal decisions involving uncertain future events. If farmers are impatient and unsophisticated about this, nudges may be effective in reducing discretionary spending and thus increase investment in the future (Duflo, Kremer, and Robinson, 2011). Dupas and Robinson (2013) find that devices which simply help individuals harness the power of mental accounting helps them to save more.

## Behavioural Constraints to Inter-temporal Arbitrage: Hypotheses and Interventions

Broadly speaking, the behavioral foundation of sell low-buy high behaviour is akin to the planning fallacy, wherein individuals typically underestimate the time it takes to complete a task despite having extensive experience with failure to complete the same task in a similar time frame in the past (Buehler, Griffin, and Peetz, 2010). The planning fallacy has different origins, including cognitive limitations and motivational factors (Buehler, Griffin, and Peetz, 2010).

The first potential behavioral explanation for the sell low-buy high puzzle that we will study focuses on household expenditure and assumes that households face challenges in accurately predicting future expenditures. In particular, we assume that farmers systematically underestimate how much money they need in the future and, as a result, sell too much immediately after the harvest. For example, farmers may budget for fresh seed from the agro-input dealer and for fertilizer immediately after harvest, but they may forget that they also need pesticides and insecticides. In general, predicting the full set of expenditures under all possible states of the world is likely to be beyond the cognitive capacity of human beings (Augenblick et al., 2021). Furthermore, farmers may underestimate the likelihood of, or simply forget to account for, unexpected events such illness within the family.

To test the first hypothesis, we designed an intervention that takes the farmer through a detailed budgeting exercise. In particular, the primary household decision-maker was provided with a template that needed to be filled out with as much detail as possible. Pre-populated expenditure categories included education expenditures like school fees or uniforms; agricultural investment expenditures such as seed and fertilizer; investment expenditures in non-agricultural businesses including retail shop inventories; health and medical expenses like medicines, preventive and doctor visits; recurrent household expenditures such as food and utilities,among others; household equipment and maintenance, including furniture and renovation; and other expenditures like loan repayment and ceremonies. For each of these expenditure item lines, farmers were then asked to provide an estimate of the total cost for each month between May 2022 and April 2023 and to write them down in the appropriate cell of the expenditure matrix. Farmers were also encouraged to provide their top three unexpected expenditures that are most likely to occur between May 2022 and April 2023, as well as between May 2023 and April 2024 for the second season. We then calculate monthly totals and a grand total for the entire year. This first intervention will be referred to as treatment one (T1).

The second hypothesis focuses on the income of the farm household and touches on the motivational origins of the planning fallacy. Immediately post harvest, farmers form expectations about how much they will get in the future from selling crops. If farmers are impatient and prone to motivated reasoning, the expected future revenue (and particularly the more stochastic elements such as price) is a function of how much they will want to spend now. This may lead farmers to expect higher prices in the future to justify current discretionary spending.

To test if the sell low-buy high puzzle is predominantly caused by motivated reasoning, we develop, together with the farmer, a detailed sales plan for the year which is assumed to function as a commitment device closely modeled on the idea of mental accounting. Again using a template, we start by asking the farmer about the expected marketable surplus for maize, groundnuts, and soybean. For each month between May 2022 and April 2023 (and between May 2023 and April 2024 for the second season), we then ask how much the farmer is planning to sell for each of the crops, and what the minimum price and point in time should be before they sell. For the sales plan, we also calculate monthly totals and a grand total for the entire year. This second intervention will be referred to as treatment two (T2).

Note that there is a dynamic aspect to this, which we will use to differentiate motivated reasoning from alternative mechanisms. Over time, as the farmer draws down stocks, the motivated reasoning effect will become stronger: the farmer has to expect ever larger windfall gains in the future to justify additional discretionary spending. Our treatment reduces the motivated reasoning effect by confronting farmers with their expected prices at a time when the motivated reasoning effect was still weak. We thus expect that as the season progresses into the lean season, price expectations of untreated farmers will go up.

We not only asked farmers to create these expenditure and sales plans but also encouraged them to hang them in a central place in the house or store them in a convenient location. Furthermore, to increase the likelihood that farmers use the plan, we also referred to the plan during midline surveys, and reiterate the importance of following these plans.

# Experimental Design and Specifications

The experiment was initially designed as a parallel design with one common control group and two treatment arms (or a factorial design where the interaction cell is left empty). Augenblick et al. (2021) find that, in a similar budget neglect experiment, treated farmers enter the hungry season with 20 percent more maize (valued by current prices at 405 Zambian Kwacha instead of 335 Zambian Kwacha in the control group). If we assume that the standard deviation is about 592 (1.6 times the mean of treatment and control means – the 1.6 is derived from maize production data in Uganda), we get a sample size of 1,123 in each treatment arm. For one control group and two treatment arms we will thus need about 3,400 farmers. For logistical reasons, we will apply cluster sampling in villages and randomly selected 31 farmers per village. Statistical power is optimal when approximately 42 percent of the sample is allocated to the control and when 29 percent of the sample is divided equally to each treatment arm (Muralidharan, Romero, and Wüthrich, 2019). We, therefore, chose 13 households for the control and 9 households in each of the two treatment groups per village. This means we included about 110 villages in our study.

Right before the April 2023 survey round (which was supposed to be the last round), a follow-up round of treatment was decided for the subsequent season. As such, we re-treated some of the farmers. However, instead of simply repeating the treatment according to the original randomization, we also decided to include variation in treatment over time (year 1 versus year 2). In particular, we wanted to differentiate between farmers that were never treated (CC); farmers that were always treated (T1T1 and T2T2); farmers that were treated only in the first year (T1C and T2C); and farmers that started receiving treatment in the second year (CT1 and CT2).[1]

- In control households in year 1, we assign 28 percent to the first treatment (CT1) and 28 percent to the second treatment (CT2), while the remaining 44 percent remains in the control group in the second year (CC).
- Among households that received the first treatment in year 1, we assign 50 percent to the first treatment again in year 2 (T1T1). The remaining 50 percent did not receive the treatment again (T1C)
- Among households that received the second treatment in year 1, we assign 50 percent to the second treatment again in year 2 (T2T2). The remaining 50 percent did not receive the treatment again (T2C).

The initial model we pre-registered is the following:

$$Y = \mu_v + \beta_1 T_1 + \beta_2 T_2 + \theta Y_b + \varepsilon \tag{1}$$

Here $Y$ is the outcome of interest post treatment, and $Y_b$ is the outcome of interest measured at baseline. $T_1$is a dummy indicator for the first treatment and $T_2$ for the second. We will focus on the within-village dimension of the data and so include village fixed effects $\mu_v$. The parameters of interest are $\beta_1$, the average treatment effect for $T_1$, and $\beta_2$, the average treatment effect for $T_2$.

For the second season and in light of the new treatment cells, we expand equation 1 to:

$$Y = \mu_v + \beta_1 T_1 C + \beta_2 T_2 C + \beta_3 C T_1 + \beta_4 C T_2 + \beta_4 C T_2 + \beta_5 T_1 T_1 + \beta_6 T_2 T_2 + \theta Y_b + \varepsilon \tag{2}$$

where the reference category is the group that did not receive treatments in the first nor second season.

[1]In addition to measuring a dosage effect (once versus twice treated) the decision was also influence by the fact that we found significant imbalance on a range of baseline characteristics for the second treatment. We hope that concerns related to this imbalance can be addressed by comparing differences between C and T2 in year one to differences in year 2 (comparing CC and CT2).

## Data Collection

Baseline data collection took place around the end of May and beginning of June 2022. Using tablet computers and Open Data Kit software, 31 enumerators interviewed 3,534 farmers that were sampled from four districts in the Central and Northern Regions of Malawi (Kasungu, Ntchisi, Dowa, and Mchinji). The study areas are characterized by rain-fed agriculture with a single agricultural season.

We selected farmers that produce maize, groundnuts, and/or soybean. Maize is planted early in the year and harvest usually starts in April and proceeds through May. Soybean is harvested somewhat earlier and groundnuts somewhat later. Soybean and groundnuts can be sold almost immediately after the harvest; maize needs to be dried first.

To get a nationally representative sampling frame of the smallholder farmer population in Malawi, we rely on the list created by the Ministry of Agriculture for their Agricultural Input Programme (AIP). The AIP targets smallholder farmers in the villages who mostly registered with the village chiefs. We used a two-stage sampling procedure where we first sampled villages with the likelihood of a village being selected proportionate to the number of people that live in this village (such that larger villages are more likely to end up in the sample). We then randomly sampled 31 households in each of the sampled villages. Figure 1 gives a sense of the coverage and dispersion of the interviewed households.

The study focuses on market participation. Thus, the targeted study population consists of farmers that are likely to engage with markets. As such, we included qualifier questions in our survey, where we asked farmers if they were planning to sell maize, soybean, or groundnuts during the 2022 and 2023 season. Restricting our study population to a particular sub-population has implications for the interpretation of results. For instance, we will see later that we find relatively high proportions of households reporting to sell to the market. Given that the study population consists of semi-subsistence smallholder farmers, we need to keep in mind that results may be different from, for example, predominantly self-sufficient farmers.

Baseline data was collected in April 2022. That same month, treatments were administered using the simple design consisting of a control group and two treatment groups. A first round of follow-up data collection took place in September 2022; detailed data was collected on transactions that occurred between the start of the project and the time of the survey. A second follow-

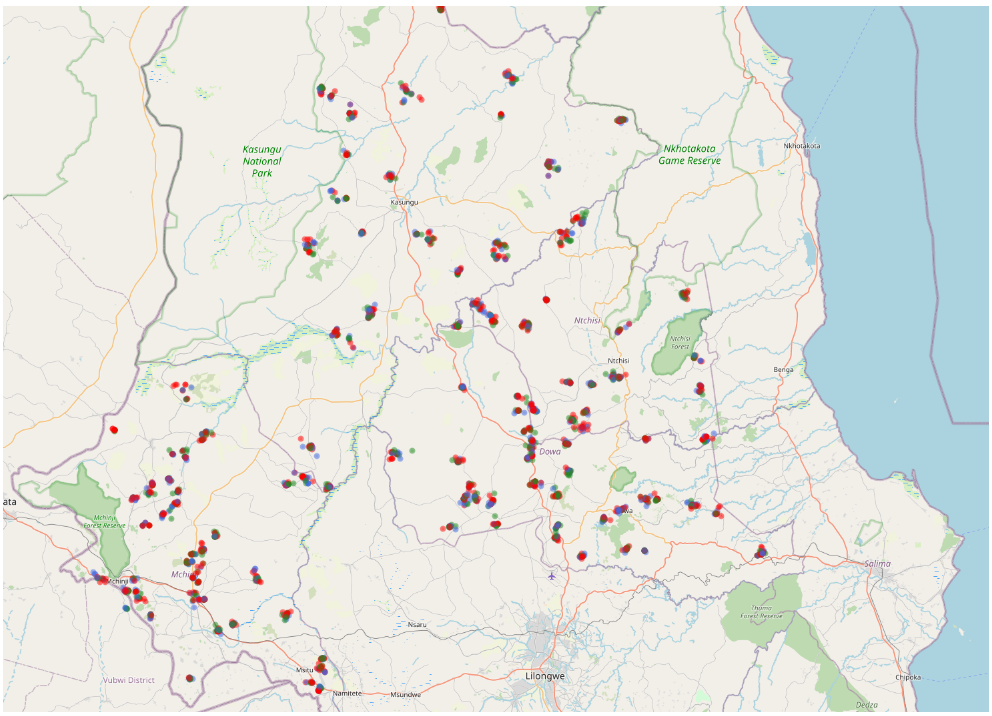

Figure 1: map of study area with sampled villages

up survey was organized in January 2023 and asked about transactions between September 2022 and January 2023. These two follow-up surveys were phone based.

Farmers were visited in person in April 2023 to inquire about transactions between January 2023 and April 2023. At that time, the treatment was repeated according to a new design consisting of seven treatment groups. Similar to the first season, we organized phone-based surveys in September 2023 and January 2024. The last survey in April 2024 was also phone based since treatment was not repeated, and data was only collected on transactions between January 2024 and April 2024.

## Farmer Characteristics

Table 1 presents summary statistics of sampled households and their heads at baseline. Eighty percent of households are headed by men. The average household is headed by a 43-year-old with six years of schooling (primary level) and has five household members living in houses with three bedrooms. Four in every 10 households are roofed with corrugated iron sheets (as opposed to thatch roofing). We find that the average distance of the households to the nearest all-weather road and nearest market is 1.3 and 4.1 km, respectively.

We also collected information on access to transport facilities or assets (either through ownership or hire). Results in Table 1 show that households mostly have access to a bicycle (72 percent of respondents) and ox-carts (60 percent of the respondents). Ox-carts are particularly important for transportation of harvest from the farms to the market. We also collected information on livestock asset ownership, as these are often a form of savings that can be used as a buffer stock to smooth consumption.

Other household characteristics that affect market participation included access to credit, access to storage, membership of cooperatives, and whether farmers had already promised part of the 2022 harvest to a buyer. Table 2 shows that among the farmers surveyed, about 40 percent indicate that they have access to credit and that less than a quarter had outstanding debts averaging Malawian Kwacha (MK) 57,000 to repay after harvest. Regarding access to storage, 60 percent of the households reported to have access, and of this 60 percent, half indicated that the storage was crop specific. We also find that, while farmer participation in cooperatives is limited, a moderate share (40 percent) have access to storage space provided by the cooperative.

Table 1: Household characteristics

| | Mean | Std dev | N |
|---|---|---|---|
| | *Household head* | | |
| Household head is male (1=yes) | 0.791 | 0.407 | 3,534 |
| Age of household head (years) | 43.426 | 14.831 | 3,414 |
| Schooling of household head (years) | 6.329 | 3.489 | 3,427 |
| Roof of main building is grass thatch (1=yes) | 0.609 | 0.488 | 3,534 |
| | *Household characteristics* | | |
| Roof of main building is corrugated iron (1=yes) | 0.39 | 0.488 | 3,534 |
| Household size (number of people) | 5.043 | 1.992 | 3,530 |
| Number of rooms in the house | 3.202 | 1.178 | 3,534 |
| Distance (kms) to nearest all weather road | 1.308 | 3.433 | 3,346 |
| Distance (kms) to nearest market | 4.107 | 4.78 | 3,243 |
| | *Transport* | | |
| Household has access to bicycle (1=yes) | 0.719 | 0.45 | 3,534 |
| Household has access to saloon car (1=yes) | 0.218 | 0.413 | 3,534 |
| Household has access to pick-up or lorry access (1=yes) | 0.221 | 0.415 | 3,534 |
| Household has access to ox-cart (1=yes) | 0.595 | 0.491 | 3,534 |
| Household owns a motorbike (1=yes) | 0.11 | 0.313 | 3,534 |
| | *Livestock assets* | | |
| Number of bulls/oxen/steers owned by household | 0.123 | 0.653 | 3,533 |
| Number of cows or heifers owned by household | 0.128 | 0.799 | 3,532 |
| Number of calves owned by household | 0.053 | 0.495 | 3,533 |
| Number of pigs owned by household | 0.708 | 1.943 | 3,534 |
| Number of goats owned by household | 1.241 | 2.569 | 3,533 |
| Number of sheep owned by household | 0.055 | 0.519 | 3,531 |
| Number of chicken owned by household | 4.743 | 6.509 | 3,532 |
| Number of ducks owned by household | 0.282 | 1.501 | 3,533 |

Lastly, we look at the proportion of farmers that commit a part of their crop to buyers before harvest—a scenario that may often lead farmers to sell at unfavorable prices, or reduces the amount of harvest that farmers can sell after harvest. We find that only a negligible share of farmers (8 percent) had already promised (part of) the 2022 crop to buyers prior to harvest.

### Baseline Balance

We follow our pre-analysis plan and test baseline balance by constructing a standard balance table consisting of the following household variables/demographic characteristics (inspired by balance tables in Duflo, Kremer, and Robinson (2011); Karlan et al. (2014)): household head is female (1=yes), household size (number of people), age of household head (years), number of years of education of the household head (years), material of roof (1=corrugated iron), number of rooms in the house, cultivated acreage (maize+groundnuts+soybean), whether the household hired agricultural labour (1=yes), distance to nearest all-weather road (km), and distance to nearest market (km). We report t-tests comparing treatment and control (unadjusted for multiple hypothesis testing), as well as a joint F-test from a regression of the treatment assignment on all variables in the balance table. Results are summarized in Table 3.

We find significant imbalance on some of the variables, particularly for the sales plan treatment (T2). While joint F-tests for separate treatment control comparisons are not significant, we do find signs of imbalance when we use a likelihood ratio test derived from a multinomial model where the left hand side has three levels (T1, T2, and C).

## Impact

### Market Participation Dynamics

Table 4 shows results for the comparisons between different treatment groups for five primary outcomes. A first primary outcome we consider is stocks held of the commodity at the time of the midline survey. In particular, we asked farmers how many bags of the commodity (standard 50 kg bags) they have in store. As the distributions are skewed to the right and includes zeros as well, we use an inverse hyperbolic sine transformation (Bellemare and

Table 2: Household characteristics that affect market participation

| | Mean | Std dev | N |
|---|---|---|---|
| | | *Credit* | |
| Do you have access to credit? (1=yes) | 0.383 | 0.486 | 3,532 |
| Do you have debts (cash or in-kind) to be repaid after harvest? (1=yes) | 0.236 | 0.425 | 3,532 |
| Estimated amount (Malawian Kwacha) of debt | 56,878 | 92,788 | 819 |
| | | *Storage* | |
| Do you have access to storage? (1=yes) | 0.599 | 0.49 | 3,532 |
| Is the storage crop specific? (1=yes) | 0.482 | 0.5 | 2,114 |
| | | *Cooperation* | |
| Are you member of a Cooperatives? (1=yes) | 0.134 | 0.34 | 3,532 |
| Does this cooperative provide access to storage? (1=yes) | 0.388 | 0.488 | 472 |
| Is this Cooperative certified by the Agriculture Commodity Exchange? (1=yes) | 0.727 | 0.446 | 472 |
| | | *Advance selling* | |
| Did you already promise part of the 2022 harvest to a buyer? (1=yes) | 0.077 | 0.267 | 3,532 |

Table 3: Balance table

| | mean ctrl | T1 | T2 | nobs |
|---|---|---|---|---|
| Household head is female | 0.219 | -0.022 | -0.011 | 3534 |
| | (0.413) | (0.016) | (0.016) | |
| Household size (number of people) | 5.011 | -0.017 | 0.19* | 3534 |
| | (2.04) | (0.083) | (0.083) | |
| Age of household head (year) | 43.138 | -0.018 | 0.977 | 3414 |
| | (14.885) | (0.608) | (0.61) | |
| Years of education of household head | 6.237 | 0.248+ | 0.107 | 3428 |
| | (3.457) | (0.14) | (0.14) | |
| Roof of main building is corrugated iron | 0.37 | 0.029 | 0.038* | 3534 |
| | (0.483) | (0.019) | (0.019) | |
| Number of rooms in house | 3.174 | 0.042 | 0.058 | 3534 |
| | (1.17) | (0.046) | (0.046) | |
| Area of cultivated land (acres) | 2.452 | 0.06 | 0.204** | 3489 |
| | (1.736) | (0.071) | (0.071) | |
| Hired labour for maize, soybean or gnut productions? | 0.408 | 0.015 | 0.059** | 3528 |
| | (0.492) | (0.02) | (0.02) | |
| Distance to nearest all weather road (km) | 1.415 | 0.348 | -0.092 | 3350 |
| | (4.585) | (0.257) | (0.258) | |
| Distance to nearest market (km) | 4.342 | 0.584 | -0.059 | 3251 |
| | (8.407) | (0.377) | (0.377) | |
| F-test C/T1 (p-value) | 1.064 | (0.386) | | |
| F-test C/T2 (p-value) | 1.414 | (0.168) | | |
| Likelihood Ratio Test (p-value) | 29.229 | (0.083) | | |

Note: First column reports control group means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels. F-test test for joint significance in a regression with treatment status on the left hand side (T1/C or T2/C). Likelihood ratio test is derived from a multinomial model where the left hand side has three levels (T1,T2,C). All models include village fixed effects.

Wichman, 2020). For both treatments, we expect a positive effect. Similar to Augenblick et al. (2021), we expect that when making households aware of future needs, they will reduce discretionary expenditures and save more for the future. Furthermore, if farmers expect prices to go up over time and this is reflected in their sales plan, farmers that are encouraged to commit to this sales plan will also be more likely to have saved more early on in the season. As such, we expect a positive effect on stocks, particularly in the months immediately following the harvest.

A second primary outcome tests if the household sold any of the crop in the interval between the intervention and the midline survey. As with stocks, we expect that treatment would reduce the likelihood of selling early on in the season, and more towards the end of the season when prices go up. The third primary outcome is the quantity that was sold during the period between the intervention and the first midline survey, which is related to the second.

We also consider behaviour related to purchases of the commodities as key primary outcomes. We expect that households will have to buy back less later in the season because of our interventions. As for sales, we look at actual quantities to better understand intensive margin effects.

The top half of Table 4 shows results for the first season, while the bottom half shows results for the second season. For the second season, we only report results for the groups where the treatment was repeated (that is, we compare CC to both T1T1 and T2T2). For each season, we report results derived from the three surveys: the first midline survey done in September and covering transactions done in the period of April to September; the second midline survey done in January and covering transaction done in the period of October until January; and the endline survey done in April and covering transactions from the period from February to April.

Looking at maize stocks in the first season (2022-2023), we see that, as expected, stocks deplete as time goes by. In the control group, stocks are at an average of 5.56 bags in September and reduce further to just 1.38 bags in January. At the time of the next harvest, stock have virtually depleted. The table also shows that there is no difference in stocks at these three points in time in the sub-group that received T1. However, we do see that stocks are significantly higher in September for the group that was asked to prepare a sales plan. In this group, stocks are 2.5 percent higher, suggesting that the intervention encourages farmers to hold on to their maize longer. In the second season, we also see that average stock reduces over time. Even though the estimated treatment effects for T2 are very close to the ones from the first season, the difference is not statistically different from zero. This is likely due to the smaller sample size as a result of introducing more treatment groups in season 2.

In the first season, we see that about 34 percent of our sample reports at least one sales transaction in the six months following the 2022 harvest. In the period from October to January, this number falls to about 24 percent. During the last few months of the lean season, only 5 percent of households report to be making sales transactions. This suggests that most sales indeed happen during periods where prices are likely to be low due to excess supply. Interestingly, we see that households that were exposed to T2 report a higher incidence of sales later into the season, indiating that the sales plan induces farmers to sell more later in the season when prices are higher. Somewhat surprisingly, we also find a significant effect from T1. Perhaps, due to better budgeting, farmers in this group are also left with higher stocks (and the coefficient for T1 on stocks in the previous survey is indeed positive but not significant) which they can now sell. A similar pattern holds for amounts sold. In the second season (bottom part of Table 4) we also see an increase in sales transactions among T2 farmers from October 2023 to January 2024.

Purchase transactions mirror sales transactions. At the time of the first survey, about 27 percent of households in the control group reported buying maize. This increases over time, and during the final months of the lean season when maize prices are likely to be at their highest, 73 percent of households turn to the market to obtain maize. There are also some indications that T2 is especially effective in reducing the likelihood that farmers will turn to the market later in the season. In the T2 group, farmers are 4.5 percentage points less likely to buy maize during the hunger months. There are no differences between the treatment groups in the second season.

Using the same analysis, Table 5 shows the primary outcomes for soybean. As with maize, we see that T2 seems to be more effective than T1 in countering the sell low-buy high trend. In T2, soybean stocks are significantly higher, especially in January when T2 farmers have 45 percent higher stocks than the control group. T2 also seems to result in delayed sales: while 15 percent of farmers made sales transactions in the period between October 2022 and January 2023, this percentage increased to almost 20 percent in the group asked to prepare a sales plan. The effect on purchases is less straightforward, with significant effects only during the first six months after the harvest and especially for T1. This could be because soybean is generally

Table 4: Primary outcomes maize

| | April - Sept | | | Oct - Jan | | | Feb - April | | |
|---|---|---|---|---|---|---|---|---|---|
| | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 |
| | | | | *first season (2022 - 2023)* | | | | | |
| Stocks (abs) | 5.565 | 0.04 | 0.136** | 1.383 | 0.057 | 0.058 | 0.1 | 0.005 | 0.005 |
| | (10.657) | (0.048) | (0.048) | (8.089) | (0.035) | (0.035) | (0.723) | (0.013) | (0.013) |
| Sold (yes/no) | 0.341 | 0 | 0.006 | 0.237 | 0.022 | 0.043* | 0.051 | 0.027* | 0.021* |
| | (0.474) | (0.019) | (0.019) | (0.426) | (0.018) | (0.018) | (0.221) | (0.01) | (0.01) |
| Quant sold | 1.528 | 0.064 | 0.039 | 1.56 | 0.026 | 0.073+ | 0.454 | 0.063* | 0.047+ |
| | (3.823) | (0.041) | (0.042) | (5.09) | (0.041) | (0.041) | (3.331) | (0.025) | (0.025) |
| Bought (yes/no) | 0.269 | 0.011 | -0.026 | 0.706 | -0.027 | -0.045* | 0.733 | -0.005 | -0.001 |
| | (0.444) | (0.018) | (0.018) | (0.456) | (0.019) | (0.019) | (0.442) | (0.019) | (0.019) |
| Quant bought | 0.844 | 0.039 | -0.002 | 2.434 | -0.017 | -0.073+ | 3.315 | 0.002 | 0.01 |
| | (2.369) | (0.033) | (0.033) | (3.024) | (0.04) | (0.04) | (5.096) | (0.044) | (0.044) |
| | | | | *second season (2023 - 2024)* | | | | | |
| Stocks (abs) | 4.772 | 0.07 | 0.12 | 0.875 | 0.005 | 0.066 | 0.238 | 0.013 | 0.022 |
| | (8.981) | (0.077) | (0.077) | (2.697) | (0.045) | (0.029) | (1.185) | (0.029) | (0.029) |
| Sold | 0.331 | 0.039 | 0.01 | 0.207 | 0.023 | 0.056* | 0.086 | 0.012 | -0.01 |
| | (0.471) | (0.029) | (0.029) | (0.406) | (0.025) | (0.017) | (0.281) | (0.017) | (0.017) |
| Quant sold | 1.932 | 0.1 | 0.041 | 1.34 | 0.047 | 0.121* | 0.678 | 0.01 | -0.018 |
| | (5.431) | (0.065) | (0.065) | (5.009) | (0.057) | (0.04) | (3.99) | (0.04) | (0.04) |
| Bought | 0.41 | 0 | 0.008 | 0.76 | -0.01 | -0.02 | 0.578 | 0.015 | 0.005 |
| | (0.492) | (0.029) | (0.029) | (0.428) | (0.026) | (0.029) | (0.494) | (0.029) | (0.029) |
| Quant bought | 1.488 | 0.038 | 0.061 | 4.798 | -0.035 | -0.077 | 10.16 | 0.007 | -0.01 |
| | (3.433) | (0.058) | (0.058) | (20.022) | (0.063) | (0.065) | (175.503) | (0.064) | (0.065) |

Note: **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

used as a cash crop, which is reflected in the low share of households that bought in the market.

Lastly, Table 6 shows the primary outcomes for groundnuts. Again, we see that households that received T2 enter the hunger season with higher stocks. To a lesser extent, this is also the case for farmers that received T1. As with maize, similar results are observed during the second season, but due to smaller samples the results are not precisely measured. The effects on transactions are less in line with our theory. We find a significant increase in sales due to T2 in the first 6 months after the harvest, and only a marginal increase in sales transactions from the period between October 2022 and January 2023. We do not find any effect on purchases.

## Prices

The interventions aim to reverse sell low-buy high behaviour. On the supply side, this means reducing the propensity to sell early at low prices and increasing the likelihood of selling later when prices have recovered. At the demand side, this means reducing the propensity to buy late when prices are high, and perhaps buy early in the season when prices are low and store for consumption later on. In addition to looking at the dynamics in market participation in the previous section, sell low-buy high behaviour may also affect prices. In particular, we would expect that treated farmers, and T2 farmers in particular, report higher sales prices as they wait longer.

Table 7 therefore looks at the average prices reported by farmers in the different treatment groups. We look at both sales prices (first three columns) and prices at which the commodities were bought (last three columns), and do this for the three commodities.

Results show that one kilogram of maize was sold at an average price of MK 205. The price was about 7 percent higher in the group that made a budget plan, and the price at which farmers in the control group bought maize was more than double. However, there are no difference between the different groups.

One kilogram of soybean was sold for about MK 590 and there is no difference between the control group and the treatment. When buying soybean, prices reached MK 865 on average. Contrary to expectations, we find that among farmers that were asked to provide a sales plan, the purchase price was significantly higher.

Finally, one debe (a kind of plactic bucket) of groundnuts was sold for

Table 5: Primary outcomes soybean

| | April - Sept | | | Oct - Jan | | | Feb - April | | |
|---|---|---|---|---|---|---|---|---|---|
| | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 |
| | | | | *first season (2022 - 2023)* | | | | | |
| Stocks (abs) | 1.114 | 0.007 | 0.056$^{+}$ | 0.055 | 0.008 | 0.025$^{*}$ | 0.016 | 0.003 | 0.014$^{+}$ |
| | (3.551) | (0.03) | (0.031) | (0.498) | (0.01) | (0.01) | (0.243) | (0.008) | (0.008) |
| Sold (yes/no) | 0.55 | 0.01 | 0.04$^{+}$ | 0.152 | -0.002 | 0.047$^{**}$ | 0.07 | -0.005 | -0.005 |
| | (0.498) | (0.024) | (0.024) | (0.359) | (0.015) | (0.015) | (0.256) | (0.012) | (0.012) |
| Quant sold | 2.376 | -0.006 | 0.113$^{*}$ | 0.562 | 0.001 | 0.084$^{**}$ | 0.123 | -0.003 | 0.003 |
| | (4.347) | (0.052) | (0.052) | (2.688) | (0.028) | (0.028) | (0.833) | (0.016) | (0.016) |
| Bought (yes/no) | 0.058 | -0.022$^{**}$ | -0.018$^{*}$ | 0.174 | 0.02 | -0.015 | 0.052 | -0.014 | -0.006 |
| | (0.234) | (0.009) | (0.009) | (0.379) | (0.015) | (0.015) | (0.222) | (0.009) | (0.009) |
| Quant bought | 0.049 | -0.008 | -0.014$^{+}$ | 0.091 | 0.013 | -0.002 | 0.041 | 0 | -0.003 |
| | (0.375) | (0.008) | (0.008) | (0.448) | (0.01) | (0.01) | (0.499) | (0.007) | (0.007) |
| | | | | *second season (2023 - 2024)* | | | | | |
| Stocks (abs) | 0.574 | -0.011 | 0.074$^{*}$ | 0.049 | -0.009 | -0.005 | 0.042 | -0.018 | -0.017 |
| | (1.268) | (0.036) | (0.036) | (0.193) | (0.01) | (0.012) | (0.267) | (0.012) | (0.012) |
| Sold | 0.545 | 0.001 | -0.021 | 0.198 | -0.038 | 0.003 | 0.068 | -0.002 | 0.003 |
| | (0.499) | (0.035) | (0.035) | (0.399) | (0.024) | (0.017) | (0.252) | (0.017) | (0.017) |
| Quant sold | 1.685 | 0.046 | 0.005 | 0.526 | -0.074$^{+}$ | 0.004 | 0.181 | -0.015 | -0.01 |
| | (2.784) | (0.068) | (0.067) | (1.724) | (0.039) | (0.027) | (0.914) | (0.027) | (0.027) |
| Bought | 0.023 | 0.011 | 0.005 | 0.261 | -0.013 | -0.018 | 0.04 | -0.014 | 0 |
| | (0.149) | (0.011) | (0.011) | (0.439) | (0.026) | (0.011) | (0.197) | (0.011) | (0.011) |
| Quant bought | 0.015 | 0.01 | -0.002 | 0.261 | 0.003 | -0.008 | 0.062 | -0.009 | -0.001 |
| | (0.184) | (0.009) | (0.009) | (2.515) | (0.021) | (0.015) | (0.703) | (0.015) | (0.015) |

Note: **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

Table 6: Primary outcomes gnuts

| | April - Sept | | | Oct - Jan | | | Feb - April | | |
|---|---|---|---|---|---|---|---|---|---|
| | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 |
| | | | | *first season (2022 - 2023)* | | | | | |
| Stocks (abs) | 1.716 | 0.075* | 0.11** | 0.09 | -0.002 | 0.019 | 0.011 | 0.001 | 0.007 |
| | (7.124) | (0.038) | (0.038) | (0.719) | (0.013) | (0.013) | (0.121) | (0.007) | (0.007) |
| Sold (yes/no) | 0.674 | 0.021 | 0.057* | 0.153 | 0.02 | 0.028+ | 0.034 | -0.005 | -0.008 |
| | (0.469) | (0.026) | (0.026) | (0.36) | (0.016) | (0.015) | (0.182) | (0.01) | (0.01) |
| Quant sold | 3.909 | 0.015 | 0.166* | 0.748 | 0.036 | 0.031 | 0.185 | -0.002 | -0.016 |
| | (6.334) | (0.068) | (0.067) | (3.386) | (0.031) | (0.031) | (1.742) | (0.022) | (0.022) |
| Bought (yes/no) | 0.071 | -0.014 | -0.01 | 0.131 | 0.021 | 0.009 | 0.053 | -0.005 | -0.007 |
| | (0.257) | (0.01) | (0.01) | (0.338) | (0.014) | (0.014) | (0.225) | (0.009) | (0.009) |
| Quant bought | 0.104 | -0.014 | -0.01 | 0.101 | 0.018 | 0.016 | 0.054 | -0.004 | -0.005 |
| | (0.551) | (0.012) | (0.012) | (0.454) | (0.012) | (0.012) | (0.54) | (0.008) | (0.008) |
| | | | | *second season (2023 - 2024)* | | | | | |
| Stocks (abs) | 2.135 | 0.012 | 0.096 | 0.054 | 0.006 | 0.006 | 0.068 | -0.009 | 0.001 |
| | (5.733) | (0.063) | (0.063) | (0.31) | (0.015) | (0.017) | (0.329) | (0.017) | (0.017) |
| Sold | 0.72 | 0.018 | 0.005 | 0.222 | -0.03 | 0.006 | 0.071 | -0.012 | -0.029+ |
| | (0.45) | (0.037) | (0.036) | (0.416) | (0.024) | (0.017) | (0.257) | (0.017) | (0.017) |
| Quant sold | 4.618 | -0.045 | -0.041 | 1.034 | -0.089+ | -0.048 | 0.279 | -0.006 | -0.04 |
| | (6.801) | (0.096) | (0.094) | (3.099) | (0.049) | (0.034) | (1.262) | (0.033) | (0.034) |
| Bought | 0.059 | 0.014 | -0.002 | 0.295 | -0.004 | -0.044+ | 0.073 | -0.018 | -0.007 |
| | (0.236) | (0.014) | (0.014) | (0.457) | (0.026) | (0.014) | (0.261) | (0.014) | (0.014) |
| Quant bought | 0.048 | 0.028+ | -0.007 | 0.306 | 0.005 | -0.009 | 0.164 | -0.018 | -0.015 |
| | (0.244) | (0.016) | (0.016) | (1.853) | (0.025) | (0.016) | (1.57) | (0.016) | (0.016) |

Note: **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

about MK 5,400. Here, there is also no difference between the groups that made a budget compared to groups that made a sales plan. The price when buying groundnut is only marginally higher. We do not find differences in purchase prices between the different groups.

### Revenue and Expenses

We now combine marketing patterns with prices to calculate how much revenue was derived from the sales of the three commodities and how much was spent on them. Results, in thousands of MK, are in Table 8.

In the first three columns of Table 8, we look at total revenue over the entire first season (multiplying quantities sold by prices at which these quantities were sold). We do this for the three commodities, and then also sum over the three commodities. The results show that the average household in the control group received about MK 146,000 from the sales of maize, about MK 80,000 from the sales of soybean, and about MK 43,000 from the sale of groundnuts. In all, the average control group household had a revenue of about MK 270,000 (about USD 160). For soybean, we find a significant and positive effect of the sales plan on revenue: farmers in that group report revenues totaling about MK 95,000. Similarly, we find that groundnut revenues are higher in the T2 sub-group. The positive treatment effects for T2 are also reflected in a slightly higher total revenue.

On the expense side (columns 4-6), we see farmers buy maize totaling just under MK 120,000, but households do not really buy soybean and groundnuts in the market. We do not find that the treatments affected expenses.

Finally, the last three columns looks at the net position of the household on the three commodities, as well as the total (final two rows). We see that the average net position for maize is marginal, as much of the buying happens in the control group. Net positions for soybean (as a cash crop) and groundnuts are higher. We see that the sales plan increased net positions for soybean and groundnuts.

## Conclusion

Smallholder farmers often sell their marketable surplus or cash crops immediately after harvest to itinerant traders at the farm gate, which results in sub-optimal outcomes due to low prices and poor market conditions. Post-

Table 7: Prices

| | Sales price | | | Purchase price | | |
|---|---|---|---|---|---|---|
| | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 |
| maize | 205.34 | $14.99^{+}$ | 5.52 | 455.76 | 4.16 | 6.55 |
| | ( 95.25) | ( 8.45) | ( 8.37) | ( 127.50) | ( 5.50) | ( 5.53) |
| soybean | 590.03 | -0.98 | 0.06 | 865.89 | -13.99 | $50.30^{*}$ |
| | ( 137.28) | ( 6.91) | ( 6.74) | ( 262.32) | ( 23.65) | ( 24.67) |
| gnuts | 5414.91 | -14.91 | 27.75 | 5977.76 | 144.77 | 290.31 |
| | (1658.56) | ( 101.06) | ( 98.44) | (2430.83) | ( 242.22) | ( 245.89) |

Note: **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

Table 8: Revenue and expenses

| | Revenue | | | Expenses | | | Revenue - Expenses | | |
|---|---|---|---|---|---|---|---|---|---|
| | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 | mean ctrl | T1 | T2 |
| maize | 146.96 | 13.56 | 5.47 | 118.16 | 4.95 | 2.83 | 8.63 | 13.03 | 9.37 |
| | (361.49) | ( 14.50) | ( 14.56) | (114.98) | ( 4.55) | ( 4.56) | (310.73) | ( 13.06) | ( 13.10) |
| soybean | 81.07 | 5.28 | 14.62** | 3.95 | 0.10 | -0.45 | 72.08 | 2.35 | 10.95* |
| | (123.32) | ( 5.11) | ( 5.14) | ( 10.57) | ( 0.41) | ( 0.42) | (105.23) | ( 4.29) | ( 4.30) |
| gnuts | 43.57 | 4.45 | 8.70* | 3.01 | 0.02 | -0.41 | 36.99 | -1.77 | 6.25* |
| | ( 93.59) | ( 3.90) | ( 3.92) | ( 9.58) | ( 0.37) | ( 0.37) | ( 79.94) | ( 3.07) | ( 3.09) |
| all | 268.14 | 24.92 | 27.68+ | 123.69 | 4.46 | 1.98 | 144.37 | 20.52 | 25.60 |
| | (405.69) | ( 16.38) | ( 16.44) | (117.41) | ( 4.61) | ( 4.63) | (427.32) | ( 17.33) | ( 17.38) |

Note: **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

harvest prices drop significantly, and the condition of the produce, such as undried maize, is often used by buyers to further reduce the price. Farmers then face higher prices later in the season when they need to repurchase their crops, creating the "sell low-buy high" puzzle. This behavior can be attributed to several factors, including lack of storage facilities, urgent cash needs, market access limitations, and risk aversion. Behavioral causes to the "sell low-buy high" puzzle have received less attention in research. These include issues related to "budget neglect," where farmers underestimate future financial needs due to the cognitive effort needed to predict all future needs over an extended period of time, or motivated reasoning, where future earnings are overestimated to justify discretionary spending now.

This study tested these behavioral explanations through a field experiment in Malawi targeted to maize, groundnuts, and soybean producers. The experiment employed a parallel design with two treatment arms and a control group. The first treatment tested the budget neglect hypothesis by having farmers complete a detailed budgeting exercise immediately post-harvest. The second treatment tested the motivated reasoning hypothesis through a sales planning intervention, where farmers committed to sales plans and minimum prices. The impact of these interventions was compared to a control group. The experiment was repeated in a second year to assess the effectiveness of repeated treatments, resulting in seven distinct treatment arms to evaluate various combinations of one-off and repeated interventions.

In terms of smallholder market participation, we found that for maize, the sales planning intervention (T2) led to higher stocks immediately after harvest and encouraged delaying sales for higher price periods, reducing the need for later market purchases. The budgeting intervention (T1) showed mixed results with some positive impacts on stock levels but less consistency in influencing sales timing. For soybean, T2 was notably effective in maintaining higher stocks and delaying sales, while T1's impact was less clear. Groundnuts showed similar trends, with T2 increasing stocks entering the hunger season but showing inconsistent effects on transaction timing. Overall, the interventions, particularly T2, helped mitigate the sell low-buy high phenomenon by promoting better stock management and sales timing among farmers.

The idea behind the interventions is to delay sales and reduce incidences of purchase if prices are high. Analysis of average prices reported by farmers revealed that maize sold for 205 Malawian Kwacha per kilogram, with a 7 percent higher price for those who created a budget plan. There was no significant difference in purchase price of maize among different groups. Soybean sold for about 590 Kwacha per kilogram without significant price differences across groups, but the purchase price was higher for farmers with a sales plan. Groundnuts sold for about 5,400 Kwacha per debe, with no significant differences between treatment and control groups in both sales and purchase prices. Overall, budgeting interventions increased sales prices for maize, but other commodities showed less consistent effects.

Finally, we combine market participation dynamics with prices to look at effects of revenue, expenses, and the value of marketed surplus (or deficit). The average household in the control group earned about 146,000 Kwacha from maize, 80,000 Kwacha from soybean, and 43,000 Kwacha from groundnuts, totaling 270,000 Kwacha (approximately USD 160). The sales plan intervention (T2) significantly increased revenue for soybean (95,000 Kwacha) and groundnuts, resulting in a slightly higher total revenue. On the expense side, households spent about 120,000 Kwacha on maize, with minimal spending on soybean and groundnuts, and no significant effect from the treatments. Net positions, considering both revenues and expenses, were marginal for maize due to substantial purchasing, but higher for soybean and groundnuts. The sales plan intervention improved net positions for both soybean and groundnuts.

Overall, while our results support the hypotheses to some extent, the evidence is much less convincing than what Augenblick et al. (2021) report. Furthermore, our study suggests that an intervention that focuses more on planning of sales is more effective than an intervention that focuses on expenses. This finding is potentially important for policy makers and practitioners: We found that budgeting is something that is often used by nongovernmental organizations during extension and training programs. Our study suggests that a sales plan, which was far easier to do than a complete budget, is likely to be more cost-effective than budgeting.

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