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

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June 30, 2023

Results from the first endline (April 2023)

preliminary and incomplete version – please do not cite

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 apparently sub-optimal behavior focus on economic or infrastructural issues, such as credit constraints or lack of storage facilities. In this study, we zoom in on two potential behavioral explanations. One explanation is situated at the household expenditure side, and assumes that households face challenges in accurately predicting future expenditures, systematically underestimating future needs. A second potential explanation is situated at the household income side, 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. We find few effects of the treatments during the lean season when prices are high and farmers remain with virtually no stocks.

Keywords: smallholder marketing, cash crops, budget neglect, commitment failure.

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1 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. In addition to high supply immediately post harvest, 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 a multiple of what 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 loose out twice, as transaction costs are passed on by traders to farmers when traders buy commodities from farmers in rural areas immediately after the harvest and store in warehouses in towns, but farmers also incur transaction costs when they have to go to town to buy back maize from the same traders.

The literature suggest many possible reasons why farmers choose the sell early at low prices instead of waiting a few months until prices recover. 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). They may be in urgent need of cash after the lean season (Burke, Bergquist, and Miguel, 2018; Dillon, 2021). Price movements may be unpredictable and farmers may be too risk averse to engage in intertemporal arbitrage (Cardell and Michelson, 2020). It may be 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 zoom in on two potential behavioral explanations why farmers seemingly sell at sub-optimal timing. One potential explanation is situated at the household expenditure side, 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 farmer to sell more early on and save too little for later in the year (Augenblick et al., 2021). A second potential explanation is situated at the household income side. 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 part is 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. Here, a trained enumerator sits with the household head and plans 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.

This document has been compiled immediately after the first endline survey was done, exactly one year after the treatment.[1] It is based on the pre-analysis plan and the mock report, and compares outcomes in the treatment groups to outcomes of households in the control group for the last few months (December 2023 up to April 2023).

During the last few months of the season, effects of the treatments are muted. There is some evidence that farmers that received a treatment were more likely to sell (and sold slightly more) maize than the control group. However, we do not find effects on other variables nor for other crops, often because sample size becomes too small as few transactions were made at the height of the lean season when prices are high and farmers remain with virtually no stocks.

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 that was collected in April 2023 and report attrition and impact on primary and secondary outcomes. A last section concludes.

2 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 to meet consumption needs later in the year, many

[1] A similar document was prepared after the first midline was completed around August 2022. The document can be found here. Another document was prepared after the second midline was completed around January 2022. The document can be found here

farmers end up buying back grain from the market a few months after selling it, 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 intertemporally. 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%. Dillon (2021) uses the fact that in Malawi, primary school began 3 months earlier in 2010 than in 2009, and notes that this prompted households with children 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 as well. While credit constraints thus seems 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 that are less affected by price seasonality, like small livestock. 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 price in the future. A recent article by Cardell and Michelson (2020) 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, 2020). However, their analysis use 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 economy, and so will be less prone to the extreme spikes and slumps that smallholder farmers in more remote areas experience.

A third reason may be that farmers have nowhere to safely store crops, so they just sell. This could be a lack of space, as the average smallholder often harvest 20-40 bags of 50kg of maize. But there are also risks related to pests and diseases affecting the stored maize. If lack of safe storage is the main reason why farmers do not engage in intertemporal 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. Again, we feel storage is indeed part of the reason, but 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.

Another reason may be related to social taxation. If a farmer has a lot of maize stored in his house, this is visible for family and neighbors, and it will be very hard to deny if neighbors come and 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 important in a similar marketing decisions where household seem to forgo the benefits of buying in bulk (Dillon, De Weerdt, and O'Donoghue, 2020).

Related research on the more behavioral and psychological front that helps explain the puzzle is ongoing. Augenblick et al. (2021) study recurrent seasonal hunger in Zambia, which could be a direct consequence of suboptimal marketing behaviour, and conjecture that individuals tend to overestimate their available resources and consequently 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 an established literature on lack of self-control in cases where individuals have to make complex intertemporal decisions involving uncertain future events. If farmers are impatient and unsophisticated about this, nudges may be effective in reducing discretionary spending and 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.

3 Behavioural constraints to intertemporal arbitrage: Hypotheses and Interventions

Broadly speaking, the behavioral foundation of the sell low-buy high behaviour is akin to the planning fallacy, where individuals typically underestimate the time it takes to complete a task, despite 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 is situated at the household expenditure side, 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, immediately after harvest, they may budget for fresh seed from the agro-input dealer and for fertilizer, 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 main decision maker within the household was provided with a template that needed to be filled as detailed as possible. Pre-populated expenditure categories included education expenditures (school fees, uniforms,...), agricultural investment expenditures (seed, fertilizer,...), investment expenditure in non-agricultural businesses (retail shop inventories,...), health and medical expenses (medicines, preventive doctor visit,...), household recurrent expenditure (food, utilities,...), household equipment and maintenance (furniture, renovation,...), and other expenditures (loan repayment, 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 write it down in the appropriate cell of the expenditure matrix. Farmers were also encouraged to provide their top 3 unexpected expenditures likely to occur between May 2022 and April 2023. We then calculate totals per month and also a grand total for the entire year. This first intervention will be referred to as treatment one (T1).

The second hypothesis is at the income side 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 the 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 cause 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 in 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. We then ask for each month between May 2022 and April 2023 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. Also for the sales plan, we calculate totals per month and also 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 did not merely ask 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 refer to the plan during midline surveys, and reiterate the importance of following these plans.

4 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 3534 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 starts usually starts in April and proceeds through May. Soybean is harvested somewhat earlier, groundnuts somewhat later. Soybean and groundnuts can be sold pretty much 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 coverage and dispersion of the interviewed households.

The focus of the study is on market participation and so 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 season. Restricting our study population to a particular sub-population has implications for the interpretation of the results. For instance, we will see later that we find relatively high proportions of households reporting to sell to the market. As such, the particular nature of the study population, semi-subsistence smallholder farmers, needs to be kept in mind when interpreting results, as they may be different from for example predominantly self-sufficient farmers.

Midline data was collected twice by phone (first in September 2022, then in January 2023). Results reported here are from an in person visit to farmers in April 2023, about one full year after the treatments. This round of data collection was supposed to be the endline, however, given encouraging results, we decided to extend the research for an additional year. Hence we refer to this round of data collection as the first endline.

4.1 Farmer characteristics

Table 1 presents a number of summary statistics of sampled households and their heads at baseline. Eighty percent of households are headed by men. The average

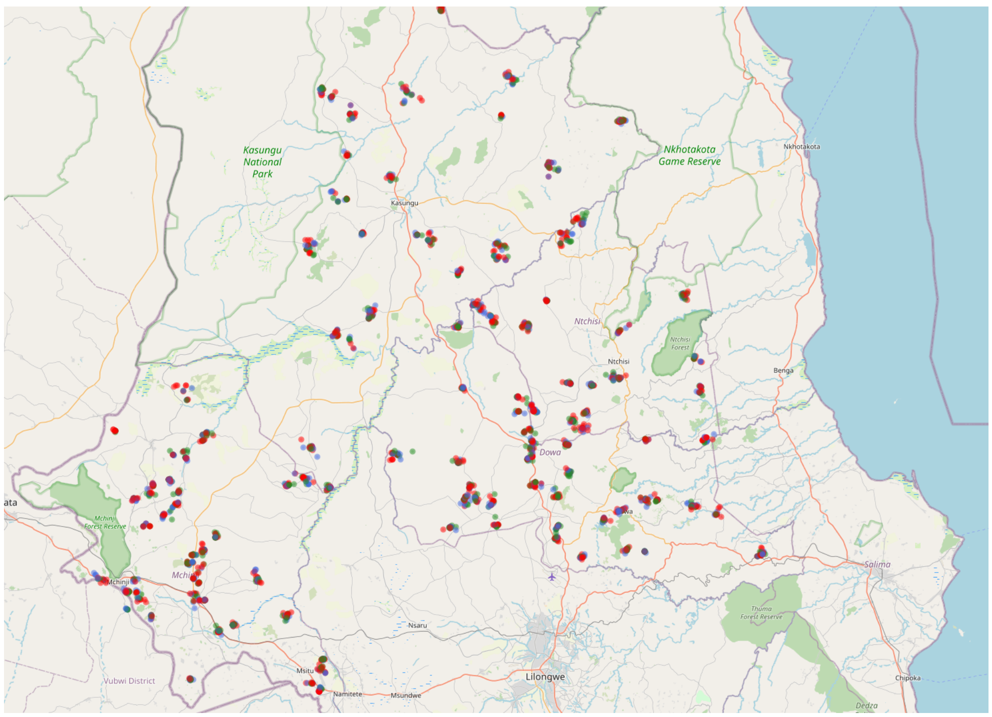

Figure 1: map of study area with sampled villages

household is headed by a 43 year old with six years of schooling (primary level). The typical household has five members, living in houses with three rooms. Four in every 10 households have their main houses 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% of respondents) and ox-carts (60% 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 surveyed farmers, about 40 percent indicate that they have access to credit, and that less than a quarter had outstanding debts averaging MK 57,000 to repay after harvest. With regards to access to storage, 60 percent of the households reported that they have access, of which half indicated that the storage was crop specific. We also find that, while farmer participation in cooperatives is limited, a moderate share (40%) have access to storage space provided by the cooperative. 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%) had already promised (part of) the 2022 crop to buyers prior to harvest.

4.2 Baseline balance

We follow our pre-analysis plan and test baseline balance by constructing a standard balance table consisting of the following variables household/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 (corrugated iron = 1), number of rooms in the house, cultivated acreage (maize+groundnuts+soybean), whether the household hired in 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-test 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

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

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.

Table 4: Balance table for conditioning variables

	mean ctrl	T1	T2	nobs
Household has access to credit	0.384	0.002	-0.008	3534
	(0.487)	(0.019)	(0.019)	
Household has access to storage	0.592	0.004	0.02	3534
	(0.492)	(0.019)	(0.019)	
Cooperative member	0.137	-0.012	-0.001	3534
	(0.344)	(0.014)	(0.014)	
Has livestock	0.484	0.012	0.041*	3532
	(0.5)	(0.02)	(0.02)	
Makes a budget	0.694	0.008	0.012	3534
	(0.461)	(0.018)	(0.018)	
F-test C/T1 (p-value)	0.284	(0.922)		
F-test C/T2 (p-value)	1.176	(0.318)		
Likelihood Ratio Test (p-value)	7.452	(0.682)		

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.

has three levels (T1, T2, Ctrl).

The pre-analysis plan also states that we assess balance on a range of characteristics that we will use to investigate heterogeneous treatment effects. The variables mentioned there are access to credit, access to storage facility, membership of (marketing related) cooperative, livestock asset ownership, and whether the household already makes a budget. Results for these variables are in Table 4.

5 Impact at endline

5.1 Attrition

Data collection for the endline was done in persons. We expected that we would not be able to reach some farmers, even though at baseline we always collected information on alternative ways to reach the farmers (for instance through village leadership). From the original 3534 farmers that were interviewed at baseline, we successfully reached 3187 farmers, leading to an attrition rate of just under 10 percent. Treatments are correlated to the likelihood that farmers are missing from the data (χ^2 test of independence of proportions is rejected at p=0.034).

5.2 Primary outcomes

We start with the most parsimonious specification by reporting simple differences between treatment and control farmers obtained from an Ordinary Least Squares regression that regresses the outcome of interest on two dummy variables indicating if the household received T1 or T2 respectively. Results are in the top panel of Table 5. In the bottom panel of Table 5 we show results after including additional controls. These include the outcome at baseline, and village fixed effects. We start with Table 5, which reports results for maize; Tables 6 and 7 are similar tables but for groundnuts and soybean, respectively.

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 Wichman, 2020). For both treatments, we expect a positive effect. Similar to Augenblick et al. (2021), we expect that when making households aware about 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.

We see that the average control farmer has about 0.1 bags of maize in store at the time of the survey. At this stage, late in the season, there are no differences in stocks between the treatment groups anymore. However, for the second primary outcome that tests if the household sold any maize in the interval between the second midline survey (January 2023) and the endline survey (April 2023) we do find significant effects from both treatments. While 5.1 percent of households in the control group indicated that they made at least one sales transaction between second midline and endline, this share increase to 7.6 percent for households in the T1 group and 7 percent for households in the T2 group.

In addition to testing if farmers are more likely to sell after treatment, we also wonder if farmer sell more. The third primary outcome is thus the quantity that was sold during the period between the second midline and the endline survey. We find that farmers in the control group sell on average 0.454 bags of maize. We also find quantities are somewhat higher for treated farmers, but the difference is only significant for farmers that were exposed to the budget plan intervention.

For farmers that did engage in sales, we can calculate the average price that farmers received for their crop. The aim of the intervention is to increase the price at which farmers sell. The farmers that sold in the control group got on average 360.467 MKW per kilogram of maize. We do not find that prices differ significantly in any of the treatment groups. However, we expect that effects of the intervention will only become apparent at endline and prices over the entire period are taken into consideration. This is because the price effect is expected to come from more people selling later in the season.

We also consider behaviour related to purchases of the commodities as key primary outcomes. We expect that, especially later in the season, due to our interventions households will have to buy back less. We see that in the control group about 73 percent also made at least one purchase of maize in the last three months. This is similar to what we found in the previous survey round (70 percent), but substantially higher than what we found in the first midline (30 percent). At this stage, we do not see that this share differs with treatment. As for sales, we also look at quantities bought and prices at which the commodities were bought. We find that for maize, the average control group household bought 3.3 bags on average and there is no difference between treatment groups. Average price paid is about 545.

In Table 6, we repeat the entire analysis, but now for groundnuts. Households in the control group remain with virtually no stocks. Because already in the second mildine, farmers remained with virtually no stocks, there are no effects on quantities sold, nor on prices received.

As for maize, we also asked if farmers had already bought groudnuts in the last three months prior to the endline. About 5 percent of farmers reported that they made at least one purchase. Interestingly, we find that farmers in the T1 treatment group were more likely to have bought groundnuts. But also here, there are no effects from the treatments during this period.

Finally, Table 7 shows impact of the interventions on primary outcomes for soybean. We find some indications that stocks are higher in T2. Furthermore, we find a negative effect on the price from the second treatment, however, the sample size is very low.

5.3 Secondary outcomes

In this section, we look at some additional outcome which may be indirectly affected by the interventions. These outcomes may help explain some of the effect on primary outcomes, or they may be outcomes for which the expected effects are ambiguous. We again present separate tables for maize (Table 8), for groundnuts (Table 9) and for soybean (Table 10).

A first outcome we look at is the price in the near future. In particular, we asked all households what they expected the price would be around the beginning of September 2023. Table 8 shows that farmers still expect a sizable price increase: while we saw in the previous section that the average farmer in the control group only got about 360 MKW per kilogram for sales between the second midline and the endline, the price is expected to increase to about 700 MKW per kilogram a few months from now.

We also wonder if our intervention would affect intra-household dynamics, in particular who is in charge of sales of the commodity. We see that in about 48 percent of households, the decisions related to the sales of maize is taken by the male and female co-head jointly, with both co-head having equal voice. We find that this percentage is slightly lower among farmers that were exposed to treatments. This is surprising given that we found a positive effect of the interventions between the first and the second mildine. Note that the sample size has become very small.

Table 5: Primary outcomes maize

	mean ctrl	T1	T2	nobs
	treatment-control			
Stocks (abs)	0.1	0.006	0.004	3120
	(0.723)	(0.014)	(0.014)	
Sold (yes/no)	0.051	0.025*	0.019+	3120
	(0.221)	(0.011)	(0.011)	
Quantity sold (abs)	0.454	0.055*	0.041	3111
	(3.331)	(0.026)	(0.026)	
Price sold (MKW)	360.467	9.753	-9.592	122
	(147.989)	(30.464)	(32.001)	
Bought (1=yes)	0.733	-0.005	0.001	3183
	(0.442)	(0.019)	(0.019)	
Quantity bought	3.315	0.003	0.01	3154
	(5.096)	(0.045)	(0.045)	
Price bought	545.281	6.155	-0.844	2239
	(214.882)	(10.886)	(10.814)	
	full models			
Stocks (abs)	0.1	0.005	0.005	3120
	(0.723)	(0.013)	(0.013)	
Sold (yes/no)	0.051	0.027*	0.021*	3120
	(0.221)	(0.01)	(0.01)	
Quantity sold (abs)	0.454	0.063*	0.047+	3111
	(3.331)	(0.025)	(0.025)	
Price sold (MKW)	360.467	29.019	25.08	122
	(147.989)	(47.615)	(56.512)	
Bougth	0.733	-0.005	-0.001	3183
	(0.442)	(0.019)	(0.019)	
Amount bougth	3.315	0.002	0.01	3154
	(5.096)	(0.044)	(0.044)	
Price bougth	545.281	3.838	-1.691	2239
	(214.882)	(10.36)	(10.297)	

Note: First column reports control group means (and standard deviations below); **, * 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

	mean ctrl	T1	T2	nobs
		treatment-control		
Stocks (abs)	0.011	0.003	0.007	1742
	(0.121)	(0.007)	(0.007)	
Sold (yes/no)	0.034	-0.005	-0.01	1742
	(0.182)	(0.01)	(0.01)	
Quantity sold (abs)	0.185	-0.003	-0.019	1742
	(1.742)	(0.022)	(0.021)	
Price sold (MKW)	562.685	-180.37	296.783	52
	(463.052)	(222.302)	(232.587)	
Bought (1=yes)	0.053	-0.005	-0.007	3183
	(0.225)	(0.009)	(0.009)	
Quantity bought	0.054	-0.004	-0.005	3180
	(0.54)	(0.008)	(0.008)	
Price bought	756.546	186.093	128.883	154
	(775.498)	(153.036)	(153.036)	
		full models		
Stocks (abs)	0.011	0.001	0.007	1742
	(0.121)	(0.007)	(0.007)	
Sold (yes/no)	0.034	-0.005	-0.008	1742
	(0.182)	(0.01)	(0.01)	
Quantity sold (abs)	0.185	-0.002	-0.016	1742
	(1.742)	(0.022)	(0.022)	
Price sold (MKW)	562.685	40.03	-103.094	52
	(463.052)	(120.967)	(102.555)	
Bougth	0.053	-0.005	-0.007	3183
	(0.225)	(0.009)	(0.009)	
Amount bougth	0.054	-0.004	-0.005	3180
	(0.54)	(0.008)	(0.008)	
Price bougth	756.546	228.029	214.733	154
	(775.498)	(208.269)	(218.097)	

Note: First column reports control group means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

Table 7: Primary outcomes soy

	mean ctrl	T1	T2	nobs
		treatment-control		
Stocks (abs)	0.016	0.003	0.015^{+}	2418
	(0.243)	(0.008)	(0.008)	
Sold (yes/no)	0.07	-0.004	-0.008	2418
	(0.256)	(0.012)	(0.012)	
Quantity sold (abs)	0.123	-0.002	0	2418
	(0.833)	(0.016)	(0.016)	
Price sold (MKW)	522.256	-2.203	-68.647^{+}	151
	(203.381)	(40.983)	(40.983)	
Bought (1=yes)	0.052	-0.014	-0.006	3183
	(0.222)	(0.009)	(0.009)	
Quantity bought	0.041	0.001	-0.003	3176
	(0.499)	(0.007)	(0.007)	
Price bought	902.863	-151.148	-25.921	136
	(485.315)	(94.941)	(89.838)	
		full models		
Stocks (abs)	0.016	0.003	0.014^{+}	2418
	(0.243)	(0.008)	(0.008)	
Sold (yes/no)	0.07	-0.005	-0.005	2418
	(0.256)	(0.012)	(0.012)	
Quantity sold (abs)	0.123	-0.003	0.003	2418
	(0.833)	(0.016)	(0.016)	
Price sold (MKW)	522.256	-86.948	-72.848	151
	(203.381)	(52.491)	(50.131)	
Bougth	0.052	-0.014	-0.006	3183
	(0.222)	(0.009)	(0.009)	
Amount bougth	0.041	0	-0.003	3176
	(0.499)	(0.007)	(0.007)	
Price bougth	902.863	-194.112	-43.422	136
	(485.315)	(134.856)	(126.585)	

Note: First column reports control group means (and standard deviations below); **, * 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: Secondary outcomes maize

	mean ctrl	T1	T2	nobs
		treatment-control		
Expected price (dec)	698.04	10.138	4.515	3073
	(180.322)	(7.972)	(7.964)	
Sold jointly	0.485	-0.142+	-0.116	201
	(0.504)	(0.084)	(0.085)	
Sold to market	0.136	-0.051	0.002	201
	(0.346)	(0.056)	(0.057)	
Pay education	0.182	0.032	0.049	201
	(0.389)	(0.07)	(0.071)	
Pay health	0.091	-0.034	-0.014	201
	(0.29)	(0.045)	(0.046)	
		full models		
Expected price (dec)	698.04	7.547	0.986	3073
	(180.322)	(7.691)	(7.694)	
Sold jointly	0.485	-0.167+	-0.224*	201
	(0.504)	(0.1)	(0.109)	
Sold to market	0.136	-0.003	0.02	201
	(0.346)	(0.064)	(0.07)	
Pay education	0.182	-0.004	-0.023	201
	(0.389)	(0.078)	(0.085)	
Pay health	0.091	-0.007	-0.02	201
	(0.29)	(0.057)	(0.062)	

Note: First column reports control group means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

Another secondary outcome we consider is related to who was sold to. In particular, we test if, in response to our interventions, farmers increase the likelihood that they sell directly to the market, as this is often the place where they can get the best price for their crop Fafchamps and Hill (2005). We find that few farmers in our sample sell maize directly to the market, and that there are no difference between the different treatment groups.

Finally, we asked farmers that sold between the harvest and the midline survey what the proceeds from the transaction was used for. We examine the effect of our interventions on two categories. One expenditure type, payment of school fees, is likely to be predictable by the farmer. A second expenditure type, health related expenses, is probably less predictable. We do not find that the treatment intervention changed the propensity that sales of maize were made for any of these expenses.

Turning to Table 9 for secondary outcomes of groundnuts, we find no effect on expected prices. For other secondary outcomes, there are too few observations

Table 9: Secondary outcomes gnuts

	mean ctrl	T1	T2	nobs
		treatment-control		
Expected price (dec)	9040.951	52.718	-189.82	3144
	(3530.544)	(152.137)	(151.704)	
Sold jointly	0.292	0.175	-0.061	52
	(0.464)	(0.156)	(0.163)	
Sold to market	0.208	-0.075	-0.054	52
	(0.415)	(0.128)	(0.134)	
Pay education	0.208	-0.008	0.022	52
	(0.415)	(0.138)	(0.145)	
Pay health	0	0.067	0	52
	(0)	(0.045)	(0.048)	
		full models		
Expected price (dec)	9040.951	37.625	-198.619	3144
	(3530.544)	(142.744)	(142.456)	
Sold jointly	0.292	0.417	0.146	52
	(0.464)	(0.247)	(0.209)	
Sold to market	0.208	-0.139	-0.299^{+}	52
	(0.415)	(0.185)	(0.157)	
Pay education	0.208	0.083	-0.271	52
	(0.415)	(0.322)	(0.273)	
Pay health	0	0.222^{+}	0.028	52
	(0)	(0.115)	(0.098)	

Note: First column reports control group means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

to come to reasonable conclusions with respect to impact on the other secondary outcomes.

Finally, Table 10 shows results for secondary outcomes for soybean. Also here we find not effects on expected prices of the treatments, and there are too few observations to detect impact on other secondary outcomes.

Conclusion

In this paper, we test two behavioral explanations for the "sell low-buy high" puzzle. The first explanation assumes that farmers underestimate how much money they will need later on in the season, leading them to sell too much immediately post harvest at prices that are too low. We test this explanation through an intervention in which households are asked to prepare a detailed budget of what they will need for the entire year. It is expected that by making future expenditure more explicit, farmers will suffer less from budget neglect

Table 10: Secondary outcomes soy

	mean ctrl	T1	T2	nobs
	treatment-control			
Expected price (dec)	831.969	6.296	-8.276	3183
	(249.21)	(10.776)	(10.763)	
Sold jointly	0.235	0.069	0.169^{+}	161
	(0.427)	(0.088)	(0.087)	
Sold to market	0.221	-0.068	0.035	161
	(0.418)	(0.078)	(0.078)	
Pay education	0.206	-0.032	0.028	161
	(0.407)	(0.078)	(0.077)	
Pay health	0.088	-0.023	-0.024	161
	(0.286)	(0.051)	(0.05)	
	full models			
Expected price (dec)	831.969	6.93	-9.148	3183
	(249.21)	(9.978)	(9.974)	
Sold jointly	0.235	0.028	0.11	161
	(0.427)	(0.109)	(0.102)	
Sold to market	0.221	-0.035	0.034	161
	(0.418)	(0.097)	(0.091)	
Pay education	0.206	0.018	0.088	161
	(0.407)	(0.106)	(0.1)	
Pay health	0.088	0.004	-0.003	161
	(0.286)	(0.07)	(0.066)	

Note: First column reports control group means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for outcome at baseline.

when making market participation decisions.

The second explanation assumes that farmers expect higher future returns to justify current consumption. To counter this dimension of the planning fallacy, we designed a light touch intervention where we ask farmers to prepare a detailed sales plan, indicating how much of each crop will be sold when during the coming year, and what the minimum price is they want for it, and hope this serves as a commitment device for the farmer.

We implemented our field experiment in a sample of about 3500 farmers in four districts in the Central and Northern Regions of Malawi. Treatments were administered during baseline data collection immediately after the maize harvest in April 2022. A first (telephone based) midline survey was done in September 2022, and a similar midline report based on that data can be found here. A second (telephone based) midline survey was done in January 2023, and a similar midline report based on that data can be found here. Results in this paper are based on a first endline survey, which was done in April 2023.

During the last few months of the season, effects of the treatments are muted. There is some evidence that farmers that received a treatment were more likely to sell and sold slightly more maize than the control group. However, we do not find effects on other variables nor for other crops, often because sample size becomes too low as few transactions were made at the height of the lean season when prices are high and farmers remain with virtually no stocks.

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