Why do farmers sell immediately after harvest when prices are lowest? Impact at September midline

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Abstract

It is often observed that smallholder farmers sell most—if not all—of their marketable surplus or cash crops immediately after the harvest during which seasonal price movement reach their lowest point. Most explanations for this apparently sub-optimal behavior focus on economic or infrastructural issue, such as credit constraints or lack of storage facilities. In this study, we zoom in on two potential behavioural explanations. One potential explanation is situated at the household expenditure side, and assumes that households face challenges in accurately predicting future expenditures. Such budget neglect leads farmer to sell more of their marketable surplus immediately after the harvest and save too little for later in the year. A second potential explanation is situated at the household income side. Here the assumption is that farmers face cognitive challenges in making inter-temporal cost benefit calculations and fail to commit to certain thresholds. This document reports impact about half a year after the intervention.

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

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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 transport costs are passed on by traders to farmers when traders buy commodities from farmers in rural areas to aggregate in consumer centers, and farmers need to incur transaction costs when they buy back (often from the same traders in towns or large warehouses in trading centers).

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 arbitrate. 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. Such budget neglect leads farmer to sell more early on and save too little for later in the year. A second potential explanation is situates at the household income side. Here the assumption is that farmers face cognitive challenges in making inter-temporal cost benefit calculations (Drexler, Fischer, and Schoar, 2014) and fail to commit to certain thresholds (Ashraf, Karlan, and Yin, 2006; Duflo, Kremer, and Robinson, 2011).

The above hypotheses are tested with a field experiment among smallholder farmers in Malawi. These farmers produce (a mix of) maize, groundnuts and soybean for which at least part is destined for the market. We set up a field experiment with two treatment arms. 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. 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. We also ask the household head to indicate, for each planned sale, what the minimum price is that her or she expects. 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 midline survey was collected (via telephone). It is based on the pre-analysis plan and the mock report, and compares outcomes about 6 months post intervention of households in the treatment groups to outcomes of households in the control group. Similar documents will be produced when additional survey rounds are completed.

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 farmers end up buying back grain from the market a few months after selling it, in effect 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 during the lean season, Fink, Jack, and Masiye (2020) offered subsidized loans in randomly selected villages in rural Zambia and conclude that liquidity constraints contribute to inequality in rural economies. 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. 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: prices in main markets 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 that is often heard in the field is that farmers have nowhere to store, 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 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 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 very similar to the intervention we do. 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 second treatment is related to behavioral research on to the cognitive burden of complex intertemporal optimization. It has been found that farmers use various decision heuristics and rules of thumb when making decisions about how much to sell, when and at what price. For instance, farmers may anchor their reservation price the price they received in the previous season. Or, they may interpret particular signals, such as the arrival of traders from large towns in their village, as a sign that prices have reached their peak. Furthermore, the treatment is also grounded the theory on individual's often observed failure to commit in light of time preference and self control issues, and how mental accounting can remedy this.

3 Behavioural constraints to intertemporal arbitrage: Hypotheses and Interventions

We want to test two potential explanations that are rooted in behavioral sciences. The first potential behavioral explanation 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. Furthermore, farmers may underestimate the likelihood of, or simply forget to account for, unexpected events such illness within the family.

This hypothesis touches on cognitive limits of the household on the expenditure side. It is also related 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). Part of it may also be related to optimism bias if farmers neglect or underestimate the risk that adverse effects will happen to them (Sharot, 2011). For instance, farmers may not budget for pesticides or insecticides because they believe they will not be affected by pests or insects.

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 in 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 also related to cognitive limitations when planning, but this time at the income side of the farm household. Farmers may have difficulties in making the intertemporal cost-benefit calculations necessary to determine the optimal reservation price and/or storage period. They often lack precise information about the fixed and variable costs involved, about the level and variability of the future stream of income from sales, or about the time frame of both cost and income (Van Campenhout, 2021). The fact that farmers are faced with uncertain prices and uncertain expenditures often means they abandon plans and engage in impulsive or distress sales.

To test the second hypothesis, we develop, together with the farmer, a detailed sales plan for the year which is assumed to function as a commitment device. 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 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).

We asked farmers to not just forget about these plans, but to hang them in a central place in the house or store them in a convenient location. We also encouraged them to update them regularly. Furthermore, to increase the likelihood that farmers use the plan, we also refer to the plan during midline surveys, and reiterate the importance of using 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 smallholders farmers 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

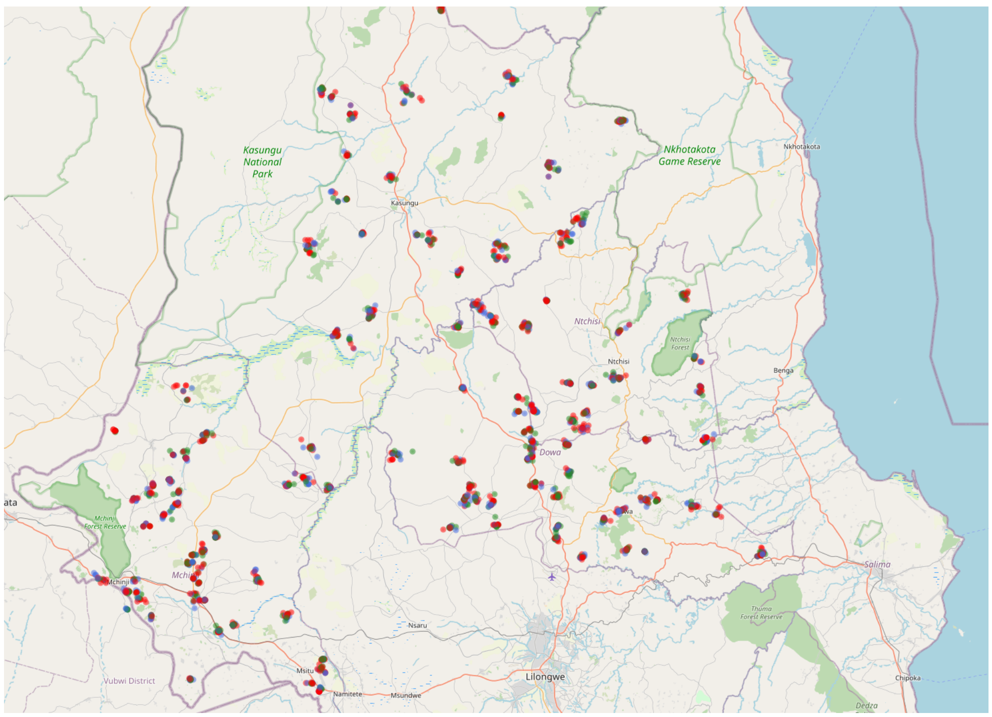

Figure 1: map of study area with sampled villages

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 by phone over the course of one month (September 2022).

5 Farmer characteristics

Table 1 presents a number of summary statistics of sampled households and their heads. 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). The typical household has five members, living in houses of 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 and 4 km respectively.

We also collected information on the households' 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 insulate consumption from income fluctuations.

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 MWK. 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 under unfavorable price conditions, or reduce 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.

6 Baseline balance

We follow our pre-analysis plan and demonstrate 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

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

(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), hired in agricultural labour (1=yes), distance to nearest all weather road (km), distance to nearest market (km). We also 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. While joint F-test for separate treatment control comparisons are not significant, we do find signs of imbalance when we us a likelihood ratio test derived from a multinomial model where the left hand side has three levels (T1, T2, C).

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, whether the household already makes a budget. Results for these variables are in Table 4.

7 Impact at midline

7.1 Attrition

As data collection was by phone, 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 headship). From the original 3534 farmers that were interviewed at baseline, we successfully reached 3382 farmers, leading to an attrition rate of just under 5 percent. Enumerators made on average 10 attempts before indicating the farmers could not be reached. Treatments are not correlated to the likelihood that farmers are missing from the data (χ^2 test of independence of proportions is rejected at p=0.912).

7.2 Primary outcomes

We start with the most parsimonious specification by reporting simple difference 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 outcomes at baseline, baseline variables for which we found imbalance in Table 3, and village fixed effects. Table 5 reports results for maize; Tables 6 and 7 are similar tables but for groundnuts and soybean, respectively.

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.

A first primary outcome we consider is stocks of the three commodities 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 include 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 received T2 will also be more likely to have saved more early on in the season.

We see that the average control farmer has about 5.565 bags of maize in store at the time of the survey. We do not find that this is significantly different in the sample of farmers that were taken through a budgeting exercise. However, we do find that stocks are significantly higher among farmers that made a sales plan. Farmers that were asked to commit to a sales plan have stocks that are about 13.4 percent higher than maize stocks of farmers in the control group. If we add controls to the regression, the effect reduces substantially and falls just below the significance threshold.

A second primary outcome tests if the household sold any of the crop in the interval between the intervention and the midline survey. We expect that the treatment would reduce the likelihood of selling early on in the season.

We find that 34.1 percent of households in the control group indicated that they made at least on sales transaction between in the first few months after the start of the project. We do not find that this proportion differs for farmers in T1 nor for farmers in T2.

The third primary outcome is related to the second and is the quantity that was sold during the period between the intervention and the first midline survey. While we may not find that the treatment reduced the fact that farmers sell early, we still may find that farmers sell less of the crop immediately after harvest.

We find that farmers in the control group sell on average 1.528 bags of maize. Contrary to our expectations, we see that these quantities are higher in both treatment groups, but the differences are not significant.

For farmers that did engage in sales, we can calculate the average price that farmers received for their crop. The farmers that sold in the control group got on average 224.349 MKW per kilogram of maize. We again do not find that prices differ significantly in any of the treatment groups.

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, more than a quarter of the farmers already made at least one purchase before midline and this proportion is similar in both treatment groups.

As for sales, we also look at quantities bought and prices at which the commodities were bought. We find that the average control group household bought less than one bag on average and paid slightly more than the sales price. We do not see any effects from the interventions.

In Table 6, we repeat the entire analysis, but now for groundnuts. Households in the control group remain with less than 2 bags of groundnuts in stock. Also here, we see that households that drew up a sales plan have stocks that are about 10.6 percent higher than in the control group. Now, we also see that stocks are significantly higher in the group that was asked to make a detailed expenditure plan.

A surprisingly larges share of households, over two thirds, indicate that they made at least one sales transaction between the intervention and the midline survey. We now also find that households with a sales plan are more likely to have already sold—5.4 percentage points more according to the full model in the second panel of Table 6—and appear to have sold large quantities. Prices (here express in MKW per debe) do not appear to be different from the control group.

We also asked if farmers already bought groudnuts in the first few months post harvest. Significanlty less farmers appear to have bought groundnuts than maize. We find no effects of the interventions on the likelihood that farmers buy, nor on the quantity bought. Finally, we also do not find an impact on prices, but as very few farmers bought sample size becomes too small to come to reasonable estimates.

Finally, Table 7 shows impact of the interventions on primary outcomes for soybean. Interestingly, we do not find that that stocks at midline differ significantly between treatment groups and the control. We also do not find that

Table 5: Primary outcomes maize

	mean ctrl	T1	T2	nobs
	treatment-control			
Stocks (abs)	5.565	0.04	0.134*	3381
	(10.657)	(0.052)	(0.052)	
Sold (yes/no)	0.341	-0.004	0.005	3270
	(0.474)	(0.02)	(0.02)	
Quantity sold (abs)	1.528	0.053	0.032	3263
	(3.823)	(0.043)	(0.043)	
Price sold (MKW)	224.349	4.402	1.434	1109
	(55.837)	(3.87)	(3.866)	
Bought (1=yes)	0.269	0.013	-0.022	3381
	(0.444)	(0.018)	(0.018)	
Quantity bought	0.844	0.044	0.004	3370
	(2.369)	(0.034)	(0.034)	
Price bought	258.509	4.48	-1.343	895
	(47.985)	(4.011)	(4.181)	
	full models			
Stocks (abs)	5.565	0.016	0.062	3333
	(10.657)	(0.043)	(0.043)	
Sold (yes/no)	0.341	-0.004	-0.003	3224
	(0.474)	(0.019)	(0.019)	
Quantity sold (abs)	1.528	0.051	0.002	3217
	(3.823)	(0.041)	(0.041)	
Price sold (MKW)	224.349	3.244	-0.478	1086
	(55.837)	(3.768)	(3.778)	
Bougth	0.269	0.014	-0.018	3333
	(0.444)	(0.017)	(0.018)	
Amount bougth	0.844	0.044	0.008	3323
	(2.369)	(0.033)	(0.033)	
Price bougth	258.509	4.29	-3.881	878
	(47.985)	(4.064)	(4.262)	

Note: First column reports control group means (and standard deviations below); mean stock is current situation in 50kg bags, ATE is ihs transformed. Sold or bought is since intervention untill midline survey, quantity bought/sold is total quantity between intervention and midline survey, prices are average prices of transactions that occured between intervention and midline survey **, * and + denote significance at the 1, 5 and 10 percent levels. All models include village fixed effects and controls for baseline characteristics that show imbalance at the 5 percent level or less in Table XXX.

Table 6: Primary outcomes gnuts

	mean ctrl	T1	T2	nobs
		treatment-control		
Stocks (abs)	1.716	0.071^{+}	0.106*	3381
	(7.124)	(0.041)	(0.042)	
Sold (yes/no)	0.674	0.009	0.038	1704
	(0.469)	(0.027)	(0.027)	
Quantity sold (abs)	3.909	0.008	0.138^{+}	1689
	(6.334)	(0.072)	(0.071)	
Price sold (MKW)	4855.443	85.648	27.597	1154
	(1093.01)	(82.348)	(80.658)	
Bought (1=yes)	0.071	-0.014	-0.01	3381
	(0.257)	(0.01)	(0.01)	
Quantity bought	0.104	-0.013	-0.01	3370
	(0.551)	(0.012)	(0.012)	
Price bought	5310.753	217.025	6.555	199
	(1888.09)	(330.339)	(334.334)	
		full models		
Stocks (abs)	1.716	0.059^{+}	0.063^{+}	3333
	(7.124)	(0.035)	(0.036)	
Sold (yes/no)	0.674	0.022	0.054*	1678
	(0.469)	(0.027)	(0.026)	
Quantity sold (abs)	3.909	0.018	0.156*	1665
	(6.334)	(0.066)	(0.066)	
Price sold (MKW)	4855.443	35.676	10.178	1130
	(1093.01)	(76.576)	(74.999)	
Bougth	0.071	-0.013	-0.01	3333
	(0.257)	(0.01)	(0.01)	
Amount bougth	0.104	-0.014	-0.012	3323
	(0.551)	(0.012)	(0.013)	
Price bougth	5310.753	-22.967	-358.472	196
	(1888.09)	(369.172)	(377.633)	

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 baseline characteristics that show imbalance at the 5 percent level or less in Table XXX.

sales behaviour in any of the treatment groups differs from sales behaviour on the control group. We do find, however, that buying of soybean does seem lower in both the T1 and T2 groups and that the average quantities are significantly lower for households that made a sales plan.

7.3 Secondary outcomes

In this section, we look at some additional outcome which may be indirectly affected by the interventions.

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 end of the year. 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 225 MKW per kilogram of maize during the first few months after harvest, the price is expected to be about 380 per kilogram around new year. Interestingly, we see that farmers who were taken through a budgeting exercise expect price to be higher still.

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 37 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.

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 sold 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 very 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 they used the proceeds 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 are probably less predictable. We do not find that the treatment intervention changed the propensity that sales were made for any of these expenses.

Table 9 looks at secondary outcomes for groundnuts, and is similar to Table 8. Also here, farmers in the control group expect a further 60 percent increase of the price by the end of the year. Now, we see that farmers that were asked to provide a sales plan estimate that future prices will be lower than what control group farmers think.

We further find that decisions related to the sales of groundnuts are made jointly in slightly more households than was the case for maize. However, also here, there is no effect of the interventions. Groundnuts are rarely sold directly to the market, and there is also no effect of T1 not T2. Finally, for the expense categories, we see that households that were asked to provide a detailed budget are more likely to have sold groundnuts to pay for school fees than farmers in the control group.

Table 7: Primary outcomes soy

	mean ctrl	T1	T2	nobs
		treatment-control		
Stocks (abs)	1.114	0.005	0.05	3381
	(3.551)	(0.032)	(0.033)	
Sold (yes/no)	0.55	0.003	0.033	2447
	(0.498)	(0.024)	(0.024)	
Quantity sold (abs)	2.376	-0.019	0.084	2438
	(4.347)	(0.054)	(0.053)	
Price sold (MKW)	565.29	-5.195	-2.73	1367
	(144.846)	(9.817)	(9.558)	
Bought (1=yes)	0.058	-0.022*	-0.018*	3381
	(0.234)	(0.009)	(0.009)	
Quantity bought	0.049	-0.007	-0.015+	3371
	(0.375)	(0.008)	(0.008)	
Price bought	651.707	-43.93	11.113	157
	(202.672)	(39.846)	(38.766)	
		full models		
Stocks (abs)	1.114	-0.003	0.017	3333
	(3.551)	(0.029)	(0.029)	
Sold (yes/no)	0.55	0.011	0.033	2405
	(0.498)	(0.024)	(0.024)	
Quantity sold (abs)	2.376	-0.012	0.082	2399
	(4.347)	(0.051)	(0.051)	
Price sold (MKW)	565.29	-2.045	-1.063	1350
	(144.846)	(9.73)	(9.491)	
Bougth	0.058	-0.022*	-0.017+	3333
	(0.234)	(0.009)	(0.009)	
Amount bougth	0.049	-0.008	-0.014+	3325
	(0.375)	(0.008)	(0.008)	
Price bougth	651.707	-27.059	-11.852	153
	(202.672)	(57.189)	(50.605)	

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 baseline characteristics that show imbalance at the 5 percent level or less in Table XXX.

Table 8: Secondary outcomes maize

	mean ctrl	T1	T2	nobs
	treatment-control			
Expected price (dec)	379.339	7.64^{+}	-1.011	3377
	(107.932)	(4.591)	(4.609)	
Sold jointly	0.368	-0.001	0.024	1181
	(0.483)	(0.034)	(0.034)	
Sold to market	0.051	-0.002	0	1181
	(0.22)	(0.015)	(0.015)	
Pay education	0.174	0.01	-0.016	1181
	(0.379)	(0.027)	(0.026)	
Pay health	0.121	0.011	-0.009	1181
	(0.326)	(0.023)	(0.023)	
	full models			
Expected price (dec)	379.339	7.693^{+}	-2.36	3329
	(107.932)	(4.394)	(4.423)	
Sold jointly	0.368	0.012	0.005	1157
	(0.483)	(0.028)	(0.028)	
Sold to market	0.051	-0.007	-0.001	1157
	(0.22)	(0.015)	(0.015)	
Pay education	0.174	0.009	-0.017	1157
	(0.379)	(0.027)	(0.027)	
Pay health	0.121	0.012	-0.015	1157
	(0.326)	(0.024)	(0.024)	

Note: Sold jointly is one if all transactions between intervention and midline were taken by co-heads together, sold to market is 1 if all sales between intervention and midline were to the market. 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 baseline characteristics that show imbalance at the 5 percent level or less in Table XXX.

Table 9: Secondary outcomes gnuts

	mean ctrl	T1	T2	nobs
		treatment-control		
Expected price (dec)	7811.299	111.451	-126.976	3381
	(2442.11)	(101.788)	(102.187)	
Sold jointly	0.405	-0.021	0.014	1221
	(0.491)	(0.034)	(0.034)	
Sold to market	0.026	0.002	0	1221
	(0.161)	(0.011)	(0.011)	
Pay education	0.145	0.052^{*}	0.03	1221
	(0.352)	(0.026)	(0.026)	
Pay health	0.063	-0.023	0.008	1221
	(0.243)	(0.016)	(0.016)	
		full models		
Expected price (dec)	7811.299	88.634	-155.786^{+}	3333
	(2442.11)	(89.668)	(90.262)	
Sold jointly	0.405	-0.015	-0.003	1196
	(0.491)	(0.027)	(0.026)	
Sold to market	0.026	0.005	0.003	1196
	(0.161)	(0.011)	(0.011)	
Pay education	0.145	0.044^{+}	0.037	1196
	(0.352)	(0.026)	(0.026)	
Pay health	0.063	-0.025	0.01	1196
	(0.243)	(0.017)	(0.017)	

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 baseline characteristics that show imbalance at the 5 percent level or less in Table XXX.

Table 10: Secondary outcomes soy

	mean ctrl	T1	T2	nobs
	treatment-control			
Expected price (dec)	1095.522	5.913	-20.266	3381
	(323.506)	(13.371)	(13.423)	
Sold jointly	0.27	0.01	-0.001	2237
	(0.444)	(0.023)	(0.023)	
Sold to market	0.029	-0.003	0.007	2237
	(0.168)	(0.009)	(0.009)	
Pay education	0.1	0.009	-0.008	2237
	(0.3)	(0.015)	(0.015)	
Pay health	0.027	-0.007	0	2237
	(0.162)	(0.008)	(0.008)	
	full models			
Expected price (dec)	1095.522	5.268	-21.486^{+}	3333
	(323.506)	(12.633)	(12.716)	
Sold jointly	0.27	0.015	0	2195
	(0.444)	(0.021)	(0.02)	
Sold to market	0.029	-0.003	0.004	2195
	(0.168)	(0.009)	(0.009)	
Pay education	0.1	0.005	-0.011	2195
	(0.3)	(0.016)	(0.015)	
Pay health	0.027	-0.008	0	2195
	(0.162)	(0.008)	(0.008)	

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 baseline characteristics that show imbalance at the 5 percent level or less in Table XXX.

Finally, Table 10 shows results for secondary outcomes for soybean. Control group farmers estimate that prices will be almost double what they were during the first few months post harvest. As was the case for groundnuts, farmers that were assigned to the sales plan treatment (T2) provide slightly lower estimates for the price at the end of the year than farmers in the control group.

There is significant less joint decision making when it comes to sales of soybean. However, also here, who makes decisions is not affected by the interventions. Results for who was sold to are similar to those for groundnuts. We also do not find any impact of the interventions on what happens with the proceeds from soybean sales.

Conclusion

In this paper, we test two behavioral explanations for the sell low buy high hypothesis. The first explanation assumes that farmers underestimate how much money they will need later on in the season, leading them to sell too much at prices that are too low. We test this explanation through an intervention in which households are asked to prepare immediately post harvest 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 when making market participation decisions.

The second explanation assumes that farmers face challenges in planning and committing on the income side. To test this, 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.

We implement 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. Results in this paper are based on a first (telephone based) midline survey.

We find some evidence that households that were exposed to the interventions have higher stocks at the time of the midline survey. The effect on stocks is strongest for ground nuts and for the treatment that involves drawing up a sales plan. We also find that for groundnuts, households that committed to a detailed plan on when to sell and at what price, were more likely to sell and sold larger quantities. Finally, we find some evidence that for soybean, farmers that were exposed to the treatment are less likely to engage in buying back later in the season (at higher prices). For secondary outcomes, there is some evidence that farmers who are asked to draw up a sales plan expect more modest price increases than farmers in the control group.

While the results are much more muted that for example that large increases in savings found immediately after implementing a similar budgeting intervention in Augenblick et al. (2021) in Zambia, we do think that results are encouraging. We do for instance find that for the crop that is harvested first and so households are likely to start running out of stock earlier, households that were exposed to the treatment were less likely to have bought the crop.

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