Why do farmers sell immediately after harvest when prices are lowest? A pre-analysis plan

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Motivation

It is often observed that smallholder farmers sell most—if not all—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 mean that immediately post harvest, prices in excess supply areas drop. Later, during the lean season when some of the farmers run out of stock, prices have recovered, or even increase further since farmers start to buy back. This leads to the "sell low buy high" puzzle (Stephens and Barrett, 2011; Burke, Bergquist, and Miguel, 2018). 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 a reason to further drive down the price paid to the farmer.

There are 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 into 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,

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issues related to social taxation may mean farmers convert maize to cash, which is easier to hide from friends and family.

Most of the explanations above focus on hard constraints to farmers' exploiting intertemporal arbitrate. In this study, we zoom in on three potential behavioural explanations why farmers seemingly sell at sub-optimal time. One potential explanation is situated at the household expenditure side, and assumes that households face challenges in accurately predictive 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). In a third potential explanation, we test if farmers are subject to recency bias—a cognitive bias that favors recent events and under-weight less salient data such as long-term averages.

This document serves as a pre-analysis plan for the study that will be registered in a public repository. It provides background information, outlines hypotheses which will be tested, tools that will be used in the field, power calculations and sample size projections on which sampling is based, outcome variables that will be used to assess impact, and specification that will be estimated. As such, it will provide a useful reference in evaluating the final results of the study (Humphreys, Sanchez de la Sierra, and van der Windt, 2013).

Literature

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 generally sell all maize immediately post harvest at low prices.

Risk averse farmers may also fail to delay sales if there is considerable uncertainty about the price in the future. A recent article argues that the "sell low buy high" puzzle is not a puzzle at all, as price movements are insufficient 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 extreme spikes and slumps. While we agree that uncertainty about prices is indeed an important reason to sell immediately post harvest for loss averse farmers (and indeed loss aversion lies at the core of one of our research hypotheses), we do feel that this is not a sufficient explanation in the face of large recurrent seasonal price movements.

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 10-20 bags of 100kg of maize. But there are also risk related to pests and diseases affecting the stored maize. If storage is the main reason why farmers do not engage in intertemporal arbitrage more, then providing storage technology should delay sales. Omotilewa et al. (2018) indeed find that households that received PICS bags stored maize for a longer period, 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 Agricultural Commodities Exchange (ACE) in Malawi provides storage technology but still 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 neighbours, and it will be very hard to deny if they come and ask for help. 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).

Behavioural constraints to intertemporal arbitrage: Hypotheses and Interventions

The first potential behavioural explanation is situated at the household expenditure side, and assumes that households face challenges in accurately predicting future expenditures. In other words, the first hypothesis assumes farmers suffer from budget neglect, which may lead to an overoptimistic view of the future. In particular, farmers may neglect some future expenditures when deciding on how much to sell 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 at 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. Budget neglect is also found to be a main contributing factor to recurrent hungry seasons in Zambia.

To test the first hypothesis related to budget neglect, the focus will be on the expenditure side and we will design an intervention that takes the farmer through a detailed budgeting exercise. The budget exercise will involve three components. A first component uses recall to provide a first approximation of what will be necessary in the future. A second component consists of segmentation, which involves defining categories of expenditures for cognitive ease. Finally, we will look at a range of risks, which involve expenses that are not certain but may materialize. We try as much as possible to attach objective probabilities to these risks and also incorporate this in the budget.

This 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 will develop, together with the farmer, a detailed plan of how much the farmer will sell over the coming year (per month or per quarter). For each sales event, the farmer will also be asked to commit to a minimum price. This will be done on a special form that farmers can than hang up in their house. Enumerators will be asked to take a picture of the plan. This is to 1) check if enumerators did their job 2) to signal to farmers that we will check if they keep to their commitments.

A third hypothesis focuses on projection bias and recency effects when making marketing decisions. It is well known that individuals place disproportional weight on observations from the recent past or extrapolate recent trends. Farmers seem to use decision rules. For instance, during qualitative fieldwork, farmers indicated that they sell when traders from Lilongwe are visiting, as this is an indication that prices are good. Many farmers also indicate that they sell when the price reaches the break-even point. A better strategy would be to commit to a certain limit price, much like traders on the stock market do, and this price should be based on seasonal price movements that reflect increased demand and reduced supply in the lean season, as apposed to the break-even price.

To test the third hypothesis, we will develop an intervention where we provide farmers with historical (5 years) monthly price movements for maize, soybean and groundnuts. The price data will be for the market that is closest to the treated household. We will show price movements, but also provide summary statistics like minimum price, maximum price and average price to summarize price distribution data in a few easy to understand figures (Hanna, Mullainathan, and Schwartzstein, 2014; Drexler, Fischer, and Schoar, 2014). Price data will be obtained from the Malawian Agricultural Commodity Exchange (ACE).

Experimental design and power calculations

We propose parallel design with one control group and three treatment arms. Kaur et al (personal communication) find that, in a similar budget neglect experiment, treated farmers enter the hungry season with 20 percent more maize (valued by current prices at 405 zambian kwacha instead of 335 zambian kwacha in the control group). If we assume that standard deviation is about 592 (1.6 times the mean of treatment and control means – the 1.6 is derived from maize production data in Uganda), we get a sample size of 1123 in each sample. For one control group and three treatment arms we will thus need about 4500 farmers. As we are interested in all possible comparison between the different arms, we will allocate equal sample sizes to each treatment arm. We will choose 10 villagers in each arm per village, which means we will need about 113 villages.

Burke, Bergquist, and Miguel (2018) document significant effects of a credit intervention on seasonal price fluctuations in local grain market. To study these kind of general equilibrium effects of our intervention, we will also record prices at regular intervals in the villages we work in. These prices will then be compared with prices collected in similar villages nearby where the intervention is not implemented. We will collect prices in 30 additional villages.

Sampling

We use a multi-stage sampling procedure to create a self-weighting sample up to the village level and then just sample a fixed number of households per village. We then sample villages with the likelihood of a village being selected being proportionate to the number of people that live in this village (such that larger villages are more likely to end up in the sample).

Context and study area

The study focuses on the Central and Northern Region of Malawi (Kasungu, Mzimba, Ntchisi, Rumphi, Dowa and Mchinji). In these areas, maize is generally regarded as the food crop for auto-consumption or to pay laborers in kind. Maize was also sometimes marketed, but mostly not as the most important one cash crop. The main cash crops in the area are soybean, ground nuts and tobacco.

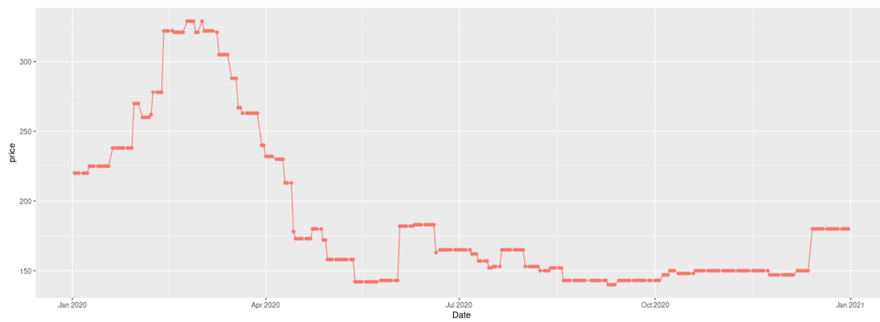

Figure 1: Price of maize in Rumphi

Prices of tobacco do are not seasonal. For the other crops, most farmers also mentioned significant seasonality similar to seasonal price movements of maize.

These areas are characterized by rained agriculture with a single season. The resulting seasonal price movements is illustrated in Figure 1 that shows maize price in kwatcha per Kg in Rumpi over 2020. Planting of maize starts in December, and maize becomes increasingly scarce during the growing season. Harvesting starts around April 2020, which takes the pressure off the prices when farmers start consuming from their own maize. However, farm gate sales are still low as traders wait for maize to dry. This results in a relatively long period of low prices all the way to the start of the planting season towards the end to the year. The aim of the study is to encourage farmers to wait just a few months longer before they sell.

Figure 2 shows that most sales happen only around August. So farmers do seem to hold on to their maize for reasonably long periods (suggesting some of the other explanations like lack of storage space or social taxation are less likely). Sales for other crops follows a similar pattern.

Taken together, the figures suggest that the best time for the interventions would be around April or May, immediately before farmer start to sell.

Farmers often indicate to have access to finance, but note that interest rates are prohibitively high (30-40%). There is also a strong cooperative movement in Malawi. Some of these cooperatives also provide access to warehousing and engage in collective marketing. Qualitative research suggests that it is pretty easy for farmers to sell even in the off-season. Traders operate in trading centers, writing prices on a blackboard. The trader we interviewed mentioned there were many others like him in the small trading center he was operating in. Traders also visit villages, often using ox carts. If they buy at farm gate, prices are discussed and depend on distance traveled. Traders buy from May to August and sell from December to February. Farmers are suspicious about scales used.

Figure 2: Quantities of maize bought and sold

Data collection and endpoints

We will not organize a dedicated baseline survey, but rather ask a limited number of questions immediately prior to the interventions in May 2022. This information can then be used to demonstrated balance, to control for baseline outcomes for the primary outcome variables in and ANCOVA regression, and to explore heterogeneous treatment effects.

To demonstrate baseline balance, we will construct 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), hired in agricultural labour (1=yes), distance to nearest all weather road (km), distance to nearest market (km).

We will 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.

To explore heterogeneity in treatment effects, we will measure the following during baseline: Access to credit, access to storage facility, membership of (marketing related) cooperative, livestock asset ownership, whether the household already makes a budget. We will also assess balance on these characteristics at baseline.

Instead of relying on a single endline, we will evaluate the interventions through multiple rounds of data collection, often using phone interviews. There are different reasons for this. First, when measuring noisy and relatively less autocorrelated outcomes such as amounts of commodities sold or household expenditure, one can increase power by taking multiple measurements at relatively short intervals to average out noise (McKenzie, 2012; Burke, Bergquist, and Miguel, 2018). Furthermore, it will allow us to assess the effect of the interventions at multiple points in time instead of just at endline. The follow-up surveys will focus on tracking data on storage inventory of maize, groundnuts and soybean, marketing behavior of the three crops, consumption, and credit and savings behavior

Intermediate data will be collected in July 2022, September 2022, November 2022, and January 2023. A slightly more elaborate in-person endline survey will be organized in March 2023.

Primary outcomes in this study include stocks of ground nuts, maize and soybean held by the farmers and how they evolve over time. As there is a particualr focus on marketing behaviour, we will also collect detailed information on sales made, including quantities sold, prices received and who was sold to. Further down the impact pathway, we compare welfare, both subjective and through consumption expenditure, between treatment and control households.

To investigate impact pathways, we will also include a range of questions related to expenditure, and how easy it was for farmers. For instance, did treated households have less issues in meeting expenditures for eg. fertilizer or improved seed for the next season? Furthermore, we include a module on price expectations, which will be useful to see how expectations influence eventual prices obtained, and how interventions affect the relation between expectations and behaviour.

Unresolved questions:

farmers also use product to pay labourers, how do we handle that?

References

Ashraf, N., D. Karlan, and W. Yin. 2006. "Tying Odysseus to the Mast: Evidence From a Commitment Savings Product in the Philippines*." *The Quarterly Journal of Economics* 121 (2): 635–672.

Buehler, R., D. Griffin, and J. Peetz. 2010. "The planning fallacy: Cognitive, motivational, and social origins." In "Advances in experimental social psychology," vol. 43, 1–62. Elsevier.

Burke, M., L. F. Bergquist, and E. Miguel. 2018. "Sell Low and Buy High: Arbitrage and Local Price Effects in Kenyan Markets*." *The Quarterly Journal of Economics* 134 (2): 785–842.

Cardell, L. and H. Michelson. 2020. *"Sell Low, Buy High?" - A New Explanation for a Persistent Puzzle*. 2020 Annual Meeting, July 26-28, Kansas City, Missouri 304448, Agricultural and Applied Economics Association.

Dillon, B. 2021. "Selling Crops Early to Pay for School: A Large-Scale Natural Experiment in Malawi." *Journal of Human Resources* 56 (4): 1296–1325.

Dillon, B., J. De Weerdt, and T. O'Donoghue. 2020. "Paying More for Less: Why Don't Households in Tanzania Take Advantage of Bulk Discounts?" *The World Bank Economic Review* 35 (1): 148–179.

Drexler, A., G. Fischer, and A. Schoar. 2014. "Keeping It Simple: Financial Literacy and Rules of Thumb." *American Economic Journal: Applied Economics* 6 (2): 1–31.

Duflo, E., M. Kremer, and J. Robinson. 2011. "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya." *American Economic Review* 101 (6): 2350–90.

Fink, G., B. K. Jack, and F. Masiye. 2020. "Seasonal Liquidity, Rural Labor Markets, and Agricultural Production." *American Economic Review* 110 (11): 3351–92.

Hanna, R., S. Mullainathan, and J. Schwartzstein. 2014. " Learning Through Noticing: Theory and Evidence from a Field Experiment *." *The Quarterly Journal of Economics* 129 (3): 1311–1353.

Humphreys, M., R. Sanchez de la Sierra, and P. van der Windt. 2013. "Fishing, Commitment, and Communication: A Proposal for Comprehensive Nonbinding Research Registration." *Political Analysis* 21 (1): 1–20.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. " Agricultural Decisions after Relaxing Credit and Risk Constraints *." *The Quarterly Journal of Economics* 129 (2): 597–652.

McKenzie, D. 2012. "Beyond baseline and follow-up: The case for more T in experiments." *Journal of Development Economics* 99 (2): 210–221.

Omotilewa, O. J., J. Ricker-Gilbert, J. H. Ainembabazi, and G. E. Shively. 2018. "Does improved storage technology promote modern input use and food security? Evidence from a randomized trial in Uganda." *Journal of Development Economics* 135: 176–198.

Sharot, T. 2011. "The optimism bias." *Current biology* 21 (23): R941–R945.

Stephens, E. C. and C. B. Barrett. 2011. "Incomplete Credit Markets and Commodity Marketing Behaviour." *Journal of Agricultural Economics* 62 (1): 1–24.

Van Campenhout, B. 2021. "The role of information in agricultural technology adoption: Experimental evidence from rice farmers in Uganda." *Economic Development and Cultural Change* 69 (3): 1239–1272.