Study Protocol: Why do farmers sell immediately after harvest when prices are lowest?

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Motivation

It is often observed that smallholder farmers sell most—if not all—of their marketable surplus immediately after the harvest to itinerant traders at the farm gate. For example, in a survey among maize farmers in Uganda, more than 75 percent of farmers that sold maize sold everything in a single transaction, 77 percent sold to a middlemen and 50 percent immediately after harvest.

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). 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 as a reason to further drive down the price paid to the farmer.

There are many reasons for this observed behaviour. 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). Farmers 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,

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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. There may also be behavioural factors, such as present bias, anchoring of prices to past experience where negative experiences are more salient than positive experiences, etc.

In this study, we zoom in on two potential explanations why farmers seemingly sell at sub-optimal time. A first is related to budget neglect, whereby farmers underestimate expenses later in the season and as a result sell too much of their harvest too soon. To test this hypothesis, we implement a field experiment that aims to make reduce budget neglect by drawing up expenditure plans up to the next harvest. A second potential explanation is that farmers consistently underestimate the price during the lean season, reducing the incentive to store. There are various reasons why farmers may underestimate the price in the future. One explanation may be that negative experiences tend to stick more than positive experiences (Ledgerwood and Boydstun, 2014). To overcome this negativity bias, we implement a treatment where past experience is compared to price data to generate more objective beliefs about future prices.

Literature

Why do farmers sell low and buy high? One of the most obvious, 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 29% . Dillon (2021) uses the fact that primary school began 3 months earlier in 2010 than in 2009 to demonstrate 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.

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 by arguing that 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.

A 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 farmers 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

Another reason may be related to social taxation. If a farmer has a lot of maize in 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).

Our study is related to this literature in several ways. The hypothesis related to budget sees liquidity requirements as the main driving force behind the sell low - buy high puzzle. The hypothesis related to the fact that farmers tend to underestimate the future price of maize is related to risk aversion where losses are given a higher weight than gains.

Model

Consider a very simple 2 period model where a farmer maximizes utility by choosing how much to consume in the first and second period (c_1, c_2). We further add an expenditure that is only relevant in period 2 (e_2), and that is affected by a parameter $0 \leqslant \gamma \leqslant 1$ that represents the probability that the agent remembers the expenditure. δ is the discount rate.

$$\underset{c_1,c_2,e_2}{max}\, u_1\left(c_1\right) + \delta\left(u_2\left(c_2\right) + \gamma v_2\left(e_2\right)\right) \tag{1}$$

$$st\; c_1 + c_2 + \gamma e_2 = \left(\lambda p_L + (1-\lambda)p_H\right) Q$$

On the right hand side of the budget constraint, we model believes about the future price, which can be low (P_L) or high (P_H). The parameter λ represents the subjective probability that the price will be low. The model will be used to compare a benchmark case, where there is no budget neglect $(\gamma = 1)$ and the future price is high $(\lambda = 0)$, against alternatives and formulate a series of predictions that can be taken to the data.

Hypotheses and Interventions

In a first hypothesis, we assume that farmers suffer from budget neglect— $\gamma < 1$ on the left side of the budget constraint—which may lead to an overoptimistic view of the future. In particular, farmers may neglect some future expenditures when constructing plans. 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. This hypothesis is similar 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 something happens. 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.

A second hypothesis is related to the right side of the budget constraint and focuses on price expectations. Here, the hypothesis is that farmers are, for some reason, too pessimistic about the future price. Farmers may rely on experience an anchoring to attach probabilities to the price distribution. There is some evidence that people provide more weight to negative experiences in the past than to positive experiences, implying that $\lambda > 0.5$ (Ledgerwood and Boydstun, 2014).

To test the first hypothesis related to budget neglect, 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.

To test the second hypothesis, a second intervention will be designed to reduce negativity bias and come to a more objective view on seasonal price movements. This will be done by asking farmers to recall price movements in previous years, and then comparing this with data on price movements derived from theoretical models and price surveys. As such, we consider negativity bias as a kind of learning failure that we hope to solve by drawing attention to particular features of the data that farmers otherwise fail to notice (Hanna, Mullainathan, and Schwartzstein, 2014).

Experimental design and power calculations

We propose parallel design with one control group and two 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. If we run a factorial design and want to power all treatment cell for similar effect sizes, we will need about 3369 observations. To account for attrition, we will increase this to 3500. Note for designs with a common control group, maximize power, is attained when allocating approximately 42% of the sample to the control units, and then equally (29% each) to the two treatments. In our case, this means about 1470 farmers in the control group and 1015 in each treatment arm. We will implement this in 100 villages, such that in each village we will have 20 farmers in the control group, and 10 farmers in each treatment group.

The intervention will be implemented at the individual level, which raises concerns about potential spillover effects. We expect that farmers that are allocated to the control group may learn from treated farmers. This will thus affect outcomes of control farmers in the same direction as outcomes for treated farmers, making it harder to detect an effect if there is one. To get a sense of the importance of these spillover effects, we stratify on village size. Using census data, we subdivide villages in the study area in small and large villages based on the median number of inhabitants and then make sure we implement the study in 50 small and 50 large 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 in 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.

Context and study area

The study focuses on the Central and Northern Region of Malawi (Kasungu, Mzimba, Ntchisi, Rumphi, Dowa and Mchinji). 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).

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

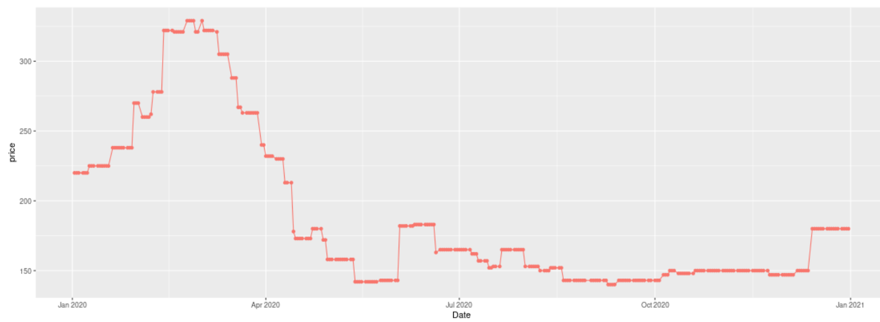

Figure 1: Price of maize in Rumphi

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. This information can then be used to demonstrated balance and potentially explore heterogeneous treatment effects.

Instead of relying on a baseline and 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 maize to sell or household expenditure, one can increase power by faking multiple measurements at relatively short intervals to average out noise (McKenzie, 2012). Furthermore, it will allow us to assess the effect of the interventions at multiple points in time instead of just at endline.

Limited baseline information will be collected in April/May 2022 during the intervention phase. 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 amounts of maize sold at different points in time. As the main aim of waiting is intertemporal arbitrage, we will also compare prices obtained between treatment and control farmers. We will equally look at purchases. 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? We will also elicit a full set of future prices to look at impact pathways for the second hypothesis.

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