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## Abstract

This paper uses data on farmers' price expectations from a randomized survey of smallholder farmers in Mozambique. Survey data show that across all crops most interviewed farmers expect prices to be higher in the lean season. Yet, farmers report selling most of their output shortly after harvest when prices are lower. We find that higher expected prices and lower current sale prices are associated with increased storage for liquidity constrained farmers versus unconstrained farmers. We develop an intertemporal model of market timing in the presence of liquidity constraints that is consistent with these findings and discuss other model predictions.

JEL Classification: D14, D15, G51, O13, O16, Q11, Q12, Q14

Keywords: liquidity constraints, market timing, household expectations, Pricing, Storage, developing economies

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# 1 Introduction

In many developing countries produce crops display low prices right after harvest and high prices later on in the lean season ahead of the next harvest season (e.g., Stephens and Barrett 2011 and Burke, Bergquist, and Miguel 2019). Given these patterns, it is somewhat puzzling that farmers in these countries, especially poorer farmers, sell most of their crop shortly after harvest. Starting with Barrett (2007) and Stephens and Barrett (2011), a prime argument for this behavior is that farmers face liquidity constraints. This paper contributes to this literature by developing and testing new predictions on how a liquidity constrained farmer behaves in response to expected market conditions and by bringing new data to bear on this question. We develop a model of the optimal timing to sell a crop. The main premise of the model is that the farmer is faced with a desire to smooth consumption over time as in Stephens and Barrett (2011). When confronted with a price path that is back loaded (i.e., lower following harvest and higher in the lean season) an unconstrained farmer chooses to store all her harvest in order to take advantage of the high prices if potential losses from storage are not too large. What makes the farmer unconstrained in the model is the liquid wealth the farmer has at the time of harvest that allows her to have high consumption after the harvest even without selling any of the harvested crop. In contrast, a constrained farmer must sell some of the crop immediately after harvest so as to smooth consumption optimally.

The market-timing model produces several hypotheses regarding the behavior of liquidity constrained farmers. The first two results are standard in the literature. First, a farmer that has higher liquid wealth at the time of harvest is less constrained and chooses to sell more of the crop later on in anticipation of higher future prices. Second, farmers with better storage technology also sell later. The next three results are novel, directly linked to the mechanism we study, and also somewhat less obvious. Third, the higher prices in the lean season make liquidity constrained farmers want to store more if and only if they have high elasticity of intertemporal substitution. To understand this prediction, note that a higher future price carries two effects on consumption. By the income effect, the farmer is wealthier and would like to consume more already at the time of harvest, leading to less storage of the harvested amount. But, by the substitution effect, it is more advantageous to sell the crop later on. The substitution effect dominates when the elasticity of intertemporal substitution is high. In contrast, the model predicts that an unconstrained farmer that expects higher prices in the future stores all her crop and thus is not sensitive to further increases in future price expectations. Fourth, in a model extension that allows for stochastic prices, we show that higher future price variance leads the farmer to store more of the output due to a precautionary savings motive. Fifth, a higher harvested amount leads the farmer to sell more earlier on to achieve higher consumption smoothing. The intuition for this result is that the good news for the farmer makes her want to consume more already at the time of harvest, which for a constrained farmer is possible only by selling some of the harvested produce.

To test the model, we use survey data from a randomized sample of smallholder farmers in Mozambique. The survey, conducted in September of 2020, just before the lean season started, includes four provinces in Mozambique, Nampula, Zambezia, Sofala, and Manica, and covers eight crops, maize, peanut, bean, cowpea, pigeon pea, cassava, sesame, and soya bean. According to the 2016/2017 Inquérito Agrícola Integrado (2017) (Integrated Agricultural Survey) of Mozambique, these provinces represent over 50% of the total area cultivated in Mozambique in each of the crops with the exception of peanut with 36.4%, bean with 29.3%, and cowpea with 40.9%, and these eight crops account for 65.1% of the country's cultivated area in the same period (see Zavale et al. 2021).

The survey includes demographic characteristics of farmers as well as specific questions on the ability to time the market. These questions include the time it takes to sell the crop, prices obtained by farmers at the moment of sale, loss due to inadequate storage, place of sale, if crop is mainly for market or own consumption, and, whether availability of credit represented a concern when placing the output in the market, which we take to be our definition of a liquidity constrained farmer. A novel aspect of our survey are expectations of prices during the upcoming lean season. Figure 1 shows the histograms of farmers' percentage expected price appreciation per crop in our main sample, i.e., the percentage change of the expected future price relative to the sale price. The histograms show that across all crops, the vast majority of farmers expect prices to be higher in the lean season ahead. From top to bottom, the crops in the figure have decreasing percentage of farmers indicating that they produce mostly to market. Still, it is evident that there is no significant difference across crops. This evidence is novel and is consistent with aggregate average price paths reported in other studies, suggesting that the farmers in our sample are well aware of the usual market price dynamics when forming their expectations. Farmer-crop data on price expectations is critical in our study of the role of liquidity constraints.[1] We discuss in the paper the assumptions needed to interpret the expectations that farmers report in the survey as a proxy for the expectations that farmers had at the time of the decision to store or to sell.

[Figure 1 here]

We estimate a proportional-hazards parametric model of the dependent variable of interest, the time it takes the farmer to sell the crop. In line with our theoretical model, which focuses on marketable crops, our tests exclude maize because it is a staple crop where less than 6.2% of the surveyed farmers in the sample report producing mainly for market and sell on average only 37% of the crop, significantly less than any other crop in our sample. Our estimation results reveal that storage decisions of smallholder farmers in Mozambique are consistent with the model's main predictions. More liquidity constrained farmers sell their crops faster, closer to the harvest season, and farmers with poorer storage conditions also sell faster, though the latter effect is statistically insignificant. Novel to the literature, farmers expecting high price growth take longer to sell. The empirical model controls for a host of variables including demographic characteristics of farmers (i.e., gender, education level of the household head, the level of crop diversification, and others) and market-level variables (i.e., the frequency with which farmers obtain price information, where the farmer sells the crop to proxy for transportation costs, and whether the crop is produced mostly for own consumption).

We then interact the farmer's liquidity constraint dummy with the variables expected price growth, the storage dummy, and output to be closer to the model predictions. We expect the effect of storage, expected price growth, and output to only be present for constrained farmers. In these tests, the effect of expected price growth interacted with the liquidity constraint dummy is larger than the effect of expected price

[1]Others have shown that data on expectations in general are important to understand farmers' decision making. For example, Gignoux et al. (2021) find that farmer's expectations about future subsidies influence their decisions regarding input use, production, and indebtedness. Delavande et al. (2011) show that survey respondents in developing economies can make probabilistic assessments of future outcomes and that these are relevant for decision making.

growth alone, and the effect of the expected price growth alone is no longer statistically significant. These results suggest that liquidity constraints are the reason why farmers adjust the timing of sales in response to future price expectations as predicted by the model. In addition, poorer storage conditions also make liquidity constrained farmers sell faster than unconstrained farmers and constrained farmers with larger output sell faster than unconstrained farmers, though both results are not statistically significant.

We are also able to disentangle the effect of expected future prices from the effect of current prices. Farmers report selling quicker when they face relatively higher current prices controlling for future prices. This suggests that they understand what the current price level is and what is comparatively speaking a good price. However, our main result maintains, that even controlling for current prices, farmers that expect high future prices store longer if they are liquidity constrained.

Lastly, we document the effect of future price variation on storage. We measure price variation by taking the cross-sectional sample variance of expected future prices by the farmers in the vicinity of each farmer using GPS coordinates collected during the survey. We find that price variance is associated with increased storage, though the effect is weaker for liquidity constrained farmers.

In a robustness exercise, we study the effect of selection in our sample. Our main sample uses household-crop observations for those farmers that choose to sell. It is therefore possible that the main independent variable of interest, expected price growth, is linked to the decision to sell and not to the decision to store. When we model the time to sell and the decision to sell jointly, we observe that expected price growth interacted with the liquidity constraint dummy remains significant and negative in the time to sell equation while it is not significant in the decision to sell equation.

In related literature, Stephens and Barrett (2011) show that households with access to liquidity, either in the form of off-farm income or debt, avoid selling low in the harvest season. Sun, Qiu, Bai, Liu, Lin, and Rozelle (2013) show evidence of liquidity constraints only among poor households. Fink, Jack, and Masiye (2018) show that liquidity constrained farmers are forced to offer off-farm labor to meet their expenses. Omotilewa, Ricker-Gilbert, Shively, and Ainembabazi (2016) also find that higher cash on hand is associated with higher storage. Kadjoa, Ricker-Gilbert, Abdoulaye, Shively, and Baco

(2018) show that liquidity constraints affect households that store for own consumption but not those that store to sell in the market. Dillon (2020) finds that households in Malawi with unanticipated school expenses sell early, but does not have data on expected prices. Karlan, Osei, Osei-Akoto, and Udry (2014) show that farmers constrain their investment choices due to uncertainty about future crop output. Burke, Bergquist, and Miguel (2019) document that in a randomized trial, farmers offered a loan after harvest stored significantly more maize in order to sell later at higher prices. Our paper complements this literature by offering a new prediction on how expected price growth post harvest is linked to storage by liquidity constrained farmers and by providing data and evidence in support of this prediction.

There is a recent literature focusing on the explanatory power of survey expectations to corporate investment. Campello, Graham, and Harvey (2010) use survey evidence to discuss how the 2008 financial crises affected firm decisions. And, Gennaioli, Ma, and Shleifer (2015) show that CFO survey expectations on earnings growth explain well corporate investment plans. This literature is consistent with the studies reported above using farmer expectations (Gignoux et al. 2021 and Delavande et al. 2011).

There is a large literature on corporate inventories. Here, we cite only two papers for brevity to illustrate that the storage decisions at the household level, a novel aspect of household finance that we highlight, and at the corporate level appear quite different. First, Dasgupta, Li, and Yan (2019) document that financially constrained firms in the United States hold more inventory than unconstrained firms. Second, Kashyap, Lamont, and Stein (1994) document that as the cost of carry increases, inventories decrease. The first of these observations stands in contrast with our findings for farmers. The second illustrates the differential nature of the considerations by firms and households. Smallholder farmers often have no access to credit but engage in consumption smoothing in the face of significant intertemporal price variation via their storage decisions.

This paper is also related to a literature where financial constraints interact with product market decisions. Examples include Adelino, Lewellen, and McCartney (2018) who show that hospitals decreased investment significantly after the 2008 financial crisis, Philios and Sertsios (2013) who show, in the airline industry, that product quality decreases in financial distress, Mendes (2020) who shows that financially constrained firms change their product mix toward products with short cash flow maturity, and Granja and Moreira (2020) who show that firms reduce product innovation after the great recession. In this paper, we explore the timing of sales in the product market by constrained farmers given predictable price movements.

The paper proceeds as follows. The next section develops a model of market timing in the presence of liquidity constraints and derives the paper's main hypotheses. Section 3 describes the survey data used in the tests. Section 4 details the empirical specification and Section 5 describes the results from our hypotheses testing. Section 6 discusses robustness tests and Section 7 concludes the paper.

## 2 A model of farmers' market timing

We model a smallholder farmer that faces a standard consumption and savings problem and decides when to sell her crop. The model is an extension of the well-known cake-eating problem (see for example Adda and Cooper 2003), which is a simple version of the consumption and savings model of Ramsey (1928). In this extension of the cake-eating problem, we add another asset (the crop) that can be transformed into cash at a price.

Time is discrete and indexed by subscript $t = 0, 1, 2, \ldots$. The farmer is assumed to live for an infinite number of periods. Denote consumption at time $t$ by $c_t$, and let the period utility function be $c_t^{1-\gamma}/(1-\gamma)$, where $\gamma > 0$ is the coefficient of relative risk aversion.[2] The farmer discounts future utility at the rate $\beta < 1$.

We assume that period $t = 0$ is the harvest period when the farmer obtains $y_0 \geq 0$ units of the crop. For simplicity we assume that the farmer has no additional future harvests.[3] For any $t \geq 1$, the farmer starts with real money balances $m_{t-1} \geq 0$, and stored units of the crop $y_{t-1} \geq 0$. The farmer may choose to sell the quantity $s_t \geq 0$ of her crop in period $t$ at price $p_t$, in which case her money balances next

[2]When $\gamma = 1$, the period utility function is $\ln(c_t)$.
[3]In the model, there is no cycle of harvest seasons. We return to this issue below.

period are

$$m_t = m_{t-1} + s_t p_t - c_t. \tag{1}$$

The price of the consumption good is normalized to 1, so $p_t$ is the price of the crop in units of the consumption good. Implicit in this formulation is that the consumption good is a bundle of goods and cannot be substituted for by the crop. Without loss of generality, we assume that the farmer does not have access to an interest-bearing account.

The stock of the farmer's crop next period is

$$y_t = (1 - \delta)\, y_{t-1} - s_t, \tag{2}$$

where $\delta > 0$ is the depreciation caused by an imperfect storage technology. Depreciation can be due to poor humidity conditions, pests, or theft.

Formally, the farmer's problem at any time $t \geq 1$ is to solve

$$U(m_{t-1}, y_{t-1}; p_t) = \max_{m_t, y_t, c_t, s_t \geq 0} \left\{ \frac{c_t^{1-\gamma}}{1-\gamma} + \beta U(m_t, y_t; p_{t+1}) \right\}, \tag{3}$$

subject to the constraints (1) and (2).

In the next subsections, we solve different versions of this problem assuming different price patterns. For the most part, we assume price paths are known with certainty. An extension with price uncertainty is left for subsection 2.5.

## 2.1 Trading in a flat market

Suppose that $p_t = p > 0$ for all $t \geq 1$. If the farmer sells one unit of the crop produce at $t$, she receives $p$. Instead, the farmer can save that unit to sell at $t+1$. Because of imperfect storage, at $t+1$ she'll have only $1-\delta$ units to sell at the same price $p$, so she receives $(1-\delta)\, p$. Thus, with constant prices, it is optimal to sell the entire crop immediately. If the farmer starts with $y_0$, then optimal sales are $s_1^* = (1-\delta)\, y_0$.[4] and optimal money balances are

$$m_1^* = m_0 + (1-\delta)\, y_0 p - c_1. \tag{4}$$

[4]An '*' is used to denote optimality of the variable.

Problem (3), at $t = 1$, can be rewritten as

$$U(m_0, y_0; p) = \max_{c_1 \geq 0} \left\{ \frac{c_1^{1-\gamma}}{1-\gamma} + \beta U(m_0 + (1-\delta) y_0 p - c_1, 0; p) \right\}. \quad (5)$$

Note that from period $t = 2$ onward the farmer has no crop to sell, i.e., $y_t^* = 0$, for all $t \geq 1$. Since there is no more crop to sell, optimal sales are $s_t^* = 0$ for all $t \geq 2$. The problem then is one of how to consume the money balances over time. At any time $t \geq 2$, let $V(m_{t-1}) \equiv U(m_{t-1}, 0; p)$. Thus

$$V(m_{t-1}) = \max_{c_t, m_t \geq 0} \left\{ \frac{c_t^{1-\gamma}}{1-\gamma} + \beta V(m_t) \right\},$$

subject to

$$m_t = m_{t-1} - c_t.$$

This problem is the classical cake-eating problem. The solution to it is well known and it can be verified that for any $m_t$,

$$V(m_t) = \left(1 - \beta^{1/\gamma}\right)^{-\gamma} \frac{m_t^{1-\gamma}}{1-\gamma},$$

and that the optimal consumption is to always consume a constant fraction of money balances

$$c_t^* = \left(1 - \beta^{1/\gamma}\right) m_t,$$

and that optimal money balances decline monotonically

$$m_t^* = m_{t-1} - c_t^* = \beta^{1/\gamma} m_{t-1}.$$

To conclude, if the farmer enters time $t = 1$ with wealth $m_0 + (1-\delta) y_0 p$ and the consumption rule is to consume the fraction $(1 - \beta^{1/\gamma})$ of wealth, then lifetime utility at the beginning of time 1 is

$$\begin{aligned} U(m_0, y_0; p) &= \max_{c_1 \geq 0} \left\{ \frac{c_1^{1-\gamma}}{1-\gamma} + \beta V(m_0 + (1-\delta) y_0 p - c_1) \right\} \quad (6) \\ &= \left(1 - \beta^{1/\gamma}\right)^{-\gamma} \frac{(m_0 + (1-\delta) y_0 p)^{1-\gamma}}{1-\gamma}. \quad (7) \end{aligned}$$

## 2.2 Market timing by an unconstrained farmer

We assume the farmer solves her decision problem facing the following price path.

**Definition 1** *Let $t = 0$ be the harvest period. The market timing price path is $p_1 = q$ and for $t \geq 2$, which we interpret as the lean season, $p_t = p$, with $q < (1-\delta)p$.*

To motivate this price path, we continue to assume that period $t = 0$ corresponds to the harvest period and period $t = 2$ corresponds to the lean season. This price path has been extensively documented (Stephens and Barrett 2011, Sun et al. 2013, Burke et al. 2019, and Kadjoa et al. 2018) and is also what the farmers in our sample expect as shown in Figure 1.[5]

In this subsection, we assume the farmer has high enough money balances that she is not liquidity constrained,

$$m_0 \geq \left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p. \tag{8}$$

Lifetime utility at the start of time $t = 2$ is

$$U(m_1, y_1; p) = \left(1 - \beta^{1/\gamma}\right)^{-\gamma} \frac{(m_1 + (1-\delta) y_1 p)^{1-\gamma}}{1-\gamma}, \tag{9}$$

because from $t = 2$ onward the farmer faces a market with a flat price forever; a problem we solved for in the previous subsection.

At time $t = 1$, using constraints (1) and (2), the farmer solves

$$\begin{aligned} & U(m_0, y_0; q) \\ = & \max_{c_1, s_1} \left\{ \frac{c_1^{1-\gamma}}{1-\gamma} + \beta\left(1 - \beta^{1/\gamma}\right)^{-\gamma} \frac{(m_0 - c_1 + s_1 q + (1-\delta)((1-\delta) y_0 - s_1) p)^{1-\gamma}}{1-\gamma} \right\}. \end{aligned} \tag{10}$$

The unconstrained farmer can perfectly time the market and take advantage of higher prices in the future by postponing sales til time $t = 2$. Thus, it is optimal to set $s_1^* = 0$. Substituting the solution for

[5]In the alternative path where $q > (1-\delta)p$, the farmer chooses to sell all of the crop at time $t = 1$ taking advantage of the high price. This alternative path, with high prices at harvest, would not have represented a puzzle given the tendency for farmers to sell shortly after harvest. We therefore omit further discussion of this alternative price path.

optimal sales into (10) and taking the first order condition with respect to consumption yields the interior solution

$$c_1^* = \left(1 - \beta^{1/\gamma}\right)\left(m_0 + (1-\delta)^2 y_0 p\right). \tag{11}$$

For this solution to be optimal it must satisfy the non-negativity constraint on money balances going forward

$$m_1^* = m_0 - c_1^* \geq 0,$$

which holds if initial money balances satisfy condition (8).

In summary, a liquidity unconstrained farmer stores all of the crop. An important consequence of this result is that the amount of storage is not sensitive to small variations in the expected price, $p$. That is, provided that $p(1-\delta)/q > 1$ so that the farmer is timing the market, storage is independent of the level of expected prices.

### 2.3 Market timing by a liquidity constrained farmer

The farmer faces a market timing price path, and in this subsection, we assume the farmer is liquidity constrained. Thus, we assume that at beginning of time $t = 1$ the farmer's money balances are $\left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p > m_0 > 0$, and constraint (8) binds. The farmer is more likely to be constrained when she has a better harvest of the crop ($y_0$ is high), faces high future prices, has better storage technology (low $\delta$), or is less patient (low $\beta$).[6]

With a liquidity constraint, some of the crop must be sold at time $t = 1$, constraining the ability of the farmer to time the market perfectly. We again use the fact that from $t = 2$ onward the farmer faces a flat price forever and has lifetime utility (9). The farmer's problem at time 1 is to solve

$$\begin{aligned} & U(m_0, y_0; q) \\ = & \max_{c_1 s_1 \geq 0} \left\{ \frac{c_1^{1-\gamma}}{1-\gamma} + \beta\left(1-\beta^{1/\gamma}\right)^{-\gamma} \frac{\left(m_0 - c_1 + s_1 q + (1-\delta)\left((1-\delta)\, y_0 - s_1\right) p\right)^{1-\gamma}}{1-\gamma} \right\}, \end{aligned}$$

with the constraint that money balances are non-negative

$$m_1 = m_0 - c_1 + s_1 q \geq 0.$$

[6] Ruhinduka et al. 2020 show that patient farmers store more.

Since the unconstrained optimum choice for consumption violates the non-negativity condition on money balances, the optimum constrained consumption must imply that money balances next period at are optimally set to zero. We may therefore eliminate $c_1$ from the problem. The problem is then to determine how much to sell in period $t = 1$:

$$U(m_0, y_0; q) = \max_{s_1 \geq 0} \left\{ \frac{(m_0 + s_1 q)^{1-\gamma}}{1-\gamma} + \beta \left(1 - \beta^{1/\gamma}\right)^{-\gamma} \frac{((1-\delta)((1-\delta) y_0 - s_1) p)^{1-\gamma}}{1-\gamma} \right\}. \tag{12}$$

Taking the first order condition with respect to $s_1$ yields an equation that can be solved for the optimal interior value of sales, $s_1^*$,

$$q \left(m_0 + s_1^* q\right)^{-\gamma} = (1-\delta) p \beta \left(1 - \beta^{1/\gamma}\right)^{-\gamma} \left((1-\delta)\left((1-\delta) y_0 - s_1^*\right) p\right)^{-\gamma}. \tag{13}$$

Selling an extra unit of the crop today yields $q$ units of the consumption good and each unit of the consumption good increases utility by $\left(m_0 + s_1^* q\right)^{-\gamma}$. The cost of selling that extra unit of the crop today is that the farmer gives up the ability to sell it tomorrow and get $(1-\delta) p$ units of the consumption good, where a unit of consumption increases utility by $\beta(1-\beta^{1/\gamma})^{-\gamma} \left((1-\delta)\left((1-\delta) y_0 - s_1^*\right) p\right)^{-\gamma}$. Solving for $s_1^*$ yields

$$s_1^* = \frac{\left[\frac{(1-\delta) p}{q}\right]^{\frac{\gamma-1}{\gamma}} \left(\beta^{-1/\gamma} - 1\right)(1-\delta) y_0 - \frac{m_0}{q}}{1 + \left[\frac{(1-\delta) p}{q}\right]^{\frac{\gamma-1}{\gamma}} \left(\beta^{-1/\gamma} - 1\right)}. \tag{14}$$

Notice that for $s_1^*$ to be an interior solution two conditions must be met. First, the farmer cannot sell more than the stored crop, $(1-\delta) y_0 \geq s_1^*$, which can be verified that it holds for all parameters. Second, $s_1^* \geq 0$, which can be verified happens for initial money balances $m_0 \leq \left[\frac{(1-\delta) p}{q}\right]^{-\frac{1}{\gamma}} \left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p$; for all other values of initial money balances, the farmer chooses to sell nothing at $t = 1$.

Next we analyze the properties of period 1 sales, $s_1^*$. Not surprisingly, $s_1^*$ declines with money balances, $m_0$. It is optimal to save the entire crop if money balances are high enough since $(1-\delta) p > q$; thus, more crop is stored if the farmer starts with higher money balances. Also, higher crop, $y_0$, implies that more of it is sold at $t = 1$. A higher crop implies higher income for the farmer, but the liquidity constraint limits the farmer's ability to take advantage of it already at $t = 1$; by selling more, the farmer achieves higher consumption smoothing.

The effect of the price tomorrow $p$ on sales is more subtle. There are two effects from an increase in $p$: by the substitution effect, the farmer sells more at $t = 2$ when prices are higher; by the income effect, the farmer sells more at $t = 1$ to achieve greater consumption smoothing if $p$ increases. When $\gamma < 1$, the substitution effect dominates. In this model there is no uncertainty, so $\gamma$ plays the role of the elasticity of intertemporal substitution ($EIS$), where $EIS = 1/\gamma$. Thus, the substitution effect dominates for high values of the $EIS$.

At the interior solution for sales for the liquidity constrained farmer, stored crop equals

$$\begin{aligned} y_1^* &= (1-\delta) y_0 - s_1^* \\ &= \frac{(1-\delta) y_0 + \frac{m_0}{q}}{1 + \left[\frac{(1-\delta)p}{q}\right]^{\frac{\gamma-1}{\gamma}} \left(\beta^{-1/\gamma} - 1\right)}. \end{aligned}$$

At $t = 2$, the farmer sells all her remaining crop immediately since the price will stay constant from $t = 2$ onward. Thus

$$\begin{aligned} s_2^* &= (1-\delta) y_1^* \\ &= (1-\delta) \frac{(1-\delta) y_0 + \frac{m_0}{q}}{1 + \left[\frac{(1-\delta)p}{q}\right]^{\frac{\gamma-1}{\gamma}} \left(\beta^{-1/\gamma} - 1\right)}. \end{aligned}$$

## 2.4 Model predictions

We start by summarizing the discussion of the model with market timing price path. The next proposition combines the solutions for the case from subsection 2.2 with an unconstrained farmer (i.e., money balances are $m_0 \geq \left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p$), and for the case from subsection 2.3 with a liquidity constrained farmer (i.e., $m_0 < \left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p$).

**Proposition 1** *The time $t = 1$ optimal consumption and sales under market timing, denoted by $\left(c_1^m, s_1^m\right)$, for a farmer starting with $(m_0, y_0)$ are,*

$$s_1^m = \begin{cases} \frac{\left[\frac{(1-\delta)p}{q}\right]^{\frac{\gamma-1}{\gamma}} \left(\beta^{-1/\gamma}-1\right)(1-\delta) y_0 - \frac{m_0}{q}}{1+\left[\frac{(1-\delta)p}{q}\right]^{\frac{\gamma-1}{\gamma}} \left(\beta^{-1/\gamma}-1\right)} & , m_0 \leq \left[\frac{(1-\delta)p}{q}\right]^{-\frac{1}{\gamma}} \left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p \\ 0 & , else \end{cases} , \quad (15)$$

*and*

$$c_1^m = \begin{cases} m_0 + s_1^m q & , m_0 \le \left[\frac{(1-\delta)p}{q}\right]^{-\frac{1}{\gamma}} \left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p \\ m_0 & , else \\ \left(1 - \beta^{1/\gamma}\right)\left(m_0 + (1-\delta)^2 y_0 p\right) & , m_0 \ge \left(\beta^{-1/\gamma} - 1\right)(1-\delta)^2 y_0 p \end{cases} \tag{16}$$

Our main proposition states comparative statics on $s_2^m/s_1^m$, a ratio that indicates how the farmer wishes to postpone sales for later in the season. These results follow from comparative statics on $s_1^m$, because $s_2^m = (1-\delta)\left((1-\delta)\,y_0 - s_1^m\right)$, and so $s_2^m/s_1^m = (1-\delta)\left((1-\delta)\,y_0/s_1^m - 1\right)$.

**Proposition 2** *Under the market timing price path:*

1. *A liquidity constrained farmer sells relatively more later in the season:*
   - *(a) if her money balances are higher;*
   - *(b) if her harvest output is lower;*
   - *(c) if the price later in the season increases and the farmer has high elasticity of intertemporal substitution.*
2. *A liquidity unconstrained farmer stores all her crop to sell later in the season independently of prices.*

These results constitute our main hypotheses to be tested below. It is important to emphasize the last portion of the proposition that the liquidity constrained farmer stores all her crop in a way that is insensitive to prices. The reason for this result is that once the farmer's wealth is large enough so the farmer is unconstrained, if $p(1-\delta)/q > 1$, then any increase in the future price does not change the farmers' decision as the farmer is already storing all the crop output.

Storage quality has two effects on sales at time $t = 1$. Better quality of storage has an effect similar to price growth (via $(1-\delta)p/q$), leading to higher storage. This is the usual model prediction relating storage to the quality of storage. In the current setup, storage quality also affects the net size of the corp output (via $(1-\delta)y_0$), and this effect works against the initial effect (see Proposition 2). However, this second effect results from a modeling assumption whose sole purpose is to simplify the exposition of the model, and we do not think it carries any weight in terms of model predictions.

### 2.5 Discussion

The model is stylized in several dimensions. Here we discuss the implications of removing some of the assumptions in the model. First, suppose the farmer cultivates multiple crops instead of just one. A constrained farmer picks the produce with lowest expected price growth to sell first in order to induce consumption smoothing. Again, higher price growth would be associated to higher storage for the farmer. Second, suppose the farmer has some off-farm income. This income accumulates to the initial liquid wealth that the farmer brings into each period making the farmer less constrained. Thus, all else equal, a farmer with greater off-farm income is less constrained and relatively less sensitive to future price changes. Recall that an unconstrained farmer should be storing all of her crop to sell during the lean season when prices are higher and would not change her decision for small price changes.

Third, we modeled only one harvest cycle (harvest season followed by the lean season) when in fact harvest cycles repeat themselves. It would be straightforward to add harvest cycles in the model, though at the cost of some complexity and without any additional insight. The restart of another cycle bringing more crop output changes the threshold on money balances for a farmer to qualify as unconstrained, but otherwise it does not significantly change the main predictions.

Fourth, Simtowe and De Groote (2022) predict that if consumption is below current requirements, then current consumption should not vary in response to future prices. This would be the case if the farmer had a subsistence level at which marginal utility is infinite. Whether farmers have such subsistence levels is an empirical question, one that we can indirectly assess if despite the low consumption levels, storage is insensitive to future prices.

Fifth, the farmer in the model cannot borrow or lend. If the farmer could borrow risk free, she would be willing to do so at any interest rate that is below $(1-\delta)p/q-1$. Intuitively, at this rate or lower the farmer can borrow against the income that she will attain once the price increases. Given the large expected price changes, why don't we see more borrowing going on? One possible answer is that there are market frictions that prevent borrowing from occurring at an acceptable rate of interest. This is likely the case given the underdevelopment of banking in Mozambique (on the lack of credit, including micro-finance, and on desirable policy interventions see the discussion in Barrett 2007).[7] Another possible answer is that there is uncertainty about prices in the lean season making borrowing riskier for banks and households.

Consider lastly the effect of price uncertainty on storage decisions. The risk that farmers face has been shown to be a relevant decision variable for their investment decisions (see Karlan et al. 2014). For simplicity, assume that the price $p$ is a random variable defined in the positive numbers and that once its value is realized at time $t = 2$ it stays fixed for ever after. Uncertainty is therefore resolved after time $t = 2$. For the results below we assume only that a moment generating function of $p$ exists.

For low enough starting wealth, $m_0$, the modified first order condition for the optimal amount sold at time $t = 1$ for a constrained farmer in the problem with random prices, $s_1^r$, is similar to equation (13),

$$q\left(m_0 + s_1^r q\right)^{-\gamma} = E\left[(1-\delta)\, p\beta \left(1-\beta^{1/\gamma}\right)^{-\gamma} \left((1-\delta)\left((1-\delta)\, y_0 - s_1^r\right) p\right)^{-\gamma}\right], \tag{17}$$

which gives the solution for selling

$$s_1^r = \frac{E\left[\left(\frac{(1-\delta)p}{q}\right)^{1-\gamma}\right]^{-1/\gamma} \left(\beta^{-1/\gamma}-1\right)(1-\delta)\, y_0 - \frac{m_0}{q}}{1 + E\left[\left(\frac{(1-\delta)p}{q}\right)^{1-\gamma}\right]^{-1/\gamma} \left(\beta^{-1/\gamma}-1\right)}. \tag{18}$$

In this solution, the non-linearity of the expected value due to the exponent $(1-\gamma)$ means that not just the expected price matters, but other moments of the price do as well. To make this point evident, note that

$$E\left[\left(\frac{(1-\delta)\, p}{q}\right)^{1-\gamma}\right] = \exp^{(1-\gamma)\ln\left(\frac{1-\delta}{q}\right)} \exp^{c_p(1-\gamma)}, \tag{19}$$

where $c_p()$ is the cumulant generating function of $\ln p$ (see Martin 2013), defined as the natural logarithm

[7] Zavale et al. (2021) provide evidence that surveyed farmers that obtain formal credit tend to do so from NGOs rather than the traditional banking sector.

of the moment generating function, and equals

$$c_p(1-\gamma) = (1-\gamma)E(\ln p) + (1-\gamma)^2 V(\ln p)/2 + \ldots \tag{20}$$

The terms omitted in the expression (for brevity) involve centered moments of the random variable $\ln p$ of third order and higher, i.e., skewness, kurtosis, and so on.

Selling, $s_1^r$, is decreasing in $E\left[((1-\delta)\,p/q)^{1-\gamma}\right]$, and because of equations (19) and (20), higher expected future prices, $E(\ln p)$, lead the constrained farmer to store more when $\gamma < 1$ as it did in the deterministic case. Moreover, higher variance of prices, $V(\ln p)$, lead to more storage for any value of risk aversion, $\gamma \neq 1$. The intuition for the variance result is that for precautionary reasons a high future variance induces increased savings (i.e., increased storage). Below, we provide a test of the hypothesis that higher variance is associated with higher storage. The reason for precautionary savings in our model–where the household is constrained–differs from that in Lee and Sawada (2010) where precautionary savings arises due to the expectation of a future binding liquidity constraint.

# 3 Data

The empirical tests use data from a survey of 443 smallholder farmers in Mozambique covering the 2019/2020 agricultural season (see Zavale et al. 2021 for full details on the survey). The survey was conducted between September 6, 2020 and September 30, 2020. The survey covers 13 districts in four provinces, Manica and Sofala in the Beira Development Corridor, and Zambezia and Nampula in the Nacala Development Corridor, in central and northern Mozambique, respectively. Data were collected on eight crops, namely maize, peanut, bean, cowpea, pigeon pea, sesame, soya bean, and cassava. For all crops the end of the harvest season is in May or June, except for maize, where the harvest season may extend to July.[8] In Mozambique, the lean season starts in October.

The studied crops are among the priority crops identified under the Plano Operational para o Desenvolvimento Agrário (2015) (Operational Plan for Agricultural Development) for the Beira and Nacala

[8]Crop calendars for all crops in Mozambique are available at the website of the Food and Agriculture Organization (http://www.fao.org/agriculture/seed/cropcalendar/welcome.do) of the United Nations.

Corridors and make up a significant portion of crops grown and marketed by smallholder farmers in Mozambique. According to Mozambique's Inquérito Agrícola Integrado (2017), in 2016/2017 these provinces represented over 50% of the total area cultivated in Mozambique for maize, pigeon pea, sesame, soya bean, and cassava, whereas for peanut, bean, and cowpea they represented, respectively, 36.4%, 29.3%, and 40.9% of the cultivate area. Overall, the eight crops studied account for 65.1% of the cultivated area in the same period.

The survey was constructed using a two-stage sampling procedure. As Zavale et al. (2021) explain, in a first stage, two administrative posts per district were selected based on an assessment of their biophysical potential for the eight chosen crops. This assessment was made by public official technicians on the ground based on the potential for each crop. In a second stage, we randomly sampled smallholder farm households from the list of farm households in the named administrative posts.

The survey contains household demographic characteristics and data on the eight crops mentioned above. The survey includes information on whether the farming household produced each of the crops and how much, the resources farmers had available for production (including storage), and the share of each crop sold to markets. Importantly, the survey also asked farmers about current prices (i.e., the prices at which the output was sold), the expected price for each crop 30 days after the survey (that is, already into the lean season), and how long farmers waited to take their crop to market since harvest. Table A1 lists the variables used in this study with the respective definitions.

We have complete data for 835 farmer-crop observations, representing 389 farmers who sold some of their crop. Of these, we drop all 226 observations linked to maize. This leaves us with a sample of 609 farmer-crop observations, representing 362 farmers, with each farmer producing an average of 1.7 crops. There are two main reasons to drop maize from our study. First, maize is a staple crop and is used primarily for own consumption. Of the 226 farmers that produce and sell maize, only 6.2% of the farmers report that the majority of the crop is for market. Cassava is in a somewhat similar situation in that 8.5% of all producers say the crop is mainly to market. For other crops, the numbers range from 20% for butter bean and 30% for large groundnut to 98.6% for sesame and 100% for soya (see Table 2).

However, there is a significant difference between maize and cassava. There is a large number of farmers that sell a substantial part of their cassava crop even if they are not answering that they produce to sell mainly to market. The average share of production sold of cassava is 64% whereas for maize it is only 37%, the lowest across all crops (the second lowest is large groundnut with 60% as shown in Table 2). In a robustness exercise, we drop the observations relating to cassava as well (see Section 6). The second reason to drop maize from our sample is that maize is the only crop in our sample whose harvest period extends potentially through July, which would give it less than 3 months to the survey.

[Table 1 here]

Table 1 presents summary statistics on the variables extracted from the survey used in this study. We describe first the variables at the crop level. The average number of weeks that it took to sell the harvested output (*Time to sell*) is 1.7. Below, we describe in greater detail how this variable is constructed. The expected price growth variable represents the ratio of a farmer's expected price 30 days after the interview (in Mozambican meticais per kilo) to the price at which the crop was sold (in Mozambican meticais per kilo). We winsorize expected price growth at 1%. The expected price is on average 10% higher than the actual price of sale across all households and crops. The table also reports on the expected price separately from the actual sale price as reported by the farmers for each crop they sell (both in logarithms due to skewness in the price levels). Farmers are generally well informed, as 41.9% of observations correspond to crops where the farmer indicates having received price information at least once a week. The price variation is 0.391 on average across farmers and crops (this variable is in meticais per kilo). The output variable is denoted in logarithms of kilos. The own consumption dummy takes the value of 1 if most of the crop is destined for own consumption. On average, 44% of crops are mostly for own consumption. Place of sale indicates that 30% of all crops were sold at the farm gate. Only about 10% of crops were sold via an intermediary.

The remaining variables are constructed at the household level. The poor storage variable is a dummy that takes the value of 1 if the farmer reports storage conditions as poor. About 10% of farmer-crop observations are associated with farmers that report having poor storage conditions as opposed to fair or good conditions (for the few farmers that did not answer the question, we inputed that conditions were fair). The variable *liquidity constrained* is a dummy that takes the value of 1 if the farmer reported having trouble placing output in the market for lack of availability of credit. The vast majority of the surveyed farmers (79% of farmer-crop observations) are classified as liquidity constrained. Only 10% of farmer-crops are linked to female farmers, and farmers have on average 4.9 years of schooling. About 17% of observations are of farmers who own land use rights certificates (referred to as DUAT from its Portuguese acronym for *Direito de Uso e Aproveitamento de Terra*). Household size is on average 6.3 people. Crop concentration is the Hirschman-Herfindahl index of the share of total cultivated surface of each crop. A high value of crop concentration indicates a greater dependence on a smaller number of crops and less diversification of farm income.

Table 2 describes the average expected price ratio per crop and province. The table relies on the same information used to construct Figure 1. Across all crops, and provinces, farmers expect prices in the lean season to be higher relative to the prices they obtained at the time they sold their crop, with only three exceptions, pigeon pea in Nampula province and cassava in Zambezia and Sofala provinces. Overall, the information from Figure 1 and Table 2 shows that higher expected prices in the lean season are a pervasive phenomenon by crop and province for all farmers.[9] The next section offers further discussion on the expected price growth variable, potential measurement noise, and fixes.

[Table 2 here]

Table 3 gives the correlation matrix for the variables used in the study. It is worthwhile noting that higher harvest output tends to be associated with lower actual sale prices. This may be because storage conditions limit farmers' ability to hold on to a large output and force them to sell at worse prices and we can account for it by controlling for storage conditions (see also Stephens and Barrett 2011). Place of sale is associated with lower output, as more output may justify going to the local market to sell to get a

[9]Because we collect data at a single month across all farmers, it is possible that a common shock could drive the perception of high future prices. This, however, is unlikely as 2020, the year of the COVID-19 pandemic, saw continued uncertainty through the end of the year. For example, in Mozambique, total credit to the agricultural sector topped at 9.9 billion meticais in June of 2020, then dropping through the rest of the year to a bottom of 7.1 billion meticais in January of 2021 (see Banco de Moçambique 2021).

better price. There is a large positive correlation of the actual price with the expected price: farmers that sold at higher prices expect prices to go up by more later in the season. This is an indication that even those farmers that seemed to have done well, may be constrained if they sold at prices significantly below their expectations. Expected price growth also correlates positively with there being an intermediary. Intermediaries tend to trade with farmers with poor storage and with liquidity constraints.

[Table 3 here]

# 4 Empirical specification

We test the model's main predictions using a parametric hazard model. The dependent variable is the time it takes the farmer to sell a crop, given that the farmer is producing and selling that crop. In the survey, for each crop, farmers were asked how long it took them to sell what they wanted to of their output and were given six possible choices: less than 2 weeks, between 2 and 4 weeks, between 4 weeks and 2 months, between 2 and 3 months, between 3 and 4 months, and other (i.e., more than 4 months). Figure 2 plots, for each crop, the percentage of farmers that reply affirmatively to each of the time periods above. The vast majority of farmers that sell some of their crops do all their selling in less than two weeks after the harvest, especially for maize, bean, cowpea, pigeon pea, sesame, and soya bean. It is noteworthy that the survey was conducted in September of 2020, several months past the harvest season for all crops except maize, and one month before the start of the lean season. At the time of the survey, most farmers who say they sold their crop, have sold all they wanted to.[10]

[Figure 2 here]

Following the evidence in Figure 2, we combine the time it took to sell the crop from 4 weeks to 4 months into a single bucket. Thus, in our tests, we use three intervals for the time to sell variable, 0-2 weeks, 2-4 weeks, and 4-16 weeks.[11] Note that no farmer answered 'other' to the time to sell question, so this choice does not lead to right censoring of the data. With these data we build a categorical variable

[10]The setting of our exercise is therefore quite different from that analyzed in Cafiero et al. (2015) where stockouts are infrequent.

[11]In Table 1, we report statistics for *time to sell* using the left boundary of each of these intervals.

that defines the time to sell as intervals in terms of weeks. A higher value of this variable means that the farmer stores the crop for a longer period. We take this variable to be the empirical counterpart to $s_2/s_1$ from the model.

We estimate a model for interval-censored survival data with a proportional-hazards parameterization. The hazard rate function for the time it takes farmer $f$ to sell crop $c$, $t_{c,f}$, is

$$h_j(t_{c,f}) = h_0(t_{c,f})\exp(-\mathbf{x}_{c,f}\beta), \tag{21}$$

where $j$ indexes the observation associated with $(c, f)$, $h_0(t) = \alpha t^{\alpha-1}$ is given by the Weibull distribution and $\mathbf{x}_{c,f}$ is a vector of explanatory variables and controls. As is standard, the survivor function solves $h_j(t) = -\frac{dlogS_j(t)}{dt}$.[12]

The model is estimated by maximum likelihood. The likelihood function is written as $\mathcal{L} = \prod_{j=1}^{N}(S_j(t_{i-1})h(t_i))^{y_{j,i-1}}S_j(t_{i-1})^{1-y_{j,i}}$. It is adjusted to account for the fact that the data are grouped into intervals $(i-1 < t < i)$, with $y_{j,i} = 1$ if the farmer corresponding to observation $j$ sells the crop in interval $i$. The model is estimated using Stata's `stintreg` command in the accelerated failure-time metric. The intervals are defined using the lower and upper bounds in weeks the farmers reported when asked about the time it took to sell the harvest (see Table A1). Reported standard errors are clustered at the household level.

We include in the model specification crop fixed effects, province fixed effects, and crop times province fixed effects. These fixed effects are meant to capture unobserved characteristics by crop and province. For example, a province fixed effect captures local weather conditions or road conditions that affect all farmers in a province differently from farmers in other provinces. A crop fixed effect may capture a disease that affected one crop (independently of the province) but not other crops. And a crop and province fixed effect may capture for example the availability of intermediaries or more local markets in some locations for some crops, thus facilitating access to market. In general, market segmentation at

[12]The Weibull distribution is a more flexible distribution than the exponential distribution, also used in duration models, as it allows for a varying hazard rate. It is also more flexible than the lognormal distribution because it easily accommodates heterogeneity in its ancillary parameters. In any case, with our sample and empirical specifications, the Weibull distribution was also preferred by the Bayesian information criterion.

the crop level justifies crop times province fixed effects.[13]

The main explanatory variable of interest is the farmer's *expected price growth* into the lean season, which corresponds to $p/q$ in the model of Section 2 (the subsection 2.5 discusses specifically the case with price uncertainty). We observe price expectations at the time of the survey after the farmer has finished selling to the market, not when the farmer was making the decision of when to sell.[14] We therefore assume that there is persistence in expectations about prices in the lean season (so that the expectations the farmers used to decide when to sell are correlated with the measured expectations). This assumption relies on the fact that price patterns from harvest time to lean season are well established and consistent over time (though of course the price level may vary from year to year). Indeed, as Figure 1 illustrates, across all farmers and crops, the vast majority of observations indicate that prices are higher in the lean season. Still, revisions in price expectations could affect the time to sell. If revisions are random across farmers, then the noise they introduce to the independent variable should make it harder to detect any effect. Instead, if revisions occur in the same direction for all farmers within a province-crop due to market segmentation (for example, the demand for peanut in Nampula goes up for all farmers during the survey leading all the farmers in Nampula to lower their peanut-price expectations), our use of crop times province fixed effects partly absorbs this effect.[15] The other main explanatory variables in the empirical model are the dummies for liquidity constraints and for storage conditions, and output by crop.

The reported coefficients indicate the impact of an independent variable on duration: a positive coefficient implies that an increase in the corresponding variable increases the time to sell the crop. We therefore predict that duration (hazard rates) increases (decrease) if the farmer is liquidity constrained, and that among liquidity constrained farmers, duration (hazard rates) increases (decrease) if the farmer has high expectations of price growth, has better storage conditions, and has lower output.

[13] We also allow crop fixed effects to affect the ancillary parameter $\alpha$ of the Weibull distribution in all specifications.

[14] Ideally, we would observe expected prices and current sale prices at every point a farmer decided to sell or not sell. This, however, is impractical.

[15] The introduction of crop times province fixed effects, due to their nonlinear effects, can help even if the measurement error associated with the expectation revisions are classical (Chesher, 1991).

## 5 Results

Table 4 presents the baseline estimations of equation (21) with demographic controls. In each new column, the table repeats the baseline empirical model adding, one at a time, controls relating to alternative hypotheses. Estimations are conducted at the farmer-crop observation level and include crop fixed effects, province fixed effects, and crop times province fixed effects.

The main result is that a higher expected price growth is associated with the farmer taking longer to sell the crop. This result is consistent with the model prediction in Proposition 2 assuming the farmer has high elasticity of intertemporal substitution (an assumption that is common in models of household financial behavior as in Bansal and Yaron 2004) and is constrained. To give an indication of the economic significance of the effect, note that the dependent variable in the estimations is the logarithm of time to sell. Thus, using the estimates in the baseline model specification in column 1, one standard deviation change in the expected price (equal to 0.239) translates into an increase in the time to sell of 8% (equal to $0.247 \times 0.239$).[16]

In terms of other model predictions, the liquidity constrained dummy is highly statistically significant and with a sign that is consistent with the model's prediction. A liquidity constrained farmer sells a crop about 50% faster than a farmer that is not liquidity constrained. This effect is quite large and significantly larger than that associated with the role of storage (see also Stephens and Barrett 2011, Sun et al. 2013, and Kadjoa et al. 2018). Poor storage speeds the time to sell by roughly 10%, but the effect is not statistically significant (poor storage is insignificant also in Ruhinduka et al. 2020, and it is significant in Omotilewa et al. 2016 and Omotilewa et al. 2018). We also find that one standard deviation increase in output (equal to 1.182) translates into an increase in the time to sell of 10% (equal to $0.066 \times 1.182$). This effect is inconsistent with the model's prediction on output. One possibility is that the output variable captures another effect: more output may take longer to sell because it requires more trips to the market

[16] As far as we know, we are the first to document such an effect. The only other paper we are aware of that uses expected price data is Kadjoa et al. 2018. They use the village price to generate price expectations and fail to find an effect. They study only one crop, maize, in Benin. Note that we exclude maize from our analysis because only a very small percentage of farmers say they produce mostly to market and the average amount sold relative to output is the smallest among the studied crops by a sizeable amount as documented in Table 2. In Kadjoa et al. 2018, the percentage of farmers that say they produce mostly to market is quite small as well at 5%.

place. The next table produces a test that is more in line with the model as it interacts output with the dummy for liquidity constraint.

For the control variables, the female dummy variable is not significant (similarly see Ruhinduka et al. 2020 and Sun et al. 2013), more years of schooling lead to longer time to sell, trading via an intermediary speeds the time to market as does having a DUAT, and household size is associated with longer times to sell (this last finding is also present in Omotilewa et al. 2016 though just for legumes).

Columns 2 through 5 consider, in turn, variables that capture alternative hypotheses, and column 6 considers all the controls simultaneously. Overall, the results indicate that the effects from the baseline model specification continue to hold. Following Aker and Mbiti (2010) and Gupta et al. (2021), we analyze the role of price information. In column 2, we find that having more frequent price information is associated with less storage. As Aker (2010) documents that price dispersion decreases with use of mobile phones, one possible explanation is that there is a smaller precautionary savings motive. The role of transportation costs is studied in column 3 through the place of sale dummy (see Shilpi and Umali-Deininger 2007). Selling at own farm gate (place of sale dummy) is statistically insignificant indicating that transportation costs do not affect the storage decision once controlling for other variables, though the variable becomes significant in column (6) when all the alternative controls are considered (place of sale is also found insignificant in Ruhinduka et al. 2020 and Omotilewa et al. 2016). Contrary to Kadjoa et al. (2018), we find no significant effect of own consumption on time to sell (column 4). It is possible that this is because we have excluded from the analysis the crop that is mostly produced for own consumption, maize. In addition, the variable that indicates crop concentration is insignificant, suggesting that the lack of product diversification is not a factor for the storage decision (column 5). Separately, we also include a dummy variable that captures whether a farmer reported being affected by the Idai or Kenneth cyclones the year before the survey. In our sample, 54% of all farmer-crop observations were affected by the cyclones Idai and Kenneth. Including this dummy as a control variable does not change our results (available upon request).

[Table 4 here]

Table 5 adds to the baseline specification in column 1 of Table 4 interaction terms of expected price growth, output, and poor storage with the liquidity constraint dummy. Column 1 shows that the expected price growth is only significant when interacted with the liquidity constraint dummy as predicted by the model. Furthermore, the economic and statistical significance of the expected price growth interacted with the liquidity constraint dummy remains when we control for additional interactions of liquidity constraints with output and storage conditions (columns 2 through 4). The total effect of the coefficients on expected price growth and expected price growth interacted with the liquidity constraint dummy is between 0.37 and 0.39 across the four specifications (untabulated), significant at 1% or better, implying an increase in the time to sell of about 9% (equal to $0.38 \times 0.239$). That expected price growth alone is no longer significant (except in column 3) is as predicted by the model since unconstrained farmers should be irresponsive to further increases in price expectations.[17] The effects of output and that of storage interacted with the liquidity constraint dummy have the predicted signs (columns 2-4): for example, liquidity constrained farmers increase their storage amount compared to unconstrained farmers if storage conditions are better. However, these interactions are not statistically significant.

[Table 5 here]

Table 6 splits the expected price growth into its numerator, the expected price, and its denominator, the price at which the farmer currently sold her crop, the actual price. We do this do guarantee that the main result is tied to farmer expectations and not simply as a response to current prices. We use the logarithm of expected price and the logarithm of actual price because price levels are 25% more skewed than the variable expected price growth. In the first column, we see that our main effect appears to come only from the expected price. When we include an interaction of expected price with the liquidity constraint dummy none of the effects are significant (column 2), though the combined linear effect is a statistically significant at 5% and equal to 0.269 (untabulated), in line with the model. When in column 4 we add also an interaction of the actual price with the liquidity constraint, then both the expected price and the actual price interacted with the liquidity constraint dummy are significant and with the expected

[17] This result is in the spirit of Sun et al. 2013 who show that the effect of liquidity constraint appears only for poorer households.

signs, and the linear combination of the expected price is statistically significant at 1% and equal to 0.398 (untabulated). This evidence supports the model's predictions (the negative coefficient associated with the actual price interacted with the liquidity constraint is also consistent with Kadjoa et al. 2018).

[Table 6 here]

The last result that we discuss deals with the model prediction that farmers that face greater price variation store more due to a precautionary savings motive as discussed in subsection 2.5. Our main challenge is to obtain a measure of price variation. To do that, for each farmer, we define a geographic area with fixed diameter using GPS coordinates obtained at the time of the survey. We then look for the smallest diameter that guarantees that every farmer has at least ten other farmers in the neighborhood from the surveyed farmers. Price variation is the standard deviation of expected prices across the neighboring farmers. Price variation is calculated at the household-crop level. We do not have GPS coordinates for six farmer-crop observations, so our sample is reduced to 603 observations.

Table 7 presents the results. We use an empirical specification as in Table 6 because the model with stochastic prices suggests separate roles for expected price, price variation, and actual price. Column 1 shows that adding price variation reduces the significance of the expected price effect. It also shows that price variation has a positive and significant effect as predicted if all farmers are constrained. In column 2 we add an interaction of price variation with the liquidity constraint dummy and in column 3 we add interactions of the liquidity constraint dummy also with the expected price and with the actual price. The results with expected price are as before, where only the interaction with the liquidity constrained dummy is significant. The interaction of price variation with liquidity constrained is not significant, but the price variation effect remains significant and positive (columns 2 and 3).

There are two issues with our measure of price variation. One is that we assume that the farmer builds its assessment of price variation in a way that is correlated with what the neighbors think. In that way, our measure is a noisy proxy for the proper metric and the estimated coefficients may suffer from an attenuation bias. The other is that there may be a confounding effect related to population density. In low density areas, high price variance may be associated with the ability of buyers to extract rents from farmers by engaging in greater price discrimination. In that way, price variation would not be linked with precautionary savings, but rather with market segmentation. Without a proper model, it is unclear how market segmentation would bias the effect on time to sell.

[Table 7 here]

## 6 Robustness

In this section, we address the issue of selection. Our sample includes only farmers that chose to sell some or all of a crop. If the decision to sell is non-random and is correlated with duration of time to sell, then the covariates we use to explain the time to sell could instead be capturing the decision to sell. We use the following specification:

$$t_{c,f} = \mathbf{x}_{c,f}\beta + u_{c,f}, \tag{22}$$

$$w_{c,f} = 1(\mathbf{z}_{c,f}\gamma + \varepsilon_{c,f} > 0), \tag{23}$$

where $t_{c,f}$ is the time that farmer $f$ takes to sell crop $c$, $w_{c,f}$ is an indicator variable that takes value 1 if farmer $f$ sells crop $c$ and 0 otherwise, $\mathbf{x}_{c,f}$ are the same covariates used in the benchmark specification (see equation 21), and $\mathbf{z}_{c,f}$ are covariates explaining selection. The covariates that explain selection include all the variables that explain the time to sell with the exception of the variable *Intermediary* which is only defined when $w_{c,f} = 1$ and therefore would make equation (23) redundant. We also add three variables that we use in Table 4 to capture alternative explanations of the time to sell and which we hypothesize to explain the decision to sell: *Price information*, *Own consumption*, and *Crop concentration*. Like with *Intermediary*, we do not include *Place of sale* in the selection process for lack of information for farmers that do not sell. We use crop, province, and crop times province fixed effects in the outcome equation but only crop and province fixed effects in the selection equation. The model cannot be estimated with crop times province fixed effects in the selection equation.

We jointly estimate equations (22) and (23) by maximum likelihood. The sample is composed of 362 farmers that sell crops (for a total of 609 farmer-crop observations) and 79 farmers that do not sell their crops (an additional 304 farmer-crop observations for which we have price data). As noted before, we do not observe $t_{c,f}$ but only the intervals that correspond to the farmers' answers and, therefore, use an interval-regression approach. The estimation assumes that $u_{c,f}$ and $\varepsilon_{c,f}$ are jointly normally distributed,[18] with errors $u_{c,f}$ and $\varepsilon_{c,f}$ that are allowed to be correlated. The correlation in the residuals that we estimate is what makes the decision to sell possibly nonrandom with respect to the time to sell variable. As before, the standard errors are clustered at the household level.

The results for our baseline model specification expanded with selection are shown in column 1 in Table 8). The results are quite similar to what we get when we disregard selection (column 1 in Table 4), except that the expected price growth is no longer significant. Expected price growth is also not significant for the decision to sell (column 2). The variable that captures farmers being liquidity constrained remains significant as an explanation to the time to sell, but is not significant for the decision to sell. We also find that having a larger output increases the chances that the farmer will sell a crop, as does having information on prices of that crop. Furthermore, having a larger household or using a crop mostly for own consumption decrease the propensity to sell, as would be expected.

[Table 8 here]

When we include interactions of the expected price growth with liquidity constraints (columns 3 and 4), we continue to find that the time to sell of constrained farmers is significantly more sensitive to increases in the expected price growth (column 3), as predicted by the model, although only at the 10% level. Overall, after accounting for selection, when the expected price growth increases by one standard deviation, liquidity-constrained farmers increase the time they take to sell a crop by roughly 12% relative to the median, a value that is quite close to that reported above for the regressions that do not allow for selection.

The remaining four columns in Table 8 redo the analysis while using price levels (i.e., the expected price and the actual price) instead of the expected price growth. In columns 5 and 6 prices are not

[18] This makes estimation simple in Stata even if it relies on somewhat different assumptions than what we use in the rest of the paper. The specifications would be closest if we had used the time to sell intervals in logs in (22) and had used the lognormal distribution instead of the Weibull in (21). The results using logs are qualitatively similar.

significant in either the equations describing the time to sell and the decision to sell. Overall, these results are very similar to those shown in the specifications in columns 1 and 2. When we interact the price levels with the liquidity constrained dummy (columns 7 and 8), both the expected price interacted with the liquidity constraint dummy and the actual price interacted with the liquidity constraint dummy are significant and have the predicted sign. Again, these results mimic those of columns 3 and 4 and are consistent with the model where the price effects occur only for liquidity constrained farmers. Note that in both columns 3 and 7 the linear combinations of the effect of expected price growth on time to sell is large (0.579 in column 3 and 0.539 in column 7) and statistically significant at 5% or better (untabulated).

We conduct another robustness exercise by excluding from the analysis the observations relating to cassava. This crop is, like maize, also a staple food with only a small fraction of farmers reporting that they produce it mainly for market. Excluding cassava results in a sample of 550 farmer crop observations. Despite the loss of degrees of freedom, the results are qualitatively similar with a small increase in statistical significance. The results are available upon request.

# 7 Conclusion

This paper documents that smallholder farmers in rural Mozambique are well aware of market conditions: they expect prices to be higher in the lean season viz-à-viz the harvest season. Yet, they fail to store their crops long enough to capture the higher prices occurring in the lean season. Our model of liquidity constraints suggests that they do so in order to meet the consumption needs right after the harvest season. We document that for liquidity constrained farmers, the amount of produce stored increases with the expectation of higher future prices and decreases with the actual market prices. These effects are consistent with the model of liquidity constrained farmers that we develop.

How much income is it necessary so as to observe that farmers better capture market conditions? Several papers have advanced our knowledge on this question (e.g., Basu and Wong 2015, and Burke et al. 2019). Aggarwal et al. (2018) show that providing savings schemes designed around communally storing lead to increases in storage and in the cases where farmers sold, to increases in the time to sell.

Channa et al. (2018) show that improving storage conditions in parallel with granting loans to households can lead them to save more. More research is needed to follow the wealth patterns of farmers over time as they attempt to leave the vicious cycle of low wealth and low ability to time the market.

More research can also be done on the causes of the price patterns observed in the data. One possible reason for prices to be lower earlier in the season is that buyers are aware of the liquidity constraints of farmers and their low bargaining power. Another is associated with the costs of storage and the limited storage capacity at the time of harvest that creates an excess supply around harvest time. Also, more research should be dedicated to understanding the role that farmer associations can play in alleviating the inability to time the market.

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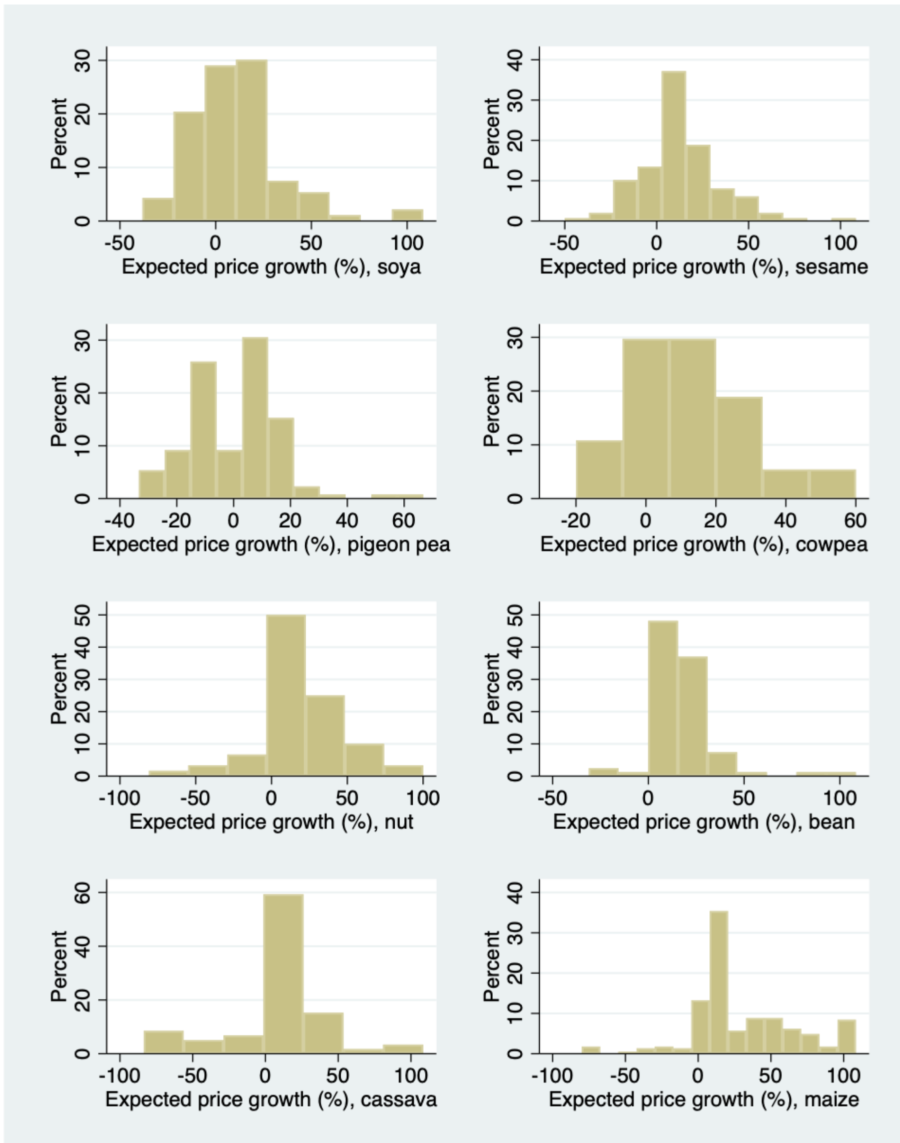


Figure 1: Histograms of farmers' expected price appreciation 30 days after surveyed by crop

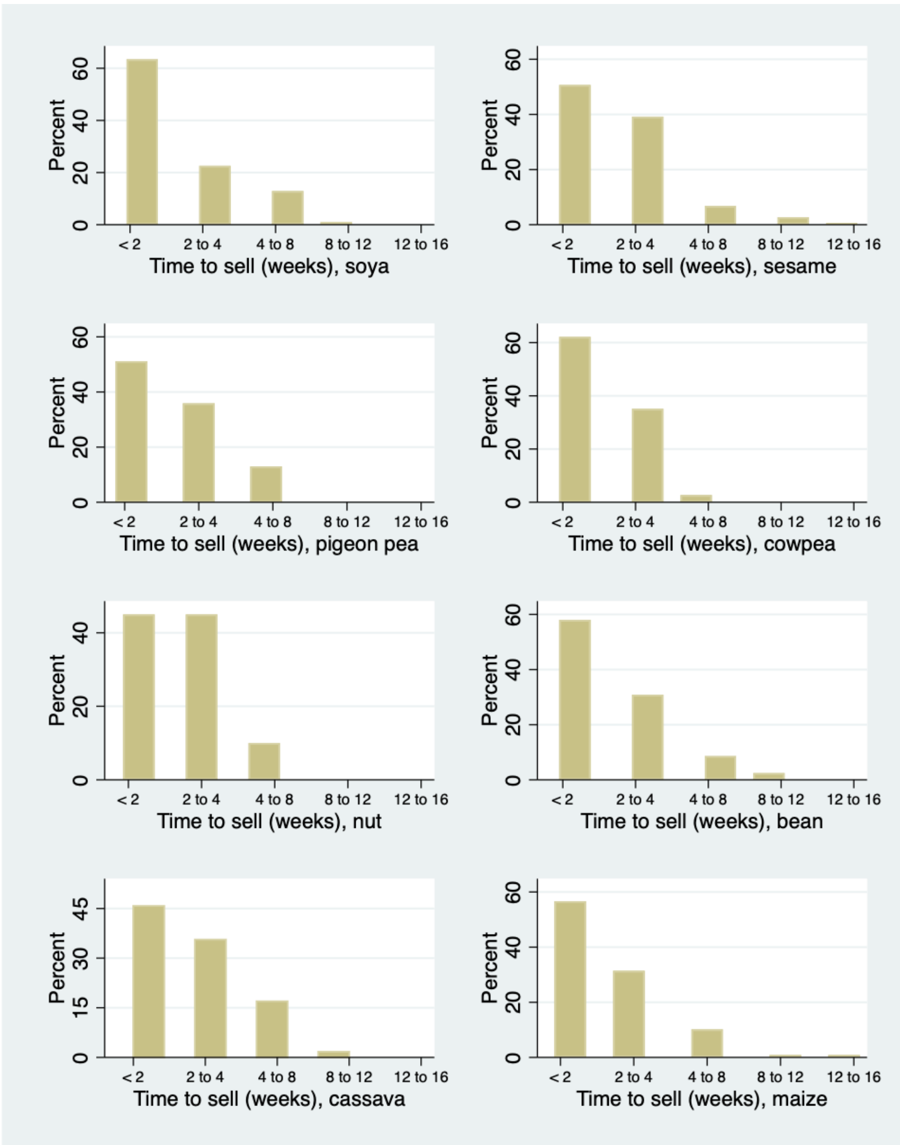


Figure 2: Histograms of farmers' time to sell since harvest by crop

Table 1: Summary statistics

This table shows summary sample statistics for the variables used in the analysis from pooled data: the number of observations, the mean, the standard deviation, and the 25th and 75th percentiles. The variables are described in the appendix Table A1.

| | Observations | Mean | Standard deviation | 25th percentile | 75th percentile |
|---|---|---|---|---|---|
| Time to sell | 609 | 1.169 | 1.386 | 0 | 2 |
| Expected price growth | 609 | 1.106 | 0.239 | 1 | 1.2 |
| Expected price | 609 | 3.557 | 0.513 | 3.199 | 3.977 |
| Actual price | 609 | 3.482 | 0.482 | 3.091 | 3.872 |
| Output | 609 | 5.367 | 1.182 | 4.654 | 6.133 |
| Poor storage | 609 | 0.103 | 0.305 | 0 | 0 |
| Liquidity constrained | 609 | 0.793 | 0.405 | 1 | 1 |
| Female | 609 | 0.105 | 0.307 | 0 | 0 |
| Schooling | 609 | 4.892 | 3.071 | 3 | 7 |
| Intermediary | 609 | 0.099 | 0.298 | 0 | 0 |
| Has DUAT | 609 | 0.174 | 0.379 | 0 | 0 |
| Household size | 609 | 6.297 | 2.659 | 4 | 8 |
| Own consumption | 609 | 0.442 | 0.497 | 0 | 1 |
| Price information | 609 | 0.419 | 0.494 | 0 | 1 |
| Place of sale | 609 | 0.304 | 0.460 | 0 | 1 |
| Crop concentration | 609 | 0.387 | 0.132 | 0.295 | 0.469 |
| Price variation | 603 | 0.391 | 0.190 | .256 | .484 |

Table 2: Farmer's price information and market participation

This table shows sample means for variables that describe market access and price information at the farmer-crop level. Market is a dummy variable that equals 1 if the farmer reports selling the respective crop primarily to the market, share sold is the percentage of output that the farmer sells, and expected price growth is the ratio of the expected price 30 days after the survey to the price the farmer obtained when selling the crop. Data on expected price growth is reported by crop and by province.

| | | | | Expected price growth by province/total | | | | |
|---|---|---|---|---|---|---|---|---|
| Crop | Obs. | Market | Share sold | Nampula | Zambezia | Manica | Sofala | Total |
| Maize | 226 | 0.062 | 0.372 | 1.453 | 1.320 | 1.229 | 1.325 | 1.309 |
| Large groundnut | 60 | 0.300 | 0.600 | 1.222 | 1.197 | 1.218 | 1.103 | 1.185 |
| Butter bean | 81 | 0.198 | 0.683 | 1.137 | 1.192 | 1.185 | 1.063 | 1.165 |
| Cowpea | 37 | 0.324 | 0.620 | 1.121 | 1.246 | 1.070 | 1.114 | 1.123 |
| Pigeon peas | 131 | 0.382 | 0.740 | 0.967 | 1.003 | 1.251 | 1.143 | 1.009 |
| Cassava | 59 | 0.085 | 0.638 | 1.096 | 0.959 | 1.219 | 0.878 | 1.062 |
| Sesame | 148 | 0.986 | 0.945 | 1.029 | 1.026 | 1.193 | 1.160 | 1.136 |
| Soya bean | 93 | 1 | 0.875 | 1.035 | 1.145 | 1.055 | 1.298 | 1.113 |
| Total | 835 | 0.424 | 0.665 | 1.153 | 1.130 | 1.200 | 1.154 | 1.161 |

Table 3: Correlation between explanatory variables

This table reports the matrix of linear correlation coefficients for the variables used in the analysis. The variables are described in the appendix Table A1.

| Variables | Expected price growth | Output | Expected price | Actual price | Poor storage | Liquidity constrained | Female | Schooling | Intermediary | Has DUAT | Household size | Own consumption | Price information | Place of sale | Crop concentration | Price variation |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Expected price growth | 1.00 | | | | | | | | | | | | | | | |
| Output | -0.10 | 1.00 | | | | | | | | | | | | | | |
| Expected price | 0.36 | -0.30 | 1.00 | | | | | | | | | | | | | |
| Actual price | -0.14 | -0.27 | 0.86 | 1.00 | | | | | | | | | | | | |
| Poor storage | 0.04 | -0.03 | -0.04 | -0.05 | 1.00 | | | | | | | | | | | |
| Liquidity constrained | -0.00 | -0.06 | 0.06 | 0.06 | 0.08 | 1.00 | | | | | | | | | | |
| Female | 0.05 | -0.07 | 0.01 | -0.01 | 0.02 | -0.16 | 1.00 | | | | | | | | | |
| Schooling | -0.01 | 0.10 | -0.05 | -0.05 | -0.07 | -0.04 | -0.18 | 1.00 | | | | | | | | |
| Intermediary | 0.21 | 0.08 | 0.10 | 0.02 | 0.21 | 0.17 | -0.02 | -0.06 | 1.00 | | | | | | | |
| Has DUAT | 0.01 | 0.09 | -0.06 | -0.07 | 0.06 | -0.00 | -0.03 | 0.00 | 0.18 | 1.00 | | | | | | |
| Household size | 0.13 | 0.10 | 0.11 | 0.05 | -0.07 | -0.01 | -0.01 | -0.01 | 0.09 | 0.13 | 1.00 | | | | | |
| Own consumption | -0.09 | -0.08 | -0.07 | -0.01 | 0.05 | -0.04 | 0.05 | 0.08 | -0.03 | -0.06 | -0.05 | 1.00 | | | | |
| Price information | -0.02 | -0.09 | 0.03 | 0.03 | -0.09 | 0.04 | 0.06 | 0.03 | -0.03 | 0.07 | -0.01 | -0.21 | 1.00 | | | |
| Place of sale | 0.07 | -0.16 | 0.07 | 0.04 | -0.01 | 0.10 | 0.11 | -0.07 | -0.10 | -0.02 | -0.07 | -0.13 | 0.22 | 1.00 | | |
| Crop concentration | 0.11 | -0.14 | 0.11 | 0.06 | 0.01 | -0.05 | -0.02 | 0.07 | 0.02 | -0.09 | -0.03 | -0.03 | 0.02 | -0.09 | 1.00 | |
| Price variation | -0.02 | 0.03 | 0.06 | 0.08 | -0.07 | -0.00 | -0.04 | 0.11 | -0.11 | 0.10 | 0.11 | 0.06 | 0.02 | -0.03 | 0.01 | 1.00 |

Table 4: Time to Sell - Benchmark specification and alternative explanations

This table reports coefficients from the maximum likelihood estimation of the model for interval-censored survival data with a proportional-hazards parameterization. The dependent variable is *Time to sell* and the regressors are described in the appendix Table A1. The empirical model includes crop, province, and crop × province fixed effects. p-values are computed using robust standard errors and significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Expected price growth | 0.247** | 0.225* | 0.217* | 0.259** | 0.254** | 0.202* |
| | (0.047) | (0.059) | (0.078) | (0.040) | (0.041) | (0.084) |
| Output | 0.064** | 0.048* | 0.067** | 0.064** | 0.062** | 0.046* |
| | (0.024) | (0.076) | (0.020) | (0.025) | (0.028) | (0.095) |
| Poor storage | -0.097 | -0.120 | -0.100 | -0.109 | -0.095 | -0.133 |
| | (0.342) | (0.218) | (0.322) | (0.287) | (0.356) | (0.165) |
| Liquidity constrained | -0.507*** | -0.469*** | -0.525*** | -0.502*** | -0.513*** | -0.493*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Female | 0.088 | 0.118 | 0.088 | 0.083 | 0.083 | 0.114 |
| | (0.335) | (0.193) | (0.349) | (0.362) | (0.371) | (0.233) |
| Schooling | 0.029*** | 0.029*** | 0.030*** | 0.029** | 0.030*** | 0.029*** |
| | (0.008) | (0.008) | (0.007) | (0.011) | (0.007) | (0.007) |
| Intermediary | -0.275** | -0.326*** | -0.271*** | -0.283*** | -0.266** | -0.316*** |
| | (0.010) | (0.001) | (0.009) | (0.009) | (0.014) | (0.001) |
| Has DUAT | -0.392*** | -0.375*** | -0.384*** | -0.383*** | -0.395*** | -0.356*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Household size | 0.036*** | 0.034*** | 0.037*** | 0.036*** | 0.035*** | 0.035*** |
| | (0.002) | (0.002) | (0.001) | (0.002) | (0.003) | (0.002) |
| Price information | | -0.225*** | | | | -0.244*** |
| | | (0.001) | | | | (0.000) |
| Place of sale | | | 0.104 | | | 0.137** |
| | | | (0.148) | | | (0.048) |
| Own consumption | | | | 0.070 | | 0.050 |
| | | | | (0.371) | | (0.488) |
| Crop concentration | | | | | -0.209 | -0.229 |
| | | | | | (0.427) | (0.365) |
| Constant | 0.503* | 0.715*** | 0.498* | 0.497* | 0.592** | 0.823*** |
| | (0.057) | (0.005) | (0.061) | (0.059) | (0.040) | (0.004) |
| Observations | 609 | 609 | 609 | 609 | 609 | 609 |

Table 5: Time to Sell - Interactions with liquidity constraints

This table reports coefficients from the maximum likelihood estimation of the model for interval-censored survival data with a proportional-hazards parameterization. The dependent variable is *Time to sell* and the regressors are described in the appendix Table A1. The empirical model includes crop, province, and crop × province fixed effects. p-values use robust standard errors and significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Expected price growth | -0.464 | -0.383 | -0.526* | -0.453 |
| | (0.101) | (0.216) | (0.076) | (0.159) |
| Liquidity constrained | -1.459*** | -1.010* | -1.510*** | -0.990 |
| | (0.000) | (0.093) | (0.000) | (0.106) |
| Liquidity constrained x expected price growth | 0.860*** | 0.757** | 0.919*** | 0.820** |
| | (0.007) | (0.030) | (0.005) | (0.021) |
| Output (log) | 0.056* | 0.109* | 0.057** | 0.122* |
| | (0.055) | (0.065) | (0.048) | (0.051) |
| Poor storage | -0.082 | -0.069 | 0.105 | 0.180 |
| | (0.426) | (0.510) | (0.565) | (0.329) |
| Female | 0.073 | 0.082 | 0.071 | 0.082 |
| | (0.417) | (0.366) | (0.426) | (0.366) |
| Schooling | 0.029*** | 0.029** | 0.029*** | 0.029** |
| | (0.008) | (0.010) | (0.008) | (0.010) |
| Intermediary | -0.305*** | -0.302*** | -0.302*** | -0.296*** |
| | (0.005) | (0.005) | (0.006) | (0.006) |
| Has DUAT | -0.385*** | -0.374*** | -0.382*** | -0.369*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Household size | 0.035*** | 0.035*** | 0.035*** | 0.034*** |
| | (0.002) | (0.003) | (0.003) | (0.003) |
| Liquidity constrained x Output | | -0.062 | | -0.076 |
| | | (0.313) | | (0.247) |
| Liquidity constrained x Poor storage | | | -0.217 | -0.286 |
| | | | (0.318) | (0.188) |
| Constant | 1.347*** | 0.963 | 1.383*** | 0.937 |
| | (0.001) | (0.101) | (0.001) | (0.115) |
| Observations | 609 | 609 | 609 | 609 |

Table 6: Time to Sell - Source of effect

This table reports coefficients from the maximum likelihood estimation of the model for interval-censored survival data with a proportional-hazards parameterization. The dependent variable is *Time to sell* and the regressors are described in the appendix Table A1. The empirical model includes crop, province, and crop × province fixed effects. p-values are computed using robust standard errors and significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Expected price | 0.243** | 0.133 | 0.248** | -0.333 |
| | (0.044) | (0.503) | (0.041) | (0.207) |
| Actual price | -0.079 | -0.080 | -0.035 | 0.458** |
| | (0.499) | (0.494) | (0.853) | (0.045) |
| Output | 0.065** | 0.063** | 0.065** | 0.058** |
| | (0.019) | (0.024) | (0.019) | (0.043) |
| Poor storage | -0.097 | -0.099 | -0.096 | -0.089 |
| | (0.322) | (0.307) | (0.331) | (0.359) |
| Liquidity constrained | -0.518*** | -1.000 | -0.320 | -0.761 |
| | (0.000) | (0.139) | (0.619) | (0.267) |
| Female | 0.086 | 0.084 | 0.086 | 0.071 |
| | (0.345) | (0.360) | (0.348) | (0.430) |
| Schooling | 0.029*** | 0.029*** | 0.029*** | 0.029*** |
| | (0.008) | (0.009) | (0.008) | (0.009) |
| Intermediary | -0.248** | -0.251** | -0.249** | -0.274*** |
| | (0.017) | (0.014) | (0.017) | (0.008) |
| Has DUAT | -0.382*** | -0.383*** | -0.381*** | -0.375*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Household size | 0.036*** | 0.036*** | 0.036*** | 0.035*** |
| | (0.001) | (0.002) | (0.001) | (0.002) |
| Expected price x liquidity constrained | | 0.136 | | 0.732** |
| | | (0.466) | | (0.019) |
| Actual price x liquidity constrained | | | -0.057 | -0.679** |
| | | | (0.753) | (0.015) |
| Constant | 0.240 | 0.648 | 0.075 | 0.480 |
| | (0.507) | (0.381) | (0.913) | (0.513) |
| Observations | 609 | 609 | 609 | 609 |

Table 7: Time to Sell - Price variation and expected prices

This table reports coefficients from the maximum likelihood estimation of the model for interval-censored survival data with a proportional-hazards parameterization. The dependent variable is *Time to sell* and the regressors are described in the appendix Table A1. The empirical model includes crop, province, and crop × province fixed effects. p-values are computed using robust standard errors and significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

| | (1) | (2) | (3) |
|---|---|---|---|
| Expected price | 0.227* | 0.226* | -0.369 |
| | (0.060) | (0.059) | (0.150) |
| Expected price x liquidity constrained | | | 0.755** |
| | | | (0.013) |
| Price variation | 0.383* | 0.765* | 0.761* |
| | (0.093) | (0.074) | (0.080) |
| Price variation x liquidity constrained | | -0.508 | -0.498 |
| | | (0.265) | (0.278) |
| Actual price | -0.086 | -0.095 | 0.430* |
| | (0.455) | (0.407) | (0.051) |
| Actual price x liquidity constrained | | | -0.665** |
| | | | (0.014) |
| Output | 0.061** | 0.064** | 0.056** |
| | (0.026) | (0.021) | (0.047) |
| Poor storage | -0.096 | -0.087 | -0.082 |
| | (0.333) | (0.380) | (0.403) |
| Liquidity constrained | -0.513*** | -0.311 | -0.687 |
| | (0.000) | (0.122) | (0.303) |
| Female | 0.079 | 0.083 | 0.069 |
| | (0.388) | (0.363) | (0.446) |
| Schooling | 0.030*** | 0.030*** | 0.029*** |
| | (0.008) | (0.008) | (0.009) |
| Intermediary | -0.257** | -0.262** | -0.290*** |
| | (0.011) | (0.011) | (0.004) |
| Has DUAT | -0.382*** | -0.382*** | -0.374*** |
| | (0.000) | (0.000) | (0.000) |
| Household size | 0.034*** | 0.035*** | 0.034*** |
| | (0.002) | (0.002) | (0.003) |
| Constant | 0.208 | 0.056 | 0.411 |
| | (0.560) | (0.886) | (0.564) |
| Observations | 603 | 603 | 603 |

## Table 8: Time to Sell - Selection in the decision to sell

The table reports coefficients from the maximum likelihood estimation of the model for interval-censored data with selection. The dependent variables are *Time to sell* (the outcome variable) and *Sell* (the selection indicator that equals 1 if the farmer sells the crop and zero otherwise). The table presents four different specifications, two of them with expected price growth (columns 1 and 2, and columns 3 and 4), and two others with expected price and actual price showing separately (columns 5 and 6, and columns 7 and 8). The variables are described in the appendix Table A1. The empirical model includes crop, province, and crop × province fixed effects for the outcome variable, and crop and province fixed effects for the selection process. p-values are computed using robust standard errors and significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

| Dependent variable | (1) Time | (2) Sell | (3) Time | (4) Sell | (5) Time | (6) Sell | (7) Time | (8) Sell |
|---|---|---|---|---|---|---|---|---|
| Expected price growth | 0.339 | 0.238 | -0.564 | 0.827* | | | | |
| | (0.193) | (0.285) | (0.304) | (0.070) | | | | |
| Liquidity constrained x Expected price growth | | | 1.142* | -0.713 | | | | |
| | | | (0.051) | (0.164) | | | | |
| Expected price | | | | | 0.345 | -0.018 | -0.582 | 0.658 |
| | | | | | (0.178) | (0.935) | (0.281) | (0.141) |
| Liquidity constrained x Expected price | | | | | | | 1.121* | -0.765 |
| | | | | | | | (0.055) | (0.123) |
| Actual price | | | | | -0.048 | -0.095 | 0.767 | -0.493 |
| | | | | | (0.858) | (0.669) | (0.144) | (0.283) |
| Liquidity constrained x Actual price | | | | | | | -0.977* | 0.431 |
| | | | | | | | (0.091) | (0.395) |
| Liquidity constrained | -0.930*** | -0.107 | -2.197*** | 0.675 | -0.937*** | -0.104 | -1.521 | 1.101 |
| | (0.000) | (0.453) | (0.002) | (0.251) | (0.000) | (0.458) | (0.190) | (0.286) |
| Output | 0.198*** | 0.544*** | 0.189*** | 0.553*** | 0.197*** | 0.535*** | 0.187*** | 0.547*** |
| | (0.002) | (0.000) | (0.005) | (0.000) | (0.001) | (0.000) | (0.003) | (0.000) |
| Poor storage | -0.097 | 0.018 | -0.076 | 0.014 | -0.078 | 0.031 | -0.059 | 0.027 |
| | (0.583) | (0.923) | (0.667) | (0.942) | (0.651) | (0.866) | (0.734) | (0.883) |
| Female | 0.262 | -0.141 | 0.256 | -0.153 | 0.255 | -0.127 | 0.255 | -0.141 |
| | (0.174) | (0.394) | (0.188) | (0.354) | (0.180) | (0.444) | (0.181) | (0.399) |
| Schooling | 0.047** | 0.028 | 0.047** | 0.028 | 0.047** | 0.027 | 0.047** | 0.026 |
| | (0.032) | (0.187) | (0.034) | (0.184) | (0.033) | (0.188) | (0.034) | (0.212) |
| Intermediary | -0.503*** | | -0.546*** | | -0.513*** | | -0.541*** | |
| | (0.002) | | (0.001) | | (0.002) | | (0.001) | |
| Has DUAT | -0.769*** | -0.275* | -0.742*** | -0.298* | -0.743*** | -0.267* | -0.718*** | -0.292* |
| | (0.000) | (0.083) | (0.000) | (0.064) | (0.000) | (0.096) | (0.000) | (0.071) |
| Household size | 0.068*** | -0.061*** | 0.065*** | -0.059** | 0.069*** | -0.059** | 0.067*** | -0.059** |
| | (0.003) | (0.010) | (0.005) | (0.013) | (0.002) | (0.012) | (0.003) | (0.012) |
| Price information | | 0.367** | | 0.354** | | 0.371** | | 0.371** |
| | | (0.010) | | (0.014) | | (0.010) | | (0.012) |
| Own consumption | | -1.409*** | | -1.412*** | | -1.431*** | | -1.437*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Crop concentration | | 0.022 | | 0.056 | | -0.013 | | 0.007 |
| | | (0.964) | | (0.911) | | (0.979) | | (0.989) |
| Constant | 1.412** | -0.997* | 2.484*** | -1.684** | 0.824 | -0.279 | 1.348 | -1.304 |
| | (0.023) | (0.061) | (0.008) | (0.023) | (0.246) | (0.702) | (0.270) | (0.228) |
| Observations | 609 | 913 | 609 | 913 | 609 | 913 | 609 | 913 |

Table A1: Variable definitions

| Variable name | Definition |
|---|---|
| Time to sell | Farmers that sold their crop were asked: "How long does it take to sell output?" Farmers were provided six possible answers: "Up to 2 weeks", "Up to 4 weeks", "Up to 2 months", "Up to 3 months", "Up to 4 months", and "Other." Most respondents answered either "Up to 2 weeks"or "Up to 4 weeks" and no farmer answered "Other". The time to sell is codified to belong to one of three intervals: [0-2], [2-4], or [4-16]. The variable summarized in Table 1 measures the time in weeks (lower bound of the interval) it took to sell share of crop destined for sale according to the farmer's answer. |
| Actual price | Price at which crops were sold (in Mozambican meticais by kilo and in logs). The variable collects the answers the farmers gave when asked "What was the price perceived for the output already sold?" |
| Expected price | Expected price by farmer 30 days after the interview (in Mozambican meticais by kilo and in logs). The variable collects the answers the farmers gave when asked "What price do you expect to prevail next month (30 days after interview)?" |
| Expected price growth | Ratio of expected price to actual price, winsorized at the top 1 percent. |
| Output | Total crop output in kilos (in logs) according to farmer's answer to the question: "What was the volume of harvest (by crop)?" |
| Poor storage | Farmers were asked "Store conditions can be considered as...?". The possible answers were "Good", "Fair", or "Poor". The variable is a dummy taking value 1 if farmer reports storage conditions as "Poor". |
| Liquidity constrained | Farmers were asked "Do you have trouble placing your output in the market?" and given the choice to answer "Yes" or "No". If they answered "Yes", they were asked to explain and were given 16 possible answers. The variable is a dummy taking value 1 if farmer answered "Yes" and selected the explanation "Availability of credit". |
| Female | Dummy taking value 1 if head of household is female based on demographic information provided by survey respondent for each member of the household, including her/himself. |
| Schooling | Number of years of schooling of the head of household based on demographic information provided by survey respondent for each member of the household, including her/himself. |
| Has DUAT | Farmers were asked if her/his farm had a DUAT (a title granted by the government securing the right to use and benefit from the land). The variable is a dummy that takes value 1 if the farmer answered "Yes". |
| Household size | Number of individuals in the household based on demographic information provided by survey respondent for each member of the household, including her/himself. |

Table A1: Variable definitions (continued)

| Variable name | Definition |
|---|---|
| Own consumption | Farmers were asked "What is the main destination of the harvest?" The possible answers were "Own consumption", "Market", or "Both". The variable is a dummy taking value 1 if most of crop is destined for sale (or "Market"). |
| Price information | Farmers were asked "How often did you get information on prices?" The possible answers were "Weekly", "Monthly", "Quarterly", "Biannually", "Yearly", or "Other". The variable is a dummy taking value 1 if farmer gets information on prices weekly. |
| Place of sale | Farmers were asked "Where do you sell your harvest?" The possible answers were "Own farm", "Local store", "Local market", "Local warehouse", "Processing plant", "Local mill". The variable is a dummy that takes value 1 if most crop is sold at farm. |
| Crop concentration | Farmers were asked "What surface is destined to each crop?" Based on their answers, we calculate a Hirschman-Herfindahl index of share of total cultivated surface of each crop. A higher value means higher dependence on fewer crops. |
| Price variation | The variance of the expected price calculated over the answers provided by the 10 nearest neighbors to the farmer. Distance (in kms) is calculated using GPS coordinates using P.W. Jeanty's `nearstat` module for Stata. |