Negative returns are a general explanation for failure to exploit temporal arbitrage

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Abstract

We propose a new explanation for the frequently observed "sell low, buy high" behavior among small farmers in developing countries: frequent negative returns to storage due to price *decreases* after harvest. We use 20 years of data from 781 markets in 23 African countries to demonstrate that the lean season price (the "high price" season) fails to rise above the harvest season price (the "low price" season) 27.5% of the time. On the basis of that stylized fact, we propose a new explanation for farmers opting out of storage: aversion to these negative returns. We show that moderately risk averse farmers rationally opt out of storage in 37% of market-years.

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Staple cereal grain prices exhibit recurring patterns of seasonal price fluctuations in rural markets in developing countries, often with low prices at harvest, followed by steady rises to an annual high by planting season (Kaminski et al., 2016, 2014; Devereux et al., 2008). This pattern is a documented contributor to seasonal hunger, malnutrition, and food insecurity among small farm households (Sahn, 1989; Christian and Dillon, 2018).

Even so, small farm households have often proved unable or unwilling to exploit inter-temporal arbitrage opportunities for storable staple cereals including maize and rice. Instead, they are observed to sell their crops when prices are low, often repurchasing the same commodity for consumption later in the year when prices tend to be substantially higher (Barrett, 2007). As Stephens and Barrett (2011) observe, farmers engaging in this pattern of selling low and buying high are essentially using staple grain markets as a lender of last resort. Explanations for this pattern of behavior have centered on liquidity constraints and transaction costs (Stephens and Barrett, 2011; Burke et al., 2019; Aggarwal et al., 2018),consumption price-hedging (Saha, 1994; Park, 2006), inadequate storage technologies (Walker et al., 2018; Channa et al., 2019) and time-inconsistent preferences (Le Cotty et al., 2019).

We provide a new explanation for this documented reluctance among small farmers to store across seasons: a risk of realizing negative returns on stored cereals in years in which prices fail to rise after harvest. While on average across years prices do rise after harvest, and while on average those increases are economically significant, we document that prices do not always rise, and we demonstrate the importance of this possibility for poor farmers who cannot borrow across years.

Our analysis has three parts. First, we review 20 years of data from 781 markets in

23 African countries to establish the distribution of price differences across seasons. We demonstrate that market prices in lean ("high price") seasons do not always exceed the prevailing price during the harvest ("low price") season; we calculate returns for each season as the percent change from the harvest season price to the following lean season price. Moreover, we find a high frequency of *negative* returns to storage: returns are negative 27.5% of the time across markets and years, ranging from a low of 11.5% in Burkina Faso to a high of 50.0 % in Tanzania. We document the phenomenon of harvest season prices failing to rise in every year since 2000 and across all countries in our data.

In fact, a lean season price can not only fail to rise relative to the harvest season price; it can also prove considerably lower. For example, in years when the lean season price fails to exceed the price at harvest, the average difference has recently ranged between 5.7% lower in Burkina Faso to 19.2% lower in The Gambia. Our comparisons are conservative; we abstract away from the costs of storage equipment and space, post-harvest losses in storage, foregone interest on sales revenue, and any added costs farmers might incur associated with selling in the lean season.

Second, because price dynamics varying from year to year are not sufficient to imply that farmers face a high and recurring risk of financial loss, we show that farmers cannot reliably predict intertemporal returns from the realized harvest price. Years with high and low harvest season prices (relative to average) exhibit negative returns, and regressions of the returns to storage on the harvest price z-score fail to explain the observed variation. We demonstrate that farmers cannot predict with certainty the years in which prices fail to rise after harvest and returns to storage are negative.

Third, based on insights from analysis of the price data, we use a simplified version of a rational expectations commodity storage model to calculate the degree of risk aversion required to rationalize farmers selling at harvest. Focusing on households storing for later sales, we show that farmers with a moderate level of risk aversion would opt out of storage 37% of the time (across markets and years).

Economists have long focused on the effects of price volatility and stabilization on consumers and producers (Waugh, 1944; Oi, 1961; Stiglitz, 1969; Deaton and Laroque, 1992; Sarris et al., 2011; Bellemare et al., 2013). Barrett and Dorosh (1996) show that price uncertainty reduces the incentive to store among poor farmers in Madagascar. Saha and Stroud (1994) use risk aversion to explain what they characterize as an excess of precautionary storage among small farmers in India. Park (2006) considers both price and yield risk and finds that farmers in China store grain as a consumption price hedge, not as a substitute for credit, and that the non-negativity of grain storage can explain why many subsistence farmers are net buyers across seasons. The commodity storage literature has modeled endogenous storage decisions under different expectation models: Maître d'Hôtel and Le Cotty (2018); Mitra and Boussard (2012); Boussard (1996) find that grain storage often fails to mitigate price shocks, and imperfect storage behavior may increase price volatility.

Our contribution is the breadth of data we bring to the analysis. Existing studies documenting price fluctuations and proposing interventions related to storage and credit have two important limitations: first, these analyses are commonly based on only one or two years of data; second, they normally analyze the differences between mean harvest season prices and lean season prices by averaging either across years or across markets or both.[1] By analyzing more data over a longer time span, we demonstrate how price variations can affect storage choice. Our work builds on Gilbert et al. (2017), who use data from 193 markets in 7 countries to document food price seasonality in Sub-Saharan Africa and demonstrate that short samples (between 5-15 years) can produce upwardly biased estimates of the extent of seasonality in food markets.

The price risk we describe and quantify has particular salience in the context of a credit market failure that prevents farmers from borrowing across years. Our analysis therefore draws an important distinction regarding the sort of credit farmers need to access to take advantage of inter-temporal arbitrage opportunities between harvest and lean season. Average returns across years are high and positive; with credit access permitting borrowing across years farmers could pursue a buy-low sell-high strategy backed by the ability to borrow in bad years and pay back their loans in good years. Yet the focus in the literature has long been on credit permitting farmers to borrow within the same year between harvest and lean season. Our results suggest that in the presence of downside price risk, providing credit across seasons will not be sufficient to induce storage for many farmers characterized by even moderate risk aversion.

Accordingly, numerous recent interventions by Non-Governmental Organizations and researchers have been designed to provide credit and storage options to farmers,

[1] Indeed, by pulling individual years of data or by averaging across years and markets, we can replicate the results and graphs suggesting the presence of inter-temporal arbitrage opportunities that drive the existing literature and associated interventions to promote farmer storage across seasons.

and a wealth of Randomized Control Trials (RCTs) have been implemented in recent years to evaluate such efforts. Burke et al. (2019) provide credit to farmers in Kenya; Basu and Wong (2015) distribute storage equipment to farmers in Indonesia; Aggarwal et al. (2018) encourage communal maize storage in Kenya; Channa et al. (2018) combine storage and credit in Tanzania, Le Cotty et al. (2019) and Delavallade and Godlonton (2020) offer an inventory credit system in Burkina Faso in two separate studies. Several of these studies have noted the phenomena that we discuss here, mostly when an intervention to encourage storage has achieved attenuated results because it was conducted in a year in which prices failed to rise significantly after harvest (Le Cotty et al., 2019; Channa et al., 2018).[2]

Our results indicate that the probability of negative returns is an important deterrent to storage by risk averse small farmers and small traders. The observation that negative returns to storage are widespread and economically significant challenges prevailing assumptions about the persistent puzzle of low storage uptake in much of sub-Saharan Africa.

[2] For example, Le Cotty et al. (2019) mention in their analysis of inventory credit in Burkina Faso, "In 2013, the rise in grain prices was exceptionally low (only three percent on average). As a result the capital gain was not enough to offset the cost of warrantage" (p.15). Channa et al. (2018) conduct their storage and credit RCT in a year in which the price failed to rise in Malawi and write, "Maize prices did not rise in the lean season...because the government of Tanzania imposed an export ban".

1 Empirical Analysis

1.1 Data

The World Food Programme (WFP) food price monitoring system reports monthly food prices using data collected by WFP and national agricultural ministries (Caccavale and Flämig, 2017). Data are available at a sub-national level for food staples, fruits, vegetables, and animal products. We select all countries in Sub-Saharan Africa (SSA) with monthly retail prices available for maize. Maize is an economically critical crop, the basis of the diet of many poor rural households in the region and a primary crop grown by those same households. If prices for more than one variety of maize are available for a given market in the data, e.g. yellow and white maize, we chose the country's more predominant variety. We adjust prices to 2015 local currency values using Consumer Price Index (CPI) data from the International Monetary Fund (IMF). We do this in order to control for inflation without introducing additional variability from exchange rate fluctuations.[3]

The analysis requires that we identify the harvest and lean season for each market. Agricultural season data are collected by the Food and Agricultural Organization (FAO) for the Global Information and Early Warning System (GIEWS) GIEWS reports national and sometimes sub-national harvest and planting season dates for various crops, with data provided by national ministries.

We merge the agricultural season designations with the price data to identify the prices for the "harvest" and "planting" months. If GIEWS reports multiple

[3] We have also performed the calculations and analysis in deflated USD and the conclusions of the paper hold.

agricultural regions within a country, we use the maize season data located closest to the market coordinates, within the same country.

Our designation of the harvest and lean season prices is obviously critical. We calculate inter-seasonal price differences (and associated returns) conservatively. We designate the seasons from the perspective of a farmer considering grain storage at the end of harvest: we create a "harvest season price" as the last price of the months designated by GIEWS as harvest months for a given market. The "lean season price" is the maximum price of the months designated as planting. This combination of prices has the advantage of being data-driven and conservative, providing a lower bound on the probability of negative returns. We calculate returns for each season as the percent change of the "lean season price" over the previous "harvest season price". As a robustness check, we consider arbitrage opportunities over shorter time frames.[4]

We retain in the data all years for which we have price data for both the harvest season and the following lean season: for example, if the harvest occurs in September-October of 2018 and planting in January-February 2019, the return for the 2019 market-season is the percent change from the October 2018 "harvest" price to the January or February 2019 "lean" price, depending on whichever month had the higher price. If either the harvest or planting season price was unavailable for that market-season pair, we do not include the observation in our data. We select prices

[4] The GIEWS data are a good guide, but because we do not know the precise harvest date in each geography, we also run specifications in which we use the lowest price during harvest months rather than the price in the last month of the harvest season. Our results are robust to letting the data define the harvest price rather than GIEWS.

to represent the farmers' decision-making problem – whether to store or sell at the end of harvest and the return they would have received in the lean season if they chose to store maize in a given year.

GIEWS reports multiple maize seasons for a subset of countries with two growing seasons per year, which we account for by calculating the average return across the two seasons. We remove 81 markets with only year included in the data, and two countries, Guinea and Guinea-Bissau, with fewer than 20 market-years. Our final data include 5624 market-year observations across 781 markets in 23 countries in sub-Saharan Africa between the years 2000-2019. [5]

Note that the WFP market price data are mostly collected from primary and secondary markets closer to urban population centers. Smaller, rural markets tend to be less well integrated than urban markets. It is therefore likely that these data and our analysis underestimate the degree of price fluctuation experienced by small farmers.

1.2 Results: Price differentials across seasons

We find evidence of both positive and negative price differentials between harvest and lean seasons. Returns to storage are positive on average (across years) but negative price differentials are frequent. Moreover, the phenomenon of negative price differentials across harvest and lean season is widespread, not confined to any

[5] Of the 781 markets, 573 have only one maize season annually, and the remaining 208 markets have two seasons. We average returns across seasons for each market-year instead of including them as separate observations, because it provided a closer estimate of expected annual returns. Results hold if we let these seasons enter separately into the analysis.

country or set of years. This finding is contrary to prior research that has assumed that higher lean season prices ensure positive returns to storing grain at harvest.

In Table 1, we present a summary of the data and findings. For each country, we present the years for which data was available, the number of markets in Column (1) and the total number of market-years in Column (2) (ie: for Benin, there are 58 total market-year observations across 19 markets and 12 years.) Column (3) presents the frequency of negative returns: the proportion of market-years in each country in which the price decreased from harvest to the following lean season. Column (4) presents the average returns by country across all market-years. Column (5) presents the average returns in each country for market-years in which the price increased from harvest to the subsequent lean season. Column (6) presents the average negative returns for market-years in which the price decreased, i.e. the alternative and less-discussed case: years in which the harvest season price exceeded the lean season price. As noted, these calculations are conservative and likely underestimate the frequency and magnitude of negative returns; due to storage costs and losses, farmers storing grain would need prices to rise to cover those costs just to break even.

The results presented in Table 1 demonstrate the presence of positive returns to storage on average: across all market-years in all countreis, the average returns were positive: 20.0% (Column (4)). And yet, farmers in countries across Sub-Saharan Africa also experience years characterized by important negative price trends between harvest and lean season (Columns (3) and (6)); years in which the price stays flat or even declines in the lean season relative to its level at harvest. The phenomenon of negative returns to storage occurs in all countries in our data. Tanzania has the highest incidence, with 50% of its market years exhibiting price declines after harvest;

in all countries in the data negative returns occur at least 10% of the time. Reliance on averages across years masks important variation across years and markets.[6]

1.3 Negative returns to storage across years

In Figure 1(a), we present the distribution of returns for each market-year across time. The figure demonstrates that the phenomenon of negative returns to storage is not restricted to particular years, nor is it attenuating in time. Each dot in the graph presents returns to storage for a given market in a given year. In all years, we see markets where lean season prices were lower than harvest prices.

One explanation for low returns in a given year could be local supply shocks - high maize yields in oversupplied and poorly integrated markets. We use annual national maize yield data from FAO to assess associations between maize yields and intra-annual price trends in a given year. The color of each dot in Figure 1(a) represents the national maize yield for each market-year. We see no clear relationship between these national-level yields and returns to storage, with both high and low yields associated with years of negative returns to storage. Clearly, our use of national-level yields masks significant within-country variation in maize yields in a given year here. Moreover, political and economic circumstances likely contribute idiosyncratically and unpredictably to intertemporal movements in commodity prices,

[6]Market skewness data presented in Appendix Table A1 further reinforces this: while on average, markets are positively skewed, with most averages falling between 0-1, the share of markets that are negatively skewed is high in a few countries such as Benin, Burkina Faso, Chad, and Senegal. In these countries, frequent or severe price drops might deter risk averse farmers from storing to capture future arbitrage opportunities, even if returns are positive on average.

especially in low harvest years. Food aid inflows or government release of grain stocks for example in response to poor regional harvests could contribute to the patterns we document: in years when high prices might generate a return to storing maize, such policies would decrease the price significantly in the lean season. Other government interventions or changes market policies such as export bans could be factors: an analysis of five countries in East and Southern Africa found that export bans did not have a statistically significant effect on cross-border price gaps, and moreover were associated with increases in domestic prices and price volatility (Porteous, 2017).

1.4 Negative returns to storage across markets

Figure 1(b) shows that even in markets where expected returns are high on average, the risk of loss is nontrivial. Each dot represents one market. We present the percent of seasons in which the harvest season price exceeded the lean season in that market on the x-axis and the average returns to storage for that market on the y-axis. The size of the dot represents the number of yearly observations available for that market. Consistent with Table 1 and Figure 1(a), returns are generally positive on average for a given market across years; most of the dots sit above the y-axis value of zero. The figure demonstrates the frequency and intensity of the negative returns phenomenon across markets. Note that returns are always positive in our data for 191 markets, and for five markets, returns are always negative. For those five markets, there are 11 market-year observations covering four different countries, and eight different years, i.e. each market in that group of five only has 2-3 observations. Insights hold if these five markets are excluded.

1.5 Intra-temporal Returns

We have so far defined returns to storage as the increase or decrease in lean season price over the harvest season price. However, a farmer could store for a shorter period of time (selling after the harvest but before the lean season), to take advantage of any intra-temporal returns. In the appendix, we show the distributions of returns to storage by the number of months post-harvest for each country. We present evidence that in some countries including Mozambique, Malawi, and Zambia, waiting five to nine months after harvest will yield positive results on average, however for all countries, there is a non-zero probability of negative returns for every month the farmer waits to sell. (Appendix Figure A1)

2 Can farmers predict the years with negative storage returns?

We have shown evidence of the substantial frequency of negative returns in every country in our data, However, inter-annual variation in whether returns to storage are positive is not sufficient to imply the existence of risk. The key question is whether the farmer can predict when the returns will be negative and when they will be positive. He has to be able to predict this at harvest, when he makes the decision to store or sell.

If the harvest price is a perfect predictor of whether returns to storage are negative, than the farmer knows which state of the world he is in (a year with negative returns to storage or with positive returns to storage) and can make his decision accordingly. If the harvest price signal is strong, we would see farmers opting out of storage when harvest prices are high relative to normal.

On the other hand, if the farmer cannot predict returns based on the observed harvest price, then the farmer will bear some risk associated with storing. In this case, farmers seen to opt out of storage would be opting out because of a non-trivial risk of loss associated with storage and not because they can tell that the returns to storage will be negative.

We investigate whether farmers can tell when returns will be negative in two ways. First, we graph in Figure 2 the return to storage for the primary maize season for each market-year over z-scores of harvest prices for each country. The plus signs represent years with positive returns and the circles represent years in which returns proved less than or equal to zero. If harvest price was a consistent indicator of returns, we would expect a clear negative relationship between the magnitude of the returns to storage and the price at harvest, with positive returns (plus signs) occurring when harvest prices were low, and negative returns (circles) confined to regions characterized by higher than average harvest prices. While we see some evidence of this relationship, we find that negative returns occur across the distribution of harvest prices, indicating that farmers are unable to perfectly predict the returns to storage given information at harvest.

Second, in Table 2 we evaluate country-specific regressions on returns to storage (Columns (1) and (2)) and the likelihood of negative returns (Columns (3) and (4)). The former show results from OLS regressions by country where the dependent variable is returns to storage for the primary maize season, and the latter show results from probit regressions by country where the dependent variable is binary, equal to 1 if returns are less than or equal to zero. For both models the explanatory variable is harvest price z-score with year fixed effects. Column (1) and (3) show the coefficients on z-score and columns (3) and (4) show the R^2 and pseudo-R^2, respectively. As expected, higher harvest prices are associated with lower returns to storage (Columns (1) and (3)) but considerable unexplained variation remains. Farmers cannot tell with certainty when they face a year characterized by negative returns to storage. The bottom two rows of Table 2 present the average R^2 across the regressions for all 23 countries and the R^2 from a regression pooling all observations across countries and including country and year fixed effects.

Our analysis in this and the subsequent section relies on a strong assumption that the price processes are stationary, so that the time series we use represents farmers' current beliefs about any given season's conditional seasonal price distribution. And of course, we lack additional information that the farmer may have at her disposal about for example local transport or marketing disruptions though to some degree the year fixed effect can proxy for these annual changes across markets in a given country.

3 Risk aversion and opting-out of storage

The decision to store grain in each market-year is a gamble. At harvest, the farmer observes the harvest price and decides whether to sell or store, without knowing the lean season price. We established in the previous section that farmers cannot tell with certainty when the price will decline after harvest but we know that they will use that observed harvest price to make a decision about storage in a given year, given what they know about the distribution of the lean season price.

What degree of risk aversion, given measured gains and losses, would be required to explain the strategy of not engaging in storage? We use observed prices at harvest and the distributions of lean season prices to calculate what degree of risk aversion would be required to make storage unappealing ex ante by country.

3.1 Model

We consider a simple model where the household decides at the end of harvest whether to sell grain immediately or store the grain for future sale. Households that sell and consume grain encounter both income and price risk, and the decision to store relies on the share of the household budget allocated to grain and household preferences, as shown in Barrett (1996); Finkelshtain and Chalfant (1991) and others. In order to avoid placing theoretical constraints on income and household preferences between grain and other goods, we focus on grain that is stored for the purpose of agricultural incomes, and not explicitly for household consumption.

We assume the household is a price taker in both input and output markets and complete markets exist for both. Storage is restricted to being non-negative and farmers do not have access to credit or contingent claims markets. Later, we relax this assumption. At harvest time, the price P_H of the staple grain is known , but the lean season price P_L is not known, however the farmer is aware of the distribution of prices and likelihood of those prices. As in Section 2, we assume that price processes are stationary. We do not include storage costs or losses, or other transaction costs. Prices are defined per kilogram of maize, and normalized to 2015 local currency. We do not consider the impact of output risk, as the harvest quantity is known at the time of harvest.

The household should store grain if $P_L > P_H$, however the stochastic nature of the lean season price prevents the household from evaluating this tradeoff. While on average the lean season price is higher than the harvest season price, the additional price risk faced by the household may not be welfare-improving. We assume the households have von Neumann-Morgenstern utility functions. We calculate the farmer's Certainty Equivalent (CE) over a range of risk aversion levels for all market-years. The intuition is the following: Pratt (1964) showed that an individual's certainty equivalent (CE) for a gamble is the lowest amount of money-for-certain that a decision-maker would be willing to accept instead of the gamble. For risk averse individuals, the CE will be less than the expected value of the gamble.

We calculate:

$$E[U(S_H P_L)] = U(S_H CE) \tag{1}$$

where S_H is the quantity of grain in kilograms that the farmer is considering storing at harvest. Newbery and Stiglitz (1979) showed that taking a Taylor-series approximation of the left and right hand sides of Equation (1) around the mean payoff $S_H E[P_L] = S_H \bar{P}_L$ yields an approximation of the risk premium for small risks in terms of the Arrow-Pratt measures of risk aversion.

We define those measures of absolute risk aversion $A = -\frac{U''}{U'}$ and relative risk aversion $R = -S_H \bar{P}_L \frac{U''}{U'}$, with utility evaluated at $S_H \bar{P}_L$, and variance of $S_H P_L$ equal to $\bar{S_H}^2 var_{P_L}$. The certainty equivalent can be approximated as

$$CE \approx \overline{P_L} - \frac{1}{2} \cdot R \cdot \frac{var_{P_L}}{\overline{P_L}} \tag{2}$$

Note that storage quantity S_H is not explicitly included in Equation (2), only implicitly in the determination of the relative risk aversion coefficient.

In our case, the CE is the lowest amount the farmer would accept to not face the risk of storing; he would trade the gamble of storing (and the risk of prices falling in the lean season) for this amount. The CE is increasing in risk aversion and in the variance of the lean season price distribution and decreasing in the lean season mean price. If the CE is greater than the known harvest price P_H, then the farmer will prefer to store the grain for future sales, and if the CE is less than or equal to the harvest price, the farmer would be better off selling at harvest.

We calculate the CE for each market-year in the data using the WFP price series, deflated to 2015 local currency, and identify harvest and lean season prices consistent with the analysis in Section 1.1. We focus on the primary maize season. We simulate the coefficient of relative risk aversion over the set [0,5) in increments of 0.1, drawing on findings in the experimental literature on small farmers in low income countries. (Fafchamps and Pender, 1997; Binswanger, 1982; Barrett, 1996) We calculate the first and second moments of the random lean season price P_L at the country level, with a storage decision for each market-year based on the harvest season price.

Selling at harvest is a welfare-improving decision in a given market-year if the known harvest price is higher than the certainty equivalent. The certainty equivalent is a function of the lean season price mean and variance and the risk aversion of the decision-maker. We assume price shocks are exogenous, reasonable for modelling the decision of a smallholder farmer. Other models incorporate endogenous price shocks Boussard (1996) or restrict storage markets to be competitive and markets to be positively skewed(Deaton and Laroque, 1992). Mitra and Boussard (2012) use a

Nerlovian adaptive expectation process where storage firms use information from the prior period to form expectations of future prices while Maître d'Hôtel and Le Cotty (2018) incorporate heterogeneity in farmer awareneness of storage availability. Our assumptions of stationarity and country level aggregation of prices is non-negligible, but reasonable to explain storage behavior on the extensive margin.

3.2 Results

We use the calculated CE to determine the share of market-years in each market for which selling grain at harvest is the preferred choice for each risk aversion coefficient between 0 and 5, with 0 representing risk neutral farmers.

Table 3 presents these results aggregated into three categories: risk neutral and low risk aversion, moderate risk aversion, and high risk aversion, to show the share of market-years in which farmers would rationally forgo storage. These results are given by country. Results suggest that even for risk neutral and low risk aversion farmers, selling at harvest can be the optimal choice, either because of high harvest prices, low expected lean season prices, or high lean season price variance. On average across all countries, moderately risk averse farmers would rationally sell at harvest 36.7% of the time rather than store. These results are conservative, as any storage costs or losses would make storage more costly, reducing the likelihood that a farmer should store for future sales.

Our results suggest that not all farmers would rationally store grain in all markets and all years. In the years in which they opt out, the risk of negative returns is too great relative to what they could earn with certainty at harvest.

3.3 Credit constraints

The analysis in the preceding section has no credit costs and no investment opportunities for farmers. Access to financial markets could benefit farmers considering storage in two ways: first farmers who sold at harvest could invest any profits at a rate of return i, and second, farmers with harvest season debts could take out a loan at some cost while storing grain to sell in the lean season.

For simplicity, assume the interest rate (i) is equivalent in either scenario, and known to the farmer at harvest, and there is no intertemporal discounting. Then the farmer should sell at harvest if $P_H(1+i)$ is greater than the certainty equivalent (CE), as defined in Equation (2), and he should store if the harvest price is less than $\frac{CE}{(1+i)}$. Even a conservative interest rate of 5% serves to increase the share of market-years in which a farmer opts out of storage (Appendix Table A2).

3.4 Storage costs and losses

The additional costs associated with taking on credit would result in fewer arbitrage opportunities, by reducing the payoff from storage, effectively shifting the distribution of returns toward zero. Storage costs and transaction costs would have a similar effect, and the reduction in payoffs would convince more farmers to sell at harvest. Our results, which do not consider any additional costs, are conservative, as additional costs are likely.

3.5 Predicted lean season price

Table 2 showed that the harvest price is a predictor of lean season price, and therefore seasonal returns, but not a perfect predictor. As a robustness check, we use the predicted lean season price from an OLS regression of lean season price on harvest season price with year fixed effects, separately for each country. Using the expectation and variance of the predicted lean season price, we construct the certainty equivalent of the *predicted* lean season price, and compare it to the harvest season price to determine if a farmer would choose storage. We find that the share of market-years in which a farmer avoids storage decreases slightly; however on average across countries, moderately risk averse farmers would prefer to sell at harvest for 33.1% of market-years (Appendix Table A3).

4 Discussion

A focus on average patterns of seasonal prices in the literature has led many researchers to overlook an important grain storage risk relevant to small farmer and small trader decision-making: years in which the lean season price fails to rise above the price at the time of harvest and no inter-temporal arbitrage opportunity occurs. We demonstrate that negative returns to storage occur in all countries and all years. We also find that negative returns are associated with a range of harvest season prices, thereby preventing households from predicting returns from harvest season prices and adjusting storage choice to maximize returns. We show that storing is not a welfare-improving strategy in all markets in all countries, and that risk aversion can influence the farmer's decision to store.

Our results demonstrate that in all contexts under review, storing is not always an optimal choice, compared to immediate post-harvest sales for all farmers because of this substantial probability of negative returns, even when those returns are expected to be much higher on average. This finding constitutes a new insight in the literature, helping to explain why farmers opt to sell immediately post-harvest if they have no hedging options, and also why small-scale traders (who lack the capital to engage in spatial arbitrage opportunities or to arbitrage across good and bad years) may limit the scale of their operations. Inclusion of loss aversion or present bias as well as calculations countenancing the costs of storage, transaction, and search costs would only strengthen our result.

Our results generate new hypotheses suggesting several promising directions for future work on this and other related topics. We have focused on the circumstance and storage decision of net seller farm households in this analysis. Risk aversion and price uncertainty among net buyer households would be expected to lead to more precautionary storage. Future work might take our insights to data on household storage behavior, testing for heterogeneity in the relationship between price uncertainty and storage behaviors depending on whether the household is a net buyer or net seller for example.

We demonstrate that using a conservative definition of negative returns, the assumption of positive returns to storage does not always hold, and in fact, the possibility of negative returns provides a new and important explanation for the widely-observed and persistent "puzzle" of low storage uptake.

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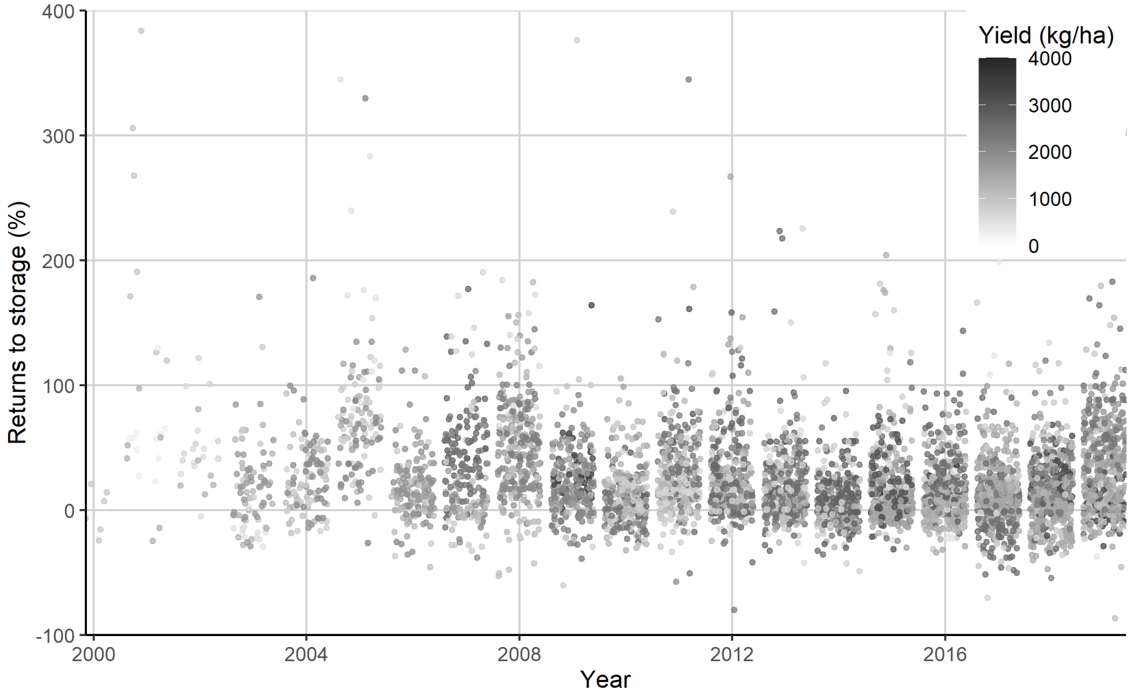
Table 1: Frequency and Magnitude of Negative Returns to Storage for 26 Countries and 20 Years of Data

Country	Years	Number of Markets (1)	Number of Market-Years (2)	Frequency of Negative Returns (3)	Average Total Returns (4)	Average Positive Returns (5)	Average Negative Returns (6)
Benin	2007-2019	19	58	19.0%	17.9%	25.6%	-14.9%
Burkina Faso	2004-2019	54	347	11.5%	17.9%	21.0%	-5.7%
Burundi	2007-2019	59	215	27.4%	21.7%	35.6%	-15.1%
Cameroon	2005-2017	5	65	20.0%	14.3%	20.0%	-8.6%
CAR	2005-2019	17	60	31.7%	25.6%	44.3%	-14.8%
Chad	2004-2019	12	75	25.3%	17.5%	27.5%	-12.3%
Cote d'Ivoire	2005-2019	10	60	30.0%	20.3%	35.7%	-15.6%
DR Congo	2008-2019	31	162	32.1%	23.3%	42.9%	-18.0%
Ethiopia	2007-2018	25	173	33.5%	19.3%	34.2%	-10.2%
Gambia	2007-2018	18	106	37.7%	5.5%	20.5%	-19.2%
Kenya	2006-2019	9	80	42.5%	3.8%	12.1%	-7.5%
Malawi	2003-2019	119	983	14.0%	31.7%	38.0%	-7.3%
Mali	2004-2019	61	541	14.8%	15.8%	19.8%	-7.3%
Mozambique	2000-2019	24	307	14.0%	56.6%	68.1%	-14.0%
Niger	2001-2019	64	624	29.5%	11.7%	20.0%	-8.0%
Rwanda	2008-2019	77	373	31.9%	13.1%	24.4%	-11.0%
Senegal	2008-2019	50	320	23.4%	15.9%	23.0%	-7.3%
South Sudan	2008-2019	6	39	41.0%	23.5%	51.9%	-17.4%
Tanzania	2016-2019	15	60	50.0%	5.5%	28.2%	-17.2%
Togo	2001-2019	6	114	29.8%	22.0%	34.8%	-8.1%
Uganda	2012-2019	8	45	33.3%	23.6%	43.4%	-16.0%
Zambia	2003-2019	69	717	18.3%	34.1%	44.7%	-13.4%
Zimbabwe	2010-2018	23	100	22.0%	19.2%	26.5%	-6.6%
Total		781	5624	27.5%	20.0%	32.3%	-12.0%

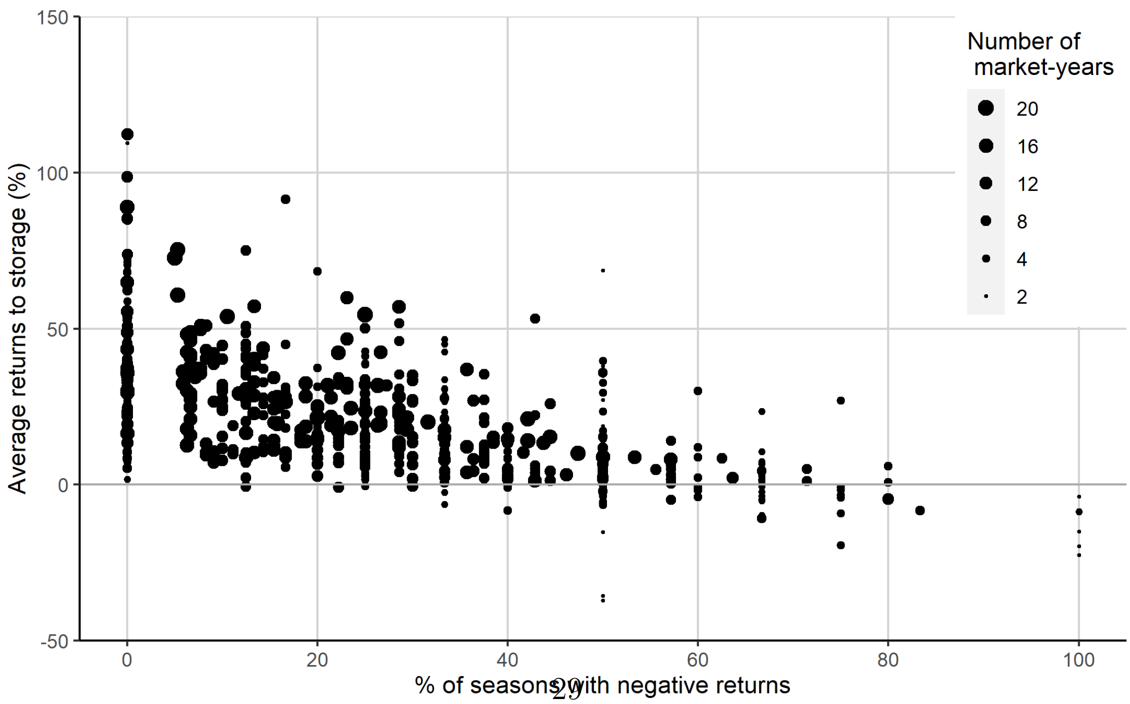
[1] Monthly maize retail price data from the WFP Global Food Prices Database for 2000-2020. Prices were adjusted to 2015 local currency value using IMF data on historical monthly CPI. National and subnational agricultural season data was reported from FAO-GIEWS via the University of Wisconsin.

[2] Columns (3)-(6): Returns are calculated for each "market-year" as the percent difference in lean season price over the previous harvest season price. The lean season price is defined as the maximum price of the months defined as planting season, and the harvest season price is the price of the last month defined as harvest season. For markets with two agricultural seasons per year, returns for each year were averaged across the two seasons for this table.

Figure 1: Historical Trends for Returns to Maize Storage



(a) Returns to maize storage over time and yield
(market-year observations)



(b) Intensity and frequency of negative returns to storage
(market observations)

Figure 2: Returns to storage by harvest price for primary maize season (market-year observations)

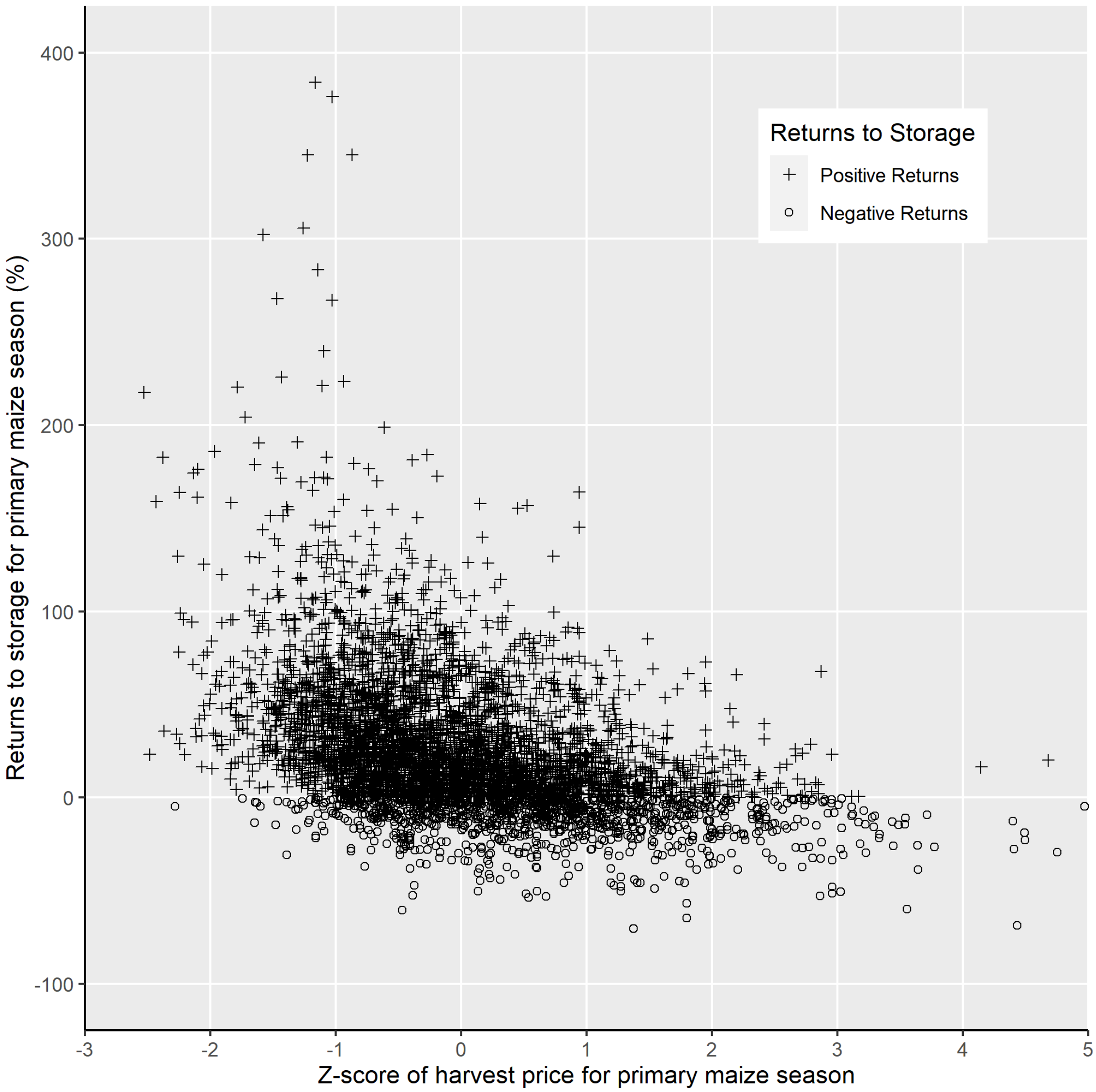


Table 2: Regressions of harvest prices on returns to storage and the probability of negative returns for the primary maize season

Dep. variable	Returns to Storage (%)		Negative Returns (=1 if Returns$\leq$ 0)	
	Harvest price z-score	R squared	Harvest price z-score	Pseudo-R squared
Country	(1)	(2)	(3)	(4)
Benin	87.831***	0.43	0.088	0.22
Burkina Faso	-4.068	0.67	0.103***	0.40
Burundi	15.576	0.57	0.252***	0.50
Cameroon	9.008	0.40	0.004	0.44
CAR	244.823**	0.44	0.465***	0.52
Chad	13.895	0.67	0.234***	0.52
Cote d'Ivoire	-0.036	0.45	0.124**	0.50
DR Congo	72.739**	0.29	0.247***	0.28
Ethiopia	-1.802	0.71	0.186***	0.32
Gambia	-16.418***	0.53	0.398***	0.51
Kenya	-27.952***	0.57	-0.045	0.47
Malawi	3.735	0.58	0.181***	0.36
Mali	-5.975	0.68	0.111***	0.33
Mozambique	-29.266**	0.70	0.136***	0.44
Niger	46.589***	0.60	0.193***	0.29
Rwanda	52.011***	0.66	0.225***	0.51
Senegal	20.651***	0.58	0.126***	0.33
South Sudan	7.725	0.56	0.28**	0.43
Tanzania	59.701***	0.76	0.189**	0.46
Togo	41.518***	0.63	0.172***	0.54
Uganda	17.678	0.72	0.172***	0.69
Zambia	46.558***	0.58	0.118***	0.52
Zimbabwe	7.115	0.42	0.123***	0.30
Cross country average		0.57		0.43
Pooled regression		0.41		0.22

[1] Columns (1) and (2) show results from OLS regressions by country of returns to storage (%) on harvest price z-score with year fixed effects. Column (1) is the coefficient on harvest price z-score and column (2) is the R squared for that regression. Columns (3) and (4) show results from regressions by country for negative returns (binary variable =1 if returns were zero or negative) on harvest price z-score with year fixed effects. Column (3) is the average marginal effect (AME) of harvest price z-score from a probit model and column (4) is McFadden's pseudo-R^2 for that country-specific regression.

[2] The cross country average R^2 is calculated as the unweighted average of R^2 for all 23 countries. The pooled regression R^2 is calculcated from the a regression of returns to storage and negative returns, respectively, on harvest price z-score, with country and year fixed effects.

[3] Returns are calculated for each "market-year" for the primary maize season as the percent difference in lean season price over the previous harvest season price. The lean season price is defined as the maximum price of the months defined as planting season, and the harvest season price is the price of the last month defined as harvest season. Harvest Price z-score were calculated at the country level.

[4] ***Significant at the 1 percent level. **Significant at the 5 percent level.*Significant at the 10 percent level.

Table 3: Share of market-years farmers should forgo storage by farmer risk tolerance (averaged over markets)

Country	Risk Neutral and Low Risk Aversion R$\in [0,1)$	Moderate Risk Aversion R$\in [1,3)$	High Risk Aversion R$\in [3,5)$
Benin	26.9%	37.6%	55.9%
Burkina Faso	22.3%	29.0%	39.0%
Burundi	23.5%	28.0%	37.1%
Cameroon	30.0%	36.8%	46.8%
CAR	21.0%	31.5%	81.8%
Chad	29.8%	30.7%	35.4%
Cote d'Ivoire	58.0%	64.0%	66.0%
DR Congo	32.7%	42.8%	67.7%
Ethiopia	25.5%	33.3%	45.9%
Gambia	32.3%	42.7%	54.4%
Kenya	36.3%	49.0%	68.6%
Malawi	21.4%	32.2%	50.4%
Mali	27.6%	32.5%	43.7%
Mozambique	12.7%	19.0%	32.5%
Niger	27.5%	32.3%	40.2%
Rwanda	33.1%	37.0%	43.2%
Senegal	35.6%	37.0%	39.4%
South Sudan	22.7%	43.3%	75.7%
Tanzania	50.0%	58.2%	69.7%
Togo	30.1%	35.8%	45.0%
Uganda	34.5%	42.1%	49.9%
Zambia	12.8%	22.0%	33.8%
Zimbabwe	19.5%	26.7%	36.8%
Cross-country average	28.9%	36.7%	50.4%

[1] Risk tolerance is calculated using the first and second moments of the lean season price for each country, and the harvest price for the primary maize season.

A Appendix

Table A1: Market skewness for 26 Countries and 20 Years of Data

Country	Markets	Average Market Skewness (1)	Share of Markets Negatively Skewed (2)
Benin	19	0.23	42.1%
Burkina Faso	54	0.07	48.1%
Burundi	59	0.49	13.6%
Cameroon	5	0.47	0.0%
CAR	17	0.77	11.8%
Chad	12	0.28	58.3%
Cote d'Ivoire	10	0.15	20.0%
DR Congo	31	0.81	19.4%
Ethiopia	25	0.86	4.0%
Gambia	18	1.17	22.2%
Kenya	9	0.88	0.0%
Malawi	119	0.78	0.8%
Mali	61	3.12	1.6%
Mozambique	24	1.21	0.0%
Niger	64	0.38	18.8%
Rwanda	77	0.51	20.8%
Senegal	50	0.29	42.0%
South Sudan	6	1.45	0.0%
Tanzania	15	0.65	0.0%
Togo	6	1.21	0.0%
Uganda	8	0.84	0.0%
Zambia	69	0.66	4.3%
Zimbabwe	23	0.40	13.0%
Total	781	0.77	14.8%

[1] Monthly maize retail price data from the WFP Global Food Prices Database for 2000-2020. Prices were adjusted to 2015 local currency value using IFS data on historical monthly CPI.

[2] Column (1) is the average market skewness in each country, where market skewness was calculated over all monthly prices for each market in the dataset. Column (2) is the share of markets that are negatively skewed. Kurtosis was positive in all markets in all countries.

Figure A1: Intra-temporal Returns to Storage by Country (for primary maize season)

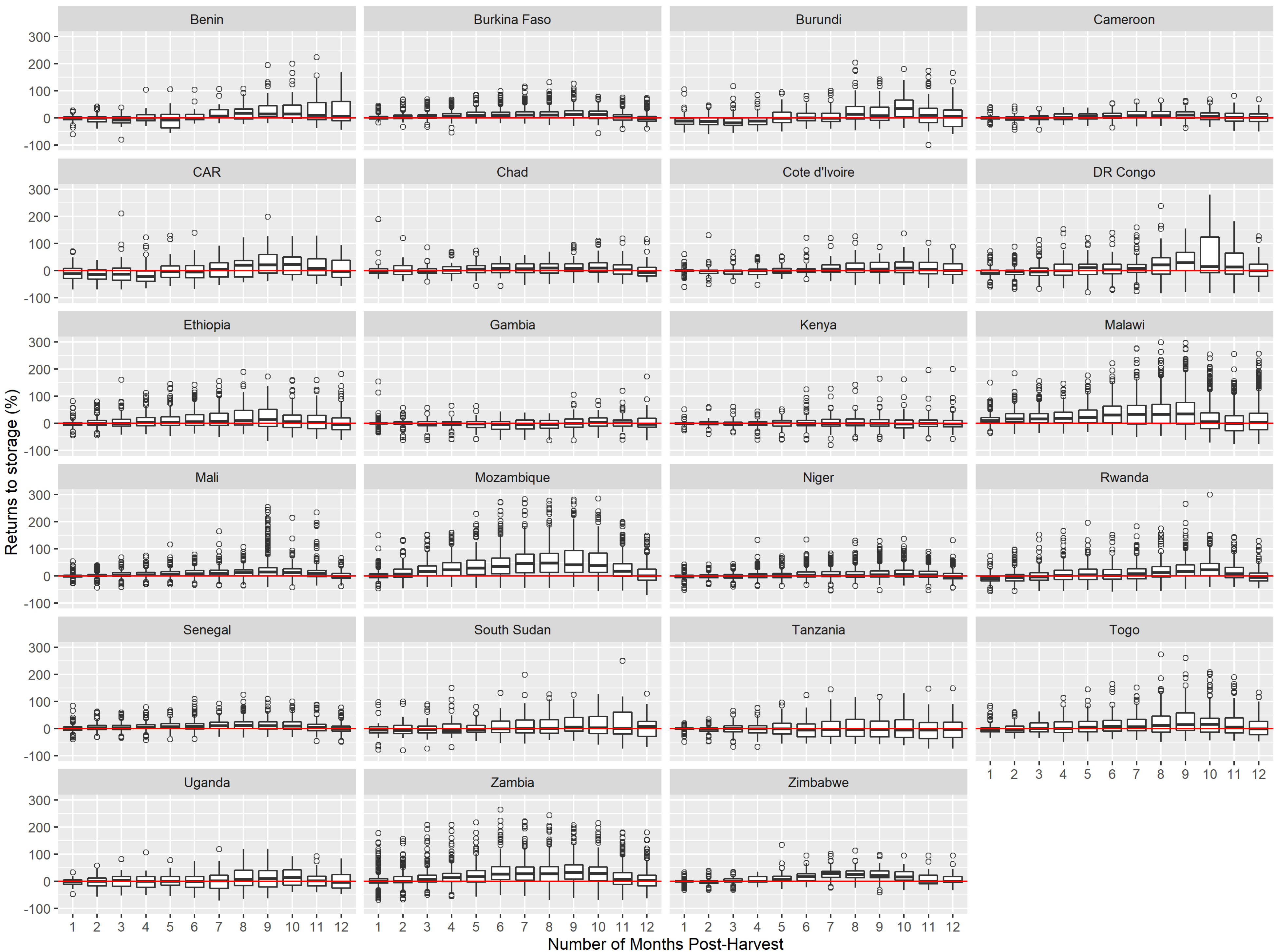


Table A2: Share of market-years farmers should forgo storage by farmer risk tolerance (averaged over markets) with an interest rate of 5%

Country	Risk Neutral and Low Risk Aversion R$\in [0,1)$	Moderate Risk Aversion R$\in [1,3)$	High Risk Aversion R$\in [3,5)$
Benin	33.4%	42.6%	62.9%
Burkina Faso	33.4%	39.8%	45.5%
Burundi	27.9%	33.8%	45.1%
Cameroon	38.0%	44.9%	50.9%
CAR	21.4%	35.3%	85.2%
Chad	30.7%	33.9%	44.2%
Cote d'Ivoire	62.8%	64.6%	68.2%
DR Congo	35.1%	47.6%	72.6%
Ethiopia	32.3%	39.9%	53.2%
Gambia	46.8%	54.1%	60.2%
Kenya	45.1%	56.5%	73.0%
Malawi	24.2%	36.4%	55.8%
Mali	37.6%	45.9%	51.6%
Mozambique	15.0%	23.0%	36.4%
Niger	39.7%	45.4%	52.2%
Rwanda	37.6%	42.9%	49.2%
Senegal	39.4%	43.5%	48.3%
South Sudan	28.4%	49.8%	81.6%
Tanzania	55.6%	61.4%	72.6%
Togo	35.8%	41.3%	49.5%
Uganda	40.8%	45.3%	59.1%
Zambia	20.5%	29.8%	39.8%
Zimbabwe	32.8%	37.7%	48.8%
Cross-country average	35.4%	43.3%	56.8%

[1] Risk tolerance is calculated using the first and second moments of the lean season price for each country, and the harvest price for the primary maize season.

Table A3: Share of market-years farmers should forgo storage by farmer risk tolerance (averaged over markets) based on predicted lean season price

Country	Risk Neutral and Low Risk Aversion R$\in[0,1)$	Moderate Risk Aversion R$\in[1,3)$	High Risk Aversion R$\in[3,5)$
Benin	26.4%	36.2%	50.5%
Burkina Faso	22.1%	27.3%	36.4%
Burundi	23.1%	24.7%	28.4%
Cameroon	29.3%	33.6%	40.3%
CAR	21.0%	27.4%	73.2%
Chad	29.5%	30.7%	30.8%
Cote d'Ivoire	57.6%	63.0%	64.6%
DR Congo	29.9%	32.5%	39.9%
Ethiopia	25.3%	30.9%	38.9%
Gambia	31.3%	33.5%	37.8%
Kenya	36.1%	47.2%	64.3%
Malawi	21.2%	30.3%	45.2%
Mali	27.6%	31.3%	39.5%
Mozambique	12.4%	16.6%	26.7%
Niger	29.1%	31.1%	35.6%
Rwanda	32.3%	35.3%	37.1%
Senegal	35.3%	36.5%	37.2%
South Sudan	20.8%	32.5%	47.9%
Tanzania	47.8%	55.8%	62.2%
Togo	29.8%	32.3%	37.1%
Uganda	33.6%	35.8%	42.8%
Zambia	12.2%	16.9%	25.7%
Zimbabwe	19.5%	20.4%	27.7%
Cross-country average	28.4%	33.1%	42.2%

[1] Risk tolerance is calculated using the first and second moments of the predicted lean season price for each country, and the harvest price for the primary maize season. The predicted lean season price is based on country level OLS regressions of lean season price on harvest price and year.