Price risk and staple grain storage decisions: new insights into a long-standing puzzle

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Abstract

We provide new insight into the often observed "sell low, buy high" behavior among small farmers in low income countries: stochastic variation in crop prices yields frequent negative returns to intra-annual arbitrage. We use 20 years of data from 506 markets in 15 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) 21.6% of the time. On the basis of that stylized fact, we propose that aversion to these negative returns may contribute to farmers' decisions to opt out of storage. We show that 22.1% of moderately risk averse farmers would rationally sell at harvest rather than store.

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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). This intra-annual price 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). For example, Burke et al. (2019) show that the median farmer in their Kenyan study switched from selling maize to purchasing maize five months after harvest and Stephens and Barrett (2011) note that 62% of the households who had been net maize sellers at harvest were purchasing maize a few months later in Western Kenya.

As Stephens and Barrett (2011) observe, farmers engaging in this pattern of selling low and buying high are essentially using staple grain markets as an expensive form of credit. 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) problems of post-harvest pest damage in storage (Kadjo et al., 2016), preferences to consume one's own maize rather than maize in the market (Hoffmann and Gatobu, 2014), and time-inconsistent preferences (Le Cotty et al., 2019).

We provide a new insight relevant to the 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 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 506 markets in 15 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 21.6% of the time across markets and years, ranging from a low of 10.0% in Mozambique to a high of 47.2% 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 5.9% lower in Burkina Faso to 22.9% lower in Tanzania. 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. Moreover, our calculation of the returns is also conservative: we use the minimum price during the harvest months and the highest realized price during 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. One source of price volatility in these markets is government export bans and related policies such as releasing government stock holdings that farmers are unable to anticipate (Porteous, 2017).

Third, based on insights from analysis of the price data, we 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 in 22.1% of markets on average across countries.

We propose that price risk and in particular the possibility of negative returns to storage may contribute to farmers' observed reluctance to hold a significantly share of their harvest across seasons for later sale. It likely interacts with and may exacerbate other critical constraints related to small farmer staple cereal marketing including inadequate storage technology, time inconsistent preferences and liquidity constraints.

Economists have long focused on the effects of price volatility and stabilization on consumers and producers (Waugh, 1944; Oi, 1961; Stiglitz, 1969; Sandmo, 1971; 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. We address precisely the opposite problem, and one that has perplexed researchers for many years working in Sub-Sharan Africa: the appearance of too little storage given average intra-annual price trends.[1]

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.[2] 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

[1]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 that imperfect storage behavior may increase price volatility.

[2]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. See Table 1, which shows (Column 6) that average total returns across market-years are positive for all countries.

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. However, Gilbert et al. deals with only averages, quantifying seasonal changes in expected returns, but not risk.

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 to exploit intra-annual arbitrage opportunities. Our results suggest that in the presence of downside price risk, providing credit across seasons may 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, 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. Yet these studies generally dismiss the possibility of risky returns to storage. For example, Aggarwal et al. (2018) write, “An older literature has looked at price risk as a potential explanation (Saha and Stroud, 1994); however, the current consensus among academics as well as policy-makers is that this is largely implausible.”

A small number of studies based on randomized controlled trials have noted incidents of 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). 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”.

Our results indicate that risky returns may be 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 contributes an important insight to solving the persistent puzzle of low storage uptake in much of sub-Saharan Africa.

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).[3] 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 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 Food and Agricultural Organization (FAO) Statistics, based on data from the International Monetary Fund (IMF). We do this in order to control for inflation without introducing additional variability from exchange rate fluctuations.

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

[3] Caccavale and Flämig (2017) describe the collection process and recommend that weekly prices are collected and averaged to generate a monthly price, however stable commodities and resource constraints might result in a once a month collection.

We merge the agricultural season designations with the price data to identify the prices for the harvest and planting season months. If GIEWS reports multiple 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. Our calculation of inter-seasonal price differences (and associated returns) is conservative and data-driven. We designate the seasons from the perspective of a farmer considering grain storage to take advantage of any arbitrage opportunities: we create a "harvest season price" as the minimum price of the months designated by GIEWS as harvest months for a given market. The "lean season price" is the maximum price of the three months prior to the subsequent harvest, when grain stocks tend to be at their lowest point. This combination of prices provides a lower bound on the probability and the magnitude of negative returns. We calculate returns for each season as the percent change in the "lean season price" over the previous "harvest season price". In the appendix, we show the distribution of average (Appendix Figure A1) and minimum and maximum (Appendix Figure A2) maize prices by month for retail markets, alongside information about the primary maize season. As a robustness check, we consider arbitrage opportunities over shorter time frames, using the last month designated as a harvest month, and calculating returns for holding grain for 1-11 months post-harvest.

We retain all markets for which we have price data for at least five market-years where a market-year contains prices for both the harvest season and the following lean season: for example, if the harvest occurs in September-October of 2018, the return for the 2018 market-year is the percent change from the September or October

2018 "harvest" price to the June, July, or August 2019 "lean" price, depending on whichever month had the lower price, and highest price, respectively. If either price was unavailable for that market-year pair, we do not include the observation in our data. We retain in the data all countries with at least ten markets for each market type (retail and wholesale).

GIEWS reports multiple maize seasons for a subset of countries with two growing seasons per year. In these countries, we calculate the separate returns for each season. Our analysis focuses on the primary maize season for retail markets, and we include analysis of wholesale markets and the second maize season in the Appendix. Our final data include 5099 market-year observations for the primary maize season across 506 retail markets in 15 countries in sub-Saharan Africa between the years 2000-2020.[4]

A concern about missing data in our analysis is that prices may be more likely to be missing in lean season markets that are thin, with little maize present, and high prices. Leaving such market-years out of the analysis will depress the returns to storage in our calculations, biasing our results. In Appendix Table A8, we show the distribution of missingness across seasons and countries. Across all countries, harvest season prices were missing 14.7% on average, while lean season prices were missing 14.3% on average.

Another concern is that the missing data correlated with returns. In Appendix Table A8, column (5) includes the mean return to storage. Appendix Table A8 is replicated in Appendix Figure A6, showing the distribution of data availability and the average returns. There is no discernable pattern between the season in which

[4]An analysis of the selection process and missing data is included in the Appendix. All data and code are available on the author's website.

data was available and the average return.

The WFP market price data are mostly collected from primary and secondary markets. We observe market prices rather than farmgate prices. A critical assumption therefore is that the intra-annual variation we observe in the market data reflects variation that farmers experience. Smaller, rural markets tend to be less well spatially integrated than urban markets due to the fact that they are supplied by smaller market basins and the fact that they tend to be characterized by higher costs of transport and information Badiane and Shively (1998); Fafchamps (1992). Dillon's analysis of the welfare effects of crop storage in Malawi includes a comparison of farmgate and market prices (using the same Malawi market series that we employ); Dillon shows that his constructed time series of farmer-reported maize sale prices exhibits intra-annual trends that are similar to the market price data. (Burke et al., 2019) engage in a similar validation exercise in Malawi, asking farmers and traders to estimate average monthly maize prices at their local market for the five year period preceding their study; they conclude that administrative price series from major markets "appear to be a lower bound on typical increase observed in smaller markets in our study area" (p.7).

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 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 retail markets in the primary maize season. For each country, we present the years for which data was available, the number of markets in Column (3) and the total number of market-years in Column (4) (ie: the Burkina Faso data consists of 401 total market-year observations across 54 markets and 16 years.) Column (5) 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 (6) presents the average returns by country across all market-years. Column (7) presents the average returns in each country for market-years in which the price increased from harvest to the subsequent lean season. Column (8) 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 countries, the average returns are positive: 35.7% (Column (6)). And yet, farmers in countries across Sub-Saharan Africa also experience years characterized by important negative price trends between harvest and lean season (Columns (5) and (8)); 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 47.2% of its market years exhibiting price declines after harvest; in all countries in the data negative returns occur at least 10.0% of the time. Reliance on averages across years masks important variation across years and markets.

While Table 1 focuses on returns to storage in retail markets for the primary maize season, the frequency of negative returns is similar in wholesale markets (26.1%, Appendix Table A1) and for the second season in countries with two maize seasons (22.5%, Appendix Table A2).[5]

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. 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

[5]Market skewness data in Appendix Table A3 further reinforces this finding: while on average, markets are positively skewed, with most averages falling between 0-1, the share of retail markets that are negatively skewed is high in a few countries such as 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.

between these national-level yields and returns to storage, with both high and low yields associated with years of negative returns to storage. Our use of national-level yields likely masks significant within-country variation in maize yields in a given year. Moreover, political and economic circumstances likely contribute idiosyncratically and unpredictably to intertemporal movements in commodity prices, 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. The figure demonstrates the frequency and intensity of the negative returns phenomenon across markets. 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. Mechanically, the graph is characterized by a downward-sloping trend, with markets characterized by higher average returns across years exhibiting a lower number of seasons with negative returns to storage. However, the figure shows the considerable variation in average returns by frequency of negative returns; for example, numerous markets have average returns across years of more than 50% (on the y-axis) but the incidence of negative returns across those markets ranges between zero and 42%.[6]

2 Can farmers predict the years with negative storage returns?

We have shown evidence of the substantial frequency of negative returns to storage 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. A key question is whether the farmer can predict when the returns will be negative or positive. The farmer has to make this prediction at harvest, when he decides to store or sell grain.

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

However, if the farmer cannot predict returns based on the observed harvest

[6] Note that returns are always positive in our data for 99 markets, covering 11 countries distributed across different regions of Africa, and across 20 years.

price, then the farmer will bear some risk associated with storing to sell. In this case, farmers seen to opt out of storage might be doing so 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 (+) occurring when harvest prices were low, and negative returns (o) 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 unlikely to be able 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 one if returns are less than or equal to zero. The explanatory variables for both estimations are harvest price z-score with year fixed effects. Columns (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 15 countries and the R^2 from a regression pooling all observations across countries and including country and year fixed effects. [7]

Our analysis in this and the subsequent section relies on a strong assumption that the returns to storage are stationary, so that the time series we use represents farmers' current beliefs about any given season's conditional seasonal price distribution. We test for the stationarity of returns by market. For only 15 out of 506 markets do we reject that the distribution of returns is stationary. Of course, we lack additional information that the farmer may have at his 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,

[7] The same regression analysis without year fixed effects shows an even weaker relationship between harvest prices and returns. (Appendix Table A4.)

given what they know about the distribution of returns.

What degree of risk aversion, given measured possible gains and losses, would be required to explain the strategy of not engaging in storage? We use the distribution of returns to calculate what degree of risk aversion would be required to make storage unappealing ex ante in each market.

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 stored for sale at a later date.

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 and likelihood of returns if he stores grain to sell in the lean season. As in Section 3, we assume that while prices might exhibit trends, returns to storage ($r = \frac{P_L - P_H}{P_H}$) are likely stationary. We test for stationarity of returns in all markets with more than three years of data using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and reject the null of stationarity in only 15 of the 506 markets and results hold if we exclude those markets. We do not include storage costs or losses, or other transaction costs. We also conduct our analysis using the distribution of lean season prices rather than of returns, and calculate the share of market-years farmers opt out of storage in each market. The results hold and are presented in Appendix Table A5. We do not consider the impact of output risk, as the yield is known at harvest, nor can we separately identify the intertemporal discount factor in this framework.

The household should store grain if returns are positive: $r > 0$, however the stochastic nature of the lean season price prevents the household from evaluating this tradeoff and 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 over a range of risk aversion levels for all markets. 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:

$$E[U(w(1+\tilde{r})] = U(w(1+C)) \tag{1}$$

where w is household wealth, $\tilde{r}$ are the risky returns and C is the certain return the household would be willing to accept to avoid storage. Newbery and Stiglitz (1979) showed that taking a Taylor-series approximation of the left and right hand sides of Equation (1) around the mean outcome $w(1 + E[r]) = w(1 + \bar{r})$ where $\bar{r}$ is the average return 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 $A = -\frac{U''}{U'}(w)$ and relative risk aversion $R = -\frac{wU''}{U'}(w)$, and variance of the risky return equal to σ^2. The certainty equivalent can be approximated as

$$C \approx \overline{r} - \frac{1}{2}R\sigma^2 \tag{2}$$

In our case, the certainty equivalent is the lowest return 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 return. The certainty equivalent is decreasing in risk aversion and in the variance of the return. If $C > 0$, then the farmer will prefer to store the grain for future sales, and if the certain return is less than or equal to zero, the farmer would be better off selling at harvest (i.e. when $r = 0$)

We calculate C for each market in the data using the WFP price series, deflated to 2015 local currency units. 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) The set of 506 retail markets with primary season data includes markets with five or more years available, and countries with at least ten markets. We calculate the first and second moments of the risky return at the market level to determine the certain return and evaluate the storage decision. Selling at harvest is a welfare-improving decision in a given market if the certainty equivalent of the risky return is less than or equal to zero, under the assumption of no additional storage costs or losses. 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).[8]

Note that we model the farmer's decision to sell or store some determined amount of the household's harvested crop production rather than the farmer's decision regarding the share of total production to store or sell at harvest, an interesting and related question. Farmers tend to sell a share of their production at harvest and store the rest for home consumption or sale later in the year. The price risk we focus on in this analysis may also help explain farmers' partial sale decision at harvest: they may sell some share in case the price does not rise, but store the rest for consumption and possible arbitrage in the case of a price increase.

3.2 Results

We use the calculated certain return C to determine the share of markets in each country 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. We present these results 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 variance in returns. On average across all countries, 22.1%

[8] 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 awareness of storage availability.

of moderately risk averse farmers would rationally sell at harvest 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 for later sale. In markets 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 as before, there is no intertemporal discounting. Then the farmer should sell at harvest if 0 is greater than the certain return C as defined in Equation (2) minus the interest cost, and he should store if $C - i > 0$. Even a conservative interest rate of 5% serves to increase the share of markets in which a moderately risk averse farmer opts out of storage to 33.6%. (Table 4).

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.

4 Robustness Checks

4.1 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 return from an OLS regression of returns on harvest season price for each market. Using the expectation and variance of predicted returns, we construct the *predicted* certainty equivalent, and compare it to the known return of 0 at harvest to determine if a farmer would choose storage. We find that the share of markets in which a farmer avoids storage decreases; on average across countries, moderately risk averse farmers would prefer to sell at harvest for 5.4% of markets (Appendix Table A6).

5 Intra-annual 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 returns within-year across seasons. 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 such as 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 A3).

Farmers face a series of decisions related to storage and sales. The optimal time to sell may be informed by changes over time, reducing the risks of holding stocks to sell. We define a harvest and lean season for each country in our analysis, with returns to storage calculated as the difference between the harvest season minimum and the lean season maximum. This works well if prices rise monotonically after harvest and peak during planting time. But it may be that in some years the price peaks in the months between harvest and lean season. In such circumstances we might falsely conclude that the returns to storage were negative when they could have been positive if farmers sold after harvest but before the decline in prices began.

In results presented thus far (Table 3), we define the relevant arbitrage period as the time from the minimum harvest price to the maximum lean season price, where the lean season is defined as the three months prior to the subsequent harvest. However, profitable storage opportunities may obtain over a shorter time frame, before the lean season. We re-estimate the farmer storage decision for each month post-harvest, over the same range of risk coefficients. We calculate the first and second moments of the returns to storage at the market-level for each post-harvest month. We include the results in Appendix Figure A4 separately for each country, with the number of months post-harvest presented on the x-axis. The y-axis presents the share of markets in which farmers would forgo storage, i.e. prefer to sell at harvest.

Farmer risk preferences are shown in three different colors. In most countries, risk aversion influences the decision to store in every month post-harvest for some farmers on average. For example in Burundi, results suggest that all risk averse farmers would forgo storage to sell one month after harvest, indicating a negative certainty equivalent return for all risk averse farmers in all markets at that time. However, as the number of months post-harvest increases, the share of farmers in Burundi optimally forgoing storage decreases as the average return for that month increases or the variation in returns decreases (see the graph for returns in Burundi in Appendix Figure A3). If only average returns mattered, we would expect to see all farmers storing when returns were positive. In Mozambique, returns are positive on average for all months from 2-11 post-harvest. (Appendix Figure A3) Appendix Figure A4 shows that the share of risk neutral farmers in Mozambique (green line) stays close to the x-axis, indicating that no farmers are optimally forgoing storage (because it makes sense to store to capture expected returns). However, the variation of returns begins to increase around months 6-10 post-harvest, driving risk averse farmers to opt out of storage, despite the fact that the average return is positive.

6 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, likely preventing households from predicting returns at harvest 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 calculations leave out the costs of storage, post-harvest losses in product quantity or quality, foregone interest on sales revenue and off-season trader search. Even our most conservative specifications using predicted lean season prices to adjust for the fact that harvest prices are observable find that a non-trivial share of both moderately and high risk averse farmers (5 and 14 percent, respectively), would forgo storage.

We find evidence of considerable spatial heterogeneity in the probability of negative returns. Important drivers of the likelihood of negative returns to storage should be investigated in future analyses including: the degree to which markets exhibiting more incidence of negative returns are those that are poorly spatially integrated, more or less maize dependent, or located in regions with more or less population density. In particular, disentangling the relationship between negative returns to storage and external shocks from international markets versus government policy responses to anticipated shortfalls would be valuable.

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 new and important insight relevant to solving the widely-observed and persistent puzzle of low storage uptake among small farmers in Sub-Saharan Africa.

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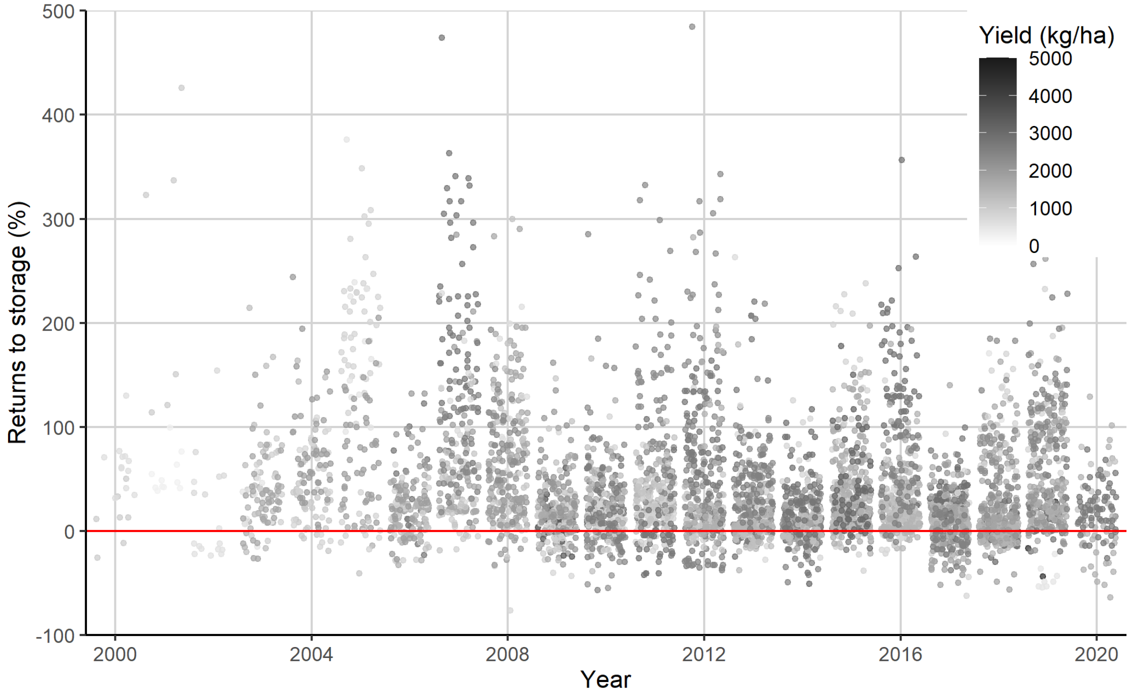
Table 1: Frequency and Magnitude of Negative Returns to Storage for Retail Markets (Primary Maize Season)

(1)	Country (2)	Number of Markets (3)	Number of Market-Years (4)	Frequency of Negative Returns (5)	Average Total Returns (6)	Average Positive Returns (7)	Average Negative Returns (8)
Burkina Faso	2003-2019	54	401	10.2%	22.5%	25.7%	-5.9%
Burundi	2007-2020	12	88	18.2%	44.0%	56.0%	-10.1%
Chad	2003-2019	12	89	16.9%	34.9%	44.4%	-11.5%
DRC	2008-2019	10	75	40.0%	22.2%	48.8%	-17.8%
Ethiopia	2006-2019	22	184	29.3%	35.0%	55.6%	-14.5%
Gambia	2006-2019	14	123	34.1%	16.6%	35.6%	-20.0%
Malawi	2003-2020	69	809	12.4%	81.9%	95.5%	-14.2%
Mali	2003-2019	55	615	16.6%	29.5%	37.6%	-11.2%
Mozambique	2000-2020	23	310	10.0%	71.3%	80.7%	-12.6%
Niger	2000-2019	62	718	24.4%	15.2%	22.8%	-8.3%
Rwanda	2008-2020	36	268	17.2%	37.0%	47.1%	-11.6%
Senegal	2007-2019	46	421	14.7%	19.7%	24.1%	-6.2%
Tanzania	2016-2020	25	125	47.2%	16.5%	51.7%	-22.9%
Zambia	2003-2020	66	873	11.8%	53.1%	61.9%	-12.2%
Total		506	5099	21.6%	35.7%	49.1%	-12.8%

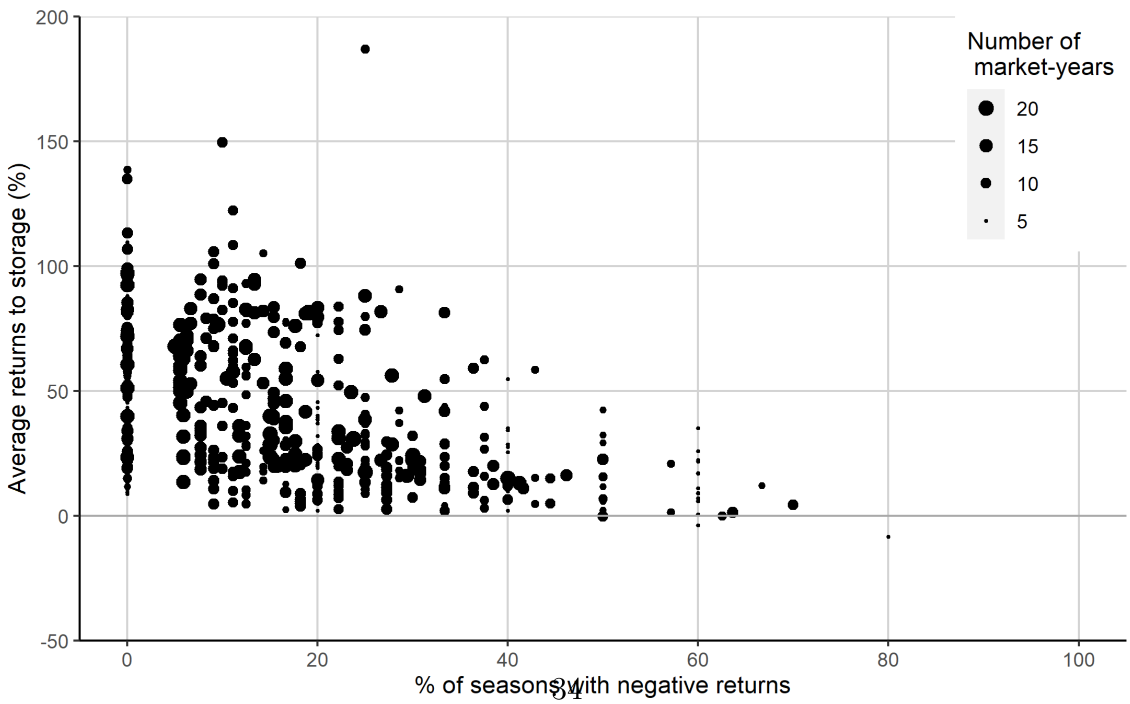
[1] Monthly maize retail price data from the WFP Global Food Prices Database for 2000-2020. Prices were adjusted to 2015 local currency value using FAO/IMF data on historical monthly CPI. National and subnational agricultural season data was reported from FAO-GIEWS via the University of Wisconsin.

[2] Columns (5)-(8): Returns are calculated for each "market-year" for the lean season price over the previous harvest season price. The lean season price is defined as the maximum price of the three months prior to the subsequent harvest, and the harvest season price is the minimum price of the months defined as harvest season. Markets were included if data were available for at least five market-years. Countries were included if data were available for at least ten markets.

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 retail maize season (market-year observations)

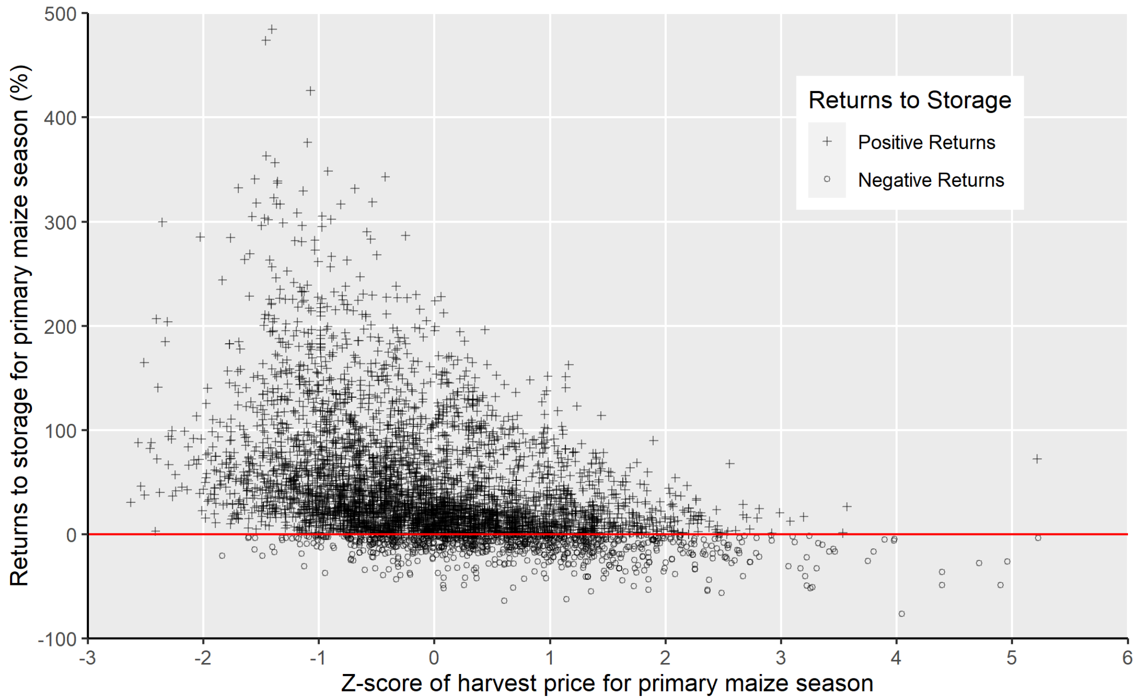


Table 2: Regressions of harvest prices on returns to storage and the probability of negative returns for the primary maize season

Dep. variable	Returns to Storage (%)		Negative Returns (=1 if Returns≤ 0)	
	Harvest price		Harvest price	
	z-score	R^2	z-score	Pseudo-R^2
Country	(1)	(2)	(3)	(4)
Burkina Faso	8.762**	0.73	0.06***	0.44
Burundi	15.995	0.76	0.173***	0.67
Chad	4.585	0.81	0.15***	0.55
DRC	27.823	0.38	0.222***	0.26
Ethiopia	20.9***	0.79	0.229***	0.54
Gambia	-11.858	0.69	0.448***	0.54
Malawi	25.917***	0.75	0.169***	0.60
Mali	-4.402	0.82	0.097***	0.49
Mozambique	-15.097	0.70	0.096***	0.41
Niger	50.888***	0.62	0.165***	0.38
Rwanda	72.081***	0.68	0.153***	0.50
Senegal	29.796***	0.56	0.117***	0.25
Tanzania	66.911***	0.70	0.125***	0.51
Zambia	67.011***	0.65	0.089***	0.49
CC Average		0.69		0.47
Pooled		0.48		0.26

[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 $R^2$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 the unweighted average of R^2 for all 25 countries. The pooled regression R^2 is calculated by regressing 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 lean season price over the previous harvest season price. The lean season price is defined as the maximum price of the three months prior to the subsequent harvest, and the harvest season price is the minimum price of the months defined as harvest season. Markets were included if data were available for at least five market-years. Countries were included if data were available for at least ten markets. 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 markets farmers should forgo storage by farmer risk tolerance (based on variation in returns)

Country	Number of Markets	Risk Neutral and Low Risk Aversion R$\in [0, 1)$	Moderate Risk Aversion R$\in [1, 3)$	High Risk Aversion R$\in [3, 5)$
Burkina Faso	54	1.5%	2.0%	4.7%
Burundi	12	0.0%	0.8%	25.8%
Chad	12	0.0%	7.1%	56.2%
DRC	10	9.0%	58.0%	80.0%
Ethiopia	22	0.0%	29.3%	86.6%
Gambia	14	7.1%	60.0%	86.4%
Malawi	69	0.4%	30.1%	86.9%
Mali	55	0.0%	20.6%	79.1%
Mozambique	23	0.0%	10.2%	49.8%
Niger	62	2.9%	5.3%	18.5%
Rwanda	36	1.1%	8.6%	33.5%
Senegal	46	0.0%	1.3%	3.2%
Tanzania	25	11.6%	71.2%	95.6%
Zambia	66	0.0%	4.5%	29.0%
Total		2.4%	22.1%	52.5%

[1] Risk tolerance is calculated using the first and second moments of the returns to storage for the primary maize season for each retail market with five or more crop years available, and countries with ten or more markets available.

Table 4: Share of markets in which farmers should forgo storage by farmer risk tolerance with an interest rate of 5% (based on variation in returns)

Country	Number of Markets	Risk Neutral and Low Risk Aversion R$\in [0, 1)$	Moderate Risk Aversion R$\in [1, 3)$	High Risk Aversion R$\in [3, 5)$
Burkina Faso	54	9.3%	10.6%	16.4%
Burundi	12	0.0%	5.4%	42.1%
Chad	12	0.0%	21.2%	71.2%
DRC	10	35.0%	80.5%	90.0%
Ethiopia	22	5.5%	46.4%	97.3%
Gambia	14	15.0%	78.2%	94.6%
Malawi	69	0.6%	34.5%	89.9%
Mali	55	2.2%	34.6%	90.6%
Mozambique	23	0.0%	12.2%	58.9%
Niger	62	13.9%	23.8%	45.7%
Rwanda	36	6.7%	17.4%	43.9%
Senegal	46	6.7%	11.2%	23.9%
Tanzania	25	29.6%	87.6%	96.0%
Zambia	66	0.0%	7.1%	36.9%
Total		8.9%	33.6%	64.1%

[1] Risk tolerance is calculated using the first and second moments of the returns to storage for the primary maize season for each retail market with five or more crop years available, and countries with ten or more markets available.

A Appendix

Table A1: Frequency and Magnitude of Negative Returns to Storage for Wholesale Markets (Primary Maize Season)

Country (1)	Years (2)	Number of Markets (3)	Number of Market-Years (4)	Frequency of Negative Returns (5)	Average Total Returns (6)	Average Positive Returns (7)	Average Negative Returns (8)
Ethiopia	2000-2019	13	167	18.0%	31.5%	41.0%	-12.1%
Ghana	2005-2019	15	160	16.9%	37.9%	48.3%	-13.5%
Nigeria	2001-2020	13	94	42.6%	22.0%	53.7%	-20.8%
Tanzania	2006-2020	20	276	27.2%	36.0%	55.7%	-16.9%
Total		61	697	26.1%	31.8%	49.7%	-15.8%

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

[2] Columns (5)-(8): Returns are calculated for each "market-year" for the lean season price over the previous harvest season price. The lean season price is defined as the maximum price of the three months prior to the subsequent harvest, and the harvest season price is the minimum price of the months defined as harvest season. Markets were included if data were available for at least five market-years. Countries were included if data were available for at least ten markets.

Table A2: Frequency and Magnitude of Negative Returns to Storage for Retail Markets (Second Maize Season)

Country (1)	Years (2)	Number of Markets (3)	Number of Market-Years (4)	Frequency of Negative Returns (5)	Average Total Returns (6)	Average Positive Returns (7)	Average Negative Returns (8)
Burundi	2007-2020	21	140	4.3%	62.3%	65.4%	-8.0%
Rwanda	2008-2020	37	276	11.2%	35.1%	40.3%	-5.7%
Tanzania	2016-2020	15	75	52.0%	6.0%	45.0%	-30.0%
Total		73	491	22.5%	34.5%	50.2%	-14.6%

[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 FAO/IMF data on historical monthly CPI. National and subnational agricultural season data was reported from FAO-GIEWS via the University of Wisconsin.

[2] Columns (5)-(8): Returns are calculated for each "market-year" for the lean season price over the previous harvest season price. The lean season price is defined as the maximum price of the three months prior to the subsequent harvest, and the harvest season price is the minimum price of the months defined as harvest season. Markets were included if data were available for at least five market-years. Countries were included if data were available for at least ten markets.

Table A3: Market skewness analysis for retail markets

Country	Markets	Average Market Skewness (1)	Share of Markets Negatively Skewed (2)
Burkina Faso	54	0.17	35.2%
Burundi	12	0.49	0.0%
Chad	12	0.51	33.3%
DR Congo	10	2.17	0.0%
Ethiopia	22	1.04	0.0%
Gambia	14	2.68	0.0%
Malawi	69	0.74	0.0%
Mali	55	2.95	0.0%
Mozambique	23	1.51	0.0%
Niger	62	0.49	14.5%
Rwanda	36	0.43	16.7%
Senegal	46	0.43	26.1%
Tanzania	25	0.61	8.0%
Zambia	66	1.16	1.5%

[1] Monthly maize 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.

Table A4: Regressions of harvest prices on returns to storage and the probability of negative returns for the primary maize season (without year FE)

Dep. variable	Returns to Storage (%)		Negative Returns (=1 if Returns$\leq$ 0)	
	Harvest price		Harvest price	
	z-score	R^2	z-score	Pseudo-R^2
Country	(1)	(2)	(3)	(4)
Burkina Faso	22.49***	0.27	0.069***	0.08
Burundi	43.973***	0.53	0.181***	0.37
Chad	34.944***	0.39	0.138***	0.18
DRC	22.168***	0.11	0.217***	0.15
Ethiopia	35.043***	0.39	0.249***	0.33
Gambia	16.614***	0.19	0.349***	0.27
Malawi	81.906***	0.22	0.076***	0.09
Mali	29.47***	0.15	0.135***	0.16
Mozambique	71.339***	0.17	0.059***	0.09
Niger	15.24***	0.27	0.152***	0.13
Rwanda	36.99***	0.46	0.154***	0.22
Senegal	19.679***	0.45	0.125***	0.16
Tanzania	16.492***	0.21	0.21***	0.13
Zambia	53.119***	0.22	0.066***	0.07
CC Average		0.29		0.17
Pooled		0.33		0.17

[1] Columns (1) and (2) show results from OLS regressions by country of returns to storage (%) on harvest price z-score. Column (1) is the coefficient on harvest price z-score and column (2) is the $R^2$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. 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 the unweighted average of R^2 for all 25 countries. The pooled regression R^2 is calculated by regressing returns to storage and negative returns, respectively, on harvest price z-score, with country fixed effects.

[3] Returns are calculated for each "market-year" for the lean season price over the previous harvest season price. The lean season price is defined as the maximum price of the three months prior to the subsequent harvest, and the harvest season price is the minimum price of the months defined as harvest season. Markets were included if data were available for at least five market-years. Countries were included if data were available for at least ten markets. 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 A5: Share of markets farmers should forgo storage by farmer risk tolerance (based on variation in lean season prices)

Country	Number of Markets	Risk Neutral and Low Risk Aversion R$\in [0,1)$	Moderate Risk Aversion R$\in [1,3)$	High Risk Aversion R$\in [3,5)$
Burkina Faso	54	11.5%	13.8%	17.4%
Burundi	12	12.8%	13.8%	18.5%
Chad	12	14.0%	17.6%	22.6%
DRC	10	35.3%	49.5%	59.3%
Ethiopia	22	15.6%	20.1%	34.5%
Gambia	14	25.1%	34.6%	56.3%
Malawi	69	10.3%	17.8%	33.2%
Mali	55	8.5%	19.8%	50.6%
Mozambique	23	6.9%	9.6%	23.3%
Niger	62	17.8%	21.6%	27.5%
Rwanda	36	11.4%	15.1%	21.1%
Senegal	46	14.9%	17.5%	19.8%
Tanzania	25	35.6%	49.4%	71.4%
Zambia	66	3.7%	7.5%	19.2%
Total		16.0%	22.0%	33.9%

[1] Risk tolerance is calculated using the first and second moments of the lean season price for the primary maize season for each retail market with five or more crop years available, and countries with ten or more markets available. The certainty equivalent return of the risk of storage is compared to the harvest price each market-year.

Table A6: Share of market farmers should forgo storage by farmer risk tolerance (based on predicted returns)

Country	Number of Markets	Risk Neutral and Low Risk Aversion R$\in [0, 1)$	Moderate Risk Aversion R$\in [1, 3)$	High Risk Aversion R$\in [3, 5)$
Burkina Faso	54	0.9%	1.9%	1.9%
Burundi	12	0.0%	0.0%	4.6%
Chad	12	0.0%	0.0%	9.6%
DRC	10	1.0%	31.5%	51.0%
Ethiopia	22	0.0%	5.2%	25.5%
Gambia	14	7.1%	7.1%	21.8%
Malawi	69	0.1%	1.4%	9.1%
Mali	55	0.0%	0.6%	4.4%
Mozambique	23	0.0%	0.0%	0.0%
Niger	62	2.7%	3.2%	3.6%
Rwanda	36	0.0%	3.5%	12.2%
Senegal	46	0.0%	0.9%	2.8%
Tanzania	25	4.4%	20.0%	43.4%
Zambia	66	0.0%	0.0%	3.0%
Total		1.2%	5.4%	13.8%

[1] Risk tolerance is calculated using the first and second moments of the returns to storage for the primary maize season for each retail market with six or more crop years available, and countries with three or more markets available. The predicted return is based on market level OLS regressions of returns on harvest price and year.

Figure A1: Monthly Average Maize prices for retail markets in primary season

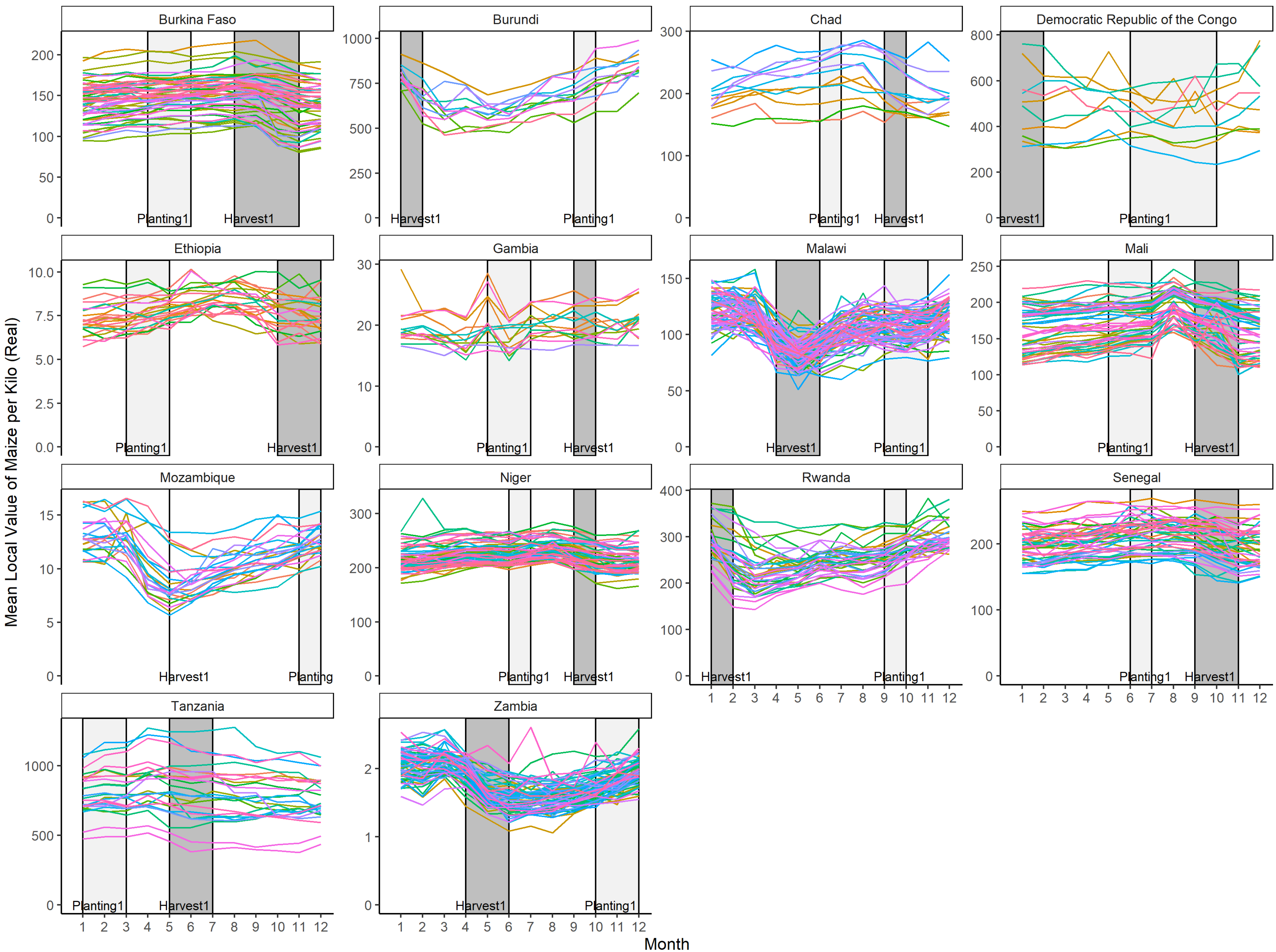


Figure A2: Minimum and maximum maize prices for retail markets in primary season

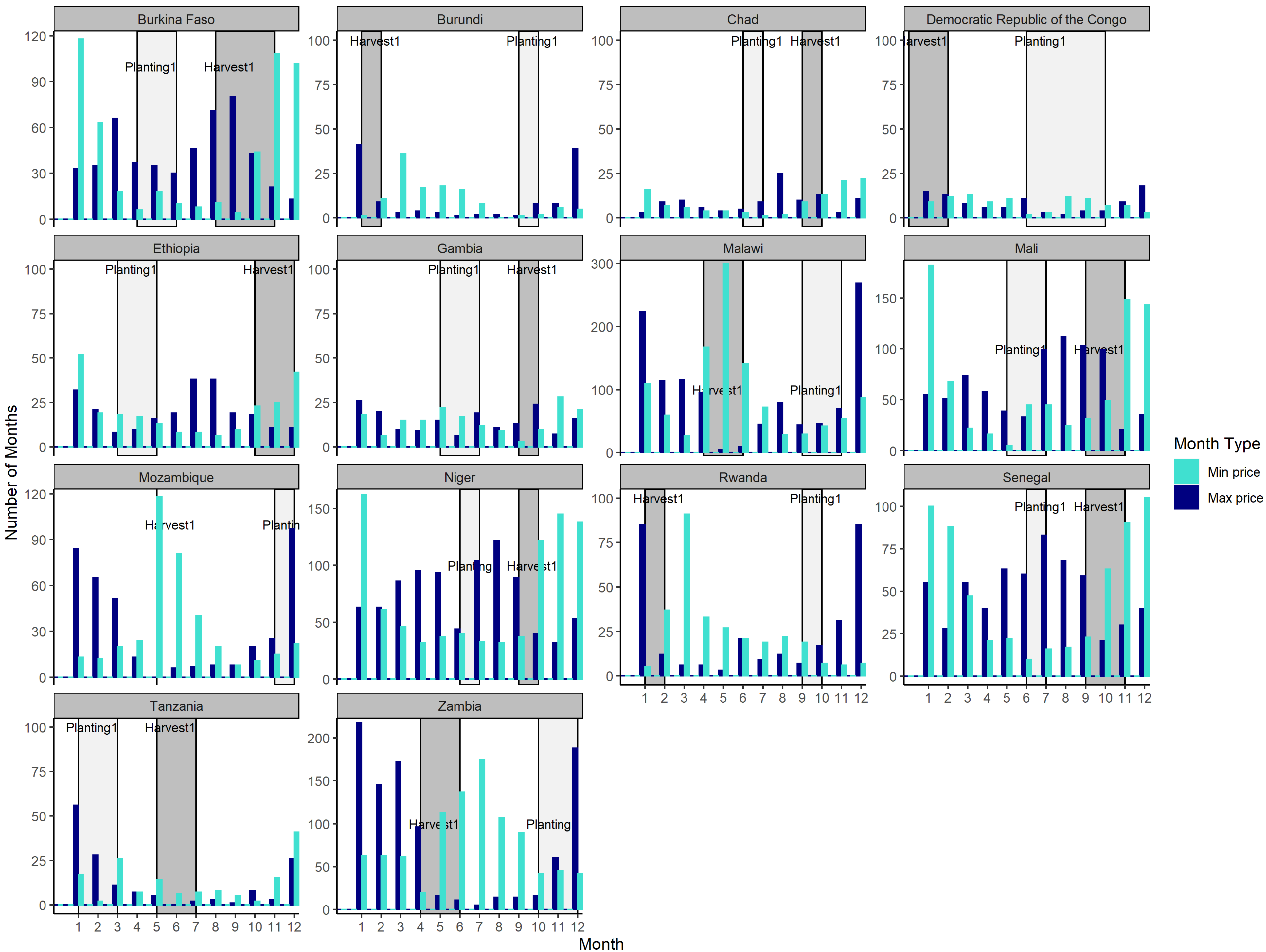


Figure A3: Intra-annual Returns to Storage by Country (for primary maize season)

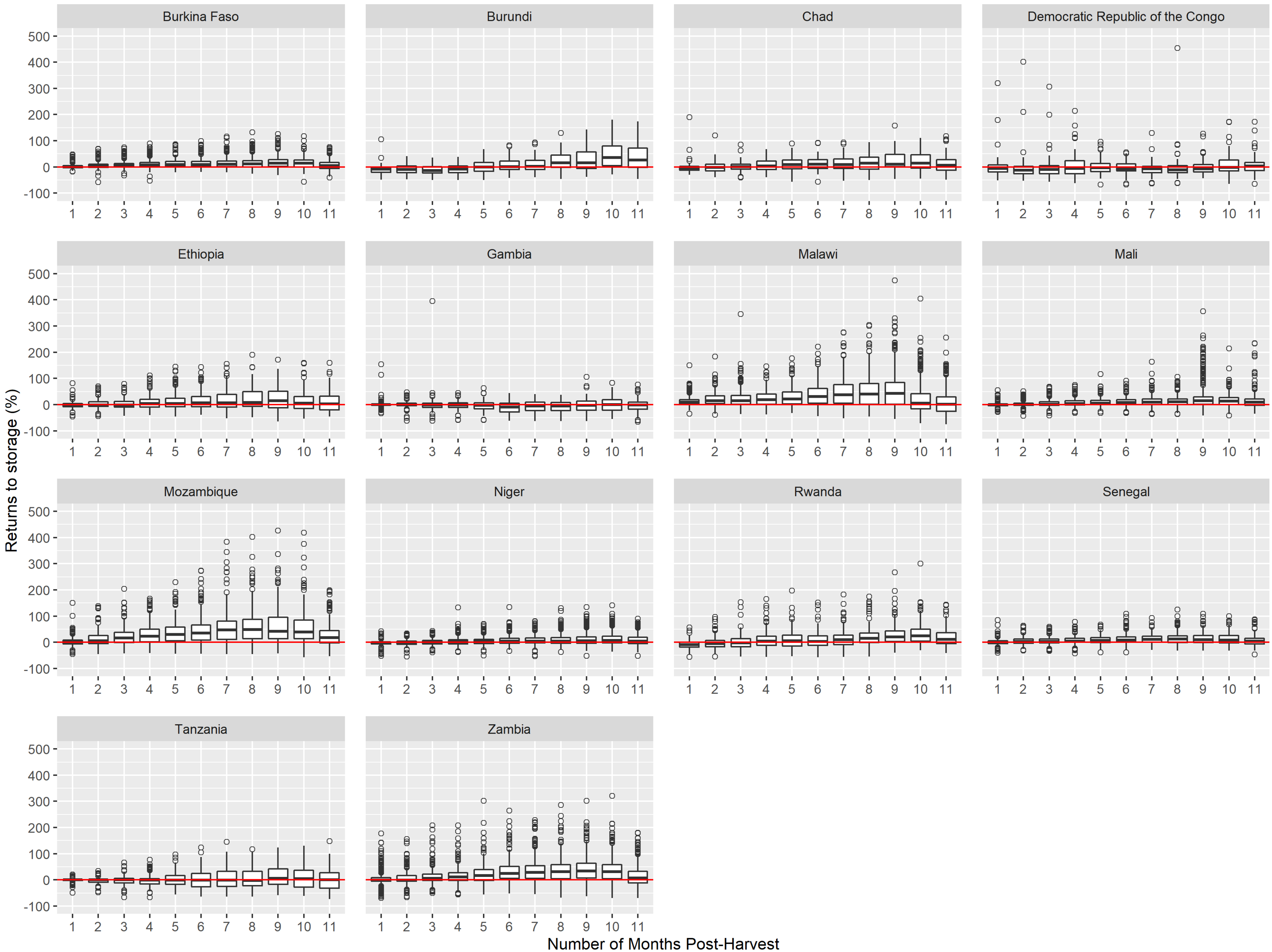
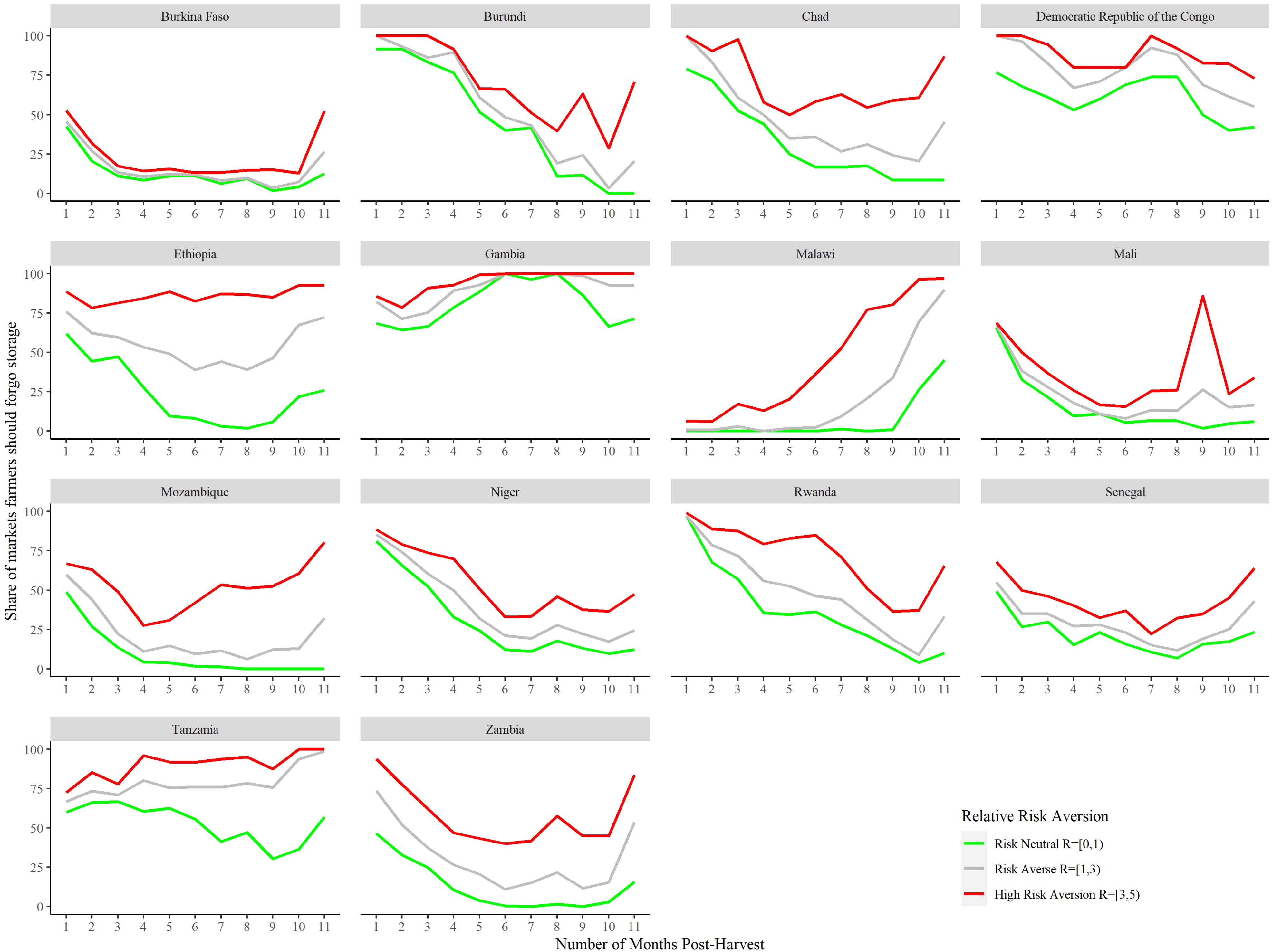


Figure A4: Share of markets farmers should forgo storage over all months post-harvest (for primary maize season)



A.1 Missing price data

We exclude markets that are missing, defined as markets with fewer than 5 years of data, and countries with fewer than 10 markets. Based on this definition, we end up with a dataset of 5099 observations from an original set of 9355 observations. The original set of observations can be viewed on the map in Appendix Figure A5, with markets delineated between retail and wholesale. In Appendix Table A7, the entire set of monthly retail price data available in the WFP Global Food Price database for 2000-2020 is shown by country, in decreasing order of markets available in the final data set. Columns (1)-(2) are the total number of years and markets for which data was available in the WFP database. Columns (3)-(4) show the resulting observations for each country based on our definition of missingness. Somalia is included in Appendix Table A7 as monthly retail prices were present, however we could not find CPI data, hence it was not included in subsequent analysis.

Figure A5: Map of markets with WFP monthly maize price data

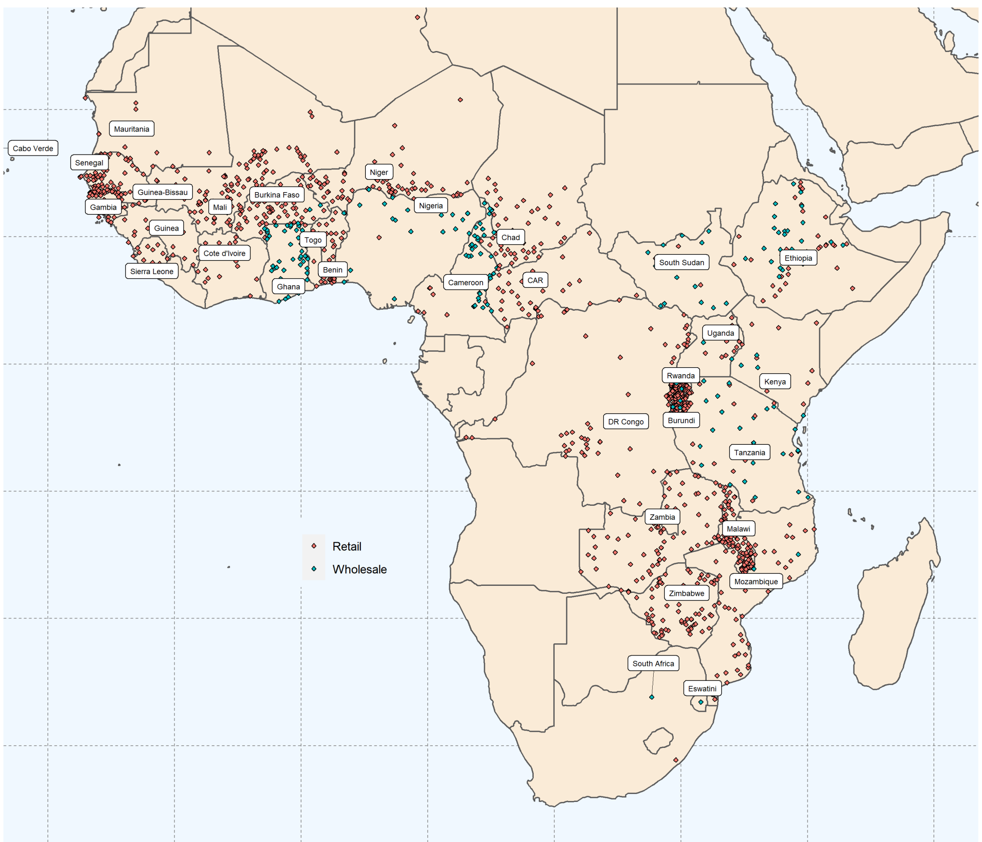


Table A7: Missing data analysis for retail markets

Country	Commodity	Total Years (1)	Total Markets (2)	Number of Markets(nyrs$\geq$ 5) (3)	Number of Observations (4)
Malawi	Maize	19	123	69	120
Zambia	Maize (white)	19	71	66	70
Niger	Maize	22	77	62	65
Mali	Maize	19	108	55	66
Burkina Faso	Maize (white)	19	56	54	54
Senegal	Maize (local)	15	63	46	53
Rwanda	Maize	14	102	36	87
Tanzania	Maize (white)	6	26	25	25
Mozambique	Maize (white)	22	49	23	39
Ethiopia	Maize (white)	15	43	22	28
Gambia	Maize	16	28	14	19
Burundi	Maize (white)	15	68	12	64
Chad	Maize (white)	19	47	12	37
DR Congo	Maize	14	70	10	39
Kenya	Maize (white)	15	9	9	9
Togo	Maize (white)	21	6	6	6
Cameroon	Maize	15	35	5	5
Cote d'Ivoire	Maize	17	14	5	13
Zimbabwe	Maize	12	105	5	28
South Sudan	Maize (white)	15	16	4	8
Uganda	Maize (white)	11	15	4	13
Benin	Maize (white)	13	51	2	49
Cabo Verde	Maize (local)	14	2	2	2
Cabo Verde	Maize (yellow)	14	2	2	2
CAR	Maize	18	33	2	24
Guinea-Bissau	Maize	15	29	1	3
Ghana	Maize	3	19	0	19
Guinea	Maize	7	15	0	11
Mauritania	Maize (local)	3	13	0	5
Nigeria	Maize (white)	6	16	0	15
Nigeria	Maize (yellow)	6	16	0	14
Sierra Leone	Maize	2	13	0	0
Somalia	Maize (white)	22	29	0	0

[1] Monthly maize price data from the WFP Global Food Prices Database for 2000-2020 for retail markets.

[2] Columns (1)-(2) are the total number of years and markets, respectively, for which data is available for each country in the WFP database. Columns (3)-(4) are the number of markets, and market-year observations that remain in the dataset after the selection process in Section 1.1.

Table A8: Missing data analysis for retail markets in primary maize season

Country	Both prices exist (1)	No harvest price (2)	No lean price (3)	Total (4)	Mean Return (5)
Malawi	71.6% (986)	11.5% (158)	16.9% (233)	100.0% (1377)	80.1%
Zambia	91.4% (884)	5.8% (56)	2.8% (27)	100.0% (967)	53.0%
Niger	78.7% (730)	11.3% (105)	9.9% (92)	100.0% (927)	15.2%
Mali	73.3% (645)	14.0% (123)	12.7% (112)	100.0% (880)	29.8%
Senegal	68.0% (437)	16.3% (105)	15.7% (101)	100.0% (643)	19.5%
Rwanda	76.8% (417)	14.0% (76)	9.2% (50)	100.0% (543)	32.8%
Burkina Faso	78.8% (401)	10.0% (51)	11.2% (57)	100.0% (509)	22.5%
Burundi	60.9% (272)	18.1% (81)	21.0% (94)	100.0% (447)	40.9%
Mozambique	78.1% (329)	15.0% (63)	6.9% (29)	100.0% (421)	71.9%
Ethiopia	69.3% (199)	19.2% (55)	11.5% (33)	100.0% (287)	34.8%
DR Congo	54.7% (141)	20.2% (52)	25.2% (65)	100.0% (258)	45.3%
Gambia	57.6% (136)	20.3% (48)	22.0% (52)	100.0% (236)	15.2%
Zimbabwe	45.2% (100)	36.7% (81)	18.1% (40)	100.0% (221)	30.7%
Benin	43.5% (93)	24.3% (52)	32.2% (69)	100.0% (214)	43.2%
Chad	62.3% (119)	13.6% (26)	24.1% (46)	100.0% (191)	48.4%
Tanzania	82.8% (125)	17.2% (26)	0.0% (0)	100.0% (151)	16.5%
CAR	49.7% (72)	26.9% (39)	23.4% (34)	100.0% (145)	39.1%
Togo	90.5% (114)	4.8% (6)	4.8% (6)	100.0% (126)	38.9%
Cameroon	60.0% (60)	10.0% (10)	30.0% (30)	100.0% (100)	18.9%
Kenya	80.8% (80)	10.1% (10)	9.1% (9)	100.0% (99)	12.1%
South Sudan	45.9% (45)	25.5% (25)	28.6% (28)	100.0% (98)	54.6%
Cote d'Ivoire	63.6% (56)	22.7% (20)	13.6% (12)	100.0% (88)	29.5%
Nigeria	40.0% (34)	28.2% (24)	31.8% (27)	100.0% (85)	77.3%
Uganda	59.0% (49)	25.3% (21)	15.7% (13)	100.0% (83)	24.8%
Guinea	49.2% (31)	25.4% (16)	25.4% (16)	100.0% (63)	32.0%
Guinea-Bissau	35.3% (18)	33.3% (17)	31.4% (16)	100.0% (51)	11.2%
Cabo Verde	88.0% (44)	8.0% (4)	4.0% (2)	100.0% (50)	8.3%
Ghana	51.4% (19)	0.0% (0)	48.6% (18)	100.0% (37)	14.7%
Mauritania	15.6% (5)	43.8% (14)	40.6% (13)	100.0% (32)	7.9%
Sierra Leone	0.0% (0)	50.0% (13)	50.0% (13)	100.0% (26)	
Total	71.0% (6641)	14.7% (1377)	14.3% (1337)	100.0% (9355)	
Overall average					40.9%

[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 FAO/IMF data on historical monthly CPI. National and subnational agricultural season data was reported from FAO-GIEWS via the University of Wisconsin.

[2] Columns (1)-(4): The lean season price is defined as the maximum price of the three months prior to the subsequent harvest, and the harvest season price is the minimum price of the months defined as harvest season.

[3] Column (5): Returns are calculated for each "market-year" for the lean season price over the previous harvest season price, as defined above.

Figure A6: Missing price data