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 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 831 markets in

25 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 29% of the time across markets and years, ranging from a low of 8.5% in Burkina Faso to a high of 73.3% in Guinea-Bissau. 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 6.0% lower in Burkina Faso to 26.1% lower in South Sudan. 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. 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 21% of markets on average across countries.

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. We address precisely the opposite problem, and one that has perplexed researchers for many years working in Sub-Sharan Africa: too little storage. 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.

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. 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. 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

[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.

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 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.

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 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 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 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. We calculate inter-seasonal price differences (and associated returns) conservatively. 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 months designated as the planting season. 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, using the last month designated as a harvest month, and calculating returns for holding grain for 1-12 months post-harvest.

We retain in the data all markets for which we have price data for at least three 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 and planting in January-February 2019, the return for the 2018 market-year is the percent change from the September or October 2018 "harvest" price to the January or February 2019 "lean" price, depending on whichever month had the lower price, and higher price, respectively. If either price was unavailable for that market-year pair, we do not include the observation in our data. We select prices to represent the farmers' decision-making problem – whether to store or sell when prices are lowest during 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. 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. For retail markets in the primary maize season, we remove 123 markets with only one year included in the data, and one country, Nigeria, with only one market reported. Our final data include 6364 market-year observations for the primary maize season across 831 retail markets in 25 countries in sub-Saharan Africa between the years 2000-2020.[2]

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 spatially integrated than urban markets due to costs of transport and information. It is therefore likely that these data and our analysis underestimate the degree of price volatility experienced by small farmers.

[2] All data and code are available on the author's website.

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 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 Benin data consists of 62 total market-year observations across 19 markets and 13 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: 23.3% (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. Guinea-Bissau has the highest incidence, with 73.3% of its market years exhibiting price declines after harvest; in all countries in the data negative returns occur at least 8.5% 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 (30%, Appendix Table A1) and for the second season (33%, Appendix Table A2).[3]

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 -

[3]Market skewness data (available in author's code) 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, Ghana, and Uganda. 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.

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. 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. 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 168 markets, and for 22 markets, returns are always negative. For those 22 markets, there are 63 market-year observations covering 12 different countries, and 15 different years, i.e. each market in that group of 22 only has 2-3 observations. Insights hold if these 22 markets are excluded.

2 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 A2).

3 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. The 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 strong, we would 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 price, then the farmer will bear some risk associated with storing. In this case, farmers seen to opt out of storage do 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 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 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 25 countries and the R^2 from a regression pooling all observations across countries and including country and year fixed effects. [4]

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. Of

[4] The same regression analysis without year fixed effects shows an even weaker relationship between harvest prices and returns. (Appendix Table A3.)

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.

4 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 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.

4.1 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 20 of the 831 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 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 A4. 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 $w(1+E[r]) = w(1+\bar{r})$ 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

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

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 increasing 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) Of the initial set of 831 retail markets with primary season data, the median number of market years across markets represented in the data is six, and we restrict our simulation to markets with six or more years available, and countries with at least three markets, yielding a set of 431 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).[5]

4.2 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

[5]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.

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, 21% 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. 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.

4.3 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 market-years in which a farmer opts out of storage (Appendix Table A5).

4.4 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.

5 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 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 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.