Reference Prices and Hedging Dynamics: Evidence from Producers' Short Positions in U.S. Grain Futures

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Abstract

This study examines how reference prices impact U.S. grain producers' pre-harvest short hedging decisions in corn, soybeans, winter wheat, and rough rice. We use a two-state Markov-switching model with time-varying transition probabilities (MS-TVTP) to distinguish active and inactive hedging regimes and evaluate the influence of both static (USDA average marketing price, harvest price, production cost) and dynamic (14-, 30-, 60-day moving averages) references. Our results find that producers significantly reduce the short position changes when futures prices fall below reference levels, especially in inactive regimes and thinner markets. Dynamic references generate stronger and more frequent effects than static references, highlighting the importance of reference effects for timely decisions. In addition, the analyses for time-varying transition probabilities show that unfavorable prices under dynamic references dampen the likelihood of switching to or staying in active hedging, particularly in soybeans and wheat. These findings provide new behavioral evidence of reference-dependent hedging across commodities with varying liquidity, offering practical insights for risk management, market advisory services, and policy design.

Key words: Markov-switching model with time-varying transition probabilities, grain producers, reference prices, short hedge

JEL codes: G13, G14, Q02, Q11

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Introduction

The timing of when and how much grain to market is critical to agribusiness success. Short hedges are initiated to manage the risk of the sale during the pre-harvest periods. Selling futures contracts to form a short hedge position can help to offset the losses for delivery of physical commodities at a lower at-harvest price. Grain producers can lock in prices on their expected production by selling new crop futures during the pre-harvest marketing window. Much of the existing literature on producer hedging behavior has focused on hedge ratios derived from forward contracting data or aggregate measures of hedge coverage (e.g., Davis et al. 2005; Jacob, Li, and Hayes 2018). Few studies have focused on position changes in futures markets during the pre-harvest period. These changes are important because they reflect the timing, magnitude, and direction of active risk management decisions, capturing the dynamic nature of hedging rather than just the level of coverage. Since grain producers are commercial hedgers, adjusting short positions can be motivated by new information about supply and demand, evolving perceptions of risk, and shifts in marketing strategy.

A growing body of evidence suggests that hedge activities might be influenced by reference points (e.g., Mattos, Garcia, and Penning 2008; Kim, Brorsen, Anderson 2010; Jacob, Li, and Hayes 2018). In the context of short hedges, producers increase short hedges to secure prices at a favorable level when futures prices are above a reference point, while they may be reluctant to expand in short positions when prices are below the reference. The reference effects on short hedges can result from the prospect theory first proposed by Kahneman and Tversky (1979) where decision makers can be impacted by psychological factors gains and losses are

evaluated relative to a salient benchmark, exhibiting an asymmetry of behavior towards risks of gains versus losses.

This paper investigates the role of reference prices in short position changes in U.S. grain futures markets. Specifically, we model weekly changes in short positions of agricultural producers in major grain futures contracts within a two-state Markov-switching framework with time-varying transition probabilities (MS-TVTP). This approach allows us to distinguish between active and inactive short hedging regimes, estimate how price movements relative to reference points influence position changes within each regime, and examine the conditions that trigger transitions between regimes.

Our framework is grounded in the predictions of Cumulative Prospect Theory, which imply sharper position adjustments in the loss domain and nonlinear thresholds in regime-switching probabilities. Our analysis compares the performance of multiple candidate reference prices (i.e., both static and dynamic reference) to assess which reference benchmark most strongly shapes short hedging decisions. Our findings contribute to the literature on agricultural hedging behavior by offering a behavioral and regime-based perspective on short position adjustments, extending prior work on reference-dependent hedging to a broader market context and a richer modeling framework. The results also have practical implications for understanding how hedgers respond to price signals, which can inform extension education, market advisory services, and policy design.

Theoretical Model for Hedging Behaviors

Hedging Behaviors and reference prices

A major strand of studies on hedging is built on the framework of Expected Utility Theory (EUT), which states that the decision makers choose between risky or uncertain choices by

comparing the weighted sums obtained by adding the utility values of outcomes multiplied by their respective probabilities (von Neumann and Morgenstern 1944; Mongin 1998). Grain producers and merchants, as owners of physical commodities, are typically classified as commercial hedgers who seek to protect against potential losses from future price declines. In the EUT framework, a rational, risk-averse producer always prefers a portfolio with less variance if the expected return is the same, and thus the farm use of futures is to minimize the variance of the producer's final income (e.g., Johnson 1960; Feder, Just, and Schmitz 1980; Schroeder et al. 1998). However, Kahneman and Tversky (1979) point out decisions can be impacted by psychological factors-certainty, reflection, and isolation effects- which appear to invalidate EUT, and thus present an alternative theory known as Prospect Theory (PT). This theory is attuned to the evaluation of changes or differences among choices rather than the evaluation of absolute magnitudes. Thus, decision makers evaluate outcomes relative to a reference point and exhibit an asymmetry of behavior towards risks of gains versus losses. In the context of agricultural markets, there are increasing theoretical studies in the framework of cumulative prospect theory and empirical evidence inconsistent with the traditional EUT (Iyer et al. 2020; Finger et al. 2024).

Theoretical framework

We focus on the short hedging behaviors of agricultural producers and explain how reference prices influence their decisions in the CPT framework.[1] Assume futures markets are efficient so

[1] In the context, the short hedging refers to the use of futures contracts to protect against the risk of falling prices for their crops between planting and harvest. Before the harvest, a farmer can sell a futures contract to lock in a selling price for a future date. At the harvest, the farmer harvests and sells the physical crop to simultaneously buy back the short positions to close the hedge. If crop prices have fallen, the loss in revenue from the cash sale is offset by a profit from the futures contract; conversely, the extra revenue from the cash sale is offset by a loss on the futures contract if prices rise. This strategy reduces price uncertainty allowing the producer to secure a price for their crop months in advance. Our analysis focuses on the timing of locking in favorable prices, without considering the influence of hedge-closing activities at harvest on the initial hedging decision.

that futures prices of new crops are unbiased forecast for spot prices at harvest and there is no basis risk. Agricultural producers can sell futures contracts that correspond to the amount they expect to produce to lock in seasonally high spring and summer prices before the harvest.

Let $p_{F,t}$ be the futures price of new crop futures following a stochastic process, $p_{F,t} = f(p_{F,t-1}, \varepsilon_t), \varepsilon_t \backsim N(0, \sigma^2)$. The producers can choose to be active or inactive to hedge their crops at time *t*, and $p_{R,t}$ represents the reference price that might trigger the switch of active and inactive hedge. In the cumulative prospect theory (CPT) framework, producers evaluate outcomes relative to this reference prices defined by,

(1) $x_t \equiv p_{F,t} - p_{R,t}$, which measure gains ($x_t > 0$) or losses ($x_t < 0$) relative to $p_{R,t}$. The CPT value function is,

(2) $$v(x_t) = \begin{cases} {x_t}^{\alpha}, & if\ p_{F,t} > p_{R,t} \\ -\lambda(-x_t)^{\beta}, & if\ p_{F,t} < p_{R,t} \end{cases}$$

where α and $\beta \in (0,1)$ is the parameter to capture the risk attitude to gains and losses, respectively. $\lambda > 1$ is the coefficient of loss aversion. Loss aversion implies that the marginal sensitivity to price changes is greater for losses than for gains of the same magnitude.

Moreover, the probability of an outcome's occurrence is no longer objective and fixed likelihood of an outcome happening. Instead, it is subjectively associated with the ranking of all possible outcomes. Suppose the fluctuation of futures prices around the reference prices ordered from lowest to highest as follows,

(3) $x_{-n} < x_{-n+1} < \cdots < x_{-1} < x_0 = 0 < x_1 < \cdots x_m$.

Let π_i be the objective (true) probability that the outcome x_i occurs, where *i*= *-n,-n+1*,..,m. The cumulative probabilities are determined separately for the losses and gains,

(4) $\Pi_j^- = \sum_{i=-n}^{j} \pi_i, \ \ \Pi_k^+ = \sum_{i=k}^{m} \pi_i$.

The decision weights $\omega^{-}(\Pi_j^{-})$ for losses and $\omega^{-}(\Pi_j^{+})$ for grains directly affect whether a producer is actively or inactively hedging since their perception drives whether they switch to a different strategy or stay in the same strategy,

(5) $\omega^{-}(\pi_i) = \omega^{-}(\Pi_j^{-}) - \omega^{-}(\Pi_{j-1}^{-}), \quad \omega^{+}(\pi_i) = \omega^{+}(\Pi_k^{+}) - \omega^{-}(\Pi_{k\mp1}^{+})$.

where $\omega^{-}(\pi_i)$ and $\omega^{+}(\pi_i)$ are nonlinear probability weighting functions, often modeled as inverse-S shaped (Prelec 1998; Ingersoll 2011).

Econometrics Model

We use a two-state Markov regime-switching model to investigate the reference effects of prices on short position changes under two states: active and inactive. The *active hedge* state represents periods of relatively large changes in short positions, whereas the *inactive hedge* state reflects periods of minimal short-hedging activities. In addition, we employ the time-varying transition probabilities to capture the role of price movements in predicting the transition between these two states.

Let $Q_{i,t}$ denote short positions of producers and merchants for commodity *i* on Tuesday of week *t* and let $\Delta Q_{i,t}$ represent the Tuesday-to-Tuesday position changes (%) for new crop futures. The latent regime variables, denoted by $s_t = 1, 2$, correspond to two separate regimes. [2]The regime-dependent regression for $\Delta Q_{i,t}$ captures the response to price movements when controlling for weeks left until the harvest ($TTM_{i,t}$) and market sentiment ($\Delta VIX_{i,t}$),

(6) $\Delta Q_{i,t} = \alpha_{0,s_t} + \alpha_{1,s_t}\Delta Q_{i,t-1} + \alpha_{2,s_t} r_{i,t} + \alpha_{3,s_t} I\left(p_{F,t} < p_{ref,t}\right) + \alpha_{4,s_t} w_t$

$+ \alpha_{5,s_t} TTM_{i,t} + \alpha_{6,s_t}\Delta VIX_{i,t} + \varepsilon_{i,t}$,

[2] According to Bayesian information criterion (BIC), a two-regime model appears best balance model fit and parsimony than three or more.

where the error term is an identically, independently, and normally distributed shock, with zero mean and variance $\sigma_{s_t}^2$, i.e., $\varepsilon_{i,t} \sim iid\ N(0, \sigma_{s_t}^2)$. Moreover, $\Delta Q_{i,t-p}$ refers to the lagged value of positions changes at time *t-p*.[3] $r_{i,t}$ represents futures returns and $I\left(p_{F,t} < p_{ref,t}\right)$ is a dummy variable equal to one for indicating if the current futures price is below the reference price. We also include an interaction term, $w_t \equiv r_{i,t} \times I\left(p_{F,t} < p_{ref,t}\right)$, to capture asymmetry in the short position changes in response to prices. In addition, $TTM_{i,t}$ represents the number of weeks remaining until the expiration of the new crop futures during the harvest for commodity *i*. $\Delta VIX_{i,t}$ measures the weekly change in the CBOE volatility index, which reflects market expectations of 30-day forwarding volatility.

Moreover, the time-varying transition probability (TVTP) is the conditional probability based on a vector of explanatory variables $\mathbf{X_{it}}$,

$$(7)\ P(S_t = j \mid S_{t-1} = i, \mathbf{X_{it}}) \equiv p_{ij}(t) = \begin{cases} \frac{\exp\left(\beta_{i0} + \mathbf{X_{it}}'\boldsymbol{\beta_{i1}}\right)}{1+\exp\left(\beta_{i0} + \mathbf{X_{it}}'\boldsymbol{\beta_{i1}}\right)}, & j = 1 \\ \frac{1}{1+\exp\left(\beta_{i0} + \mathbf{X_{it}}'\boldsymbol{\beta_{i1}}\right)}, & j = 2 \end{cases},$$

where $\mathbf{X_{it}} \equiv [r_{i,t}, w_t]$.

The model parameters are estimated by maximum likelihood using the expectation-maximization (EM) algorithm, in which the parameters are estimated by iteratively maximizing the expected joint log-likelihood of the parameters given the observations and states (Visser and Speekenbrink 2010). In addition, the transition probabilities are modeled by the multinomial logistic function of explanatory variables, capturing the dependence of regime switching on price movements and reference levels. For a more straightforward interpretation, we report average partial effects (APEs) instead of the estimated coefficients in the transition probability given by,

[3] The optimal lag is 1 based on the AIC and BIC.

(8) $APE_{x_k}(S_t) = \frac{1}{N}\sum_{\ell=1}^{N}\frac{\partial\,\widehat{\Pr}_\ell[(S_t=j\,|S_{t-1}=i,\mathbf{X_{it}}]}{\partial x_k}$,

where x_k is the k^{th} explanatory variable, N is the number of total observations for each commodity, and $\widehat{\Pr}_\ell[(S_t = j\,|S_{t-1} = i, \mathbf{X_{it}}]$ represents the predicted probability for the ℓ^{th} observation being in the regime S_t.

Data Construction

Short hedging of producers for new crops

We use publicly available data from the *Commodity Futures Trading Commission* (CFTC) to explore the pre-harvest hedging activities of corn, soybeans, soft red winter wheat, and rough rice producers, respectively. Specifically, *the Disaggregated Commitment of Trader* (DCOT) reports provide open interests on long (buying) and short (selling) sides of commodity futures traders categorized into four groups: (i) producers and merchants, (ii) swap dealers, (iii) money managers, and (iv) other reportable. The open interest on the short side (hereafter referred to as "short positions") held by producers and merchants reflects outstanding selling contracts through which producers commit to sell the futures contracts to lock in favorable prices. These positions are usually measured each week on Tuesdays but publicly released on Fridays of the same week.[4] More importantly, the position data is broken down by new and old crop years. These open interests for new crop futures can serve as a good proxy for pre-harvest hedging activities (Jacob, Li, and Hayes 2018).

Our sample covers four grain commodities traded on *the Chicago Board of Trade* (CBOT). They are selected for their common features in well-defined marketing seasons. Table 1 lists the delivery month for the first and last futures, as well as new crop futures, of each

[4] When Tuesdays fall on federal holidays, the CFTC reports the position data for the next business day. Or, if the release date also coincides with a holiday, the released date is deferred to the Mondays of the following week.

commodity during a crop year. We focus our analysis on futures trading by producers/merchants during the pre-harvest periods, defined as the month after the expiration of new crop futures to the expiration of the last futures contracts within a given year.[5] Specifically, the pre-harvest window is from December to September of the following year for corn, November to August of the following year for soybeans, July to May of the following year for winter wheat, and November to July of the following year for rice.

We construct a time series for short positions of futures traders categorized as producers and merchants, Q_t, in week *t* of new crop futures. The new futures short position corresponds to the first contract for the next marketing year and later.[6] Figure 1 compares the seasonal pattern of short positions among selected four commodities. On average, short positions of all commodities have an upward trend as their harvest season approaches, which is consistent with the fact that commodity prices are higher during off-season because of relatively insufficient supply; thus, commercial traders use futures contracts to lock in a higher spring and summer price. In addition, corn futures contracts have the highest trading contracts among these four commodities, followed by soybeans and winter wheat, the lowest is rough rice.

To capture the dynamics in the position changes, we measure the percentage change in the short positions of commodity *i* at week *t* as,

(9) $\Delta Q_{i,t} = (\ln(Q_{i,t}) - \ln(Q_{i,t-1})) \times 100,$

where *i*= c (corn), s (soybeans), w (winter wheat), and r (rough rice). Table 2 reports summary statistics of $\Delta Q_{i,t}$ for corn, soybeans, red soft winter wheat, and rice during our sample period.

[5] The new crop futures are typically the nearby contracts during the harvest, while the last futures contracts tend to be the nearby contracts before the harvest begins. This timing aligns with the planting and harvesting schedules outlined in the USDA's handbook for *U.S. Usual Planting and Harvesting Dates*, available at https://usda.library.cornell.edu/concern/publications/vm40xr56k.

[6] Since DCOT is weekly reported, our short position and hedge ratio are typically constructed for Tuesday in each week.

On average, rice producers and merchants exhibit the largest short position changes (15.43%), with a standard deviation of 31.18. In contrast, corn shows the smallest average position change (4.12%) and the lowest variability, with a standard deviation of 5.20. This finding is consistent with the fact that more liquid markets allow traders to adjust their positions more frequently and in a timely manner, resulting in smaller and less volatile weekly position changes.

Price dynamics of new crop futures

New crop futures contracts are for agricultural commodities that are growing and not harvested. They are designed to accommodate the seasonality of trading grain products and align with when physical supplies are expected to enter the commodity market. The delivery months of new crop futures are December for corn, November for soybeans and rough rice, and July for winter wheat. Prices of new crop futures contracts are widely considered as a collective forecast of future supply, demand, and market conditions.

Let $p_{i,t}$ be prices of new crop futures for commodity *i* observed at time *t*, price movements in new crop futures are measured as returns,

(10) $$r_{i,t} = (\ln(p_{i,t}) - \ln(p_{i,t-1})) \times 100.$$

Figure 2 describes the seasonal patterns of new crop futures prices for corn, soybeans, winter wheat, and rough rice during the pre-harvest periods, respectively. Seasonal prices tend to be the highest and offer the best profit opportunities. The average prices generally reach peaks in late spring or early summer, then have a downward trend as harvest approaches, reflecting the consistently negative returns that begin about two months before harvest.

Empirical Results

We use the estimated results to answer two major questions for pre-harvest short hedges: (i) how sensitive position changes are to price changes within each hedging regime, and (ii) whether

price movements provide signals for producers and merchants to switch between active and inactive hedging status. We first examine the position changes in response to reference indicators (i.e., dummy variable indicating whether futures prices are below the reference point) and price movements (i.e., futures returns) within *inactive* and *active hedge* regimes, followed by an analysis of reference effects on transitions between these two regimes.

The choice of reference prices determines the value of the indicator variable defined in equation (6). We consider three static reference prices derived from U.S. Department of Agriculture (USDA) projected price data used to establish revenue guarantees in crop insurance, including average marketing price and harvest price, as well as estimated production cost per bushel. We also model dynamic references using moving averages of new crop futures prices over 14-day, 30-day, and 60-day windows.

Reference effects on position changes within regimes

We use a Markov regime switching model to separate inactive (regime 1) and active (regime 2) states defined in equation (6). We report the estimated results for these regime regression in tables 3 (a)-(d) for corn, soybean, winter wheat, and rough rice, respectively. At the bottom of each table, we report the Ljung–Box test for autocorrelation and the Lagrange multiplier test for conditional heteroscedasticity (ARCH) effects. For most reference specifications (i.e., difference selected reference price), the null hypotheses of no autocorrelation and no conditional heteroscedasticity are not rejected at the 1% significance level. Although some tests show p-values between 0.01 and 0.05, indicating marginal evidence against the null hypothesis, the failure to reject autocorrelation and ARCH tests does not occur simultaneously; thus, they are not strong enough to suggest serious misspecification.

The coefficient α_{3,s_t} measures how much producers adjust their weekly short positions when futures prices fall below the chosen reference level, controlling for other factors. For example, weekly short position changes of corn fall by 3.43 percentage points at the 1% statistical significance when new crop futures prices are below the last year's production cost in *active hedge* regime. Among the four commodities, statistically significant reference effects are overwhelmingly negative, indicating that producers tend to reduce their short hedging when facing unfavorable prices. This pattern is consistent with risk-averse behavior: producers are reluctant to lock in unfavorable prices (i.e., current futures prices are below the reference price). For example, significant estimates of α_{3,s_t} occur in the inactive regime of corn based on all the selected references, while for the active regime, only occur at harvest price, production cost, and 60-day moving average. These findings suggest that producers tend to avoid initiating new hedges when prices fall below the reference, especially in periods of inactive hedge. In addition, dynamic references, particularly the 30-day and 60-day moving averages, more frequently contribute to statistically significant impacts on short position changes compared to static references, particularly in rough rice and winter wheat. This supports the argument that dynamic references better capture current market conditions and generate more timely signals that influence hedging decisions. Moreover, wheat and rice, which has lower trading volumes compared to corn and soybeans, exhibit much stronger reference effects, particularly in the active regime for rice (e.g., –3.99 percent points decrease in short position changes when current futures prices fall below last year's production cost), reflecting the sharp sensitivity of position decisions to market price signals in less liquid markets.

Moreover, we focus on the responsiveness of short position changes to futures returns when prices are unfavorable (i.e., below the reference price). All statistically significant

estimates of α_{4,s_t} are negative, indicating producers are less sensitive to price movements when futures prices are already deemed unfavorable. For corn, soybeans, and wheat, these asymmetric behaviors are more common under dynamic reference prices, particularly under the 14-day moving average in the *active hedge* state. In contrast, static references rarely trigger significant asymmetries in either hedge state, indicating that static references primarily influence the decision to sell contracts rather than the intensity of position responses to price movements. Moreover, rough rice exhibits significant asymmetric responsiveness only in the *active hedge* regime. The lack of significant asymmetries in the inactive regime is unsurprising, as low market liquidity limits hedging activity and leaves little room for further adjustments. Even when engaged in active hedging, rice producers become less responsive to daily returns when prices drop below the reference price, which might result from liquidity constraints and difficulty adjusting positions.

In addition, the constant α_{0,s_t} estimates the average weekly short position changes when the futures price is above the reference price, and thus the average weekly short position changes below the reference price are measured by the term $\alpha_{0,s_t} + \alpha_{3,s_t}$. In corn and soybean markets, where short hedging is more systematic, the position changes when prices are below reference prices are still positive but tend to decrease substantially.[7] For example, in soybeans under the 30-day moving average, the position change declines from 6.85 percentage points (active regime) to 3.42 percentage point when prices fall below last year's the production cost. This drop reflects the decline in hedging incentives due to weak pricing. The position changes in thinner markets are more pronounced. For example, the short positions of winter wheat and rough rice

[7] There are few exceptions to see a slight increase in the position changes when price falls below the reference price, but the direct reference effects (α_{3,s_t}) are not statistically significant.

are 5.34 percentage points (inactive hedge regime) and 8.21 percentage points (inactive hedge regime) when prices are below the average marketing prices from last year, respectively. These results suggest that unfavorable price conditions materially dampen hedging activity, especially where market is less liquid.

Moreover, the composite measure, $\alpha_{2,s_t} + \alpha_{4,s_t}$, reflects how producers respond to returns when futures prices are below the reference price. A positive sign indicates that price movements still trigger the occurrence of short hedging even though futures prices are at unfavorable levels, while the negative sign suggests that short position changes are less responsive to returns. Most of the significant responses are positive but with mixed evidence of their occurrence in either active or inactive regime, indicating that price movements still drive the changes in short hedges even though prices are under the reference. Moreover, except for soybeans, short position changes are more muted under the dynamic references than the static ones, highlighting the role of recent market trends in shaping selling decisions. These results confirm the type of reference prices (i.e., either stable within a year or dynamic over windows) can impact their selling decision. When using a static reference, producers are less likely to ignore price signals, even at unfavorable levels. This effect is stronger in high-volume trading markets, where liquidity supports tactical adjustments.

Reference effects on time-varying transitions between hedge regimes

Having explored how reference prices affect short position changes within regimes, we now turn to their role in driving transitions between inactive and active regimes. For clearer interpretation, we report the average partial effects (APEs) rather than the raw coefficients from the transition regressions defined in equation (7). These APEs, derived from equation (8), measure the average change in the probability of switching between hedging regimes in response to price movements

and reference-price conditions. The intercept represents the baseline probability of switching from inactive to active hedge regime (labeled as "Switch" in table 4) or remaining in the active hedge regime (labeled as "Stay" in table 4) when futures prices are above the reference price without impacts of returns ($r_{it} = 0$).[8] Among all commodities, the intercepts are statistically significant and relatively stable across reference specifications, suggesting that a substantial portion of regime-switching behavior reflects systematic that are not heavily conditioned on weekly price movements.

The APEs for futures returns measure capture the change in the probability of switching or remaining in a regime in response to a 1% increase in futures returns when prices are above the reference price. Marginal effects of futures returns are small and statistically insignificant for all four commodities, suggesting that an increase in short-term prices alone does not systematically trigger regime changes. This finding prompts the following question about whether producers' short hedges are more influenced by price movements when current price is below the reference price. We turn to the interaction term $w_{i,t}$, which measures how position changes respond to the returns when futures prices fall below the reference price. For soybeans and winter wheat, the APEs on this interaction term under dynamic references (e.g., 14-day moving average) are negative and statistically significant at the 5% level or lower, indicating that returns have a reduced effect on switching probabilities at unfavorable price levels. Moreover, the magnitude of these effects decreases as the moving-average window lengthens, suggesting that longer-horizon references dilute the immediate impact of returns on regime switching. For example, in soybeans, based on the 14-day moving average, a 1% increase in returns reduces the

[8] Inactive hedge regime is set to be the reference regime, and coefficients are only estimated for transitions to state 2 (active hedge).

probability of switching from inactive to active by 0.18 percentage points or the likelihood of remaining in the active regime by 0.19 percentage points. When the reference is extended to a 60-day moving average, these effects fall to 0.11 and 0.10 percentage points, respectively. A similar pattern is evident in winter wheat, but with a stronger impact of returns on switching or staying in the active hedge regime. Surprisingly, no significant effects of $w_{i,t}$ are found for corn (the most liquid market in agricultural commodities) or rough rice (the least liquid among the selected commodities), suggesting that regime switches in these markets are less sensitive to price movements relative to reference levels.

Conclusions

This study provides new evidence on whether and how reference prices influence agricultural producers' short hedging decisions. We focus on the pre-harvest periods of new crops since futures contracts can help producers to lock in seasonally high prices to hedge against potential price decline during the harvest. Our analysis uses Markov Regime Switching Model with time-varying transition probabilities to investigate the reference price effects on short position changes not only during periods of actively and inactively hedging but also explore whether reference prices can trigger the switches between active and inactive hedge.

There are four major findings after comparing corn, soybean, winter wheat, and rough rice. First, our results show that producers significantly reduce short position changes when futures prices fall below static (e.g., USDA average marketing price, harvest price, production cost) or dynamic (e.g., 14-day, 30-day, 60-day moving averages) reference levels, reflecting risk-averse behavior to avoid locking in unfavorable prices. This direct reference effect is more pronounced in the *inactive hedge* regime and in thinner markets like wheat and rice, where liquidity constraints amplify sensitivity to the reference price. Second, dynamic references,

especially for 30-day and 60-day moving averages of new crop futures, have stronger and more frequent effects than static references. This finding partially confirms the efficiency of futures markets to provide useful information for producers or merchants to adjust their hedges. Third, producers' responsiveness to futures returns weakens when prices are below reference levels, with significant negative effects primarily under dynamic references in active regimes for corn, soybeans, and wheat, but only in rice's active regime, reflecting liquidity-driven constraints in thinner markets. Fourth, the combined effect of the constant ($\alpha_{0,st}$) and reference effect ($\alpha_{3,st}$) reveals substantial reductions in short position changes under unfavorable prices, with steeper declines in thin markets (e.g., 8.21 percentage points for rice, 5.34 for wheat) compared to thick markets (e.g., soybeans dropping from 6.85 to 3.42 percentage points), highlighting liquidity's role in moderating hedging adjustments. Transition regression results further show that short-term price changes above reference levels have negligible effects on regime-switching probabilities across all commodities, as average partial effects (APEs) for futures returns are statistically insignificant, indicating that regime shifts are not driven by short-term price movements in favorable conditions. However, when prices fall below dynamic references, particularly 14-day moving averages, the interaction term ($w_{x,t}$) shows significant negative APEs in soybeans and wheat, reducing the probability of switching to or staying in the active regime (e.g., by 0.18 and 0.19 percentage points in soybeans), with stronger effects in wheat's thinner market, while corn and rice show no significant sensitivity, reflecting distinct market dynamics.

These findings advance the literature on reference-dependent preferences by demonstrating how benchmark choice and market liquidity jointly influence agricultural risk management. Thin markets exhibit heightened price sensitivity and sharper hedging reductions due to liquidity constraints, while thick markets allow more systematic and flexible adjustments,

underscoring the need for tailored risk management strategies. To address these dynamics, policymakers could develop decision-support tools providing real-time dynamic reference prices, such as moving averages, to guide producers' hedging decisions during volatile periods, particularly in liquid markets like corn and soybeans where timely adjustments are feasible. For less liquid markets like wheat and rice, policies to enhance futures market liquidity—through incentives or market-making programs—could reduce the amplified sensitivity to price signals, encouraging consistent hedging to mitigate price risk exposure. Additionally, integrating dynamic reference prices into crop insurance pricing or payout structures could align with producers' behavioral responses, offering coverage that activates when prices fall below key thresholds, thus complementing hedging strategies in both thick and thin markets. Educational initiatives through extension services could further promote proactive hedging during low-price periods, addressing risk-averse biases that lead to reduced hedging activity, thereby fostering greater financial stability across agricultural markets. Future research could extend these insights to other commodities or incorporate behavioral factors like loss aversion to refine risk management frameworks.

Overall, the findings underscore that the type of reference price, market liquidity, and prevailing hedge regime jointly shape producers' risk management behavior. Dynamic references are more closely aligned with current market trends can prompt timely adjustments, but they can also intensify hedging cutbacks in thin markets under adverse pricing. For market participants and policymakers, these results highlight the importance of considering both benchmark choice and market structure when designing tools to manage price risk.

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Table 1. Important Delivery Months of Futures Contracts based on Crop Years

Commodity	First Futures	Last Futures	New Crop Futures
Corn	December	September	December
Soybeans	September	August	November
Wheat	July	May	July
Rough Rice	September	July	November

Notes: The table reports the maturity month of futures contracts which are defined as first, last, and new crop futures based on crop year.

Table 2. Summary Statics of Changes in Short Hedge

	$\Delta Q_{c,t}$	$\Delta Q_{s,t}$	$\Delta Q_{w,t}$	$\Delta Q_{r,t}$
Mean	4.12	6.01	4.94	15.43
Std. Dev.	5.20	7.43	7.84	31.18
Min	-17.65	-17.16	-15.48	-94.91
Max	34.08	34.30	43.50	275.03
Skewness	0.89	0.63	1.02	4.24
Kurtosis	6.65	4.21	6.00	28.63
ADF test	-16.87***	-17.66***	-21.42***	-20.47***
Ljung-Box	168.70***	155.34***	65.91***	62.64***
Observations	700	705	783	649

Notes: The table reports the summary statistic of $\Delta Q_{i,t} = (\ln(Q_{i,t}) - \ln(Q_{i,t-1})) \times 100$, where $Q_{i,t}$ is the short position of producers and merchants for commodity *i* in week *t*, where i= c (corn), s (soybeans), w (winter wheat), and r (rough rice). ADF test is the augmented Dickey-Fuller test for unit root with the null hypothesis of existence of a unit root. Ljung-Box test is done by 10 lags with the null hypothesis of no autocorrelation.

Table 3.a. Parameter Estimates of State-Dependent Regressions for Corn

	Avg Marketing Price		Harvest Price		Production Cost		14-day		30-day		60-day	
	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active
α_{0,s_t}	4.49***	7.15***	4.22***	6.46***	3.67***	6.85***	4.68***	6.68***	4.39***	6.87***	4.33***	6.94***
	(0.60)	(1.93)	(0.63)	(1.45)	(0.62)	(1.54)	(0.64)	(1.82)	(0.65)	(1.46)	(0.63)	(1.16)
α_{1,s_t}	0.30***	0.31***	0.28***	0.33***	0.34***	0.30***	0.30***	0.31***	0.27***	0.29***	0.29***	0.27***
	(0.04)	(0.08)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.08)	(0.05)	(0.06)	(0.05)	(0.05)
α_{2,s_t}	0.31***	0.88***	0.20***	0.78***	0.19***	0.82***	0.21**	1.25***	0.30***	0.99***	0.39***	0.83***
	(0.07)	(0.24)	(0.05)	(0.16)	(0.04)	(0.14)	(0.09)	(0.27)	(0.08)	(0.18)	(0.07)	(0.16)
α_{3,s_t}	-0.45*	-0.34	-0.96**	-1.67*	-1.32***	-3.43***	-1.19***	0.63	-0.69*	-0.87	-0.12*	-2.90***
	(0.33)	(1.22)	(0.41)	(1.01)	(0.45)	(1.31)	(0.40)	(1.55)	(0.41)	(1.06)	(0.38)	(0.76)
α_{4,s_t}	-0.14	-0.12	0.08	-0.20	-0.40***	-1.23***	-0.13	-0.84**	-0.23**	-0.59**	-0.33***	-0.52**
	(0.09)	(0.31)	(0.10)	(0.26)	(0.14)	(0.41)	(0.11)	(0.40)	(0.10)	(0.30)	(0.09)	(0.22)
α_{5,s_t}	-0.06***	-0.07	-0.07***	-0.06	-0.06***	-0.07	-0.06***	-0.10**	-0.07***	-0.08*	-0.08***	-0.04
	(0.02)	(0.06)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)	(0.03)
α_{6,s_t}	0.01	-0.13	0.01	-0.07	0.02	-0.11*	0.01	-0.10	0.02	-0.08	0.00	-0.03
	(0.02)	(0.08)	(0.02)	(0.06)	(0.02)	(0.06)	(0.02)	(0.07)	(0.02)	(0.06)	(0.02)	(0.04)
$\sigma^2_{s_t}$	3.04***	6.39***	3.26***	5.91***	2.35**	5.83***	2.97***	6.21***	2.94***	5.68***	2.88***	5.15***
	(0.17)	(0.53)	(0.19)	(0.40)	(0.18)	(0.37)	(0.16)	(0.50)	(0.17)	(0.39)	(0.13)	(0.24)
$\alpha_{0,s_t} + \alpha_{3,s_t}$	4.04***	6.81***	5.18***	4.79***	5.00***	3.42*	3.49***	7.31***	3.70***	6.00***	4.21***	4.04***
	(0.62)	(2.16)	(0.67)	(1.62)	(0.79)	(2.02)	(0.63)	(2.04)	(0.64)	(1.52)	(0.65)	(1.10)
$\alpha_{2,s_t} + \alpha_{4,s_t}$	0.17***	0.76***	0.29***	0.57***	-0.31***	-0.41	0.08	0.41	0.08	0.40*	0.06	0.31**
	(0.05)	(0.21)	(0.09)	(0.21)	(0.13)	(0.37)	(0.06)	(0.32)	(0.06)	(0.24)	(0.06)	(0.15)
Residual Diagnostics												
Ljung-Box test	0.80	0.65	0.72	0.32	0.72	0.89	0.21	0.87	0.52	0.52	0.28	0.51
ARCH test	0.29	0.80	0.41	0.42	0.38	0.82	0.01	0.36	0.61	0.43	0.66	0.51

Notes: The estimated coefficients on short position changes are presented for equation (6). The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are given in parentheses. We perform two specification tests: autocorrelation and ARCH effect for residuals in each regime with corresponding *p*-values reported.

Table 3.b. Parameter Estimates of State-Dependent Regressions for Soybean

	Avg Marketing Price		Harvest Price		Production Cost		14-day		30-day		60-day	
	Inactive	Active	Active	Inactive	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active
α_{0,s_t}	4.76***	7.12***	3.41***	8.31***	4.26***	6.65***	4.25***	7.13***	3.95***	8.61***	4.38***	8.33***
	(0.81)	(1.93)	(0.78)	(1.85)	(0.76)	(1.76)	(0.74)	(1.61)	(0.71)	(1.60)	(0.73)	(1.54)
α_{1,s_t}	0.36***	0.28***	0.44***	0.25***	0.35***	0.29***	0.33***	0.32***	0.31***	0.28***	0.34***	0.25***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	(0.07)	(0.05)	(0.05)	(0.05)
α_{2,s_t}	0.47***	1.31***	0.47***	0.97***	0.41***	0.81***	0.22*	1.07***	0.38***	0.81***	0.40***	0.99***
	(0.11)	(0.30)	(0.08)	(0.29)	(0.08)	(0.18)	(0.12)	(0.28)	(0.10)	(0.23)	(0.10)	(0.23)
α_{3,s_t}	-0.98**	-1.28	-0.09	-1.56	0.72	0.87	-1.07*	-0.33	-0.83	-2.52**	-0.44	-3.43***
	(0.44)	(1.07)	(0.63)	(1.03)	(0.67)	(1.34)	(0.56)	(1.19)	(0.51)	(1.02)	(0.56)	(0.97)
α_{4,s_t}	-0.04	-0.78**	-0.21	-0.13	0.27	0.32	-0.32	-0.71**	0.06	-0.49**	0.05	-0.80**
	(0.14)	(0.37)	(0.18)	(0.37)	(0.26)	(0.56)	(0.19)	(0.25)	(0.16)	(0.36)	(0.15)	(0.37)
α_{5,s_t}	-0.08***	0.01	-0.06***	-0.02	-0.08***	-0.01	-0.06***	-0.05	-0.06***	-0.04	-0.07***	-0.01
	(0.02)	(0.07)	(0.02)	(0.05)	(0.02)	(0.06)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.04)
α_{6,s_t}	0.04***	0.00	0.02	0.02	0.04	0.02	0.03	0.03	0.04	0.00	0.03	0.01
	(0.01)	(0.99)	(0.03)	(0.07)	(0.03)	(0.07)	(0.03)	(0.06)	(0.03)	(0.03)	(0.03)	(0.06)
$\sigma^2_{s_t}$	3.39***	8.04***	3.50***	7.93***	3.31***	8.01***	2.99***	7.83***	3.03***	7.73***	3.36***	7.66***
	(0.26)	(0.40)	(0.20)	(0.37)	(0.28)	(0.41)	(0.26)	(0.35)	(0.25)	(0.35)	(0.21)	(0.34)
$\alpha_{0,s_t} + \alpha_{3,s_t}$	5.83***	3.78***	6.76***	3.31***	7.52***	4.98***	3.18***	6.80***	3.12***	6.09***	3.93***	4.90***
	(2.15)	(0.77)	(1.84)	(0.89)	(2.10)	(1.03)	(0.81)	(1.68)	(0.80)	(1.59)	(0.82)	(1.44)
$\alpha_{2,s_t} + \alpha_{4,s_t}$	0.53**	0.43***	0.83***	0.26	1.13**	0.69***	0.54***	0.37	0.44***	0.32	0.44***	0.19
	(0.22)	(0.09)	(0.22)	(0.17)	(0.52)	(0.25)	(0.14)	(0.35)	(0.12)	(0.28)	(0.12)	(0.29)
Residual Diagnostics												
Ljung-Box test	0.04	0.17	0.21	0.33	0.05	0.27	0.05	0.22	0.27	0.03	0.28	0.38
ARCH test	0.20	0.37	0.01	0.73	0.11	0.40	0.67	0.10	0.68	0.07	0.50	0.01

Notes: The estimated coefficients on short position changes are presented for equation (6). The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are given in parentheses. We perform two specification tests: autocorrelation and ARCH effect for residuals in each regime with corresponding *p*-values reported.

Table 3.c. Parameter Estimates of State-Dependent Regressions for Winter Wheat

	Avg Marketing Price		Harvest Price		Production Cost		Moving average					
							14-day		30-day		60-day	
	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active
α_{0,s_t}	5.47***	7.57**	5.14***	9.36***	5.58***	7.43	6.85***	7.72**	7.42***	8.49**	7.39***	10.47**
	(0.89)	(3.15)	(0.86)	(3.18)	(0.95)	(5.58)	(0.86)	(3.73)	(0.92)	(3.77)	(0.97)	(4.43)
α_{1,s_t}	0.14***	0.38***	0.14***	0.35***	0.17***	0.29***	0.16***	0.30***	0.12***	0.37***	0.13***	0.32**
	(0.04)	(0.12)	(0.04)	(0.11)	(0.04)	(0.10)	(0.04)	(0.11)	(0.04)	(0.13)	(0.05)	(0.13)
α_{2,s_t}	0.32***	0.78**	0.32***	0.78**	0.19	1.26	0.23*	1.94***	0.24**	1.65***	0.32***	1.31***
	(0.10)	(0.32)	(0.10)	(0.36)	(0.12)	(1.21)	(0.14)	(0.57)	(0.12)	(0.46)	(0.11)	(0.49)
α_{3,s_t}	-0.13	1.18	0.39	-0.52	-0.41	2.28	-2.61***	0.17	-2.97***	-1.92	-2.56***	-3.87
	(0.68)	(2.08)	(0.62)	(1.99)	(0.72)	(5.21)	(0.68)	(2.06)	(0.66)	(2.50)	(0.65)	(2.83)
α_{4,s_t}	-0.31*	0.65	-0.23	0.54	0.06	-0.23	-0.31*	-1.85**	-0.29*	-1.58**	-0.31*	-0.94
	(0.18)	(0.51)	(0.17)	(0.51)	(0.16)	(1.25)	(0.18)	(0.91)	(0.17)	(0.69)	(0.16)	(0.65)
α_{5,s_t}	-0.09***	-0.04	-0.09***	-0.06	-0.09***	-0.08	-0.09***	-0.08	-0.10***	-0.05	-0.10***	-0.03
	(0.03)	(0.08)	(0.02)	(0.08)	(0.02)	(0.07)	(0.02)	(0.09)	(0.02)	(0.08)	(0.03)	(0.09)
α_{6,s_t}	-0.03	-0.12	-0.01	-0.18	-0.02	-0.17	-0.02	-0.19	-0.02	-0.15	-0.02	-0.18
	(0.05)	(0.16)	(0.04)	(0.14)	(0.04)	(0.13)	(0.04)	(0.16)	(0.04)	(0.16)	(0.04)	(0.19)
$\sigma^2_{s_t}$	4.81***	10.26***	4.77***	10.46***	4.86***	10.38***	4.98***	11.27***	4.76***	10.59***	4.90***	10.83***
	(0.30)	(0.78)	(0.29)	(0.76)	(0.26)	(0.73)	(0.25)	(0.84)	(0.31)	(0.82)	(0.36)	(0.95)
$\alpha_{0,s_t} + \alpha_{3,s_t}$	5.34***	8.75***	8.84***	5.53***	5.17***	9.71***	7.89**	4.24***	6.57**	4.45***	4.83***	6.61**
	(0.94)	(3.14)	(3.20)	(0.93)	(0.85)	(2.75)	(3.47)	(0.81)	(3.16)	(0.81)	(0.82)	(3.34)
$\alpha_{2,s_t} + \alpha_{4,s_t}$	0.00	1.43***	1.32***	0.09	0.26**	1.03***	0.09	-0.08	0.07	-0.04	0.01	0.36
	(0.15)	(0.41)	(0.36)	(0.14)	(0.11)	(0.25)	(0.62)	(0.13)	(0.49)	(0.12)	(0.12)	(0.45)
Residual Diagnostics												
Ljung-Box test	0.94	0.06	0.36	0.95	0.62	0.07	0.24	0.97	0.34	0.34	0.25	0.72
ARCH test	0.47	0.68	0.18	0.23	0.40	0.14	0.66	0.54	0.78	0.71	0.79	0.29

Notes: The estimated coefficients on short position changes are presented for equation (6). The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are given in parentheses. We perform two specification tests: autocorrelation and ARCH effect for residuals in each regime with corresponding p-values reported.

Table 3.d. Parameter Estimates of State-Dependent Regressions for Rough Rice

	Avg Marketing Price		Harvest Price		Production Cost		Moving average					
							14-day		30-day		60-day	
	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active	Inactive	Active
α_{0,s_t}	9.72***	69.29***	9.38***	106.99***	9.93***	83.71***	10.14***	85.89**	10.43***	63.39***	10.37***	118.76***
	(2.98)	(20.06)	(2.93)	(26.57)	(3.09)	(22.15)	(3.25)	(34.92)	(3.05)	(22.39)	(2.78)	(24.89)
α_{1,s_t}	0.43	3.51*	0.25	-0.73	0.36	3.08	0.56	0.79	0.58	4.92*	0.61**	-0.45
	(0.28)	(2.13)	(0.33)	(2.59)	(0.30)	(2.30)	(0.54)	(4.66)	(0.37)	(2.66)	(0.30)	(2.29)
α_{2,s_t}	0.18***	0.34**	0.17***	0.33**	0.17***	0.26	0.20***	0.23	0.19***	0.32*	0.12***	0.25***
	(0.02)	(0.13)	(0.02)	(0.15)	(0.02)	(0.16)	(0.02)	(0.15)	(0.02)	(0.17)	(0.02)	(0.08)
α_{3,s_t}	-1.51	-7.06	-0.20	0.09	-0.28	19.66	-3.99**	-4.61	-4.66***	5.59	-2.00	-16.51
	(1.40)	(10.65)	(0.69)	(0.99)	(1.24)	(13.13)	(1.64)	(30.01)	(1.37)	(23.40)	(1.26)	(10.32)
α_{4,s_t}	-0.09	-1.01**	-0.07	-1.78***	-0.09	-1.54***	-0.08	-1.16*	-0.07	-0.93*	-0.09	-1.92***
	(0.07)	(0.47)	(0.07)	(0.62)	(0.07)	(0.55)	(0.07)	(0.61)	(0.07)	(0.52)	(0.06)	(0.51)
α_{5,s_t}	-0.08	1.28	-0.01	1.83*	-0.03	1.35	-0.04	1.59	-0.02	1.38	-0.06	1.63**
	(0.09)	(0.92)	(0.10)	(1.01)	(0.09)	(1.02)	(0.09)	(1.00)	(0.09)	(1.06)	(0.08)	(0.79)
α_{6,s_t}	-0.03	-2.60	0.81*	3.78	0.55	1.96	-0.84	5.20	-0.63	-2.34	-0.73	1.30
	(0.79)	(3.64)	(0.44)	(3.45)	(0.47)	(4.25)	(0.67)	(7.74)	(0.49)	(8.20)	(0.45)	(2.98)
$\sigma^2_{s_t}$	7.61***	31.53***	8.27***	31.61***	8.01***	31.89***	7.91***	33.79***	7.85***	34.26***	7.22***	27.66***
	(0.57)	(3.35)	(0.46)	(3.89)	(0.55)	(3.65)	(0.56)	(3.84)	(0.49)	(3.89)	(0.60)	(3.23)
$\alpha_{0,s_t} + \alpha_{3,s_t}$	8.21**	62.23***	9.18***	107.08***	9.65***	103.36***	6.15*	81.28**	5.76*	68.99**	8.37***	102.26***
	(3.22)	(22.11)	(3.04)	(27.67)	(3.33)	(28.94)	(3.28)	(32.82)	(3.26)	(29.13)	(2.89)	(22.25)
$\alpha_{2,s_t} + \alpha_{4,s_t}$	0.40	0.91	1.06***	3.06	0.92**	5.04	-0.28	5.99	-0.05	2.58	-0.13	0.85
	(0.68)	(3.00)	(0.30)	(2.74)	(0.36)	(3.69)	(0.38)	(7.09)	(0.32)	(8.11)	(0.34)	(2.19)
Residual Diagnostics												
Ljung-Box test	0.22	0.07	0.64	0.41	0.78	0.71	0.28	0.11	0.66	0.27	0.19	0.57
ARCH test	0.62	0.06	0.19	0.09	0.06	0.77	0.01	0.42	0.01	0.08	0.27	0.92

Notes: The estimated coefficients on short position changes are presented for equation (6). The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors are given in parentheses. We perform two specification tests: autocorrelation and ARCH effect for residuals in each regime with corresponding p-values reported.

Table 4.a. Marginal Effects of Estimates in Time-varying Transition Probabilities, Corn

	Avg Marketing Price		Harvest Price		Production Cost		Moving average					
							14-day		30-day		60-day	
	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay
Intercept	0.10*	0.12*	0.12	0.12**	0.15**	0.17***	0.12*	0.10*	0.12*	0.11*	0.12*	0.09*
	(0.07)	(0.07)	(0.08)	(0.05)	(0.07)	(0.06)	(0.06)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
$r_{c,t}$	-0.01	-0.04	-0.02	0.00	0.01	-0.00	-0.01	-0.04	0.00	0.00	-0.02	0.02
	(0.08)	(0.07)	(0.09)	(0.08)	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)	(0.06)	(0.08)	(0.07)
$w_{c,t}$	-0.01	-0.06	-0.03	-0.04	-0.02	-0.03	-0.13	-0.12	-0.11	-0.10	-0.08	-0.05
	(0.07)	(0.06)	(0.03)	(0.04)	(0.02)	(0.02)	(0.09)	(0.10)	(0.09)	(0.08)	(0.08)	(0.07)

Notes: The table reports the average marginal effect of explanatory variables from equation (7), which models time-varying transition probabilities in a Markov-switching framework. State 1 (inactive hedge) is the reference state in the multinomial logistic regression; thus, coefficients are only estimated for transitions to state 2 (active hedge). The "Switch" column reports the marginal effect on the probability of transitioning from State 1 to State 2, while the "Stay" column reports the marginal effect on the probability of remaining in State 2 (versus transitioning to State 1). Standard errors, shown in parentheses, are computed using 100 bootstrap replications. The standard errors are calculated using 200 bootstrap replications and are reported in parenthesis. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.b. Marginal Effects of Estimates in Time-varying Transition Probabilities, Soybean

	Avg Marketing Price		Harvest Price		Production Cost		Moving average					
							14-day		30-day		60-day	
	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay
Intercept	0.22***	0.21***	0.20***	0.21***	0.22***	0.20***	0.22***	0.21***	0.20***	0.20***	0.23***	0.21***
	(0.03)	(0.04)	(0.06)	(0.04)	(0.04)	(0.06)	(0.03)	(0.06)	(0.05)	(0.05)	(0.03)	(0.03)
$r_{c,t}$	0.02	0.02	0.02	0.02	0.03	0.06	0.04	0.00	0.04	0.01	0.01	0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)	(0.07)	(0.04)	(0.05)	(0.04)	(0.04)
$w_{s,t}$	-0.03	-0.02	-0.04	-0.04	-0.02*	-0.02	-0.18***	-0.19***	-0.11**	-0.14***	-0.11***	-0.10***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.06)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)

Notes: The table reports the average marginal effect of explanatory variables from equation (7), which models time-varying transition probabilities in a Markov-switching framework. State 1 (inactive hedge) is the reference state in the multinomial logistic regression; thus, coefficients are only estimated for transitions to state 2 (active hedge). The "Switch" column reports the marginal effect on the probability of transitioning from State 1 to State 2, while the "Stay" column reports the marginal effect on the probability of remaining in State 2 (versus transitioning to State 1). Standard errors, shown in parentheses, are computed using 100 bootstrap replications. The standard errors are calculated using 200 bootstrap replications and are reported in parenthesis. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.c. Marginal Effects of Estimates in Time-varying Transition Probabilities, Winter Wheat

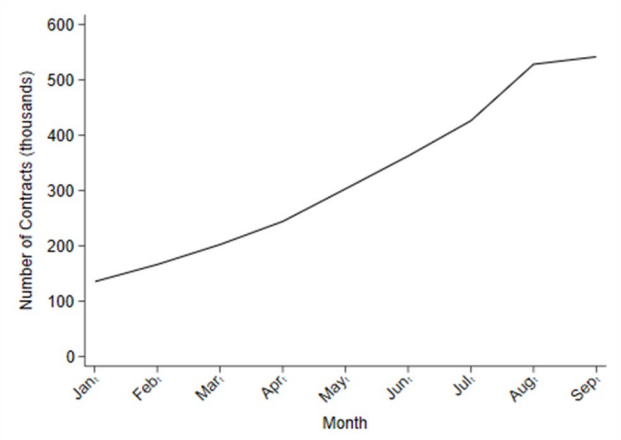
	Avg Marketing Price		Harvest Price		Production Cost		Moving average					
							14-day		30-day		60-day	
	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay
Intercept	0.17***	0.15***	0.16***	0.18***	0.17***	0.16***	0.18***	0.17***	0.17***	0.18***	0.19***	0.19***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.04)	(0.05)
$r_{c,t}$	-0.04	-0.01	-0.01	-0.04	-0.05	-0.03	-0.03	0.00	-0.03	-0.02	-0.02	-0.03
	(0.05)	(0.06)	(0.09)	(0.08)	(0.08)	(0.10)	(0.11)	(0.08)	(0.10)	(0.10)	(0.07)	(0.08)
$w_{w,t}$	-0.05	-0.05	-0.02	-0.05	-0.05	-0.04	-0.24***	-0.24**	-0.22**	-0.22**	-0.17**	-0.18***
	(0.04)	(0.06)	(0.06)	(0.05)	(0.07)	(0.09)	(0.09)	(0.10)	(0.09)	(0.10)	(0.08)	(0.06)

Notes: The table reports the average marginal effect of explanatory variables from equation (7), which models time-varying transition probabilities in a Markov-switching framework. State 1 (inactive hedge) is the reference state in the multinomial logistic regression; thus, coefficients are only estimated for transitions to state 2 (active hedge). The "Switch" column reports the marginal effect on the probability of transitioning from State 1 to State 2, while the "Stay" column reports the marginal effect on the probability of remaining in State 2 (versus transitioning to State 1). Standard errors, shown in parentheses, are computed using 100 bootstrap replications. The standard errors are calculated using 200 bootstrap replications and are reported in parenthesis. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

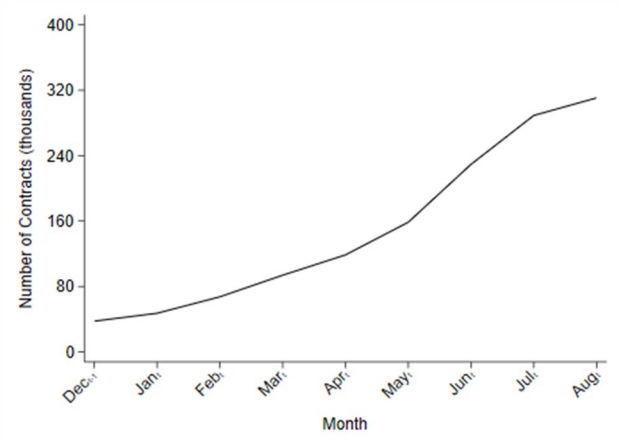
Table 5.d. Marginal Effects of Estimates in Time-varying Transition Probabilities, Rough Rice

	Avg Marketing Price		Harvest Price		Production Cost		Moving average					
							14-day		30-day		60-day	
	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay
Intercept	0.16**	0.15**	0.16***	0.14**	0.13**	0.14***	0.17***	0.14*	0.14**	0.15***	0.15*	0.14*
	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)	(0.05)	(0.05)	(0.09)	(0.07)	(0.05)	(0.08)	(0.07)
$r_{c,t}$	0.07	0.04	0.07	0.05	0.04	0.06	0.07	0.05	0.04	0.11	0.08	0.05
	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.09)	(0.11)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
$w_{r,t}$	0.00	-0.01	0.00	-0.00	-0.01	0.00	-0.14*	-0.12	-0.10	-0.09	-0.06	-0.08
	(0.03)	(0.03)	(0.06)	(0.05)	(0.05)	(0.04)	(0.07)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)

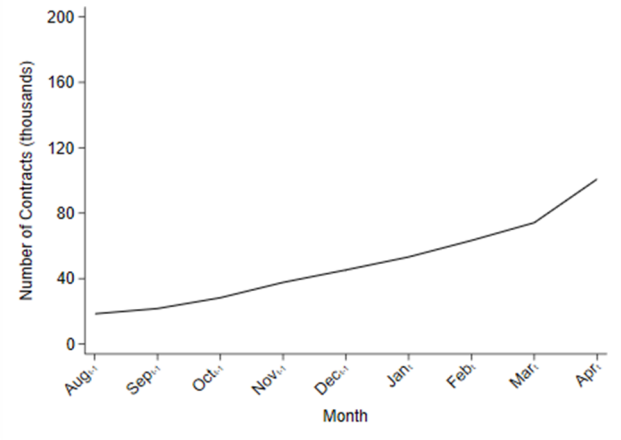
Notes: The table reports the average marginal effect of explanatory variables from equation (7), which models time-varying transition probabilities in a Markov-switching framework. State 1 (inactive hedge) is the reference state in the multinomial logistic regression; thus, coefficients are only estimated for transitions to state 2 (active hedge). The "Switch" column reports the marginal effect on the probability of transitioning from State 1 to State 2, while the "Stay" column reports the marginal effect on the probability of remaining in State 2 (versus transitioning to State 1). Standard errors, shown in parentheses, are computed using 100 bootstrap replications. The standard errors are calculated using 200 bootstrap replications and are reported in parenthesis. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.



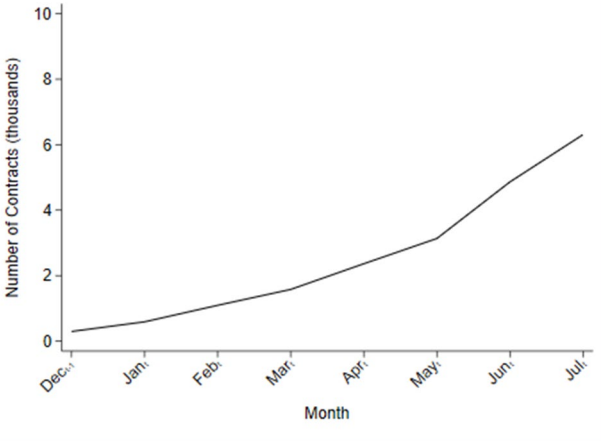
(a) Corn



(b) Soybeans

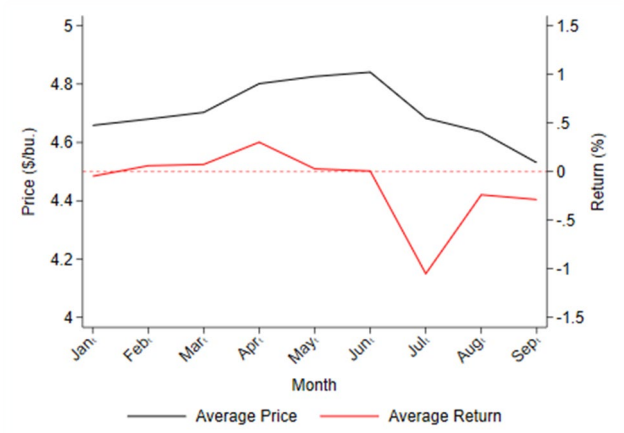


(c) Winter Wheat



(d) Rough Rice

Figure 1. Short Hedge in the Pre-Harvest Periods
Notes: The figure plot the monthly average position of futures traders categorized by producers/merchants across crop years from 2007 to 2023. We report the average short positions in the pre-harvest periods.



(a) Corn



(b) Soybeans



(c) Winter Wheat



(d) Rough Rice

Figure 2. New Crop Futures Price Dynamics in Pre-Harvest Periods
Notes: The average monthly prices are plot for corn, soybeans, winter wheat, and rice in the pre-harvest periods, respectively. We convert the price quotation to dollars per bushel. The return is measured as $r_{i,t} = (\ln(p_{i,t}) - \ln(p_{i,t-1})) \times 100$, where i =c (corn), s (soybean), w (winter wheat), and r (rice). The red dash line refers to zero return.