# An Evaluation of Corn Farmers' Use of Over-the-Counter Risk Management Products

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**Abstract**

Grain producers face significant price uncertainty, and while exchange-traded derivatives like futures and options have been extensively studied, little is known about how farmers use structured over-the-counter (OTC) derivatives. This study investigates how U.S. corn producers hedge price risk using three categories of structured OTC derivative products: Participation, Price Improvement, and Protection contracts. Using proprietary data on individual OTC corn derivative contracts executed by U.S. farmers, we employ a two-stage analytical framework combining XGBoost machine learning for feature selection and a multinomial logit model for economic interpretation. Our findings highlight distinct behavioral patterns consistent with a reference-dependent framework: producers disproportionately select Price Improvement contracts during periods of low prices, shift toward Participation contracts at price extremes under moderate volatility, and use Protection contracts less frequently, even when downside risks are elevated. Counterfactual analysis shows that in the observed falling price environment, Protection strategies generated the highest average returns, outperforming both Price Improvement and Participation by approximately 20 to 56 cents per bushels. In particular, nearly 79% of observed Price Improvement trades would have yielded higher profits had producers chosen Protection instead, indicating substantial economic losses from suboptimal contract selection. These findings provide rare empirical insight into producers' decision-making with complex OTC instruments and contribute to broader discussions on commodity market behavior, agricultural finance, and behavioral economics.

*Keywords*: OTC derivatives, corn producers, hedging behavior, commodity markets, machine learning

*JEL code*: Q13, G13, G32, D81

# 1 Introduction

Farmers have access to commodity pricing or hedging tools to address output price uncertainty. Although agricultural commodity exchange-traded derivatives, such as futures and options, receive the majority of economists' attention (e.g. Fortenbery and Sumner, 1990; Xu, 2019), US corn farmers are more likely to use marketing contracts (Prager et al., 2020). Potentially, this behavior is related to the simplicity, flexibility, and lack of exposure to margin risk associated with exchange-traded derivatives. These perceived benefits are also touted by over-the-counter derivatives dealers, and likely the reason that grain originators have expanded their marketing contract offerings with structured contracts composed of over-the-counter derivatives. This study examines the role of over-the-counter (OTC) derivatives (sometimes referred to as *structured products*) in how farmers' manage output price uncertainty. Specifically, we use a unique proprietary dataset of individual OTC corn derivative contracts executed by U.S. farmers from 2022 to 2024-—data that, to our knowledge, has never before been analyzed in academic research. We use these data for three tasks: (i) characterize OTC derivatives for corn pricing, (ii) examine corn farmers' behavior in engaging OTC derivatives, and (iii) examine the relative performance of OTC derivative corn marketing contracts.

Previous studies examining farmers' activities managing price uncertainty, or hedging, largely focus on futures, options, or crop insurance (Prager et al., 2020; Mishra and El-Osta, 2002; Poitras, 1993; Tomek and Peterson, 2001), with comparatively limited study on producers' use of OTC derivatives. Early studies focus on the theoretical benefits of using futures and options to stabilize farm income and reduce revenue volatility (McKinnon, 1967). Later empirical studies examine adoption of hedging strategies and often emphasize constraints like restricted access to markets, complexity, and basis risk (Musser et al., 1996). Subsequent studies have examined the role of revenue insurance and index-based products in mitigating production and price risk (Barnett and Mahul, 2007), offering insight on how standardized risk management tools interact with farm-level behavior and outcomes (Sherrick et al., 2004).

But the growing availability of over-the-counter (OTC) structured contracts, offered by bro-

kers and commercial hedging providers, presents a new dimension to farm risk management that has been largely unexplored. These contracts are often designed to match specific price expectations, delivery time, or risk tolerance and may include embedded features like accumulation levels, knock-in/knock-out barriers, and fixed premiums. Because OTC contracts are privately negotiated, data about decisions on structured product selection are typically unobserved in large-scale agricultural datasets, such as the USDA's ARMS or farm-level census surveys, which focus more on broad farm characteristics than on contract-level trading data. As a result, there is limited understanding of how producers choose among available OTC products or how closely their decisions align with market conditions. Our dataset fills this gap, enabling the first empirical analysis of producers' structured OTC contract choices at the individual trade level, as well as an evaluation of whether these choices were economically optimal given prevailing market conditions.

For simplicity, this study adopts a characterization of OTC contracts along their perceived marketing objectives, Participation, Price Improvement, and Protection. The dimensionality of OTC products is enormous, contracts can be designed to fit very particular risk-return profiles (Basu and Gavin, 2010; Awrey, 2010). However, high dimensionality can lead to confusion as grain originators engage farm customers. As a result, OTC derivatives dealers often seek to reduce the dimensionality into product categories that characterize the objectives and risk-return profiles of popular OTC marketing contracts. These characterizations are not mutually exclusive, one product may address several objectives, but this characterization is useful for our discussion. Participation contracts allow producers to incrementally participate in market price movement without price floors. Price Improvement contracts offer producers a premium above the market price, but offset this premium with uncertainty on the volume of production committed. Protection contracts focus on managing downside risk through establishing a price floor or fixed strike prices.

Behavioral factors may also influence contract choice. Specifically, Jacobs et al. (2018) presents a reference-dependent hedging framework, where producers make marketing decisions based on a certain reference point, rather than as a function of absolute price. For example, a producer may consider a recent contract high, contract average, or their expected price as the reference point. When the current price is above this reference point, producers view this as a gain and will be

more likely to lock in profits; similarly, when the price falls below the reference, they view it as a loss and are risk-averse or risk-seeking. We extend this behavioral reference-dependent hedging framework beyond the binary hedge/no-hedge decision to examine how farmers choose between structured OTC products. Given that multiple reference points may be psychologically meaningful (e.g., cost of production, last year average price, or recent chart highs), we adopt a machine learning approach to identify the most relevant reference points and then use an econometric analysis to derive economic intuition about how these reference points influence product choice. This two-stage empirical strategy links behavioral theory with machine learning analytics and econometric interpretation, providing a more holistic understanding of how farmers chose structured products in the OTC market.

This study uses proprietary data of farmers' individual OTC derivative corn marketing contracts provided by Marex Hedging Solutions. This dataset captures the entire trade lifecycle, from initiation to settlement. Our aim is to (i) characterize OTC derivatives for corn pricing, (ii) examine corn farmers' behavior in engaging OTC contracts, and (iii) examine the relative performance of these OTC contracts. For (i) we use summary statistics and graphs. For (ii), we adopt a two-stage analytical framework. In the first stage, we use eXtreme Gradient Boosting (XGBoost), a machine learning algorithm, to identify the most important predictors of product selection. The second stage uses a multinomial logit model (MNL), an econometric approach, to derive economic intuition, marginal effects, and statistical significance of these selected independent variables. For (iii), we simulate a counterfactual analysis that projects returns producers would have achieved had they selected an alternative structure, allowing us to quantify the opportunity costs embedded in real-world decision-making.

This study shows that corn producers exhibit distinct preferences for structured OTC derivatives based on market conditions. Price level and volatility strongly influence product selection. When prices fall into the lowest historical quartile, Price Improvement contracts dominate, which accounts for nearly 79% of all trades in that range, potentially suggesting a preference for securing above-market pricing during weak markets. Participation contracts are more common at price extremes and under moderate volatility, offering flexibility when market direction is uncertain.

In contrast, Protection products are least used among the three structures, and their adoption declines when volatility increases. Results from the multinomial logit model confirm these patterns: a one-unit increase in the price percentile significantly reduces the probability of selecting Participation, while increasing the probability of choosing Price Improvement. Volatility positively affects Participation but negatively influences Protection usage. In addition, producers respond to short-term and medium-term price movements—when the current price is above recent lows, they tend to favor Participation or Protection, while falling prices relative to recent highs increase the likelihood of choosing Price Improvement. Despite these adaptive behaviors, our counterfactual simulations reveal a striking result: in the observed falling price environment, Protection structures would have consistently delivered the highest average returns, outperforming other strategies by approximately 20 to 56 cents per bushel. Nearly 79% of observed Price Improvement trades would have earned higher profits under Protection, highlighting significant opportunity costs associated with suboptimal contract selection.

One important limitation is the fact that corn futures markets fell through our study period affecting which product types performed the best. Despite this challenge, we contribute to the commodity marketing and farmer behavior literature in several ways. First, we provide novel empirical evidence on how producers use structured over-the-counter (OTC) derivative products using individual contract-level trades. While most existing studies exclusively focus on exchange-traded products such as futures and options, we present new findings on customized, off-exchange risk management products that are designed to meet specific market expectations and pricing objectives. Second, our methodology includes characterizing the corn market as relative to some common dynamic heuristic (for example, market high in the last 30 days, market low in last 120 days, etc...) and using the XGBoost machine learning technique with multinomial logit modeling(MNL) to develop a two-stage analytical framework. This framework identifies both the key market signals that influences farmers' product selection and the economic rationale behind those decisions, bridging the gap between prediction and interpretation. Third, we use a simple backtest to demonstrate that structured OTC contracts generated substantial economic value during the study period (falling market conditions), but counterfactual analysis reveals that producers often selected sub-

optimal structures, missing opportunities to maximize returns under prevailing(falling) market conditions, though these counterfactual results may differ in a rising market where other product types, such as Participation and Price Improvement, might outperform.

This study provides important implications for farmers and grain originators. For farmers, they will want to consider the observed behavioral patterns and evaluate whether their "reference price" is appropriate for their business objectives. Additionally, farmers may be able to leverage the benefits of OTC products for long-dated marketing objectives, especially when their volume commitments are low. Grain originators may benefit from contextualizing the market in terms of shown "reference prices" and avoiding conversations related to volatility. Additionally, given the results, grain originators should use OTC products to secure volume commitments early, potentially up to 22 months prior to production.

The remainder of this paper is organized as follows. Section 2 describes the proprietary dataset, statistics and institutional context of OTC derivative products. Section 3 outlines our two-stage methodology, including the machine learning and econometric models. Section 4 summarizes the empirical results of product selection and pricing outcomes. Section 5 discusses counterfactual analysis and its implications. Finally, Section 6 provides a concluding summary of key findings.

## 2 Data

This study uses a dataset of 2,428 individual over-the-counter (OTC) corn derivatives that were traded between February 2022 to August 2024. This data is provided by Marex Hedging Solutions, a risk management and brokerage services company. Among other enterprises, Marex Hedging Solutions is an OTC derivative dealer specializing in providing grain originators a platform of customized OTC derivative products to use in marketing contracts. This dataset is rare in academic research because contract-level OTC trading data is typically proprietary and unavailable, making it uniquely suited for studying producers' decision-making in structured product selection.

The key to understanding this dataset is the context of a typical relationship between grain

originators and corn farmers. Grain orginators' objective is to purchase current and future corn production to be used for export, processing, or wholesale. To achieve this aim, grain originators offer potential farm clients contracts like spot prices, forward cash sales, hedge-to-arrive, or basis-only to ensure necessary volume to meet their commitments to processors, end users, or exporters. Because of the inherent price risk that grain originators face after executing a contract with farmers, these individuals and institutions are active in offsetting their exposure through hedging. However, given the constraints of exchanged-traded derivatives, and the desire to appeal to potential farm clients, grain originators may need to engage an OTC derivatives dealer to under-write flexible or exotic hedging mechanisms. The grain originator offers a farmer an exotic contract and the farmer commits a volume of production. In exchange, the grain originator pays a premium fee and the OTC derivative dealer manages the price risk. As a result, the dataset represents actual OTC derivatives traded by farmers, but the farmers may be unaware of the product, because they have primarily discussed the pricing mechanism and committed physical production with a grain originator like they would for other traditional marketing contracts.

The data include full details on type of trade, timing, price levels, market conditions at initiation, and execution performance realized. As mentioned earlier, we adopt a simple characterization of structured OTC derivatives: Participation, Price Improvement and Protection. These product characterizations on the different marketing objectives are discussed below.

- **Participation** contracts (primarily averaging) provide incremental exposure to markets while maintaining some flexibility. These products typically allow producers to commit a volume of grain upfront, but let that volume be priced incrementally over time while smoothing out day-to-day volatility. The resulting price is referred to as the level price, which reflects the average of market prices at which small volumes are priced throughout the contract period. While this approach offers flexibility and exposure to upward price movements, it does not include downside protection, and are best suited for low-volatility bullish or neutral markets, or strongly bullish markets where price floor is deemed unnecessary. Typically, a producer does not pay a premium for engaging a participation structure. The premium is accounted for in the risk-return construction of the product, most pronounced is

the lack of a price floor.

- **Price Improvement** contracts (primarily accumulators) offer producers a premium above the market price for volume-based or price contingent commitments. Typically, producers commit to deliver additional volumes if market prices exceed predefined thresholds, known as accumulation levels. This type of product performs well if prices remain within a range over a period of time and can yield higher returns than spot prices in such an environment. Similar to participation, producers typically do not pay a premium for engaging price improvement structures.The premium (positive delta) between the current market price and the contract's accumulation level is achieved by producers agreeing to deliver additional volume if prices rise above certain thresholds. The uncertain volume commitment functions as an implicit price ceiling, since producers are required to deliver additional corn volumes at the accumulation level once market prices surpass a predefined trigger point (the 'knock-in' level), thereby constraining potential gains from further price increases. Importantly, many of these contracts include a lower barrier level, and if market prices fall below this level, these contracts are automatically terminated.

- **Protection** contracts focus on managing downside risk through a price floor [1], ensuring a minimum guaranteed price level. They are designed to be used in uncertain or declining markets, where the priority is to secure a minimum price. Although they limit downside exposure, producers retain full upside potential if prices subsequently rise. In contrast to participation and price improvement structures, protection products often require producers to pay a premium. Like similar exchange-traded put options, the premium is directly related to time to expiry and volatility.

Table 1 reports the share of each product type used by corn producers across the corn futures price and volatility quartiles from 2022 to 2024. The price and volatility on the initial trade date is assigned into one of four quartiles based on the 252-day trailing percentile. It is important to note that in a falling market, the 252-day price percentile may exist in the lower quartile for an

[1] Price floor is a minimum guaranteed price in a Protection contract, typically defined by the strike price of an embedded put option.

extended period of time. Despite this limitation, the table reveals some clear behavioral patterns among product types. Price Improvement is the most frequently used product overall, accounting for approximately 62% of all trades. Price Improvement is used across all price and volatility quartiles, but mostly concentrated in lower and moderate volatility quartiles. For example, in the lowest price quartile, Price Improvement accounts for nearly 79% of all trades. This suggests that even during weaker market conditions, producers favored structures that offered enhanced pricing potential, possibly reflecting a desire to secure price premiums while accepting uncertainty on volume commitments.

Table 1: Product Type Share by Price and Volatility Quartiles (%)

| Price Quartile | Product Type | Volatility Quartile | | | | Total |
|---|---|---|---|---|---|---|
| | | Lower 25% | 25% to 50% | 50% to 75% | Upper 25% | |
| Lower 25% | Participation | 1.07 | 0.17 | 13.88 | 2.48 | 17.60 |
| | Price Improvement | 24.21 | 14.21 | 22.48 | 17.85 | 78.76 |
| | Protection | 1.49 | 0.00 | 1.07 | 1.07 | 3.64 |
| | Total | 26.77 | 14.38 | 37.43 | 21.40 | 100.00 |
| 25% to 50% | Participation | 16.67 | 8.33 | 27.08 | 0.00 | 52.08 |
| | Price Improvement | 16.67 | 16.67 | 0.00 | 6.25 | 39.58 |
| | Protection | 0.00 | 8.33 | 0.00 | 0.00 | 8.33 |
| | Total | 33.33 | 33.33 | 27.08 | 6.25 | 100.00 |
| 50% to 75% | Participation | 3.36 | 9.54 | 10.96 | 3.18 | 27.04 |
| | Price Improvement | 8.48 | 24.56 | 4.77 | 2.30 | 40.11 |
| | Protection | 11.13 | 18.21 | 2.12 | 1.41 | 32.86 |
| | Total | 22.97 | 52.31 | 17.85 | 6.89 | 100.00 |
| Upper 25% | Participation | 4.30 | 2.15 | 9.11 | 17.55 | 33.11 |
| | Price Improvement | 16.06 | 15.06 | 7.78 | 10.76 | 49.66 |
| | Protection | 3.48 | 6.95 | 2.15 | 4.64 | 17.22 |
| | Total | 23.84 | 24.17 | 19.04 | 32.95 | 100.00 |
| Total | Participation | 2.72 | 3.01 | 12.28 | 6.34 | 24.35 |
| | Price Improvement | 18.37 | 16.89 | 14.25 | 12.23 | 61.74 |
| | Protection | 4.20 | 6.13 | 1.56 | 2.02 | 13.91 |
| | Total | 25.29 | 25.99 | 28.09 | 20.59 | 100.00 |

*Notes:* The table above shows how producers use different OTC product types across combinations of price and volatility quartiles, based on 252-day trailing percentiles. Price Improvement is the most widely used structure, especially in lower price and volatility settings. Participation is more common at price extremes with moderate volatility, while Protection is selectively used in mid-to-high price quartiles and low to moderate volatility environments.

Participation products are mostly used by producers when the price level is extreme and volatility is moderate. Over 70% of Participation contracts are concentrated in either the lowest or highest price quartiles, while it's use is substantially lower in the middle price ranges. On the volatility axis, more than half of Participation trades occur in the 50–75% percentile, and over 25% fall in the top quartile. This pattern suggests that producers turn to simple, market-tracking Participation structures primarily at extremes of price, but only when uncertainty is neither too low nor excessively high.

Protection structures are the least used among the three structures, accounting for just 14% of all observed trades. Their usage is concentrated in mid-to-high price quartiles, with approximately 55% of all Protection trades occurring in the 50–75% price quartile and an additional 31% in the upper quartile. Only 13% of Protection contracts are used in the lowest price quartile, indicating that producers did not rely heavily on Protection even when prices are low compared to recent history. In terms of volatility, Protection is more common in low to moderate volatility environments, roughly one-third of Protection trades are executed in the lower half of the volatility, and the usage declines in higher-volatility settings. This suggests that producers tend to use Protection when prices are relatively strong and market uncertainty remains manageable, possibly seeking to lock in favorable pricing with downside protection without facing additional complexity or volume exposure.

Further insights into producers' selection of structured products are obtained by examining trade activity (number of trades and timing) by specific corn futures tickers. Table 2 reports the percentage of trades by underlying corn futures contract ticker. This table shows significant variation between the trading activity of contracts. For example, December 2023 futures contract (ZCZ23) represent more than half of total trade activity using structured products (53.42%), with a with a strong preference for Price Improvement products (35.96%). Similarly, December 2024 futures (ZCZ24) accounts for 18.57% of total trades with a more balanced product selection: Participation (8.40%), Price Improvement (7.29%), and Protection (2.88%).

The trading activity also varies by product selection and timing. Figure 1 illustrates the daily settled corn futures prices for the December 2023 and 2024 contracts and the proportion of OTC

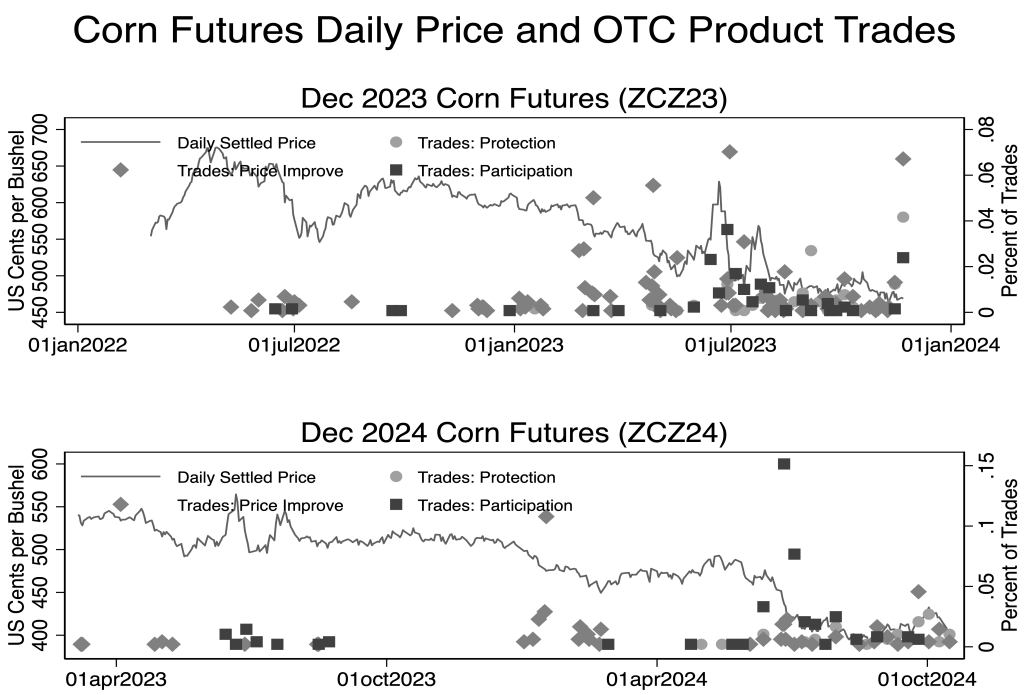
Table 2: Percent of Trades by Ticker and Product Type

| | Product Type | | | |
|---|---|---|---|---|
| **Ticker** | **Participation** | **Price Improvement** | **Protection** | **Total** |
| ZCH23 | 0.45 | 2.02 | 0.45 | 2.92 |
| ZCK23 | 0.08 | 0.86 | 0.08 | 1.03 |
| ZCN23 | 0.33 | 3.38 | 0.08 | 3.79 |
| ZCU23 | 0.21 | 0.82 | 0.41 | 1.44 |
| ZCZ23 | 9.35 | 35.96 | 8.11 | 53.42 |
| ZCH24 | 2.02 | 5.02 | 0.91 | 166 |
| ZCK24 | 0.29 | 2.18 | 0.04 | 2.51 |
| ZCN24 | 0.66 | 2.43 | 0.21 | 3.29 |
| ZCU24 | 0.29 | 1.77 | 0.37 | 2.43 |
| ZCZ24 | 8.40 | 7.29 | 2.88 | 18.57 |
| ZCH25 | 1.11 | – | 0.29 | 1.40 |
| ZCZ25 | 1.15 | – | 0.08 | 1.24 |
| Total | 24.34 | 61.74 | 13.92 | 100 |

*Notes:* This table reports the percentage of trades by underlying corn futures contract ticker from 2022 to 2024. OTC Trade activity is highly concentrated in certain maturities, particularly December contracts.

trades by product and timing. Although we observe trades for each product type across the entirety of the pre-harvest hedging window, and the majority of trades happen within a year of contract expiry, there appears to be a preference to use Price Improvement and Participation products early, as early as 22 months prior to expiry. This behavior suggests earlier pre-harvest hedging than typically assumed (Usset, 2023). However, this observation may be a product of premium or margin risk related to exchange-traded options. As discussed previously, both participation and price improvement products typically do not have producer premiums and no margin risk. Further, the average duration is 243 days for price improvement, 213 days for participation, and 93 days for protection products. This observation suggests that farmers may prefer to engage OTC derivatives for long-dated contracts. These descriptive trade statistics provide critical context for our subsequent empirical analysis of product performance and counterfactual scenarios.

Figure 1: Daily Settlement Price and Number of OTC trades with Underlying December 2023 and December 2024 Corn Futures (ZCZ23 & ZCZ24)




## 3 Research Design

This study examines how farmers interact with the OTC derivatives market, and specifically, their choice of structured risk management products from three product categories: Participation, Price Improvement, and Protection. The objective is to identify the key factors behind the choice of these structured products. To achieve this objective, we adopt a two-stage analytical framework. The first stage uses eXtreme Gradient Boosting (XGBoost), a machine learning algorithm, to identify the most important predictors of selection across product categories. The second stage uses a multinomial logit model (MNL), an econometric approach, to derive economic intuition, marginal effects, and statistical significance of these selected independent variables. Significantly, the inde-

pendent variables used in the MNL model are the most important features identified by XGBoost. Additionally, the MNL model includes time fixed effects and underlying exchange traded corn futures ticker fixed effects to adjust for temporal and contract-specific heterogeneity. This two-stage process ensures both predictive accuracy and interpretability.

## 3.1 Conceptual Framework

### 3.1.1 Modeling Farmers' Corn Market Perceptions

A key feature of our modeling is the choice to dynamically characterize the current market price as relative to some *unknown price*. This price is unknown to the researcher, we do not observe farmers' relative price, and depending on the particular farmer, they may be acting on a relative price without explicit recognition. Relative price dependent hedging is consistent with the behavioral biases *Narrow Framing* discussed by (Hirshleifer, 2001; Kahneman and Lovallo, 1993; Read et al., 2000). When a farmer is faced with complexity, it may be a benefit to limit the framing to a *reference point*. Empirically, this choice implies that the current market price is some distance from a held reference price. Economists logically suggest that this reference price is the farmers' cost of production (Usset, 2023). However, anecdotes from grain originators suggest that selling activity increases around whole dollar or quarter increments. For example, price orders are typically placed at $5.00 as opposed to $4.99. Additionally, anecdotes suggest that contract highs or lows may be used as the reference price, potentially driven by the practice of "charting" and "retracement levels". As a result of this choice, we construct numerous variables with this relative structure to populate the XGBoost and attempt to identify which reference prices may be important in farm decision making.

### 3.1.2 Reference-Dependent Utility Framework

Conceptually, our modeling approach is informed by the reference-dependent utility framework developed by Jacobs et al. (2018). Reference-dependent utility is a behavioral mechanism through which farmers evaluate current market prices relative to psychological benchmark(s) or reference

price(s). Rather than evaluating outcomes based solely on absolute prices, producers may assess outcomes as gains or losses relative to a reference point. This framework incorporates behavioral biases such as loss aversion and diminishing sensitivity (see also Kahneman and Lovallo 1993). Jacobs et al. (2018) propose that producers evaluate marketing decisions based on whether prices are perceived as gains or losses relative to a reference point $R$.

Let $R$ be a reference price held by the producer, and $p_j$ be the current price associated with product $j \in \{1, 2, 3\}$ (corresponding to Participation, Price Improvement, and Protection). The producer evaluates the utility of selecting the product $j$ as a function of how $p_j$ compares to $R$:

$$U_j = \begin{cases} (p_j - R)^{\alpha}, & \text{if } p_j \geq R \quad \text{(gain domain)} \\ -\lambda(R - p_j)^{\alpha}, & \text{if } p_j < R \quad \text{(loss domain)} \end{cases} \tag{1}$$

where:

- $\alpha \in (0, 1)$ reflects diminishing sensitivity to gains or losses,
- $\lambda > 1$ captures loss aversion,
- $p_j$ is the current price of product $j$,
- $R$ is the producers' reference price.

Equation 1 implies that producers perceive contracts offering prices above their reference as gains, and contracts below the reference as losses. When facing gains, producers tend to be risk-averse and prefer locking in favorable prices. When facing losses, producers may either exhibit risk-seeking behavior or avoid locking in unfavorable terms.

Applying this framework in the context of OTC markets, where producers choose among multiple structured products rather than making a binary hedge/no-hedge decision, we expect the following behavioral patterns in product selection:

- When the current price exceeds the reference price ($p_j > R$), producers are more inclined to secure favorable pricing by selecting Protection contracts that lock in gains.

- When the reference price is above the current price ($R > p_j$), producers can avoid locking in a loss and instead favor contracts that preserve at least some upside potential, such as Participation or Price Improvement.

Because producers may rely on various reference points, such as cost of production, recent highs or lows, previous year highs or lows, or moving averages, we construct a broad set of candidate reference variables. Instead of imposing a specific rule for reference price formation, we adopt a data-driven approach that allows the model to identify the most relevant reference points based on observed behavior. First, we use machine learning to evaluate the feature importance of each variable in an XGBoost model. Then, we conduct econometric analysis to quantify how deviations from these reference points, along with market volatility, influence the choice of structured OTC products. This empirical strategy links behavioral theory with machine learning predictions and econometric analysis, providing a more holistic understanding of how farmers chose structured products in the OTC market.

## 3.2 Modeling Trades

### 3.2.1 Feature Selection Using XGBoost

XGBoost is a powerful machine learning algorithm to address complex, non-linear relationships in the data. It is an ensemble method that constructs decision trees sequentially, with each tree correcting the errors in the previous tree. The final prediction is an additive weighted sum of predictions of all trees of the ensemble, and hence excels at both classification and regression tasks (Chen and Guestrin, 2016).

The objective function of XGBoost consists of two components: the loss function and regularization term. The loss function is an indication of how well the model fits, while the regularization term penalizes the complexity of the model to avoid the risk of overfitting. In a dataset that contains 'n' observations and 'm' features, the objective function for XGBoost model is:

$$L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k), \tag{2}$$

where:

- $y_i$ is the observed value for the $i$-th observation,
- $\hat{y}_i$ is the predicted value for the $i$-th observation,
- $l(y_i, \hat{y}_i)$ is the loss function (e.g., mean squared error for regression or log loss for classification),
- $f_k$ represents the $k^{th}$ tree in the ensemble, and
- $\Omega(f_k)$ is the regularization term for the $k$-th tree, defined as:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \|w\|^2, \tag{3}$$

where $T$ is the number of leaves in the tree, $w$ is the vector of leaf weights, and $\gamma$ and $\lambda$ are regularization parameters that control the trade-off between model complexity and accuracy.

In this study, we use the XGBoost model to analyze the feature importance of independent variables in predicting the choice of structured risk management products (participation, price improvement, and protection). We train the XGBoost model with hyperparameter tuning using grid search and K-fold cross-validation (Hastie et al., 2009) to optimize performance. This model evaluates the relative contribution of each independent variable (for example, market conditions, price volatility, and production cost) by determining the degree to which each feature adds to the model's predictive ability. This is quantified using gain metrics, which measures the improvement in accuracy brought by each variable across all splits in the decision tree. By ranking the features based on their importance, XGBoost identifies the most important factors driving farmers' choices for the selection of trade products.

### 3.2.2 Economic Interpretation Using Multinomial Logit Model

In the second stage, we employ a multinomial logit (MNL) model to analyze the effect of the selected variables on farmers' choices of products. The MNL model, first introduced by McFadden (1972), is a widely used statistical model to analyze categorical dependent variables with more than two outcomes. MNL is particularly suitable for this study as the dependent variable-product choice-involves three possible categories: participation, price improvement, and protection. The model estimates a farmer's probability of choosing each of the three product types, including controlling for interdependence of choices (McFadden, 1972).

The MNL model is consistent with the principle of utility maximization, hence we assume that farmers select the choice of the trade product that provides them with the highest utility. The utility $U_{ij}$ of farmer $i$ choosing trade product $j$ is defined by:

$$U_{ijt} = \boldsymbol{\beta}_j \mathbf{X}_i + \delta_t + \gamma_c + \epsilon_{ij}, \tag{4}$$

where:

- $\mathbf{X}_i$ represents the vector of independent variables for farmer $i$, which includes the most important features identified by XGBoost,
- $\boldsymbol{\beta}_j$ is the vector of coefficients specific to trade product $j$, capturing the relationship between the independent variables and the likelihood of choosing a particular trade product,
- $\delta_t$ denotes the time fixed effects to account for temporal variations that may influence trade product choices,
- $\gamma_c$ represents the corn futures contract fixed effect to control for differences across specific contract months.
- $\epsilon_{ij}$ is the random error term.

In this context, the probability that farmer $i$ selects trade product $j$ is given by:

$$P(y_i = j) = \frac{\exp(\boldsymbol{\beta}_j \mathbf{X}_i + \delta_t + \gamma_c)}{\sum_{k=1}^{J} \exp(\boldsymbol{\beta}_k \mathbf{X}_i + \delta_t + \gamma_c)} \quad \text{for } j = 1, 2, 3, \tag{5}$$

where $J$ is the total number of product choices (in this case, $J = 3$).

The MNL model is estimated using maximum likelihood estimation (MLE) (Greene, 2003), where the log-likelihood function is expressed as:

$$LL(\beta) = \sum_{i=1}^{n} \sum_{j=1}^{J} y_{ij} \ln P(y_i = j), \tag{6}$$

where:

- $y_{ij}$ is equal to 1 if farmer $i$ selects trade product $j$ and 0 otherwise,
- $n$ is the number of observations,
- $J$ is the total number of trade product choices.

To generate important economic implications, we compute the marginal effects of the selected independent variables, which yield the change in the probability of selecting a particular trade product when an explanatory variable change of one unit. The marginal effects for the MNL model are expressed as:

$$\frac{\partial P(y_i = j)}{\partial x_{im}} = P(y_i = j) \left( \beta_{jm} - \sum_{k=1}^{J} P(y_i = k) \beta_{km} \right), \tag{7}$$

This equation shows how a change in the $m$-th covariate for farmer $i$ affects the likelihood of choosing trade product $j$, holding all other variables constant. For example, we can assess how an increase in price volatility affects the likelihood that farmers choose protection over participation or price improvement.

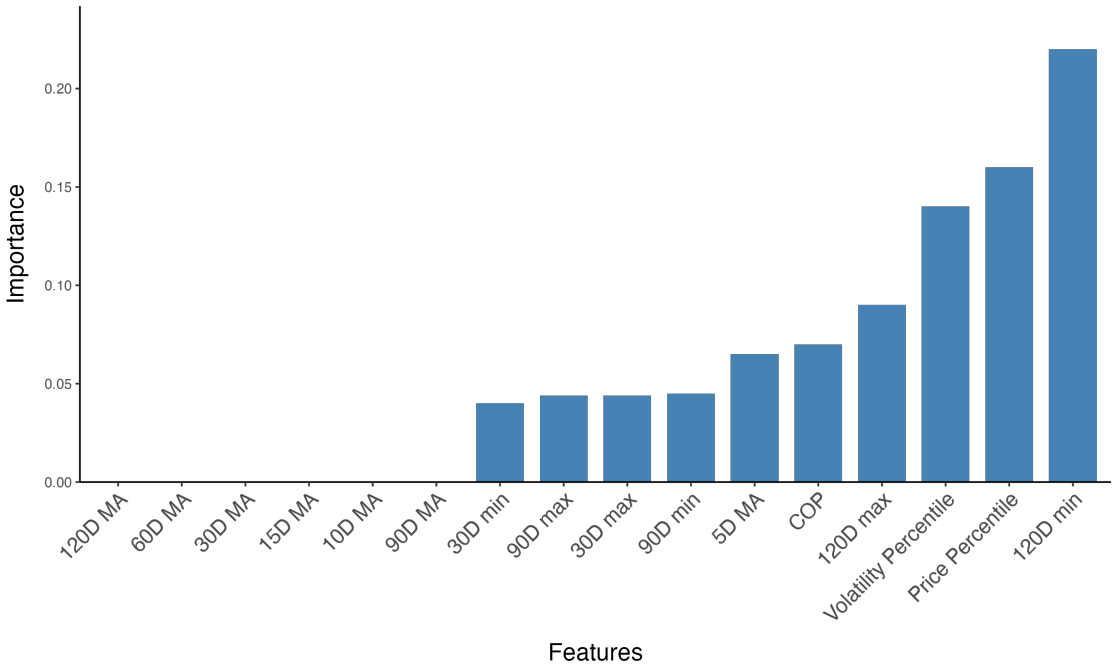
# 4 Results

Figure 2 illustrates the feature importance generated from the XGBoost model. This figure shows that the most important features determining (OTC) products are price movements relative to the 120 day contract high and low, price percentile, volatility percentile, cost of corn production, 30 day contract high and low, and the five day moving average. These findings align closely with our reference-dependent utility framework, where producers evaluate market outcomes relative to reference prices. However, several candidate reference points, especially the moving averages of 60 days or 30 days, that are often mentioned by industry experts, are not among the top predictors. This suggests that while farmers respond to reference-based signals, only a few of these actually influence their contract choices.

The estimated XGBoost model has an accuracy of 87.11%, suggesting a strong predictive performance. Table 3 presents the classification report summarizing the model's predictive performance, or accuracy. **Accuracy** measures the overall proportion of correct predictions. **Precision** is the proportion of correct positive predictions for each product category, while **Recall** is the share of correct positive predictions among all actual positives. **F1 score** is the harmonic mean of precision and recall. **Support** refers to the number of actual observations in each class. Model performance reported in table 3 are based on a 70/30 train-test split and hyperparameter tuning using GridSearchCV with cross-validation to optimize model performance. Price Improvement products are predicted with the most significant precision (0.92) and recall (0.93), followed by Participation products (precision: 0.80, recall: 0.86). The prediction of Protection products' recall is only 0.65, indicating that farmers' decisions regarding Protection products are influenced by other unobserved factors.

The multinomial logit (MNL) model provides better understanding of the determinants behind farmers' selections among the three OTC derivative products: Participation, Price Improvement, and Protection. Table 4 presents the coefficient estimates from the MNL regression, where "No Trade Activity on OTC market" serves as the base category. This table also reports the corresponding average marginal effects for each product type.

Figure 2: Feature Importance from XGBoost Model




*Notes:* The above figure presents the feature importance results obtained from XGBoost classification model used to predict OTC product choice. The most influential variables include price distance variables, percentile-based indicators, cost of production, and short-term moving averages, highlighting the role of market conditions and behavioral reference points in shaping producers' hedging decisions.

The coefficient estimates in Table 4 indicate that higher price percentiles significantly decrease the likelihood of producers choosing Participation products. This negative coefficient reflects a behavioral tendency whereby, when prices are high farmers may avoid directly locking in prices and instead shift toward more strategic or protective measures. Marginal effects in table 4 reinforce this result, which show that a one-unit increase in the price percentile decreases the probability of selecting Participation products by 0.48%, while increasing the probability of selecting Price Improvement products by 0.37%. Although the marginal effect for Protection is positive, it is not

Table 3: Classification Report

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Participation | 0.80 | 0.86 | 0.83 | 166 |
| Price Improvement | 0.92 | 0.93 | 0.92 | 450 |
| Protection | 0.79 | 0.65 | 0.71 | 113 |
| **Accuracy** | | | 0.8711 | |
| **Macro Avg** | 0.83 | 0.81 | 0.82 | 729 |
| **Weighted Avg** | 0.87 | 0.87 | 0.87 | 729 |

*Notes:* This table summarizes the predictive performance of the XGBoost model based on a 70/30 train-test split, with hyperparameter tuning using grid search and K-fold cross-validation. Overall model accuracy is 87.11%.

statistically significant. These structures (Participation and Price Improvement) exhibit similar engagement with market movements, but the Price Improvement products include a price premium for accepting uncertainty related to volume. As a result, our findings suggest that farmers may have a preference for this price premium, despite potential additional volume commitments when prices are relatively higher.

Volatility also plays an important role in the risk management choice of the producers. The results in table 4 indicate that higher volatility significantly raises the probability of choosing Participation products and decreases the probability of opting for Price Improvement. The average marginal effects reveal that an increase in the volatility percentile increases the probability of choosing Participation by 0.08% while lowering the probability of choosing Price Improvement by 0.35%. In the context of the results discussed previously, this preference for Participation over Price Improvement may be tied to the perceive potential of uncertain volume commitments being achieved. For example, in a volatile market, a producer may perceive a greater chance of doubling their volume commitment, and this may influence their preference for the participation product, forgoing the price premium offered by Price Improvement. However, Protection products are unaffected by volatility, which indicates that the demand for mitigated downside risk, may be linked to price levels and recent price movements more than short-term volatility. This result suggests that producers in uncertain or volatile markets prefer to avoid uncertainty in volume commit-

Table 4: Multinomial Logit Coefficients and Marginal Effects

| **Variable** | **Participation** | | **Price Improvement** | | **Protection** | |
|---|---|---|---|---|---|---|
| | Coef. | Marg. Eff. | Coef. | Marg. Eff. | Coef. | Marg. Eff. |
| price_percentile | -0.045*** | -0.00482*** | 0.023*** | 0.00370*** | 0.049** | 0.00038 |
| | (0.013) | (0.00060) | (0.007) | (0.00073) | (0.022) | (0.00069) |
| Volatility_percentile | 0.017*** | 0.00083*** | -0.039*** | -0.00349*** | -0.010 | -0.00015 |
| | (0.005) | (0.00019) | (0.004) | (0.00025) | (0.006) | (0.00018) |
| price × volatility | -0.001*** | – | 0.000 | – | -0.001*** | – |
| | (0.0001) | | (0.0001) | | (0.0002) | |
| diff_minprice30 | 0.024** | 0.00187*** | -0.050*** | -0.00503*** | 0.005 | 0.00058 |
| | (0.009) | (0.00039) | (0.005) | (0.00046) | (0.011) | (0.00036) |
| diff_minprice120 | 0.066*** | 0.00215*** | 0.017*** | -0.00032 | 0.060*** | 0.00119*** |
| | (0.011) | (0.00048) | (0.004) | (0.00042) | (0.014) | (0.00044) |
| diff_maxprice30 | -0.021*** | -0.00131*** | 0.023*** | 0.00255*** | -0.003 | -0.00022** |
| | (0.003) | (0.00010) | (0.002) | (0.00017) | (0.003) | (0.00009) |
| diff_maxprice120 | 0.016*** | 0.00178*** | -0.045*** | -0.00391*** | -0.042*** | -0.00089*** |
| | (0.005) | (0.00020) | (0.003) | (0.00027) | (0.008) | (0.00024) |
| diff_ma5 | -0.048*** | 0.00034 | -0.132*** | -0.01097*** | -0.025*** | 0.00122*** |
| | (0.006) | (0.00021) | (0.006) | (0.00046) | (0.008) | (0.00023) |
| diff_cop | -0.023*** | -0.00052*** | -0.011*** | -0.00020 | -0.036*** | -0.00084*** |
| | (0.004) | (0.00019) | (0.002) | (0.00020) | (0.006) | (0.00020) |
| *Year FE* | Yes | | Yes | | Yes | |
| *Symbol FE* | Yes | | Yes | | Yes | |

*Notes:* The table above presents coefficient estimates and average marginal effects obtained from the multinomial logit (MNL) model. Explanatory variables include price percentile, volatility, moving averages, price distance variables, and cost of production. Results support the reference-dependent hedging framework: producers adjust their contract choices based on how current market prices compare to historical highs, lows, and cost benchmarks. Fixed effects for the year and the corn futures contract are included to account for time and maturity variation.

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Marginal effects for interaction terms are not reported directly.

ments.

In addition to the price and volatility effects, the interaction between price percentile and volatility provides further insights regarding farmers' choice of structured products. The coefficient of the interaction term is significantly negative for both the Participation product and the Protection product. This suggests that although farmers are more likely to use Participation products in a volatile market, this preference diminishes when prices are higher. Similarly, negative significant coefficient for protection products indicates that even when prices appear to be favorable, producers will be less likely to use protective products if they anticipate high volatility or large price swings. In such situations, the potential risk of missing a favorable price swing might outweigh the benefits of downside protection provided by protection products. The non-significant interaction term for Price Improvement products suggests that their usage is driven more by price levels than the interaction effect of price and volatility. Overall, the interaction effect indicates the adaptive hedging behavior of farmers, particularly in situations characterized by both high prices and high volatility.

Short-term and medium-term price distance variables further support the behavioral reference-dependent predictions. When the current price is well above recent lows (as captured by diff_minprice30 and diff_minprice120), producers are more likely to select the Participation and Protection products, suggesting more willingness to hedge when prices have recovered from recent lows. The marginal effects show that a one-unit increase in diff_minprice30 increases the probability of choosing Participation by 0.19% and lowers the probability of choosing Price Improvement by 0.50%. This result suggests that as prices rebound from recent lows, producers prefer Participation contracts to retain exposure to furthur price increase, while viewing the Price Improvement products as less attractive in a rising markets. In contrast, when the current price has dropped from recent highs (modelled by diff_maxprice30 and diff_maxprice120), producers choose Price Improvement products, which implies that producers seek for better-than-market prices in a declining market. A one-unit increase in diff_maxprice30 increases the likelihood of choosing Price Improvement by 0.26% and decreases Participation by 0.13%.

Moreover, when the current price is below the 5-day moving average (diff_ma5), farmers are

less likely to choose Price Improvement, with a marginal effect of -1.10%, and more likely to choose Protection, which increases by 0.12%, suggesting more defensive behavior in the face of short-term downward trends. Overall, these results show that farmers dynamically adapt their marketing strategies in response to price movements, adjusting their behavior based on how current prices compare to recent trends. They adopt a more defensive approach during market downturns and become more confident when prices strengthen. Such behavior aligns closely with the theory of the reference-dependent utility framework introduced by Jacobs et al. (2018).

Similarly, cost of production(diff_cop) also plays a crucial role in decision-making. This variable captures how far the current price is above the producer's estimated cost. The marginal effects show that a one-unit increase in this difference, meaning that prices are moving further above cost, reduces the probability of selecting Participation by 0.05% and Protection by 0.08%. This result suggests that when corn price is close or near the cost of production, farmers are more likely to engage in structured Protection and Participation products, reflecting a greater concern for protecting revenue. However, as price rises further above cost, this likelihood declines, suggesting that when profitability is high, producers may delay hedging decisions, opt for simpler marketing strategies, or engage in futures and options in regulated markets. In contrast, the selection of Price Improvement products is not influenced by the cost of production. This result may be influenced by the longer average duration of Price Improvement products, indicating that farmers may be engaging these structures as preferred tools to manage longer dated pre-harvest hedging activities, prior realizing their cost of production.

# 5 Counterfactual Trade Product Outcomes

To evaluate the consequences of alternative OTC product selections, we simulate counterfactual scenarios in which producers trade a different structure than the one they originally used. This evaluation compares the relative performance of Participation, Price Improvement, and Protection structures under identical market conditions, and thus uncovers the opportunity cost or potential benefit of using one structure over another.

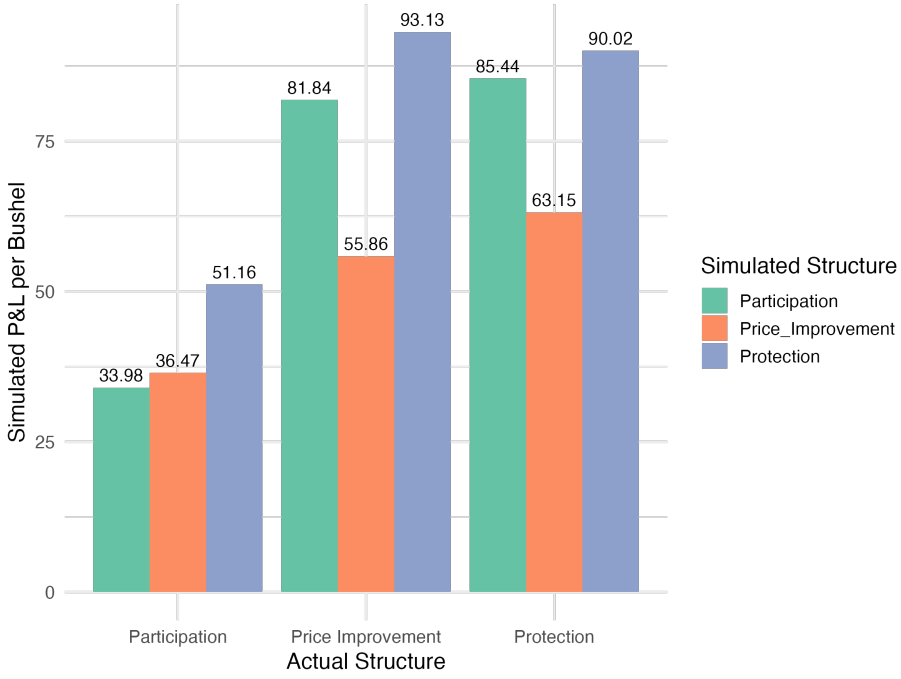
The simulation relies on realistic assumptions drawn from actual contracts provided by Marex Hedging Solutions. For each OTC structure, we compute the average percentage difference-hereafter referred to as the delta-between the current price and the relevant pricing level for the structure: the level price for Participation, the accumulation level and barrier level for Price Improvement, and the price floor for Protection structure. We then apply these structure-specific deltas to each observed trade's execution price to construct counterfactual pricing outcomes—i.e., the price at which the trade would have been executed had the producer selected a different product under the same market conditions. For Protection, we also deduct the premium cost of purchasing the contract, calculated using the Black–Scholes model[2] with a 5% risk-free rate[3]. This premium represents the cost of downside insurance and reduces the net profit or loss (P&L) from the structure. Using these counterfactual prices, we compute the hypothetical P&L per bushel for each structure by comparing the effective price of the structured contract with the market settlement price at maturity. This allows us to evaluate not only how each structure would have performed under identical market conditions but also how they performed relative to simply selling in the spot market at expiry. To maintain consistency, we preserve the originally observed P&L for trades when the counterfactual structure matches the actual one.

The simulation result is shown in figure 3. This result demonstrates that all three hedging structures, Participation, Price Improvement, and Protection, outperformed the spot market, at maturity. Producers who chose the Participation structured product made an average gain of 33.98 cents per bushel over the market price at expiry, while those who selected Price Improvement realized an average gain of 55.86 cents. Similarly, the Protection structured product, even after deducting the upfront premium, yielded a significantly larger average gain of 90.02 cents. These findings indicate that in a falling price condition, Protection products, despite their upfront cost, can yield superior outcomes due to the downside protection they provide against further price drops.

[2]Since the Protection structure closely resembles with a put option, its premium can be approximated using the Black–Scholes option pricing model. The Black–Scholes model estimates the fair value of options based on the underlying asset price, strike price, time to maturity, risk-free interest rate, and price volatility, under the assumption of lognormally distributed prices and constant volatility.

[3]We computed the premium using risk-free rates of 3%, 4%, and 5%, and found no significant change in net P&L.

Figure 3: Counterfactual Returns Under Alternative OTC Structures




*Notes:* The figure above shows the average actual and counterfactual returns for each OTC product under identical market conditions. All three OTC structures outperformed the spot market at maturity, suggesting these products added value during this period. However, farmers did not always select the most profitable structure, indicating suboptimal decisions. These results are specific to a falling market environment; in a rising market, Participation might have yielded comparatively higher returns.

In addition to these realized gains, counterfactual analysis also demonstrate how outcomes would have differed if producers had used a different structure at the time they made their original trade. Several important patterns emerge. First, for producers who chose Participation initially, the analysis suggests that they could have increased their average profits by around 17 cents per bushel had they chosen the protection structure. This differences emphasize the upside offered by Participation is relatively capped, particularly since Participation basically follows market prices without added leverage. That said, this pattern reflects the specific pricing environment observed in our sample, where prices were generally flat or declining. In a rising market, Participation

contracts may offer more favorable returns compared to the other structures.

Second, producers who initially chose Price Improvement structures would also have been better if they had chosen Protection contracts. On average, their returns would have been approximately 37 cents per bushel higher, even after reducing the upfront cost associated with Protection structure. This finding is particularly important given that Price Improvement accounts for most trades in our sample, about 79%, suggesting that the large share of producers have made suboptimal choices in this market environment. While Price Improvement contracts can capture the fixed premiums above market through incremental participation or volume commitments, their advantage diminishes in a falling markets. In such condition, the downside protection offered by Protection contracts provides a stronger safety net against price fall, allowing producers to adopt a more defensive position while still securing favorable outcomes.

Third, producers who used Protection structures had the highest average returns of the three strategies. For this group, switching to either Participation or Price Improvement would have been less profitable. This consistent outperformance of Protection structures illustrates the relative advantage of securing a firm price floor in the prevailing pricing environment. The ability to lock in a minimum price, even after accounting for the upfront premium cost, was especially effective during a period when prices were softening or trending downward. The embedded downside insurance acted as a strong defensive position, avoid substantial losses while still benefiting from the contract's guaranteed price floor. These findings imply that, in specific market circumstances, structured pricing products with protective mechanisms can provide better results than more opportunistic or market-following alternatives.

Overall, this counterfactual analysis illustrates the potential opportunity cost of strategies like Participation and Price Improvement in falling pricing environments. While Participation allows for flexibility, and Price Improvement can capture premiums in exchange for volume commitments, Protection strategies (with embedded price floor offering downside protection) consistently produced the highest risk-adjusted returns in this sample. The ability to secure a price floor proved especially advantageous when the price was trending downward, protecting producers from further losses while still allowing them to benefit from a guaranteed price floor. In contrast, in a rising

pricing environment, the relative performance of these structures could change substantially. For example, price floor may limit the gains in a bullish rally, while incremental benefit of Participation and Price Improvement could become more valuable. In this scenario, the price floor embedded with Protection as the initial trade can seem inconsequential.

The counterfactual results also highlight the need to equate the selection of products for trade with not just a producer's risk attitude but also underlying market expectations and price trends. Grain originators will benefit from providing farmers with various scenarios related to pricing levels and volume commitments based on potential market dynamics. The results of our specific analysis are influenced by the specific market conditions in this data set, which generally declined or weakened prices. In other pricing contexts, such as upward trending markets or extreme uncertainty environments, the relative performance of these structures would almost certainly change, and the apparent superiority of one approach over another will change.

# 6 Conclusion

This study examines the selection of structured over-the-counter(OTC) derivative products used by corn producers for price risk management, and evaluates the consequence of using these products. We use a proprietary dataset of individual contract-level trades between 2022 and 2024 and examine the key factors that influence producers' choices among three major product types: Participation, Price Improvement, and Protection. The results show that producers rationally adjust their hedging behavior in response to price levels, volatility, and recent price trends. Participation contracts are more common when market conditions are uncertain but not extreme, while Price Improvement structures dominate when prices are low, and Protection contracts are employed more selectively during periods of stability.

A two-stage analytical framework that combines machine learning and multinomial logit estimation shows that producers' choice on the use of structured products is strongly influenced by market signals and reference-dependent behavioral considerations. Specifically, we show that producers evaluate their marketing outcomes relative to relevant reference points, such as recent

highs or lows, moving averages, or cost of production, consistent with reference-dependent hedging framework. We use a counterfactual analysis to demonstrate the effectiveness of each product type during our marketing period. For example, during a falling market, Protection products deliver higher returns per bushel, relative to Participation and Price Improvement products. Notably, nearly 79% of observed Price Improvement trades would have earned higher profits under Protection, indicating substantial opportunity costs from suboptimal contract selection. This descriptive analysis demonstrates how important market expectations are to product selection. Overall, the findings highlight both the strategic potential of structured OTC products and the fact that behavioral gaps still exist in their use.

This study has important implications for farmers. First, farmers who are adverse to margin risk, but still would like the flexibility of hedging tools related to options, should consider working with their grain orginators on structured OTC products. Second, Price Improvement products offer relatively inexpensive long-term hedging optionality, if the volume uncertainty is acceptable. A farmer with relatively small volume commitments may want to include Price Improvement OTC products within a portfolio of marketing tools. Third, farmers should consider which is the optimal "reference price" to evaluate trades. A logical choice is cost of production, and our results suggest that this price is used by many farmers, but there is also explanatory strength in the highs and lows from the last 30 and 120 days, and the 5 day moving average. Farmers may want to incorporate the preferred reference price in their marketing plans.

This study likely has the most implications for grain originators, and how they interact with farmers. Although the data represented in this study is not the universe of farmers trades, the fact that OTC products have benefits that may be attractive to farmers, like lower margin risk and increased flexibility, may help drive future origination growth. Additionally, our findings suggest that farmers are using reference prices in their hedging activities. Grain originators may be able to harness this behavioral feature to communicate with farmers in a manner that provides more practical information. For example, the current price is XX lower than the 30 day market high, and YY lower than the 120 day market high, but we are trading above the five day moving average. Grain originators may want to devote efforts to engaging farmers up to two years prior to crop

production, especially when volume commitments are low. Lastly, our results suggest that farmers decisions do not seem to be driven by market volatility. As a result, grain originators may want to prioritize communicating about pricing level, as opposed to volatility.

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## Conflict of Interest Statement

The authors declare no potential conflicts of interest.

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# Appendix