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Reference Dependence in Commodity Marketing: Understanding Differences in Marketing Outcomes Among Farmers

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Abstract

This paper examines how heterogeneity in reference prices and beliefs shapes farmers' grain marketing behavior and realized prices. Using panel data from the Illinois Farm Business Farm Management (FBFM) program, we extend the reference dependence framework to a cross-sectional context, relaxing the common assumption of homogeneous reference prices across producers. Employing a finite mixture model with fixed effects, we identify distinct behavioral types that respond differently to identical price signals. We further construct a behavioral proxy for belief bias based on farmers' past responsiveness to price changes, enabling us to disentangle belief heterogeneity from reference dependence. Our results show pronounced asymmetric marketing behavior around individualized reference points. Both the per-bushel cost of production and the previous year's price received emerge as a salient benchmark: farmers sell more when prices exceed the reference point and withhold sales when prices fall below. These findings support the presence of reference-dependent preferences and highlight the importance of incorporating individual financial conditions into behavioral models and the design of marketing advisory services.

JEL Classification: Q11, Q12, Q13

Keywords: reference dependence, price expectations, production costs, corn, soybean, grain marketing

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1 Introduction

By definition, commodity producers operate under common market conditions — a farmer in the US Corn Belt faces the same prices as neighboring farmers at a given moment in time — yet producers often realize very different outcomes in terms of the price received. The timing of sales is the primary source of this heterogeneity for storable commodities like corn and soybeans. Farmers sell production from a given season in discrete increments throughout the marketing period; at times, they consider favorable (Cabrini, Irwin, and Good, 2007; Cunningham, Brorsen, and Anderson, 2007; Mattos and Fryza, 2012). Yet the puzzle remains: why do some producers view a particular point in time as favorable for selling when others do not?

This study seeks to explain why uniform market prices trigger diverse selling behavior and realized prices. The conceptual framework that we use to explain farmers' marketing behavior is prospect theory, which has four elements: 1) reference dependence, 2) loss aversion, 3) diminishing sensitivity, and 4) probability weighting (Barberis, 2013). We focus on reference dependence and probability weighting, following Jacobs, Li, and Hayes (2018), who formalize the application of prospect theory to grain marketing using an expected-utility nested reference-dependent hedging model that features asymmetric sensitivity to price increases and decreases and allows for heterogeneous views on the probability of price changes. Because their empirical implementation relies on time-series variation, the model is estimated under the assumption of common reference points across producers. While this approach provides insights into aggregate marketing behavior, it does not examine cross-sectional heterogeneity among farmers. In this study, we propose that farmers' reference prices are individual rather than common, which explains the heterogeneous market outcomes they receive.

We examine the nature of asymmetry and heterogeneity in individual farmers' marketing behavior. We empirically test three implications of prospect theory: 1) the presence of a threshold in grain marketing, 2) the relevance of candidate reference prices, and 3) how latent beliefs interact with reference dependence. We consider two farmer-specific anchors for reference formation: (i) the per-bushel cost of production, representing a natural profitability benchmark, and (ii) the previous year's average price, reflecting the influence of past outcomes on current marketing behavior.

Heterogeneity in marketing outcomes is not merely a theoretical possibility; it is a pervasive feature of observed farmer behavior. Empirical evidence documents substantial dispersion in farmers' risk preferences, expectations, and marketing strategies (Garcia, McCallum, and Finger, 2024; Ricome and Reynaud, 2022). Even farmers who appear similar on observable characteristics such as size and operator age may differ in unobservable traits—such as risk attitudes and perceived risk exposure—which contribute to heterogeneous marketing behavior and the use of risk management tools such as futures and options (Pennings and Leuthold, 2000). We document similar heterogeneity among corn and soybean farmers in Illinois using panel data. Within the same marketing year, the cross-sectional spread in realized corn prices often exceeds one dollar per bushel, generating substantial differences in farm profitability. Differences in realized prices are accompanied by pronounced heterogeneity in sales timing: more than 40% of Illinois corn and soybean farmers report no near-harvest sales, and even among those who do sell, near-harvest sales typically account for only a small share of total production (Janzen, 2024). At the same time, substantial dispersion exists in per-bushel production costs across farms. Variation in input use and yields leads to differences in production costs (Foreman, 2014), implying that identical market prices may allow some farmers to sell profitably while others must wait to break even.

Dispersion in realized prices and heterogeneity in sales timing are difficult to reconcile with standard expected utility models. In the absence of production risk and strongly held directional beliefs about future price movements, the framework predicts that a risk-averse farmer would hedge a substantial share—if not all—of production, largely independent of the level of the futures price itself (Lapan, Moschini, and Hanson, 1991). As a result, the model provides limited economic justification for postponing sales and storing grain for later marketing. In practice, however, many farmers report no near-harvest sales in multiple marketing years, a pattern that would require consistently strong upward price expectations to align with the standard framework.

To explain this heterogeneity in farmers' marketing outcomes, we adopt the prospect-theoretic framework of Jacobs, Li, and Hayes (2018). In this framework, producers evaluate prices relative to a subjective reference point—such as production costs, historical prices, or prior expectations—and have beliefs about future price movements. Outcomes are therefore assessed as gains or losses relative to the reference price, while beliefs about the direction of future price changes shape the perceived likelihood of these outcomes. These beliefs may be neutral, biased downward, or biased upward, while the futures price itself may lie below, above, or close to the reference price. The interaction of these two dimensions creates multiple distinct decision environments, allowing identical market prices and price movements to generate different marketing responses across farmers.

Consider a farmer at the beginning of the marketing year who has not yet sold any crop. The farmer observes the current futures price, compares it with a personal reference price, and holds a belief about how prices are likely to change going forward. As prices evolve during the marketing year, selling decisions depend jointly on how the current price compares to the reference point and on whether price movements confirm or contradict the farmer's expectations. For instance, if the price initially lies below the reference point but begins to rise, a farmer with upward-biased beliefs may postpone sales entirely—making no sales while waiting for prices to recover toward the reference point. In contrast, a farmer with downward-biased beliefs may begin selling a portion of production to avoid the possibility of even larger perceived losses. Conversely, when prices exceed the reference point and outcomes move into the gain domain, farmers may start selling. However, the intensity of selling may differ depending on beliefs: farmers with upward-biased beliefs may sell only a small share while continuing to hold grain in pursuit of additional gains, whereas farmers with downward-biased beliefs may sell a larger share—or even most of their crop—to lock in gains before prices decline.

A key empirical challenge is identifying the reference points that farmers actually use in practice. Prior studies suggest that farmers' reference points may be shaped by production costs (Kim, Brorsen, and Anderson, 2010), expectations of future outcomes (Kőszegi and Rabin, 2007), and historical price realizations (Mattos and Zinn, 2016). However, there is no consensus on a single reference point used in practice, underscoring the empirical relevance of testing multiple farmer-specific benchmarks. Following the literature, we propose two broad classes of reference points: per-bushel cost of production, and the price received in previous marketing year, each measured at the individual farm level to capture heterogeneity across farmers.

The original formulation of prospect theory interprets the reference point as the status quo (Kahneman and Tversky, 1979), making the cost of production a natural benchmark for evaluating gains and losses. For farmers, per-bushel production costs represent a fundamental decision threshold, as prices below this level imply negative margins. This is why, "Know your cost of production" is common price risk management advice from commodity marketing advisors to farmers (Parcell and Franken, 2011). In an intertemporal marketing decision, this implies that farmers evaluate current prices relative to their per-unit production cost and avoid sales that lock in losses. Although production costs are sunk once output is realized, they may continue to influence marketing decisions through liquidity needs, debt obligations, and other financial constraints, reinforcing their salience as a reference point. While such cost-based marketing strategies are widely advocated, they have limited theoretical underpinnings and incomplete empirical analysis of farmers' actual market timing and price risk management strategies.

Expectations-based models of reference dependence instead define the benchmark in terms of anticipated outcomes rather than the status quo. Kőszegi and Rabin (2006) argues that when expectations differ from the status quo, expectations-based reference points provide superior predictions of decision-making under risk. While several expectation-based measures are in principle possible, a particularly plausible proxy arises from farmers' recent price experiences. It is well established that producers form price expectations using historical price realizations, with the most recent price receiving the greatest weight (Nerlove, 1956). Accordingly, we use the previous year's farm-specific price received as an alternative expectations-based reference point. While Jacobs, Li, and Hayes (2018) also considers last year's price, their market-level measure does not capture cross-sectional heterogeneity. In contrast, the farm-specific last price received reflects individualized historical price experiences and may inform their current marketing decisions.

We follow the two-step empirical approach outlined in Jacobs, Li, and Hayes (2018). First, we test for the presence of reference-dependent behavior by examining whether farmers respond to similarly sized price changes in an asymmetric manner and then investigate whether this asymmetric behavior can be linked to economically meaningful reference prices. Finally, we leverage the ability to link current and past marketing behavior to develop a test of the relative importance of reference dependence and beliefs about market outlook.

To identify the presence of reference dependence, we examine farmers' heterogeneous responses to the same price-change signal using a finite mixture model with fixed effects, following Deb and Trivedi (2013). This approach allows parameters to vary across latent groups of farmers while controlling for unobserved, time-invariant individual characteristics, directly testing whether farmers exhibit different behavioral responses to identical market conditions. Our results reveal two distinct groups of farmers: one group is relatively more responsive to price changes, while the other exhibits a more muted reaction to the same market signals. These differences suggest the presence of heterogeneous reference prices that lead farmers to interpret the same market information differently.

In the second part of the analysis, we test the relevance of two individualized reference points: per-bushel cost of production and last year's price received. We classify gain and loss domains by comparing each benchmark to harvest-time futures prices, and examine asymmetric responses around these thresholds. Because both reference points are predetermined—either by the production process or by prior-year outcomes—they are not correlated with price changes occurring during the current marketing year. We find that farmers exhibit reference dependence across both benchmarks, increasing sales when prices exceed their reference and reducing sales when they fall below it. However, important differences emerge once we consider interactions with contemporaneous price changes. When cost serves as the reference, farmers in the loss domain increase sales as prices rise, using improved conditions to mitigate losses. In contrast, when last year's price serves as the reference, farmers in the loss domain continue to withhold sales even as prices rise. These contrasting behaviors suggest that cost-based and experience-based reference points elicit distinct responses, underscoring the presence of multiple, context-dependent reference points in farmers' marketing decisions.

Finally, to disentangle belief bias from reference formation, we construct a proxy for the belief-bias component formalized in Jacobs, Li, and Hayes (2018). In their framework, belief bias reflects distortions in the perceived likelihood of future price movements, which interact with the reference point to shape optimal sales decisions. Because these subjective distortions are not directly observable, we proxy them using farmers' historical responsiveness to realized price changes. We interpret the absolute value of this responsiveness as an indicator of belief orientation, as the theoretical model suggests. Incorporating this proxy into a finite mixture model reveals two distinct groups: one with relatively unbiased beliefs that rely primarily on contemporaneous market information, and another with more biased beliefs that respond less to the same price signals and whose responsiveness varies with the degree of bias.

The paper is organized as follows. Section 2 describes farm-level data on realized prices and cost of production, highlighting substantial variation across farmers. Section 3 updates the theoretical framework from Jacobs, Li, and Hayes (2018) to accommodate heterogeneity across farms. Section 4 presents the empirical strategy for testing the relationship among production costs, reference prices, and farmers' marketing behavior. Section 5 discusses the main results, providing evidence on the roles of both cost-based and experience-based reference points and on farmers' asymmetric reactions to the market price, depending on their reference points. Finally, Section 6 concludes, discussing the implications of our results for farm price risk management.

2 Data

The central motivation for this study is the substantial heterogeneity in marketing outcomes observed among grain producers operating under identical market conditions. This section documents that heterogeneity and establishes its economic significance. Using detailed farm-level financial records, we examine differences in realized prices, sales timing, and production costs—key determinants of heterogeneous marketing behavior.

Our data are drawn from the Illinois Farm Business Farm Management (FBFM) association, which collects comprehensive farm-level information from over 5,000 farmers across Illinois annually. The sample spans 2003 to 2023 and represents approximately 25% of Illinois farmland acreage, making it broadly representative of commercial grain farms in the state. We restrict analysis to 'certified usable' observations verified as accurate and suitable for research by Illinois FBFM field staff. FBFM data are prepared annually for tax filing, financial statement preparation, and benchmarking, and provide a snapshot of farm activities as of December 31 each year.

2.1 Farm-level commodity marketing and price

Most critical to our study, we observe some details on the timing of commodity sales. For each calendar year, FBFM records the value and quantity of realized grain sales for both old crop harvested in the previous calendar year and new crop harvested in the current year. Although each variable has a single calendar-year observation, the distinction between old and new crop allows us to observe whether farms sell commodities earlier or later in the marketing year.

Figure 1: Timeline of calendar year and marketing year crop sales in FBFM data

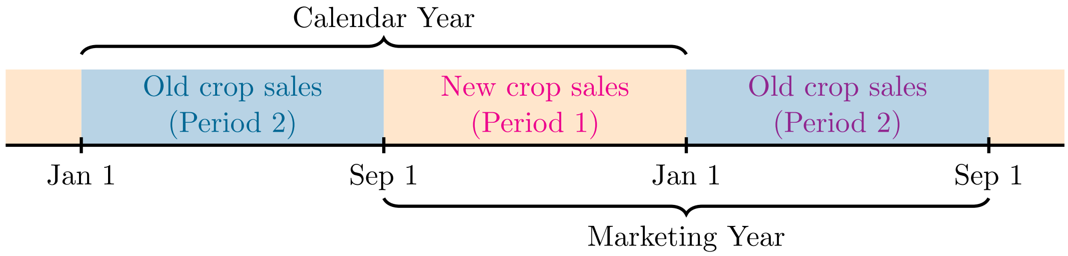
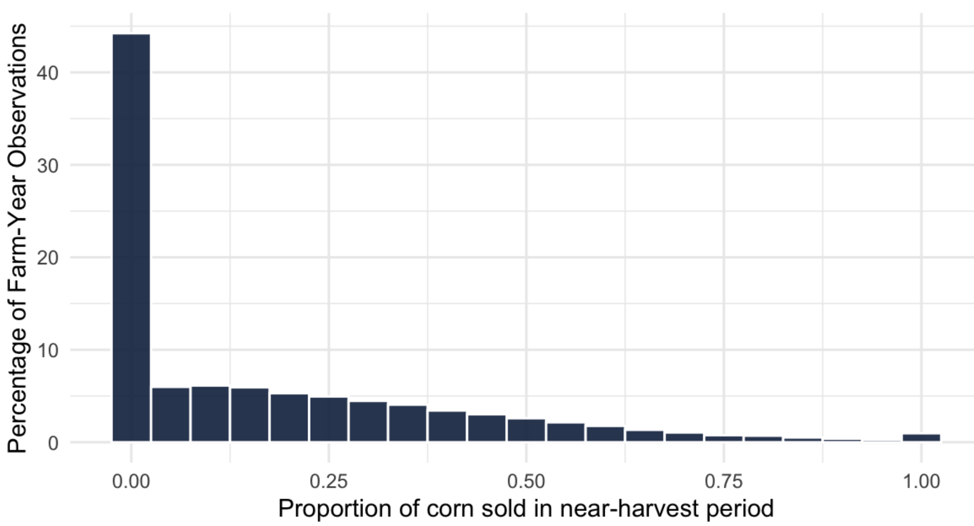


Figure 1 illustrates how we organize sales data from a calendar year into a marketing year framework. The marketing year for corn runs from September 1st of one calendar year to August 31st of the following calendar year. Sales recorded as new crop must be realized between September 1 and December 31, since the grain must be physically delivered for a sale to be realized. These new crop sales can also be referred to as the "near-harvest" sales, because the sales are realized within a short time window after harvest. Sales recorded as old-crop are typically realized in the period between January 1st and August 31st. Combining new crop sales of one calendar year with the old crop sales of the following calendar year, we get the complete picture of commodity sales for a marketing year. (While possible, farms rarely hold significant inventories across marketing years. New-crop and old-crop sales quantities almost always equal calendar year production.)

For the purpose of our analysis, we refer to the new-crop sales period as Period 1 and the old-crop sales period as Period 2. Using these two periods, we analyze whether farmers sell their production near-harvest before December 31st (Period 1) or choose to store the crop for sale in the next period from January 1st till Aug 31st (Period 2). We inevitably lose some observations when converting the data from calendar years to a marketing year format. This occurs because constructing a complete marketing year requires data from two consecutive calendar years. Given that our dataset is an unbalanced panel, not all farms appear in every year. Some farms drop out for a period and reappear after a few years, while others exit the dataset permanently. On average, each farm remains in the dataset for approximately seven consecutive years.

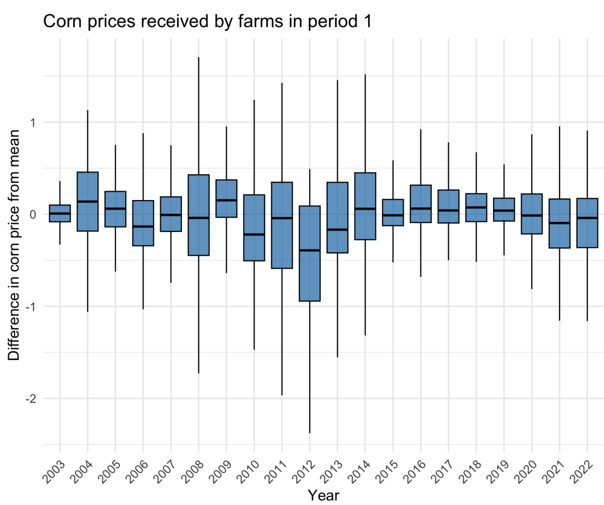
Figure 2: Proportion of corn sold in near-harvest period



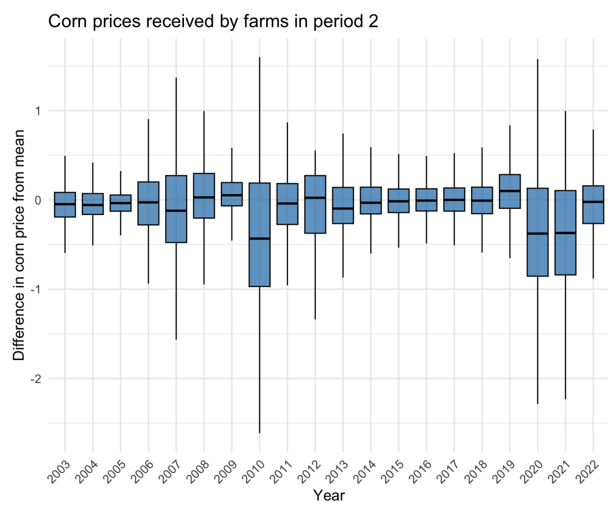
FBFM crop sales data are an incomplete picture of farmer marketing; they are not transaction-level data that might record exact timing or forward contracting activity. However, these data reveal a key fact about farmer commodity marketing highlighted in figure 2: a substantial share of corn and soybean farmers consistently refrain from selling grain near harvest (Period 1), a pattern that persists across diverse market conditions from 2003 to 2023.

Deferring sales into a subsequent calendar may imply meaningful differences in farmers' attitudes toward risk. Those who delay sales appear less sensitive to immediate price signals—potentially because near-harvest prices fall below their internal reference points, such as cost of production or profit targets—placing them in the psychological 'loss domain'. Rather than accept perceived losses, these farmers exhibit loss-averse tendencies by holding grain in hopes of better prices later. Simultaneously, by postponing sales, they willingly expose themselves to greater price risk, suggesting a higher tolerance for risk or strong optimism about future market conditions. In contrast, those who sell early may prioritize minimizing uncertainty, revealing more risk-averse behavior. This enduring divergence in marketing strategies underscores the behavioral heterogeneity in risk preferences across grain producers.

Figure 3: Distribution of corn price received by farms in period 1 (near harvest) and period 2 (deferred sales)



(a) Price received by farms in period 1



(b) Price received by farms in period 2

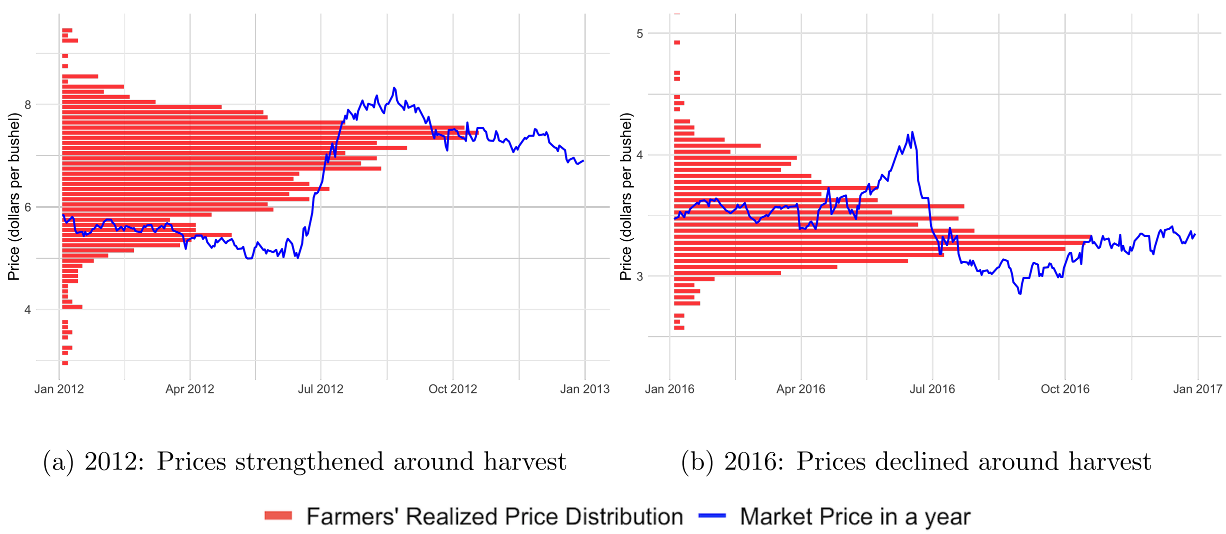
Figure 3 demonstrates the variation in prices received by farmers for corn sold in two periods. The prices are shown as a difference from the state average price received by farmers, as reported by the National Agricultural Statistics Service (NASS), to facilitate comparisons of the distribution across farms in years where price levels may differ substantially. In almost all the marketing environments, the range of price outcomes spans more than one dollar per bushel. The year-to-year variation largely stems from the differences in market conditions between years, but the variation within a year between farmers suggests that farmers do perform quite differently from one another even under the same market conditions. These differences in price received significantly impact the profitability of farmers and create disparities when compared to their more successful counterparts. Thus, we aim to explore the reasons behind these variations between farmers within the same marketing environment. Furthermore, we compare the price received by the farmers with the array of cash prices available to the farmers in Illinois at that time frame. This comparison allows us to assess whether farmers were able to effectively time the market by selling when prices were relatively high.

The price received by the farmers, in theory, should closely align with the range of prices that were being offered in the market at that time. However, we also need to consider the possibility of forward contracting by farmers, which results in a wider range of possible market prices for them. Farmers could, in fact, forward contract their crop well before the harvest period or even before planting. To account for this, we use December futures prices from January 1st to September 31st, plus the average basis prevailing at around the end of September in Illinois; to mimic the possible forward contracting prices available for the farmers from January 1st until September 31st and from October 1st until December 31st, we use cash prices representing cash sales in that period. This gives us the complete range of prices that a farmer could possibly get for selling the crop in period 1.

Figure 4 illustrates the available market prices for farmers in two representative years with contrasting conditions, along with the distribution of prices realized by farmers in those years. The blue line represents the daily price path in a given year, at which farmers could potentially time their sales, while the red histogram illustrates the distribution of realized prices across all farmers in period 1. Realized prices are observed as one value per farmer–year, so the figure should be interpreted with caution. Panel (a) illustrates the

2012 corn marketing year, during which prices were relatively low early in the year but rose sharply mid-year due to an extreme drought, resulting in elevated prices at harvest. Panel (b) shows the 2016 marketing year, when prices were relatively higher at the beginning of the year and then declined toward harvest.

Figure 4: Corn Market Prices and Farmers' Realized Price Distribution for Two Representative Years



(a) 2012: Prices strengthened around harvest

(b) 2016: Prices declined around harvest

In both marketing environments, farmers realize a wide range of prices, indicating substantial dispersion in outcomes even under the same market conditions. The red histograms highlight these disparities and provide evidence of heterogeneous market timing. Although each realized price may reflect a weighted average of prices available throughout the year, a clear pattern emerges: the highest concentration of realized prices lies near the prices prevailing at harvest. This suggests that most period-1 sales might be concentrated around the harvest period.

This pattern of high number of farmers realizing prices similar to those prevailing at harvest time, particularly mid-October, is consistent across all years. The red histograms peak during this period, aligning closely with the blue line. This pattern reinforces the idea that though there exists evidence of forward contracting, most farmers make marketing decisions around the harvest period. Accordingly, we use the mid-October futures price as a benchmark for the market price in our subsequent analysis of farmer marketing behavior.

2.2 Farm-level cost of production

Data on the farm-level cost of production is fundamental to understanding the financial risk that an individual farm faces. These costs represent a farm's break-even point, selling below which indicates financial loss, the most basic form of financial risk for a farmer. FBFM data documents all the costs incurred in the farming enterprise, which enables us to calculate the per-bushel cost of production for both corn and soybeans, which can be used as a proxy for individual farmers' reference price. However, FBFM data does not separately report the production costs for corn and soybeans; instead, it provides a combined cost for the entire farm operation. To address this, we use annually published crop budgets (Paulson et al., 2025) for different regions of the state to guide cost allocation. These budgets include the per-acre cost of each category of inputs going into both corn and soybean production. This includes direct costs, such as fertilizers, pesticides, seeds, drying, storage, insurance, power costs (including machinery hire, fuel, and oil, machinery repairs), overhead costs (including hired labor, building repairs, insurance, interest, and land costs). For example, the crop budget would tell us that in central Illinois in 2025, ideally, costs for fertilizers are \$165 per acre for corn and \$65 per acre for soybeans. Using this information, we allocate the total costs for fertilizers produced by the farm for both corn and soybean production to the individual enterprises. Likewise, we distribute the total costs of every category into corn and soybeans using the following equation:

$$TC = a_c \times C_c + \ a_s \times C_s \tag{1}$$

Where TC is the total cost required for both corn and soybeans, a_c and a_s represent the acres of corn and soybeans grown by the farm, respectively, and C_c and C_s denote the ideal cost per acre allocations for the given region, obtained from crop budgets. From this, we can get the per-bushel cost for an individual enterprise (for instance, corn) as:

$$C^{perbu\_corn} = \frac{TC_f a_c C_c}{Q_c(a_c C_c + a_s C_s)} \tag{2}$$

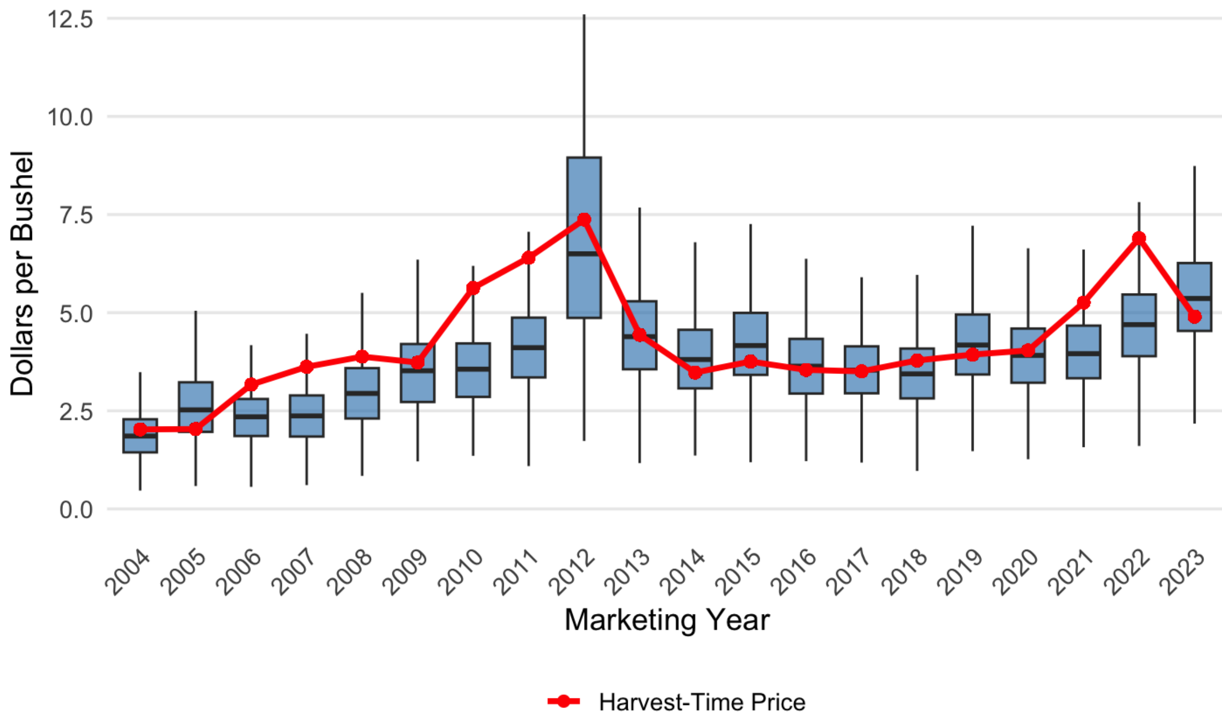
Where C^{perbu_corn} is the cost per bushel of corn production, TC_f is the total cost incurred by the farm for the given input, and Q_c is the total corn produced in bushels by the farm. This distribution of total expenditure into individual enterprises allows us to formulate models for reference pricing of each crop, as well as the interaction between the two crops. Using the categories of costs in crop budgets as well as the FBFM dataset, we further calculate different types of costs incurred in the production, such as variable costs, total costs, and direct costs.

Figure 5 illustrates the variation in per-bushel production costs for corn, as shown by the box plots, alongside the mid-October futures price, indicated by the red line. We observe substantial variation both between farmers and across years. Market conditions primarily drive year-to-year variation, but the variation between the farmers most likely depends on the individual farmer's production decisions. Notably, the mid-October futures price does not consistently lie above or below the cost of production; instead, it fluctuates around it, allowing us to compare the per-bushel cost of production to this price level and infer marketing decisions.

3 Theoretical Framework

We build on the framework developed by Jacobs, Li, and Hayes (2018) (hereafter referred to as JLH), which incorporates reference-dependent preferences into an expected

Figure 5: Per Bushel Total Economic Cost of Corn Production and Harvest Time Price (2004-2023)



utility (EU) framework to describe farmers' hedging behavior. The JLH model explains how farmers' optimal hedge ratios depend on two key factors: i) their beliefs about the directional movement of futures prices, denoted by π, and ii) the relationship between the futures price (F^t) and a psychologically salient reference price, R.

Jacobs, Li, and Hayes (2018) used the theoretical model to explain the reference-dependent hedging using the pre-harvest hedge ratio. We adapt this framework to interpret farmers' sales timing decisions in our context, where sales are broadly divided into two time periods, near-harvest and deferred sales. Conceptually, near-harvest (period 1) sale serves a similar role to a hedge. Because the period 1 sales also allow a farmer to reduce the price risk exposure to future price uncertainty by realizing a portion of the price now rather than waiting for potentially volatile future prices. Hence, this sales timing decision can be viewed as an analogous risk management choice to the pre-harvest hedging decision described in JLH. Importantly, the theoretical framework of JLH abstracts away from the production risk, and thus the implications of the model should hold in any hedging scenario where the farmer chooses to lock in a price at time t when the prevailing prices F^t differ from the price at time T.

The JLH model embeds R directly into the utility function. The farmer maximizes the following expected utility function with respect to the hedge ratio h:

$$\max_{h} \; EU = \frac{1}{1-\alpha}\pi \left[F^t h + (F^t + \epsilon)(1-h) - R)\right]^{1-\alpha} + \frac{1}{1-\alpha}(1-\pi) \left[F^t h + (F^t - \epsilon)(1-h) - R)\right]^{1-\alpha} \tag{3}$$

This expression nests a standard expected utility model as a special case when $R = 0$, meaning no reference dependence exists. The structure captures how hedging decisions vary with beliefs and the perceived gain or loss relative to R. In this framework, F^t denotes the current futures price, which can either increase or decrease by an amount ϵ at contract maturity. Specifically, the futures price at maturity can be either $(F^t + \epsilon)$ with probability π or $(F^t - \epsilon)$ with probability $1 - \pi$. Thus, $\pi \in [0, 1]$ reflects the farmer's subjective belief about the direction of price movement, where $\pi = 0.5$ corresponds to an unbiased expectation. The share of production hedged at price F^t is represented by h, and α denotes the coefficient of relative risk aversion under the constant relative risk aversion (CRRA) utility framework.

Under unbiased expectations, the model converges to a corner solution: the farmer either fully hedges or does not hedge at all, depending on the relative levels of the current futures price (F^t) and their individual reference prices. As described in Proposition 2 of Jacobs, Li, and Hayes (2018), solution can be presented as:

$$h^* = \begin{cases} 1 & \forall \quad F^t > R_i > 0 \\ 0 & \forall \quad 0 < F^t < R_i \\ [0,1] & \quad F^t = R_i \end{cases} \tag{4}$$

However, this threshold-like behavior is not supported by the data. We do not observe farmers fully hedging their production even when market prices are high and conditions appear favorable. Instead, farmers typically hedge or sell only a portion of their crop early while retaining the remainder for later sales. As illustrated in Figure 2, period-one sales are generally limited in magnitude and rarely approach 100 percent of total production. These patterns suggest that the assumption of unbiased expectations may be unrealistic. And, the interaction between the current price and the reference level alone cannot fully explain observed marketing behavior.

Jacobs, Li, and Hayes (2018) further considers the cases where producers are allowed to hold different directional beliefs about the futures price ($\pi \neq 0.5$) and explains how changes in beliefs would change the optimal hedge ratio in Proposition 3. Incorporating such belief biases provides a more complete theoretical foundation for understanding the heterogeneous outcomes among farmers. The marginal change in the optimal hedge ratio with respect to π is expressed as:

$$\frac{\partial h^*}{\partial \pi} = \begin{cases} -F^t g_1(\pi) & \textit{if } R = 0 \\ -(F^t - R) g_1(\pi) & \textit{if } F^t > R > 0 \\ -(R - F^t) g_2(\pi) & \textit{if } R > F^t > 0 \;\&\; g_3(\pi) < \epsilon/(R - F^t) \\ 0 & \textit{if } R > F^t > 0 \;\&\; g_3(\pi) > \epsilon/(R - F^t) \end{cases} \tag{5}$$

where, $g_1(\pi) = \frac{2}{\alpha\epsilon} \frac{[(1-\pi)\pi^{\frac{1-\alpha}{\alpha}}]]}{[\pi^{1/\alpha}+(1-\pi)^{1/\alpha}]^2}$, $g_2(\pi) = \frac{2}{\alpha\epsilon} \frac{[(1-\pi)\pi^{\frac{1-\alpha}{\alpha}}]]}{[\pi^{1/\alpha}-(1-\pi)^{1/\alpha}]^2}$, and $g_3(\pi) = \frac{\pi^{1/\alpha}+(1-\pi)^{1/\alpha}}{(1-\pi)^{1/\alpha}-\pi^{1/\alpha}}$

Here, three broad cases are presented: when there is no reference dependence, when current prices exceed the reference, and when prices fall below the reference. In the absence of reference dependence, the model reduces to the standard EU maximization. However, under reference-dependent preferences, optimal hedging is a function of current prices, references, and directional beliefs about future price movements. Incorporating such directional beliefs broadens the model's explanatory power, enabling it to capture a wider range of marketing behaviors that more closely reflect real-world outcomes, rather than the strict corner solutions implied under unbiased expectations.

Specifically, when the futures price exceeds the reference price, the farmer's hedge response to changes in price expectations is strongest when their beliefs about the futures market are unbiased (i.e., $\pi = 0.5$). Whereas, with the rising optimism about the futures price change ($\pi > 0.5$), the responsiveness to expected price changes diminishes, and the optimal hedge ratio declines. Conversely, when the futures price lies below the reference, farmers are generally reluctant to hedge unless they strongly expect further price declines to occur. The decision to hedge thus depends on the strength of belief regarding the directional movement of the futures price.

Jacobs, Li, and Hayes (2018) implemented the model in a time-series framework that treated reference prices as uniform and did not incorporate variation in belief biases across producers. Consequently, their empirical specification was unable to fully capture the cross-sectional heterogeneity that characterizes real-world hedging behavior.

While the theoretical structure in JLH is rich enough to explain heterogeneous marketing behavior, its empirical implementation assumes a uniform reference price across all farmers—a simplification unlikely to reflect actual decision-making. If this assumption held, farmers facing identical market conditions would make similar marketing decisions and therefore realize comparable prices. Yet, as illustrated in Figure 4, substantial variation exists in prices received by farmers within the same marketing environment, suggesting heterogeneity in reference prices, expectations, or both. Moreover, the time-series design of JLH presumes homogeneous beliefs about future price movements, overlooking key cross-sectional differences in behavior.

In this study, we extend the reference-dependent hedging framework to a panel setting, relaxing the assumptions of uniform references and belief homogeneity. This extension enables the modeling of reference prices and belief biases as farmer-specific, thereby capturing heterogeneity in cost structures, financial constraints, and price expectations. By leveraging these individual-level differences, our approach offers a more nuanced understanding of how behavioral and economic factors jointly influence marketing decisions under uncertainty.

4 Empirical Method

Estimating reference-dependent behavior alongside heterogeneous directional beliefs about futures price movements presents a key empirical challenge: neither the reference price nor individual belief structures is directly observed. The reference price is an internal, psychological benchmark shaped by each farmer's experiences and expectations, while beliefs about future price movements are a subjective assessment of market movement, which are similarly latent. This creates identification difficulties in disentangling the effects of variation in reference prices from variation in beliefs, both of which influence the observed outcome—namely, the proportion of production that is hedged.

Although we do not directly observe farmers' latent reference prices or beliefs, we do observe heterogeneous behavioral responses among farmers operating within the same market environment. These behavioral differences suggest that farmers interpret and respond to identical market signals in diverse ways, resulting in variations in marketing outcomes and ultimately, differences in profitability.

Following the JLH framework, this heterogeneity may stem from differences in reference formation or variation in farmers' outlook regarding future price movements—what JLH describe as biases in beliefs (π)—or from both. We interpret this belief bias as a directional view about the futures price that deviates from the assumption that the futures price is unbiased, reflecting either optimism or pessimism. In the theoretical model, such views determine whether farmers exhibit strict threshold-type or continuous hedging behavior, as outlined in the previous section

Because farmers' directional views about futures prices are unobservable yet central to explaining hedging behavior, we construct a behavioral proxy to capture the extent of such deviation from unbiased expectations. Specifically, we measure the past responsiveness of each farmer's sales to realized price changes and interpret this responsiveness as a reflection of the farmer's belief orientation. In the JLH framework, a farmer's belief bias determines how strongly they react to new price information: those holding more unbiased expectations adjust their marketing positions more readily to reflect updated price signals, whereas those with stronger directional biases (e.g., optimism or pessimism) exhibit weaker adjustments. Accordingly, we use the absolute value of the interaction between observed price changes and the proportion of production sold to represent the strength of this behavioral response. A smaller value indicates under-reaction to market information—consistent with more pronounced biased beliefs—while a larger value suggests stronger responsiveness and thus more unbiased expectations about futures prices. We assume that, for a given farmer, this belief–response mapping remains stable over time. We propose the following estimation equation:

$$\phi_{it} = \alpha + \beta_1 \Delta f_t + \beta_2 \left[\Delta f_t \cdot (|\Delta f_{t-1} \times \phi_{it-1}|)\right] + \epsilon_{it} \tag{6}$$

In this specification, ϕ_{it} represents the proportion of production sold in the near-harvest period by farmer i in year t. The term $(|\Delta f_{t-1} \times \phi_{it-1}|)$ is a measure of responsiveness based on the past behavior of the farmer, which serves as our proxy for belief bias. Δf_t is the current price change signal and is the same for all farmers in the given marketing year. It is calculated as the logarithmic price difference between May and the contract maturity month—December for corn futures and November for soybean futures. This specification allows us to isolate the influence of farmers' heterogeneous beliefs—captured through past behavioral responsiveness—on current-period marketing decisions, while holding constant the contemporaneous price signal common to all producers.

While this formulation allows us to include a proxy for belief biases, the standard pooled model estimates a single set of coefficients for all farmers. Our central hypothesis, however, is that farmers are heterogeneous, differing in their directional outlook on futures price movements and how they react to those expectations. Moreover, the model may suffer from endogeneity due to unobserved variables correlated with both marketing behavior and the formation of beliefs.

To address these concerns, we adopt a finite mixture model with fixed effects, following the approach of Deb and Trivedi (2013). This framework enables us to capture latent heterogeneity in farmers' response behavior, while also controlling for unobserved time-invariant individual characteristics. By combining the strengths of mixture modeling and fixed effects, we identify distinct behavioral types within the panel, thereby uncovering how heterogeneity in beliefs shapes farmers' marketing decisions.

In the mixture model, we assume that farmers' observations are drawn from different underlying distributions that reflect heterogeneous belief structures. While we do not observe the class membership of any specific farmer or observation, the mixture model probabilistically assigns observations to latent classes and estimates class-specific parameters. Accordingly, we estimate the following equation:

$$\phi_{it,w} = \beta_{1k}\Delta f_{t,w} + \ \beta_{2k}\left[\Delta f_t \cdot (|\Delta f_{t-1} \times \phi_{it-1}|)\right]_w + \epsilon_{it} \tag{7}$$

Here, k represents the categorical groups that the observations could belong to. β_1 captures the effect of a change in price in the current period, and β_2 captures the interactions with the farmers' belief biases proxies. Further, to take into account the individual fixed effects, we apply a within transformation to all the variables, such that:

$$\phi_{it,w} = \phi_{it} - \sum_{t=1}^{N} \frac{\phi_{it}}{N}$$

From this first stage of the analysis, we estimate the effect of belief bias and assess the extent of heterogeneity in farmers' directional outlooks regarding futures price movements by allowing class-specific responses. Differences in β_{1k} across classes indicate that farmers respond differently to the same market signals, suggesting the presence of heterogeneous reference points or thresholds in their marketing behavior. Meanwhile, if beliefs influence marketing decisions, the responsiveness to price changes should vary with the belief-bias proxy ($\beta_{2k} \neq 0$). Estimating class-specific coefficients therefore allows us to identify distinct belief structures and behavioral regimes consistent with heterogeneous reference dependence and directional expectations among farmers.

In the second step, we examine the role of the reference price in shaping marketing behavior, incorporating our earlier belief measurement into the model. As with beliefs, the reference price is not directly observed; instead, we infer its influence from observed farmer behavior. We argue that the reference price must be farmer-specific to account for the heterogeneity observed in marketing decisions. A natural candidate for such an individualized reference is the cost of production, which serves as an important benchmark from a profitability standpoint. Because farmers are typically more attuned to accounting profits or losses rather than economic returns, the cost of production provides the salient foundation for evaluating marketing outcomes, thereby acting as a natural reference for a profit-maximizing producer. While production costs are sunk at the time of sales, they may continue to influence decisions through associated financial commitments such as debt obligations, liquidity constraints, or storage costs.

Unlike previous studies that assume a uniform reference price, our panel dataset enables us to use individualized references. The data provides detailed information on production costs that vary across farmers and over time. This variation allows us to empirically test whether differences in costs contribute to variation in marketing behavior. If the cost of production indeed functions as a reference point, we should observe distinct behavioral responses among farmers with different cost profiles. Accordingly, we estimate the following equation:

$$\phi_{it} = \alpha + \beta_1 I_{F_t<R_{it}} + \beta_2 \Delta f_t \; + \; \beta_3 \Delta f_t \cdot I_{F_t<R_{it}} + \gamma_i + \epsilon_{it} \tag{8}$$

In this specification, ϕ_{it} denotes the dependent variable, representing the proportion of production sold during the near-harvest period (period 1). The reference price R_{it} is proxied by each farmer's per-bushel cost of production. The indicator variable $I_{F_t<R_{it}}$ equals one when the mid-October futures price F_t falls below the reference price, capturing whether the market signal is perceived as a loss relative to the farmer's benchmark. Δf_t represents the annual price change signal, reflecting the directional movement in futures prices during period 1. Finally, γ_i represents individual fixed effects controlling for farmer-specific time-invariant characteristics.

The constant term (α) captures the baseline average proportion of production sold in period 1 when the futures price is above the reference, and β_1 measures the average difference in proportion sold when a farmer is in the loss domain, which is when prices are below the reference. A negative β_1 would indicate that farmers sell a smaller share when the prices are below their reference. The parameter β_2 captures the average responsiveness to the contemporaneous price change signal (Δf_t) when prices are above the reference, while the interaction term β_3 indicates how this responsiveness changes when the futures price is below the reference.

In addition to using the per-bushel cost of production as a reference price, we re-estimate the same framework using the price received in the previous year as an alternative reference. Because this price is still fresh in farmers' recent memory, it may exert a strong influence on their current-year decision-making. Moreover, the previous year's price is inherently farmer-specific, as realized outcomes vary widely even within the same year. As a result, this reference may further contribute to persistent heterogeneity in marketing behavior and realized prices across farmers.

$$\begin{aligned}\phi_{it} = \alpha &+ \beta_1 I_{F_t<R_{it}} + \beta_2 \Delta f_t + \beta_3 r_{it} + \beta_4 \left(\Delta f_t \cdot I_{F_t<R_{it}}\right) \\ &+ \beta_5 \left(I_{F_t<R_{it}} \cdot r_{it}\right) + \beta_6 \left(\Delta f_t \cdot r_{it}\right) + \beta_7 \left(\Delta f_t \cdot I_{F_t<R_{it}} \cdot r_{it}\right) + \gamma_i + \epsilon_{it} \qquad (9)\end{aligned}$$

Finally, we estimate the joint effect of reference dependence and belief biases on the proportion sold in period 1. As outlined in proposition three in the theoretical framework of JLH, the optimal hedging is affected by both reference dependence and the farmer's belief regarding the futures price change. In equation 9, $r_{it} = (|\Delta f_{t-1} \times \phi_{it-1}|)$ represents the farmer's past responsiveness to price change signal as a proxy for belief bias. The higher the value of r, the more responsive a farmer is, and thus, it can be said that the beliefs are more unbiased. We further incorporate the interaction terms to gain a deeper understanding of the dynamic relationship between belief biases and reference dependence.

The specification allows the effect of futures price changes on hedging behavior to vary with belief bias. The interaction term β_6 and β_7 captures whether hedge responses to price movements differ depending on the degree of bias in producers' beliefs. The theory suggests that hedging decisions are most responsive to price expectations when beliefs are unbiased, that is, when $\pi = 0.5$. In this case, farmers place equal weight on favorable and unfavorable price outcomes, so changes in futures prices translate more directly into revisions of expected prices. A positive coefficient on the interaction term, therefore, indicates that futures price changes have a larger impact on hedge positions when beliefs are closer to unbiased, consistent with the theoretical mechanism.

5 Results

First, we present results for finite mixture model. Next, we evaluate reference dependence using two different reference points. Finally, we examine whether farmers substitute between corn and soybeans as part of their marketing strategy—offsetting losses in one crop with increased sales of the other.

5.1 Corn

5.1.1 Finite Mixture Model

Results for regression equations 6 and 7 for corn are presented in Table 1. The first column reports estimates from the OLS regression, where the dependent variable is the proportion sold in period 1 (ϕ_1). The second, third, and fourth columns present results using the within-transformed proportion sold ($\phi_{1,w}$) as the dependent variable. The third and fourth columns specifically display estimates from a finite mixture model with two latent classes of farmers. Heteroskedasticity-robust standard errors are reported in parentheses.

Since the dependent variable in models 2, 3, and 4 is within-transformed, interpretations are made relative to each farmer's own average behavior rather than in absolute terms. The comparison between OLS and finite mixture model estimates reveals substantial differences, highlighting that a simple pooled OLS regression masks important heterogeneity in farmers' marketing responses. In particular, the most striking divergence lies in the

Table 1: Estimation Results: OLS vs Mixture Model Components

Equation 7: $\phi_{it,w} = \beta_{1k}\Delta f_{t,w} + \beta_{2k}\left[\Delta f_t \cdot (\lvert\Delta f_{t-1} \times \phi_{it-1}\rvert)\right]_w + \epsilon_{it}, \quad k = 1, 2$				
	Dependent variable:			
	ϕ_{it}	$\phi_{it,w}$		
Variable	**OLS**	**OLS**	**Class 1**	**Class 2**
	(1)	(2)	(3)	(4)
Intercept (α)	0.047***			
	(0.003)			
Change in Price (Δf_t)	0.084***	0.084***	0.1256***	0.0399***
	(0.006)	(0.006)	(0.0131)	(0.0084)
Interaction between current price signal and past responsiveness	0.951***	0.951***	0.0123	2.1582***
$\Delta f_t \cdot (\lvert\Delta f_{t-1} \times \phi_{it-1}\rvert)$	(0.129)	(0.116)	(0.2401)	(0.2572)
Farm FE	Yes	No	No	
Observations	17131	17131	17131	
Note:		*p<0.1; **p<0.05; ***p<0.01		

responsiveness to the current year's price change signal.

The mixture model identifies two distinct behavioral groups: one group exhibits a strong response to price signals, while the other is much less reactive. Specifically, a one percent increase in the price difference leads to a 0.12 percentage point increase in crop sales (relative to own average) for the more responsive group (represented by Class 1), compared to only a 0.04 percentage point increase for the less responsive group (Class 2). This suggests that farmers interpret and respond to the same market signal in very different ways.

Moreover, the divergence between the two latent groups extends beyond differences in price responsiveness. There are also differences in how beliefs influence behavior, as captured by the interaction term involving past responsiveness, which serves as a proxy for farmers' directional outlook or belief bias. The significant variation in the β_2 coefficients across the two classes indicates that the perceived outlook on future price movements—whether optimistic or cautious—differs among farmers.

Farmers in Class 1 exhibit a strong and statistically significant reaction to contemporaneous price changes, but this relationship is unaffected by the belief proxy. This suggests that these farmers rely primarily on observable market signals rather than subjective beliefs, displaying more information-responsive behavior. In contrast, farmers in Class 2 exhibit weaker direct responsiveness to price changes; however, their responsiveness increases as the level of bias in their beliefs decreases. Importantly, a higher absolute value of the belief proxy represents more unbiased beliefs, indicating that less biased farmers adjust their sales more strongly in response to market signals. This pattern corroborates the theoretical implication of the JLH model that the strength of belief is vital in determining the extent of crop sales or hedges for the given price levels.

This division of farmers into two belief-based categories also aligns with differences in underlying risk attitudes. Farmers in Class 1 appear more risk-averse, quickly capitalizing on the positive price change environment, whereas those in Class 2 are more risk-seeking, often reluctant to sell, despite the positive price change. These findings reinforce the concept of heterogeneous reference prices, as not all farmers respond to the same market signal in a uniform manner, and thus they cannot be represented by a single, uniform reference price. Overall, the findings suggest that marketing behavior is shaped not only by observed market conditions but also by unobserved differences in farmers' beliefs, expectations, and reference formation.

5.1.2 Per Bushel Cost of Production as Reference

In the second step of the analysis, we examine farmers' behavior with respect to different reference prices, focusing on whether their responses to market signals are asymmetric. Specifically, we examine how the proportion of crops sold in the near-harvest period varies depending on whether the current futures price is above or below a farmer-specific reference price, which is proxied by their per-bushel cost of production. The estimation results for this analysis, corresponding to equation 8, are presented in Table 2.

Model 1 presents the results using the within-transformed proportion sold in period 1 as the dependent variable, accounting for fixed effects directly through demeaning. Model 2-4 uses the proportion sold, with explicit farm fixed effects. We use the mid-October futures price of the December contract as the harvest-time price for corn (F_t), because most farmers' realized prices aligned closely to the price prevailing at this time. We compare this price against the reference price to define whether the given farmer is in a gain or loss domain. The indicator variable $I_{F_{it}<R_{it}}$ equals 1 when the futures price is below the reference price, proxied by each farmer's per-bushel total cost of production. Models 3 and 4 further incorporate interaction terms to better understand the heterogeneity and differences in marketing strategies across various price environments. Heteroskedasticity-robust standard errors are reported in parentheses.

The estimates reveal clear evidence of asymmetric responses around the reference price across all specifications. When the futures price is above the reference price, farmers sell, on average, 6.4% of their total corn harvest in period 1. However, when the futures price falls below the reference point, sales decrease by 1.4 percentage points. Additionally, a one-unit increase in the price change signal is associated with a 9.5 percentage point increase in sales when prices are above the reference price. This effect intensifies when prices fall below the reference price: the interaction term suggests a combined effect of $0.095 + 0.052 = 0.147$, or a 14.7 percentage point increase in sales in response to a one-unit increase in the price change signal. A model using within-transformed variables also yields identical results.

Increasing sales when prices are below the reference point appears counterintuitive, given the findings of Jacobs, Li, and Hayes (2018), who show that farmers tend to hold grain when prices rise but remain below the reference point, anticipating that prices will eventually cross it. A closer examination of farmer behavior, however, reveals important nuances. For high-cost farmers, a rising market may still represent an opportunity to sell,

Table 2: OLS estimates exploring asymmetric response around reference point and behavioral heterogeneity across classes

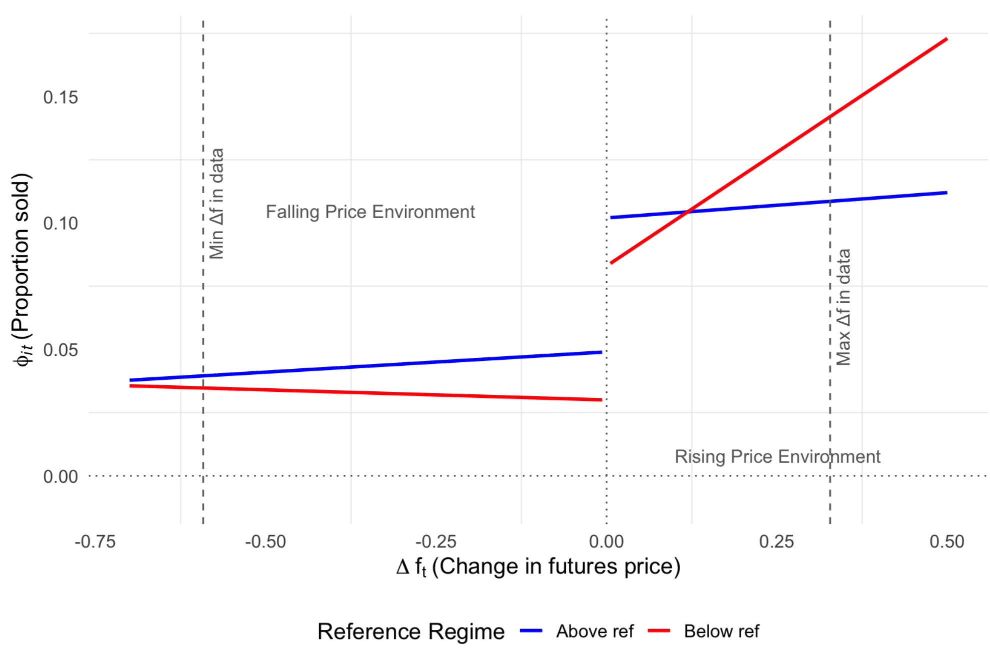
	Dependent variable: Proportion Sold			
	$\phi_{it,w}$	ϕ_{it}		
	(1)	(2)	(3)	(4)
Indicator	-0.014^{***}	-0.014^{***}	-0.019^{***}	-0.005
(Futures price < Reference Point)	(0.003)	(0.004)	(0.005)	(0.004)
Change in price (Δf_t)	0.095^{***}	0.095^{***}	0.020	0.037^{***}
	(0.005)	(0.006)	(0.017)	(0.008)
Interaction between indicator	0.052^{***}	0.052^{***}	0.160^{***}	0.074^{***}
and price change ($\Delta f_t \cdot I_{F_t<R_{it}}$)	(0.013)	(0.015)	(0.034)	(0.016)
Indicator for direction of price change			-0.053^{***}	
($I_{\Delta f_t<0}$)			(0.005)	
Interaction between price change			-0.004	
and direction of change ($\Delta f_t \cdot I_{\Delta f_t<0}$)			(0.021)	
Triple interaction:			-0.184^{***}	
$\Delta f_t \cdot I_{F_t<R_{it}} \cdot I_{\Delta f_t<0}$			(0.047)	
Absolute responsiveness ($\lvert r_{it}\rvert$)				0.307^{***}
				(0.031)
Interaction: Indicator × Responsiveness				-0.118^{**}
($I_{F_t<R_{it}} \cdot \lvert r_{it}\rvert$)				(0.057)
Interaction: Price change × Responsiveness				2.227^{***}
($\Delta f_t \cdot \lvert r_{it}\rvert$)				(0.181)
Triple interaction:				-1.182^{***}
$\Delta f_t \cdot I_{F_t<R_{it}} \cdot \lvert r_{it}\rvert$				(0.309)
Constant		0.064^{***}	0.102^{***}	0.050
		(0.004)	(0.011)	(0.112)
Farm FE	-	Yes	Yes	Yes
Observations	17,131	17,131	17,131	17,131

Note: *p<0.1; **p<0.05; ***p<0.01

even if the price is below their cost-based reference point. Their incurred costs place them under greater financial pressure, and they may perceive any upward movement in prices as an opportunity to secure liquidity and mitigate further downside risk. In this sense, the cost of production does not merely serve as a reference point; it also influences the urgency with which farmers respond to price changes.

Further, this behavior is also rooted in how farmers frame outcomes. Farmers are often more attuned to accounting gains and losses than to economic gains and losses. Selling below cost represents a realized accounting loss, which farmers are especially motivated to avoid. However, in a prolonged low-price environment, even modest price increases provide an opportunity to reduce the depth of those losses. By selling into a rising but still unfavorable market, farmers can average out losses over time and limit further financial deterioration.

Figure 6: Reference and Price Direction Effects on Outcome



Model 3 investigates whether farmers' reactions to price changes differ based on the price environment in which they operate. We include an indicator variable that identifies whether the price change is positive or negative, essentially distinguishing between a rising and a falling price environment. The results are shown in Figure 6, which illustrates farmers' responses to different price signals under each scenario. The blue line represents observations where the market price is above the reference price, while the red line represents cases where the market price falls below the reference price. The left side of the zero line corresponds to a falling price environment, and the right side corresponds to a rising price environment. The two dashed vertical lines indicate the range of price change signals observed in the data.

When the market price is above the reference point, sales increase similarly in both rising and falling price environments as price changes become more positive. In contrast, when prices are below the reference point, falling prices prompt further reductions in sales, while rising prices trigger a sharp increase in sales near harvest—surpassing levels observed when prices are above the reference point under a strong positive price signal.

This pattern indicates that farmers exploit even small upward price movements to mitigate losses. More importantly, it clarifies the positive coefficient on the interaction between price changes and the below-reference indicator in Model (2), which at first appears counterintuitive. The higher marginal response in the loss domain occurs specifically during episodes of rising prices. Although prices remain below the reference point, an observed upward trend induces farmers to sell into a recovering market to average down losses. Conversely, when prices continue to fall, farmers withhold sales, consistent with risk-seeking behavior in the loss domain when losses are expected to persist.

Finally, in Model (4), we present the results from equation 9, which incorporates the absolute value of a farmer's past responsiveness in marketing behavior as a proxy for belief bias. Higher values of this response variable indicate more unbiased beliefs regarding futures price changes. The positive coefficient on β_4 implies that farmers who are more responsive to price information sell a larger share of their production on average, consistent with a more active marketing strategy.

Reference dependence remains present in this specification, but it manifests through interaction terms rather than through a standalone loss-domain shift. Although the loss-domain indicator is not statistically significant on its own, the interaction between the loss-domain indicator and the response variable is negative and significant, indicating that the level difference in sales between the loss and gain domains varies with belief bias. In particular, as responsiveness (i.e., relatively unbiased beliefs) increases, farmers in the loss domain reduce period 1 sales more sharply relative to comparable farmers in the gain domain.

Turning to marginal responses, the positive coefficient on β_6 indicates that the marginal change in the proportion sold in response to a price change is amplified by more unbiased beliefs in the gains domain. This finding aligns with the predictions of the theoretical model, which implies that the marginal response to price expectations is strongest when beliefs are unbiased. A similar mechanism operates in the loss domain, although the effect is attenuated, as reflected by the negative coefficient on β_7. Nevertheless, the overall marginal effect remains positive, since $\beta_6 + \beta_7 = 1.045 > 0$.

Overall, Model (4) shows that reference dependence in farmers' sales behavior is jointly shaped by belief bias and price movements. More unbiased beliefs amplify responsiveness to price changes, leading to higher sales, while losses relative to the reference point dampen this responsiveness without fully eliminating the positive marginal effect.

5.2 Last-Year's Price Received as Reference

We next examine whether alternative heterogeneous reference points can explain farmers' marketing behavior in a manner similar to the cost-of-production benchmark. One such reference, widely discussed in the literature, is the average marketing price from the previous year. However, studies assume this reference to be uniform across all farmers, as it is based on the average price received by all farmers in that year. This assumption overlooks the reality that farmers receive different prices depending on timing, contracts, and other factors, thereby failing to capture the heterogeneity in reference formation.

To address this limitation, we instead use the individual farmer's own price received in the prior year as the reference point. Specifically, we focus on prices received from near-harvest sales, which are more likely to reflect the expectations farmers form for the current year based on their own past outcomes.

Table 3 reports the estimates from equation 8, where last year's individual price replaces the per bushel cost of production as the reference point. Consistent with the previous results, we see strong reference dependence in the case of last year's price as a reference point. There is an even stronger asymmetric response around the reference price. When the price falls below the reference point, sales decrease by 6 percentage points, compared to a 1.4 percentage point decrease when the per-bushel cost was used as the reference, keeping all else constant.

Table 3: Last Year's Price Received as a Reference Point

	Proportion Sold in near-harvest period (ϕ_{ict})
	Corn
Indicator for loss domain (Futures Price < Last Year's Price)	-0.060^{***} (0.004)
Change in price (Δf_t)	0.103^{***} (0.006)
Interaction between indicator and price change ($\Delta f_t \cdot I_{F_t<R_{it}}$)	-0.130^{***} (0.017)
Constant	0.063^{***} (0.009)
Farm FE	Yes
Observations	17,131

Note: Standard errors are reported in parentheses.
*p<0.1; **p<0.05; ***p<0.01

The coefficient on price change exhibits a similar reaction to that observed when using the per-bushel cost of production as a reference, with a positive marginal effect of price changes on sales. However, unlike the cost-based specification, where farmers increased sales as prices rose, even while remaining below the reference, the interaction between price change and the loss-domain indicator now enters with the opposite sign. When last year's price is used as the reference point, farmers tend to delay sales despite rising prices so long as prices remain below the previous year's average. While this behavior contrasts with the cost-based results, it is consistent with the findings of Jacobs, Li, and Hayes (2018).

The contrasting results across the two reference points warrant closer investigation. The most plausible explanation for the sign reversal is that the choice of reference point redefines the loss and gain domains for each farmer. A farmer who appears to be in the gains domain under a cost-based reference may instead fall into the loss domain when last year's price is used as the benchmark, or vice versa. This distinction matters because the cost-of-production benchmark relates directly to accounting profits and losses, which farmers are likely to prioritize, whereas last year's price represents a more relative, expectation-based reference. As a result, farmers may perceive the two reference points differently, leading to divergent behavioral responses.

Intuitively, farmers may perceive that they can wait out unfavorable prices when prices fall below last year's received price, as such declines do not necessarily imply an immediate accounting loss and may be viewed as temporary, with the possibility of future price recovery. In contrast, when prices fall below the cost of production, farmers cannot afford to wait, since delaying sales implies bearing realized accounting losses. In this sense, accounting losses appear to matter more for farmers' decision-making than economic losses defined relative to past prices.

These findings also suggest that farmers may not rely solely on a single benchmark. Instead, multiple reference points—such as production costs and past prices—may simultaneously influence marketing decisions. It is challenging to determine which reference dominates for a given farmer; yet, the consistent evidence of asymmetric responses underscores that reference dependence is pervasive. Even within heterogeneous groups, farmers systematically rely on internal benchmarks when making marketing decisions.

5.3 Interaction between corn and soybean marketing

Overall, the corn and soybean results reveal similar qualitative patterns—reference dependence, heterogeneous belief structures, and price-direction effects. In practice, most farmers who grow corn also grow soybeans, meaning these marketing decisions are interconnected rather than independent. Because crops cannot be mixed in storage and on-farm storage is limited, marketing one crop often constrains or shapes decisions for the other. Farmers also evaluate profits and losses across their entire enterprise, potentially offsetting lower returns on one crop with gains on another. To capture these dynamics, we next examine potential cross-crop substitution in marketing decisions.

Table 4 presents the estimation results on potential cross-crop substitution in marketing decisions. On average, soybeans have 2.83 percentage points higher near-harvest sales than corn when prices are above the reference price. The negative coefficient on the other crop's sales indicates substitution: when more of one crop is sold, less of the other is sold. Specifically, a 10 percentage point increase in one crop's sales is associated with a 1.75 percentage point decline in the other crop's sales. This substitution effect is further intensified when the crop is in the loss domain, as reflected by the negative coefficient on the interaction between the loss-domain indicator and the other crop's sales.

Together, these findings underscore the importance of considering heterogeneity among farmers in their formation of reference points and responses to market signals. By incorporating farm-specific cost structures and accounting for latent behavioral classes, we uncover systematic differences that would otherwise be concealed in a pooled analysis. This evidence highlights the complexity behind marketing decisions and reinforces the idea that farmers

Table 4: Switching between corn and soybean sales: reference domain and cross-crop substitution

	Dependent variable:
Variable	Proportion sold of one crop (ϕ_{ict})
Crop: Soybean	0.0283^{***}
	(0.00281)
Indicator for loss domain	-0.00670
(Futures price < Reference Point)	(0.00635)
Other crop's proportion sold (ϕ_{other})	-0.1753^{***}
	(0.01246)
Soybean × Loss domain	0.0333^{***}
	(0.00491)
Loss domain × Other crop's sales	-0.0481^{**}
	(0.01647)
Farm FE	Yes
Year FE	Yes
Observations	45,238

Notes: Standard errors clustered at the farm level in parentheses.
Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

rely not only on market conditions but also on internal benchmarks shaped by both economic realities and psychological factors. Furthermore, marketing decisions for corn and soybeans are not mutually exclusive, as the same farmer makes simultaneous decisions for both crops.

6 Conclusion

This study presents the most rigorous assessment to date of market timing–driven differences in commodity marketing, demonstrating that heterogeneity in farmers' internal benchmarks is a key driver of grain marketing behavior and realized prices. Even when facing identical market conditions, farmers evaluate sales opportunities differently because they rely on individualized reference points and hold heterogeneous beliefs about future price movements. As a result, marketing outcomes and profitability vary substantially across farms operating in the same price environment.

Using rich panel data from the Illinois Farm Business Farm Management (FBFM) program, which records farm-level production costs, realized prices, and marketing outcomes over a two-decade period, we can directly examine reference dependence in a cross-sectional setting. This richness enables us to move beyond representative-farm assumptions and examine how heterogeneity in financial conditions and behavior influences marketing decisions under risk—an empirical setting that has been largely overlooked in prior work.

Building on the reference-dependent hedging framework of Jacobs, Li, and Hayes (2018), we provide new evidence that farmers differ in how they process price information. Using a finite mixture model with fixed effects, we identify two broad behavioral types: one group that responds strongly to contemporaneous price signals and another that adjusts sales more passively. These differences reflect heterogeneity in beliefs and reference formation that cannot be captured by models imposing uniform preferences or common reference prices across producers.

With the help of the panel data, we construct a proxy for belief bias in price expectations based on farmers' past responsiveness to realized price changes. Because beliefs about future prices are not directly observable, this proxy provides a tractable way to disentangle belief heterogeneity from reference dependence in observed marketing behavior. Incorporating this measure reveals that farmers with more unbiased beliefs respond more strongly to price signals, consistent with theoretical predictions, while more biased beliefs dampen responsiveness even when prices move favorably.

Furthermore, we present evidence of asymmetric marketing behavior above and below the reference point, highlighting the existence of reference dependence among farmers in the cross-section. We use the per-bushel cost of production as a natural and individualized benchmark, as well as last year's price received by farmers as an experience- and expectation-based benchmark, both of which represent heterogeneous, individualized references. Our results show that farmers exhibit asymmetric responses to market prices: they tend to sell more when prices are above their reference price and less when prices fall below it, consistent with reference-dependent preferences.

Importantly, the nature of reference dependence depends on the benchmark used. When last year's price received serves as the reference point, farmers tend to delay sales as long as prices remain below that level, even in a rising market. In contrast, when prices fall below production costs, farmers increase sales in response to improving price conditions, reflecting the urgency associated with realized accounting losses. This contrast suggests that farmers respond differently when managing accounting losses relative to costs than when managing economic losses defined in relation to past prices, highlighting the presence of multiple, context-dependent reference points.

We also document meaningful cross-crop substitution in marketing decisions. Because most farms jointly produce corn and soybeans, sales decisions are not made in isolation. When one crop is in the loss domain, farmers partially offset potential revenue shortfalls by increasing sales of the other crop. This portfolio-like adjustment underscores the importance of modeling farm-level marketing behavior at the enterprise level rather than treating individual crop decisions independently.

Taken together, these findings suggest that effective price risk management strategies and advisory services should consider farm-specific financial conditions, belief heterogeneity, and reference formation. Policies and recommendations based on representative prices or uniform benchmarks may fail to align with how farmers actually perceive gains, losses, and risk. Advisory approaches that incorporate individualized cost structures and recognize belief-driven differences in responsiveness are more likely to support effective marketing decisions under price uncertainty.

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A Additional Material

A.1 Soybeans Marketing

We next apply the same empirical framework to soybean sales, using identical specifications as in the corn analysis. This allows for a direct comparison of price responsiveness and reference dependence across crops. Table 5 presents the results of equations 6 and 7 for soybeans.

Table 5: Estimation Results: OLS vs Mixture Model Components

	Dependent variable:			
	ϕ_t	$\phi_{t,w}$		
Variable	**OLS**	**OLS**	**Class 1**	**Class 2**
	(1)	(2)	(3)	(4)
Intercept (α)	0.471***		0.0006	0.0024
	(0.001)		(0.0012)	(0.0019)
Change in Price (Δf_t)	0.185***	0.185***	0.0357***	0.17511***
	(0.013)	(0.0013)	(0.0091)	(0.0125)
Interaction between current price signal and past responsiveness	-0.732***	-0.732***	-0.4277	-1.5099***
	(0.152)	(0.152)	(0.2843)	(0.2902)
Farm FE	Yes	-	-	
Observations	14246	14246	14246	
Log-Likelihood	4922.075	4904.86	5829.91	
Note:			*p<0.1; **p<0.05; ***p<0.01	

We observe broadly similar behavioral patterns in soybean marketing as in corn. As with corn, the OLS estimates differ substantially from those obtained from the finite mixture model, underscoring the presence of unobserved heterogeneity. The mixture model identifies two latent behavioral classes among soybean farmers. The more responsive group increases near-harvest sales by 17.5 percentage points in response to a one-unit change in the log price signal, compared to just 3.6 percentage points for the less responsive group—a gap wider than that observed for corn. Differences in the belief–price interaction term across classes also indicate heterogeneous belief structures, consistent with the patterns found in corn marketing.

Applying the reference-dependent framework to soybeans, using per-bushel cost of production as a proxy for the reference price, yields results broadly consistent with corn, though with some differences in magnitude (table 6). Reference-dependent behavior is evident across all specifications, as shown by the negative coefficient on the below-reference indicator. However, compared to corn, soybean farmers sell a larger share of their crop in the near-harvest period and reduce sales by a smaller amount when prices fall below their reference point. This result also highlights the potential differences in a crop's returns to storage, where lower returns for soybeans would prompt farmers to sell more of the soybeans near harvest and store corn for future sales. Moreover, the interaction between latent class and reference regime is not statistically significant, suggesting that reference dependence is more uniform across soybean farmers than in corn marketing.

Likewise, model 4 incorporates price-direction effects with results presented in figure 7. When the price is above the reference price, represented by the blue line, farmers increase soybean sales steadily with more positive price signals, with only modest differences between rising and falling price environments. In contrast, when the price is below the reference price, represented by the red line, a much sharper asymmetry in marketing is seen. Farmers are more reluctant to sell in a falling price environment, whereas in the presence of an upward-trending price, farmers increase their sales sharply, as seen in the case of corn. While qualitative results mirror those found in corn marketing, soybean sales made when the price is above the reference price are higher on average, and the slope is also steeper. This indicates that soybean sales react more strongly to favorable price changes, adjusting sales more quickly than for corn when market signals improve.

Table 6: OLS estimates exploring asymmetric response around reference point and behavioral heterogeneity across classes (Soybeans)

	Dependent variable: Proportion Sold			
	$\phi_{it,w}$	ϕ_{it}		
	(1)	(2)	(3)	(4)
Indicator	-0.011^{**}	-0.011^{**}	-0.012^{*}	-0.018^{**}
(Futures price < Reference Point)	(0.005)	(0.005)	(0.007)	(0.007)
Change in price (Δf_t)	0.143^{***}	0.143^{***}	0.143^{***}	0.219^{***}
	(0.013)	(0.013)	(0.013)	(0.030)
Interaction between indicator	0.030	0.030	0.030	0.212^{***}
and price change ($\Delta f_t \cdot I_{F_t<R_{it}}$)	(0.030)	(0.030)	(0.030)	(0.072)
Indicator for Class 1			0.106	
(Less responsive Group)			(0.131)	
Interaction between reference indicator			0.006	
and class 1 ($I_{F_t<R_{it}} \cdot I_{Class1}$)			(0.008)	
Indicator for direction of price change				0.010^{*}
($I_{\Delta f_t<0}$)				(0.006)
Interaction between price change				-0.098^{**}
and direction of change ($\Delta f_t \cdot I_{\Delta f_t<0}$)				(0.044)
Triple interaction:				-0.247^{**}
$\Delta f_t \cdot I_{F_t<R_{it}} \cdot I_{\Delta f_t<0}$				(0.099)
Constant		0.473^{***}	0.366^{***}	0.470^{***}
		(0.0005)	(0.131)	(0.001)
Farm FE	-	Yes	Yes	Yes
Observations	[14233]	[14233]	[14233]	[14233]
Note:		*p<0.1; **p<0.05; ***p<0.01		

Figure 7: Reference and Price Direction Effects on Outcome