Production Costs, Price Expectations and Reference Dependence in Commodity Marketing

Aayush Dhakal
University of Illinois Urbana-Champaign, adhakal3@illinois.edu

Joseph Janzen
University of Illinois Urbana-Champaign, jjanzen@illinois.edu

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Aayush Dhakal
adhakal3@illinois.edu

Joseph Janzen
jjanzen@illinois.edu

Department of Agricultural and Consumer Economics
University of Illinois Urbana-Champaign

Abstract

This study examines how heterogeneity in cost structures and belief formation shapes reference-dependent grain marketing behavior among farmers. 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 two distinct behavioral groups: one highly responsive to price changes, and another more passive. We further test whether production costs function as farmer-specific reference prices—a widely discussed but rarely empirically tested concept. Results show asymmetric marketing responses around the reference point: farmers sell more when prices exceed their cost-based reference and less 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

"Know your cost of production" is standard advice from commodity marketing advisors to farmers (Parcell and Franken, 2011). For the farmer choosing whether to sell at current commodity market price levels, it implies that the price should be considered relative to the per-unit production cost. To achieve profitability, farmers must aim for revenues that exceed the costs incurred during the production process, so 'know your cost of production' may be restated as 'don't sell below cost'. Implicitly, this means that farmers should form a reference price based on their individual cost structure and make marketing decisions accordingly.

Despite its intuitive appeal, there is limited understanding in the literature of how farmers actually time the market or develop marketing strategies. While traditional models frame this as an expected utility maximization problem (Lapan and Moschini, 1994), empirical support for such models are largely inconsistent. Instead, many studies show that farmers are differentially sensitive to profits and losses which is better explained by prospect theory. This has shifted attention toward reference dependence, where agents evaluate outcomes relative to a subjective reference point rather than in absolute terms (Tversky and Kahneman, 1991). Building on this, Jacobs, Li, and Hayes (2018) emphasize reference-dependent hedging, which we extend to a cross-sectional context by examining heterogeneity in reference point formation across farmers.

However, the process by which these reference points are formed remains unclear. Kim, Brorsen, and Anderson (2010) suggest that it may be optimal for farmers to form a target profit margin and hedge accordingly to enhance profitability. Other studies suggest that reference points are shaped by expectations of future outcomes (Kőszegi and Rabin, 2007) or by historical observations. While various candidate reference prices have been explored in the literature, the cost of production remains a natural foundation for a reference point, as it can anchor expectations and define profitability thresholds. Although this concept is plausible, empirical work testing this hypothesis remains scarce. In this study, we explore how production costs influence the marketing decisions of grain farmers. We test whether production costs shape reference prices formed by farmers. Then, we assess farmers' marketing activity when market prices fall above or below this reference price, providing insights into how market conditions and cost pressures influence farmers' pricing strategies.

During a given marketing year, realized prices vary among farmers, even though all farms face roughly the same market conditions at any given moment in time. This variation primarily stems from the timing of their sales. For example, Janzen (2024) notes realized prices vary widely among Illinois corn and soybean farmers, with over 40% of Illinois corn and soybean farmers reporting no sales near harvest, preferring to store crops for later sale. Additionally, significant variation exists in the costs of production, mainly due to variation in input usage and yield per acre (Foreman, 2014). These differing cost structures mean that some farmers can afford to sell immediately, even in a low-price environment, and still remain profitable, whereas others might need to wait for better prices to at least break even.

Differences in realized prices, combined with heterogeneous cost structures, warrant closer investigation into whether farmers are timing the market with their individual cost of production in mind. This suggests that profitability is unique from each farmer's perspective, depending not only on external market signals but also on intrinsic reference points they aim to achieve. These unique features of individual farmers is hard to be modeled as one and does not provide insights on individual behavior.

Previous studies consider how farmers form reference prices to guide marketing decisions. Kim, Brorsen, and Anderson (2010) suggests that farmers establish a target profit margin based on production costs and choose to sell when this target is met. This method of hedging has been shown to yield higher prices compared to other strategies, such as selling immediately after harvest or engaging in constant hedging across periods. However, their targets were derived from ERS economic costs of production which assumes uniform cost structure and thus reference prices across farmers. This assumption is likely to be violated when we observe farmer's cost structure varies a lot between farmers even within a same year.

Furthermore, in an experimental study with grain producers, Mattos and Zinn (2016) find that reference prices are influenced by a combination of current market prices, future price expectations, and the highest price observed to date. They argue that producers' marketing decisions are guided by the spread between the current market price and their reference price. They also assert that farmers adjust their reference prices in response to changing market conditions. This perspective provides an alternative hypothesis: that production costs may play little or no role in shaping marketing decisions once they are realized. However, while prices typically tend to rise after harvest, financial pressures such as debt obligations, cash flow needs, and storage costs often constrain farmers' ability to delay sales. These financial constraints are directly tied with the incurred cost of production, and indicates farmers financial ability to mitigate price risks faced during marketing. As a result, even when production costs are already sunk and no longer adjustable, they may continue to influence marketing behavior by shaping farmers' financial flexibility, liquidity needs and risk tolerance.

Evidence also suggests that producers exhibit varying reactions to different price levels. Jacobs, Li, and Hayes (2018) highlights the existence of reference-dependent hedging, where farmers display asymmetric behavior depending on whether the current price is above or below the reference price. They test the reference dependence hypothesis using several candidate reference prices, including the Risk Management Agency's (RMA) projected harvest price and the previous year's average market price as static reference points, and the thirty-day moving average of December corn futures as a dynamic reference point. They also propose that the cost of production may serve as a natural reference point, since selling below this threshold would effectively involve realizing a loss. Specifically, their results show that farmers tend to sell more when current prices exceed their reference price and sell less when prices fall below, consistent with reference-dependent preferences. Such findings reinforce the idea that farmers' reference prices operate as psychological benchmarks, shaping their willingness to realize gains or defer losses based on subjective perceptions rather than objective market conditions. This behavioral pattern mirrors the well-documented disposition effect in financial markets, where investors are more likely to sell assets that have increased in value while holding onto assets that have declined. Mattos and Fryza (2014) provide further evidence that the disposition effect is present in grain markets, showing that farmers tend to hold onto grain when prices are low and sell more quickly when prices rise above their reference price. They also note that cost of production may offer a meaningful benchmark for farmers' reference prices, analogous to the purchase price of a stock for an investor.

Despite its prominence in both theory and practice, the cost of production has yet to be empirically tested as a basis for farmers' reference price formation. Although marketing advisories frequently urge farmers to "know your costs" and many discussions highlight cost of production as a natural reference point, no formal empirical evidence currently validates this assumption. Most importantly, studies using cost of production as reference assume same costs for all farmers in the study, which likely does not represents reality. Not only for costs of production, all the reference prices discussed in the literature assume same reference point for all farmers specifically tied to the market conditions, but significant variation in prices received by individual farmers suggests diverse perceptions of reference prices, influencing decisions to sell or hold crops.

Although the decision-making process behind when farmers sell/hedge their production is not fully understood, it is well established that the timing of marketing decisions plays a critical role in determining farm profitability. In this study, we take a step towards understanding this marketing behavior, which is highly important for grain marketers, agricultural economists and farmers themselves.

To empirically test these hypotheses, we draw on detailed farm-level data from the Illinois Farm Business Farm Management (FBFM) program, comprising financial and agronomic information from over 5,000 farmers across Illinois since 2003. The dataset provides rich information on production costs, crop sales, and price received for corn and soybean producers. Specifically, we observe sales made right after harvest (from harvest till December 31st) and those made later in the marketing year (from January 1st till next harvest). This distinction allows us to evaluate the sales decision made by farmers in reference to their underlying unique costs structure.

We extend the reference dependence framework proposed by Jacobs, Li, and Hayes (2018), who demonstrate that farmers' hedging proportions vary based on their beliefs about futures price movements and their reference prices. However, their model treats all producers as behaviorally homogeneous, which may not reflect the diversity observed in real-world decision-making. In contrast, we leverage observed differences in farmer behavior to infer heterogeneity in both belief structures and reference point formation.

To identify this heterogeneity, we apply the finite mixture model for panel data with fixed effects as proposed by Deb and Trivedi (2013). This approach allows us to test whether farmers' observations are drawn from distinct underlying distributions, capturing unobserved latent classes. Our results reveal two distinct groups of farmers: one group is highly responsive to price changes, while the other exhibits a more muted reaction to the same market signals.

In the second part of the analysis, we investigate asymmetric marketing responses using the cost of production as a farmer-specific reference point. We use each farmer's per-bushel total cost of production as a proxy for their reference price and compare it to the harvest-time futures price. This framework enables us to examine how farmers adjust their marketing decisions when the market price is either above or below their individual reference point.

Preliminary results suggest that farmers exhibit asymmetric responses to market prices relative to their reference prices. Specifically, when the market price exceeds the reference price, farmers tend to sell more than their average proportion. Conversely, when the market price falls below the reference point, farmers reduce their sales activity.

These patterns are consistent with both reference dependence and the disposition effect. Farmers appear to base their marketing decisions on an internal target price, increasing sales when prices are perceived as gains and delaying sales when prices represent potential losses. This behavioral response highlights how subjective evaluations—rather than objective price levels—drive marketing behavior.

To further examine the robustness of our findings, we test alternative reference points discussed in the literature, including the previous year's average price received by each farmer. This approach allows us to investigate whether farmers anchor their expectations on their own past experiences. Notably, this reference measure is also heterogeneous across farmers and varies around the broader market price, reinforcing the idea that farmers use individualized benchmarks in their decision-making process.

From these empirical findings, we contribute mainly to two strands of the economics literature. First, we contribute to the reference dependence literature by incorporating farmers' individual costs of production as reference points— a factor long discussed but never empirically tested. In doing so, we also relax the standard assumption of a uniform reference price across farmers and instead propose heterogeneous, farm-specific reference points, offering new insights into variation in grain marketing behavior. Second, we contribute to the behavioral economics literature by providing further evidence of the disposition effect among farmers, showing that farmers differentially evaluate gains and losses—specifically, by exhibiting risk aversion in the domain of gains and risk seeking in the domain of losses.

The remainder of the paper is organized as follows. Section 2 describes the farm-level data from the Illinois Farm Business Farm Management (FBFM) program and outlines key variables, and highlights the variation present in between farmers. Section 3 provides the theoretical framework on which the estimation is based. Section 4 presents the empirical strategy used to test the relationship between production costs, reference prices, and farmers' marketing behavior. Section 5 discusses the main results, providing evidence on the role of cost-based reference points and farmers' asymmetric reaction to the market price based on their references. Finally, Section 6 concludes by summarizing the findings, and discussing implications for agricultural marketing strategies.

2 Data

We utilize data from the Illinois Farm Business Farm Management (FBFM) program, which provides detailed farm-level financial and agronomic information for over 5,000 farmers across Illinois since 2003. This dataset represents approximately 25% of Illinois farmland acreage. While the dataset offers observations for a wide range of Illinois farms, we focus our analysis on farms cultivating either corn or soybeans. We also filter the data that is certified usable for research purposes.

This dataset, prepared annually for tax filing, financial statement preparation, and benchmarking purposes, offers a snapshot of farm activities as of December 31 each year. We observe data on farm returns and cost incurred in production process, which is further subdivided into different itemized cost categories, like fertilizers, seeds, machineries, fuel, and such. Further, for each calendar year, we observe sales of both old crops—harvested in the previous year and remaining in inventory—and new crops—harvested in the current year, and their respective quantities. Although there is a single annual observation per calendar year, this distinction between old and new crops allows us to reframe the data into a marketing-year perspective.

Figure 1: Timeline of crop sales and organization of calendar year data into marketing year perspective.

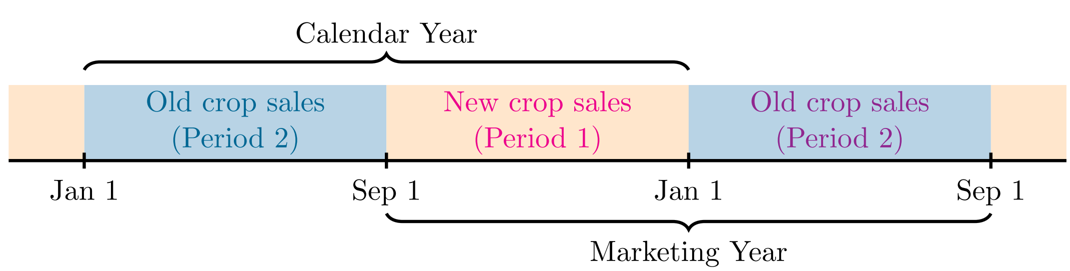
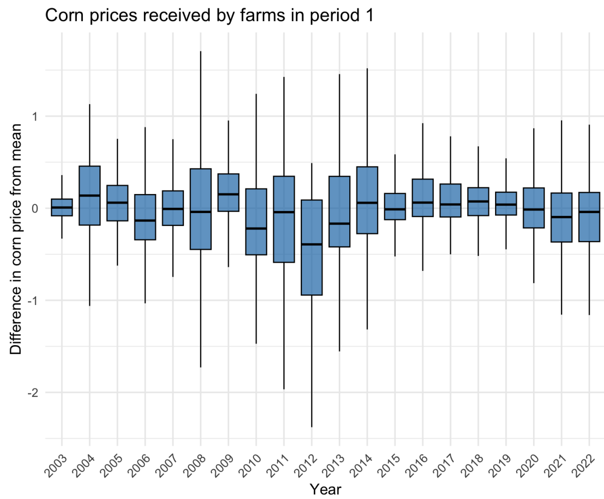


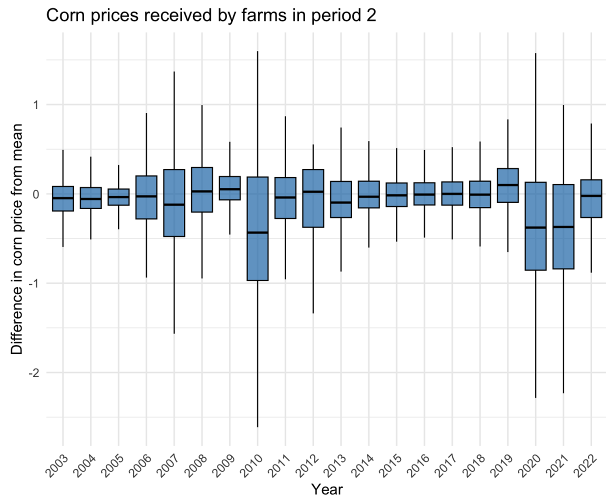
Figure 1 illustrates how sales data from a calendar year are reorganized into a marketing year framework. The marketing year for corn begins on September 1st of one calendar year and extends until August 31st of the following calendar year. Here, we can safely assume that any sales made before September 1 typically come from old crop stored in inventory, since the new crop is not yet harvested. Likewise, sales occurring after September 1 until end of the year generally come from the new harvest. These new crop sales can also be referred to as the "near-harvest" sales, because the sales are made within a short time window after the harvest, whereas old crop sales of the next calendar year would refer to as the "deferred sales" of same marketing year, because these crops are stored to be sold after December 31st. So, combining new crop sales of one calendar year with the old crop sales of the following calendar year, we get the complete picture of crop sales in one marketing year with two distinct periods. The first covering the months from harvest to the end of December, while the second encompasses the time from January 1 until the following harvest season. For the purpose of our analysis, we refer to these periods as Period 1 and Period 2. Using these two periods, we analyze whether farmers sell their produce right after harvest within December 31st (Period 1) or choose to store the crop for sale in next period (from January 1st till Aug 31st, Period 2). When converting the data from calendar years to a marketing year format, we inevitably lose some observations. 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.

The sales data do not provide the exact timing of sales or the price of each transaction within these two periods. However, we can observe the average price received by farmers during each period. This average price is calculated by dividing the total revenue from crop sales by the total quantity of crop sold in that period. Doing this, we have one price value for each farmer for each period.

Figure 2: 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



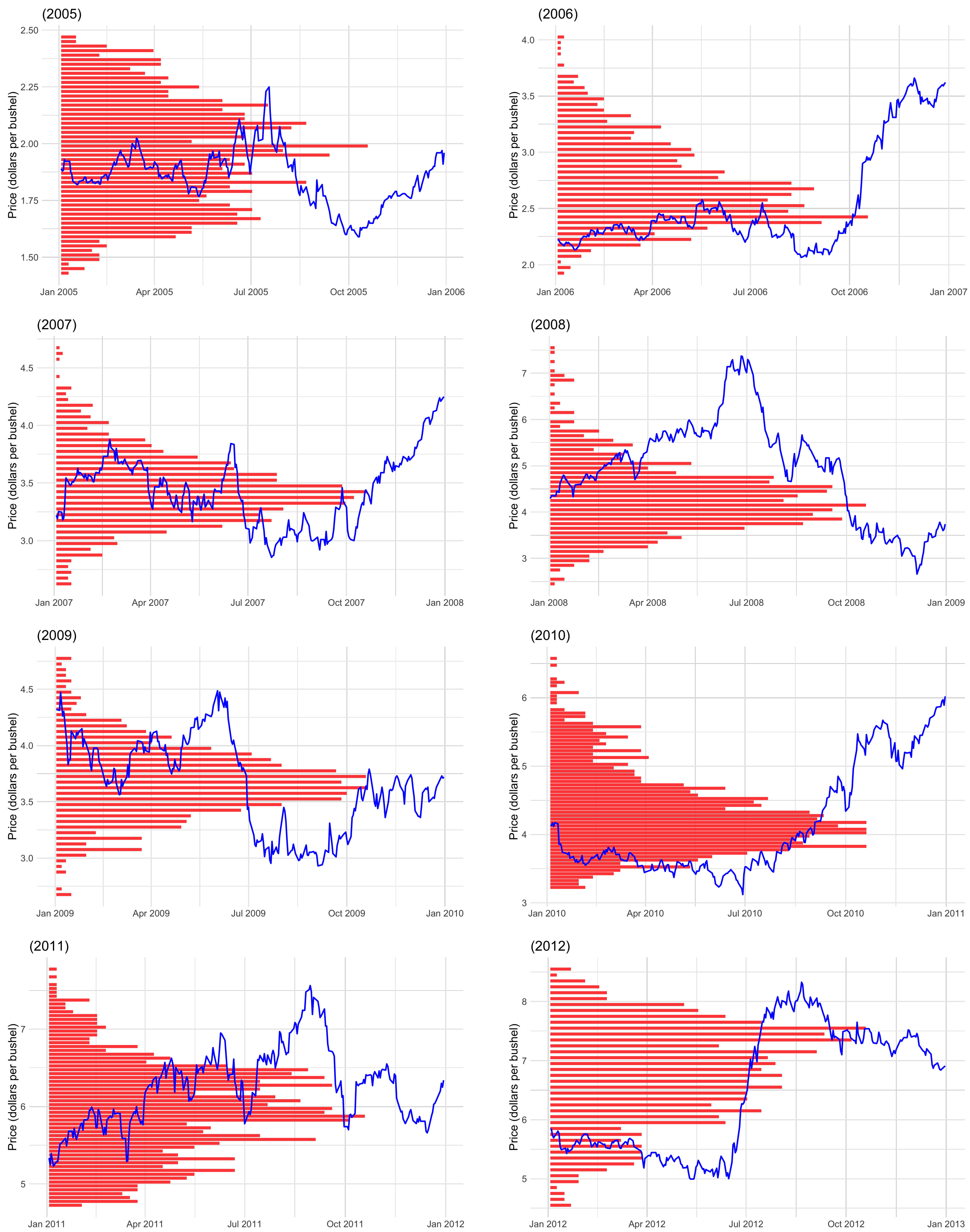
(b) Price received by farms in period 2

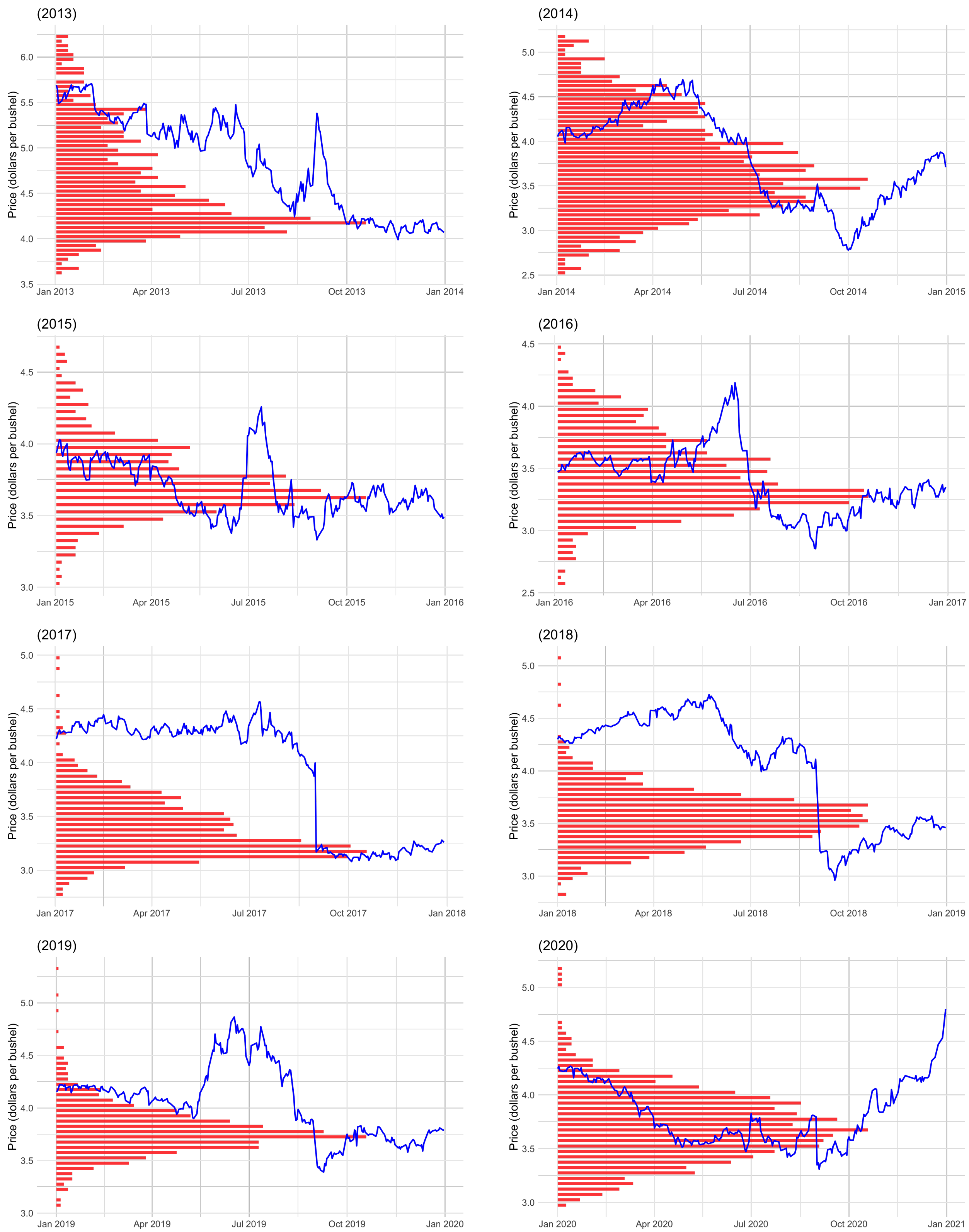
Figure 2 represents the variation in prices received by farmers for corn sold in two periods. The prices are shown as a difference from the state average reported by National Agricultural Statistics Service (NASS) to make it easy to compare variations in price received by farmers in different years. Though this figure does not depict the differences in prices between years, we can clearly see that in all the marketing environment, the range of price outcomes spans more than one dollars per bushel. The year-to-year variation largely comes from the differences in the market condition of each year, but variation within a year between farmers suggests that farmers do perform quite differently from each other even under same market conditions. These differences in price received largely affects the profitability of farmers and create differences when compared to their better performing counterparts. Thus, we aim to explore the reasons behind these variation 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. But we also need to consider the possibility of forward contracting by the farmers, which results in wider range of possible market prices for farmers. 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 August 31st plus the average basis prevailing at around end of September in Illinois (i might update this using location specific basis); to mimic the possible forward contracting prices available for the farmers from January 1st until August 31st and from September 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 3: Market Prices and Farmers' Realized Price Distribution by Year




(2013)
Price (dollars per bushel)
Jan 2013
Apr 2013
Jul 2013
Oct 2013
Jan 2014
(2014)
Price (dollars per bushel)
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
(2015)
Price (dollars per bushel)
Jan 2015
Apr 2015
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Price (dollars per bushel)
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Oct 2020
Jan 2021

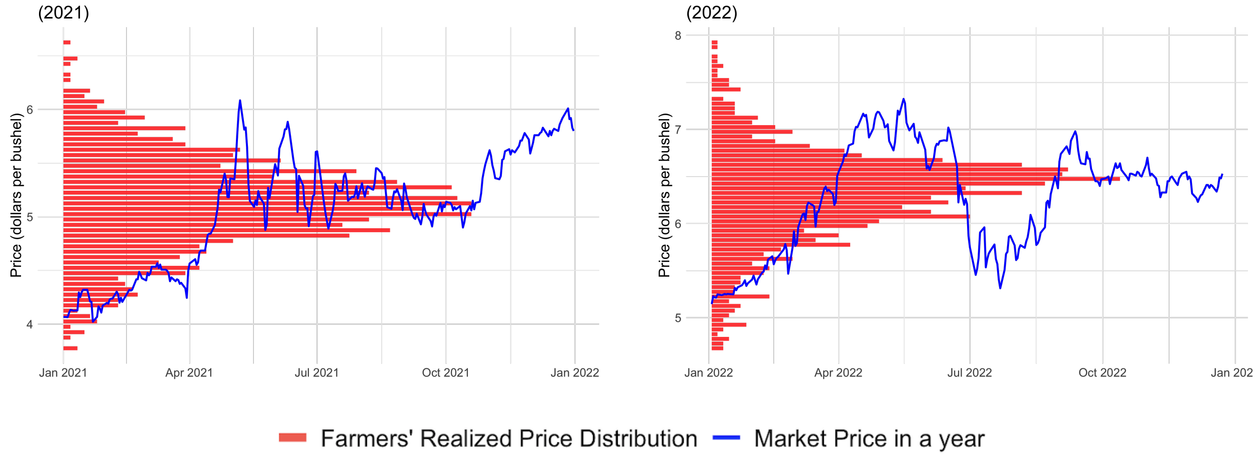

Figure 3 illustrates the available prices for farmers in each year, along with the distribution of prices realized by farmers each year from 2005 to 2022. The blue line represents the daily price in a given year that a farmer could potentially time their sales at, whereas red histogram shows the distribution of the prices realized by all farmers in that year. Realized prices showed are one price per farmer-year, so one should be cautious while interpreting the figure. These years represent different market scenarios. For example, in 2017, prices were consistently high at the beginning of the year, but dropped around September as shown by the blue line. Here, we see that very few farmers received higher prices prevalent at the beginning of the year, in contrast highest distribution of farmers are seen to receive relatively lower prices prevailing after September. This tells us two things, one, the use of forward contracting was very scarce in 2017 meaning most farmers prefer cash sales after the production risk is resolved, other, expectation of the prices might not be the only thing driving sales decision.

Across all years, a consistent pattern emerges: the highest concentration of realized prices tends to coincide with market prices prevailing around harvest time, particularly mid-October. The red histograms peak during this period, aligning closely with the blue line. This pattern holds across varying market environments, reinforcing the idea that most farmers engage in 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.

In estimating the reference price based on cost of production, we should first have per bushel cost of production of both corn and soybeans, since these are the main crops under study and most of the farmers plant some portion of both crops in their farm. 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 for different regions of the state to guide cost allocation. These budgets include per acre cost of each category of inputs going into both corn and soybean production. This includes costs related to direct costs including fertilizers, pesticides, seed, 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 dollars per acre for corn and 65 dollars per acre for soybeans. Using this information, we distribute the total costs for fertilizers made by the farm for both corn and soybean production into the individual enterprise using following equation:

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

Where TC is total costs required for both corn and soybean, a_c and a_s are the acres of corn and soybean grown by the farm respectively, and C_c and C_s are the ideal cost per acre allocation for that given region obtained from crop budgets. From this, we can get per bushel for 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 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 enterprise allows us to formulate models for reference pricing of each crop as well as interaction between the two crops. Using the categories of costs in crop budgets as well as FBFM dataset, we further calculate different types of costs incurred in the production, such as, variable costs, total costs, and direct costs.

Figure 4: Per Bushel Total Economic Cost of Corn Production and Harvest Time Price (2004-2023)

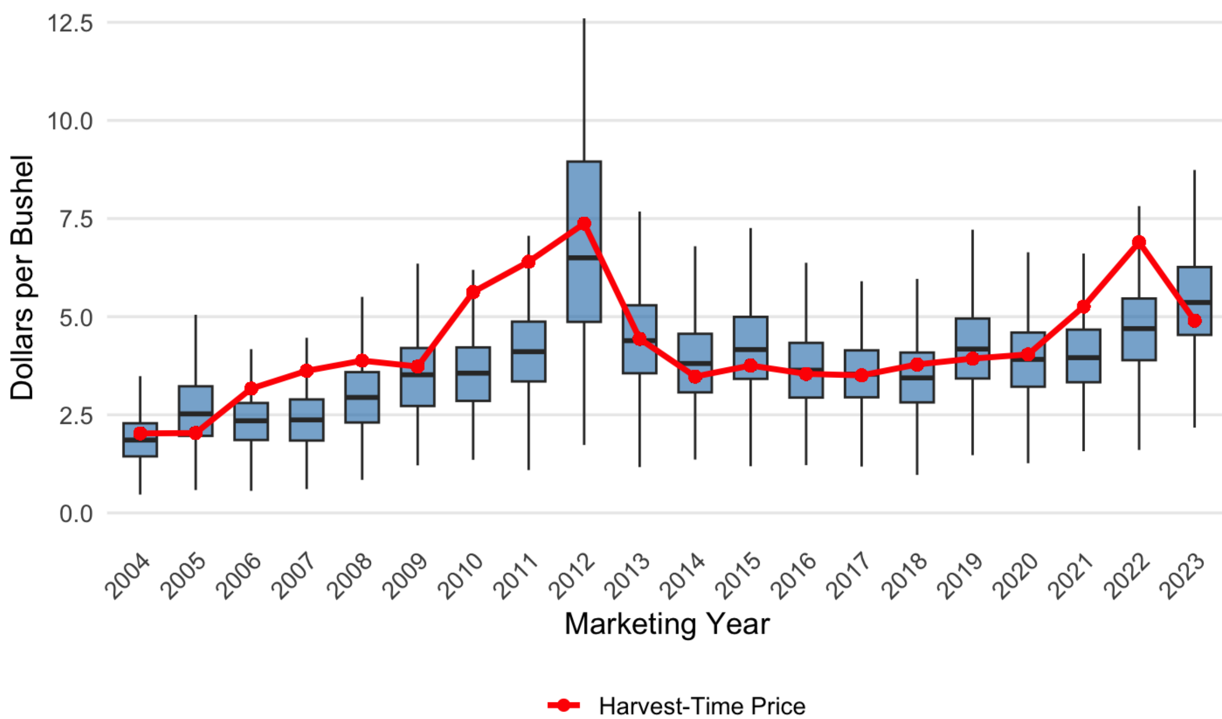

Figure 4 illustrates the variation in per-bushel production costs for corn, as shown by the box plots, alongside the mid-October futures price, indicated by the red line. We see there is substantial variation both between farmers and between years. Year to year variation is primarily driven by the market conditions, but the variation between the farmers most likely depends on the production decisions of the individual farmer. Notably, the mid-October futures price does not consistently lie above or below the cost of production; rather, it fluctuates around it.

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 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.

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:

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

This expression nests a standard expected utility model as a special case when $R = 0$, meaning there is no reference dependence. The structure captures how hedging decisions vary with beliefs and the perceived gain or loss relative to R.

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., $\pi = 0.5$). As the belief becomes more strongly biased the responsiveness to expected price changes diminishes, and thus the optimal hedge ratio also decreases.

Conversely, when the futures price is below the reference price, farmers are generally less inclined to hedge. In such cases, they may choose not to hedge at all unless they hold a strong belief that prices will rise. The decision to hedge thus depends on the perceived likelihood of favorable price movements overcoming the psychological loss associated with selling below the reference price.

However, the JLH model assumes a uniform reference price across all farmers—a simplification that may not accurately reflect real-world decision-making. If this assumption held, farmers operating under identical market conditions would make similar marketing decisions and consequently realize similar prices. Yet, as illustrated in Figure 3, there is considerable variation in the prices received by farmers within the same marketing environment. This suggests underlying heterogeneity in either reference prices or expectations—or both. Moreover, the empirical implementation of the JLH framework relies on a time-series approach that assumes a common reference price and homogeneous beliefs about future price movements, thereby overlooking important cross-sectional differences in farmer behavior.

In this study, we extend the application of reference-dependent hedging behavior to a cross-sectional context, relaxing the assumptions of uniformity in both reference prices and beliefs. This approach enables us to explore how heterogeneity in farmers' characteristics—such as cost structures, financial constraints, or market expectations—shapes their hedging decisions. By allowing for individual-specific reference prices and beliefs, we better capture the diverse motivations and behavioral responses that influence marketing behavior under uncertainty.

4 Empirical Method

Estimating reference-dependent behavior alongside heterogeneous beliefs about futures price movements presents a key empirical challenge: neither the reference price nor individual belief structures are directly observed. The reference price is an internal, psychological benchmark shaped by each farmer's experiences and expectations, and beliefs about future price movements 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—leading to variation in marketing outcomes and, ultimately, differences in profitability.

Similar to the proportion hedged used by Jacobs, Li, and Hayes (2018) as an outcome variable, we use the proportion of grain sold in period 1 (near harvest) as a dependent variable. However, to capture effect of beliefs of farmers on the proportion sold, we use the reaction of the farmer to the last year's price change as a proxy for the measurement of beliefs. This variable would efficiently capture how a farmer would have normally reacted in such a price change scenario. We propose the following estimation equation:

$$\phi_{it} = \alpha + \beta_1 \Delta f_t + \beta_2 \left[\Delta f_t \cdot (\Delta f_{t-1} \times \phi_{it-1})\right] + \epsilon_t \tag{4}$$

In this specification, ϕ_t represents the proportion of production sold in near harvest period in year t. The term $(\Delta f_{t-1} \times \phi_{t-1})$ is a measure of responsiveness based on the past behavior of the farmer and the Δf_t is the current price change signal. This price change signal is 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 framework allows us to isolate the influence of farmers' beliefs on marketing decisions made during the harvest window.

While this formulation allows us to include a proxy for beliefs, the standard model estimates a single set of coefficients for all farmers. However, our central hypothesis is that farmers differ in their beliefs about price changes. Moreover, the model may suffer from endogeneity due to unobserved variables correlated with both marketing behavior and belief formation.

To address these concerns, we adopt a finite mixture model with fixed effects, as proposed by Deb and Trivedi (2013). This approach enables us to capture latent heterogeneity across farmers in their response behavior, while also controlling for unobserved time-invariant individual characteristics. It allows us to estimate distinct behavioral types within the panel and better identify how belief heterogeneity influences marketing decisions.

In the mixture model, we assume that farmers' observations are drawn from different underlying distributions that reflect heterogeneous belief structures. Importantly, the model assumes that latent class membership is fixed over time—i.e., a farmer does not switch between classes during the observed time frame. However, we do not observe the class membership of any specific farmer or observation. The strength of the mixture model lies in its ability to probabilistically assign observations to latent classes and estimate class-specific parameters. Accordingly, we estimate the following equation:

$$\phi_{it,w} = \alpha_k + \beta_{1k}\Delta f_t + \ \beta_{2k}\left[\Delta f_t \cdot (\Delta f_{t-1} \times \phi_{it-1,w})\right] + \epsilon_t \tag{5}$$

Here, k represents the categorical groups that the observations could belong. β_1 captures the effect of change in price in the current period, and β_2 captures the interactions with the farmers' belief proxies. Further, to take into account the individual fixed effects, controlling for unobserved individual characteristics that do not change over time, we apply within transformation to the dependent variable such that:

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

This transformation effectively incorporates the individual fixed effects into the model, removing the concerns of endogeneity. Moreover, since Δf_t is constant across farmers within a given year (as it is derived from observed futures prices), it also captures time fixed effects, accounting for year-specific shocks or macro conditions affecting all farmers equally.

From this first step of our analysis, we assess the presence of heterogeneity in farmers' beliefs about futures price changes by estimating class-specific responses. This allows us to identify distinct belief structures across groups of 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 cost of production (CoP) serves as an important benchmark for farmers to follow as a reference point. While CoP is a sunk cost at the time of marketing decisions, it may still influence behavior due to associated financial obligations such as debt, liquidity constraints, and storage costs.

Unlike past literatures, who assume a uniform reference price, our dataset includes detailed cost structure information that varies across farmers. This variation allows us to empirically test whether differences in CoP contribute to variation in marketing behavior. If CoP indeed functions as a reference point, we should observe distinct behavioral responses among farmers with different cost profiles. Accordingly, we estimate the following equation:

$$\phi_{it,w} = \alpha + \beta_1 I_{F_t<R_{it}} + \beta_2 \Delta f_t \ + \ \beta_3 \Delta f_t \cdot I_{F_t<R_{it}} + \epsilon_{it} \tag{6}$$

In this specification, ϕ_{it_w} denotes the within-transformed dependent variable, representing the proportion of production sold during the near-harvest period (period 1), adjusted for farm-level fixed effects. 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. Finally, Δf_t represents the annual price change signal, reflecting the directional movement in futures prices for that marketing year.

In addition to using CoP as the reference price, we also explore an alternative reference based on the previous year's price received, which is both behaviorally plausible and heterogeneous across farmers.

5 Preliminary Results

5.1 Corn

Preliminary results for regression equations 4 and 5 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.

Table 1: Estimation Results: OLS vs Mixture Model Components

Equation 5: $\phi_{it,w} = \alpha_k + \beta_{1k}\Delta f_t + \beta_{2k}\left[\Delta f_t \cdot (\Delta f_{t-1} \times \phi_{it-1,w})\right] + \epsilon_t, \quad k = 1, 2$

	Dependent variable:			
	ϕ_t	$\phi_{t,w}$		
Variable	**OLS**	**OLS**	**Component 1**	**Component 2**
	(1)	(2)	(3)	(4)
Intercept (α)	0.048***	0.0067***	0.0028***	0.0085***
	(0.003)	(0.001)	(0.0009)	(0.0016)
Change in Price (Δf_t)	0.106***	0.0974 ***	0.0423***	0.1231***
	(0.006)	(0.004)	(0.0048)	(0.0067)
Interaction between current price signal and past responsiveness	-0.675***	0.5089**	-0.0224	0.5341**
	(0.108)	(0.239)	(0.3679)	(0.2266)
Farm FE	Yes	No	No	
Observations	17131	17131	17131	
Log-Likelihood	9043.06	8978.41	10098.95	
Note:			*p<0.1; **p<0.05; ***p<0.01	

Since the dependent variable in model 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 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-unit increase in the log price change leads to a 12.3 percentage point increase in crop sales (relative to own average) for the more responsive group, compared to only a 4.2 percentage point increase for the less responsive group. This suggests that farmers interpret and act upon the same market signal very differently.

Moreover, the divergence between groups is not limited to price responsiveness alone. There are also differences in how beliefs influence behavior, as captured by the interaction term involving past price changes and prior marketing actions. The significant variation in the β_2 coefficients across the two classes indicates that the belief structures underlying farmers' decisions are also heterogeneous. These findings support the notion that marketing behavior is shaped not only by observed market conditions but also by unobserved differences in beliefs or expectations made by farmers.

In the second stage 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 explore how the proportion of crops sold in the near-harvest period varies depending on whether the current futures price lies above or below a farmer-specific reference price. The estimation results for this analysis, corresponding to equation 6, are presented in Table 2.

Model 1 presents the results using the proportion sold in period 1 as the dependent variable, including farm fixed effects. Model 2 uses the within-transformed proportion sold, thereby accounting for fixed effects directly through demeaning. As such, the coefficients in Model 2 should be interpreted as deviations from each farmer's own average behavior over

Table 2: OLS estimates exploring asymmetric response around reference point

Equation 6: $\phi_{it,w} = \alpha + \beta_1 I_{F_t<R_{it}} + \beta_2 \Delta f_t \ + \ \beta_3 \Delta f_t \cdot I_{F_t<R_{it}} + \epsilon_{it}$		
	Dependent variable:	
	ϕ_t	$\phi_{t,w}$
	(1)	(2)
Indicator	-0.014^{***}	-0.007^{**}
(Futures price < Reference Point)	(0.004)	(0.003)
Change in price (Δf_t)	0.095^{***}	0.087^{***}
	(0.006)	(0.005)
Interaction between indicator	0.052^{***}	0.035^{***}
and price change ($\Delta f_t \cdot I_{F_t<R_{it}}$)	(0.015)	(0.012)
Constant	0.064^{***}	0.010^{***}
	(0.004)	(0.001)
Farm FE	Yes	No
Observations	17,131	17,131
Note:		*p<0.1; **p<0.05; ***p<0.01

time. We use the mid-October futures price of the December contract as the harvest-time price for corn (F_t), against which the reference price is compared. 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. Heteroskedasticity-robust standard errors are reported in parentheses.

The estimates reveal clear evidence of asymmetric responses around the reference price across both specifications. In Model 1, when the futures price is above the reference price, farmers sell, on average, 6.4% of their total 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 signal.

Model 2, which uses within-transformed variables, yields qualitatively similar results. When futures prices are above the reference price, farmers sell 1 percentage point more than their individual average; when prices fall below, they sell 0.7 percentage points less. Price change signals also elicit asymmetric responses: a one-unit increase in price change leads to an 8.7 percentage point increase in sales when the price is above the reference, and an even stronger response when prices are below the reference point.

Together, these findings emphasize the necessity of accounting for heterogeneity among farmers when it comes to how they form reference points and respond to market signals. By including farm-specific cost structures and allowing for latent behavioral classes, we identify systematic differences that would otherwise be concealed in pooled analysis. This evidence points to the complexity behind marketing decisions and reinforces the idea that farmers rely not just on market conditions, but also on internal benchmarks shaped by both economic realities and psychological factors.

6 Conclusion

This study highlights the critical role of farmer heterogeneity in shaping marketing decisions, which in turn leads to variation in prices received and ultimately farm profitability. Using rich panel data from the Illinois Farm Business Farm Management (FBFM) program, we extend the literature on reference dependence by introducing a cross-sectional perspective that emphasizes differences in beliefs and reference point formation across individual farmers.

Building on the theoretical framework proposed by Jacobs, Li, and Hayes (2018), we find substantial heterogeneity in farmers' beliefs, resulting in differential responses to the same market environment. Specifically, we identify two major groups of farmers—one that is highly responsive to price changes, and another that is more passive in its marketing behavior.

Further, we examine how farmers respond to price signals relative to their internal reference points. We use the cost of production as a natural and individualized benchmark—a concept long discussed in the literature but not empirically tested. 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, we relax the common assumption of a uniform reference price across producers and instead highlight the heterogeneity in cost structures as a driver of behavioral variation. Our findings suggest that profitability is not simply a function of external market conditions, but also of internal benchmarks that differ across farms. This has important implications for agricultural policy and marketing advisory services, emphasizing the need to account for farm-specific financial contexts when guiding marketing decisions.

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