Production Costs, Price Expectations and Reference Dependence in Commodity Marketing

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Abstract

This study examines how heterogeneity in cost structures and belief formation shapes reference-dependent grain marketing under price risk. 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 common price risk management advice from commodity marketing advisors to farmers (Parcell and Franken, 2011). For a farmer choosing whether to sell now or wait for higher prices later, it implies the current market price should be evaluated relative to the farm's per-unit production cost. To achieve profitability, the farmer must have 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'. The cost of production serves as a hard profitability floor for farmers and provides an individual-specific reference point that may lead to different marketing strategies among farmers who face the same price conditions. When prices fall below this cost-based reference point, farmers may be reticent to sell which would reduce downside price risk.

While 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. Marketing decisions are fundamentally intertemporal risk management choices. Even after production risk is resolved, farmers are exposed to continued price risk in an ever-changing marketing environment. These decisions are therefore critical for managing exposure to price fluctuations. However, farmers are far from homogeneous in their marketing behavior or cost structures; realized prices and profits differ even though all farmers face similar market conditions.

To understand differences in marketing outcomes across farms, we examine how production costs influence the marketing decisions of grain producers. Specifically, we investigate whether there is evidence of reference-dependent marketing behavior among farmers, and whether farmers' reference points are anchored to their farm-specific cost of production. To answer these questions, we extend the analysis of Jacobs, Li, and Hayes (2018), who develop a reference-dependent hedging model and provide empirical evidence from a time

series of farmer marketing activity. We apply a similar framework to a panel of individual farm-level data to consider whether reference dependence explains the diversity of marketing and risk management decisions in the cross-section. Additionally, we examine how heterogeneity in beliefs, risk preferences, and cost structures contributes to variation in marketing outcomes.

Standard theory models the sell-now-versus-later decision as an expected utility maximization problem (Lapan and Moschini, 1994), but empirical support for such models is largely inconsistent (Barberis and Thaler, 2003; Just and Peterson, 2010; Bocquého, Jacquet, and Reynaud, 2014). Instead, many studies show that farmers are differentially sensitive to profits and losses, which is better explained by prospect theory, which posits greater aversion to losses than appreciation for equivalent gains. 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).

Drawing on the idea of loss aversion around a reference point, Jacobs, Li, and Hayes (2018) study reference-dependent hedging as a key behavioral mechanism shaping farmers' marketing decisions under risk. Jacobs, Li, and Hayes (2018) introduced a theory of reference-dependent hedging activity where they embedded reference dependence into Expected Utility (EU) theory, along with the empirical evidence from corn farmers. The authors highlighted the existence of asymmetric marketing behavior among grain farmers depending on whether the current price is above or below their reference price. They also show that farmers are risk averse in gains and risk loving in losses - a behavioral pattern consistent with the disposition effect, where farmers hold onto grain when prices are low and sell more quickly when price starts to rise above their reference (Mattos and Fryza, 2014). Most importantly, Jacobs, Li, and Hayes (2018) argues that producers' marketing decisions are shaped both by their reference prices and by their beliefs about future price movements.

While some previous studies consider how farmers form reference points to guide

marketing decisions, the process by which reference points are formed is still unclear. Kim, Brorsen, and Anderson (2010) suggests that it may be optimal for farmers to form a target profit margin based on production costs 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. In an experimental study with grain producers, Mattos and Zinn (2016) find that reference prices are shaped by current market prices, future price expectations, and the highest price to date—highlighting that marketing decisions depend on the spread between current prices and these reference points.

Although existing work provides a theoretical framework and some empirical evidence for reference-dependent commodity marketing, it assumes homogeneous expectations and common reference prices tied to market conditions, which limits its ability to explain the significant heterogeneity in market outcomes and price risk management strategies among farmers. Evidence suggests that both marketing strategies and realized prices vary widely. Even farmers who appear similar on observable characteristics like size and operator age may differ in unobservable traits—such as risk attitude and perceived risk exposure—which contribute to heterogeneous marketing behaviors and preferences for risk management tools like futures and options (Pennings and Leuthold, 2000). Further, Janzen (2024) finds that over 40% of Illinois corn and soybean farmers report no sales near harvest, highlighting differences in market timing and exposure to price risk. Similarly, variation in input use and yields leads to substantial cost differences across farms (Foreman, 2014), allowing some to sell profitably even at low prices, while others must wait to break even. Those with higher costs often face financial constraints, limiting their ability to bear prolonged price risk and creating a tension between risk preferences and financial capacity.

In this study, we leverage observed differences in farmer behavior and characteristics to better understand marketing decisions under risk. We extend the reference-dependent hedging analysis of Jacobs, Li, and Hayes (2018) to a panel setting, allowing us to infer the

existence of reference point formation in cross-section. This approach contributes to a deeper understanding of farmer decision-making—an area of critical importance to grain marketers, agricultural economists, and farmers themselves.

We draw on detailed farm-level data from grain farms in Illinois. The dataset provides rich information on production costs, crop sales, and prices received. To identify the heterogeneity in the sample of farmers, 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. These belief differences may also reflect underlying differences in risk attitudes—farmers in the more responsive group may be more risk-averse and thus quicker to lock in favorable prices, while those in the less responsive group may be more risk-tolerant or speculative, choosing to delay action in anticipation of better market conditions.

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.

Results suggest that farmers exhibit asymmetric responses to market prices relative to their reference prices. Specifically, farmers tend to sell more than their average proportion when the market price exceeds the reference price. Conversely, farmers reduce their sales activity when the market price falls below the reference point. 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 to two strands of the literature on the economics of commodity market risk management. First, we contribute to the literature on decision-making under risk by extending the reference dependence framework to allow for heterogeneous, farm-specific features driving individualized reference points and thus marketing decisions. This use of individualized reference points departs from the conventional assumption of a uniform reference price and provides new insight into how perceived gains and losses shape marketing behavior under risk. Second, we contribute to the behavioral economics literature by providing further evidence of a 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 paper is organized as follows. Section 2 describes the farm-level data on realized price and cost of production, highlighting the substantial variation in these variables among farmers. Section 3 updates the theoretical framework from Jacobs, Li, and Hayes (2018) to allow for heterogeneity among farms. 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 refer-

ences. Finally, Section 6 concludes, discussing the implications of our results for farm price risk management.

2 Data

We study detailed farm financial records from the Illinois Farm Business Farm Management (FBFM) association. FBFM collects detailed farm-level information from over 5,000 farmers across Illinois annually. Our data cover the period 2003 to 2023. This dataset represents approximately 25% of Illinois farmland acreage and is widely considered representative of commercial grain farms in the state. We consider only 'certified usable' observations, that is, those data verified as accurate and usable for research purposes by Illinois FBFM field staff.

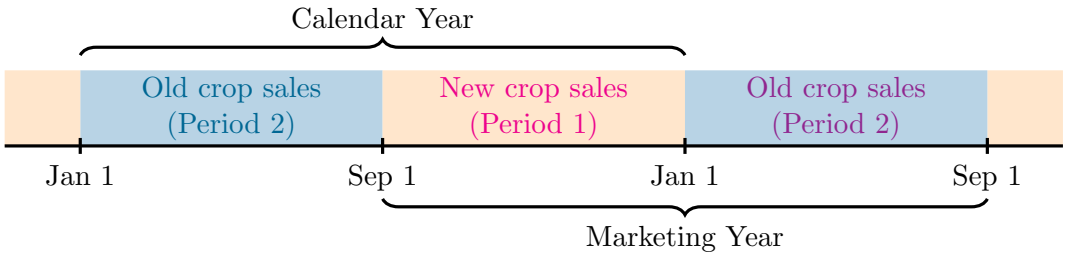
The FBFM data, prepared annually for tax filing, financial statement preparation, and benchmarking purposes, offer a snapshot of farm activities as of December 31 each year. We observe farm revenues and costs incurred in the production process, including variable costs like fertilizer, seed, and fuel and fixed costs related to land and machinery.

2.1 Farm-level commodity marketing and price

Most critical to our study, we observe some detail 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 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

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

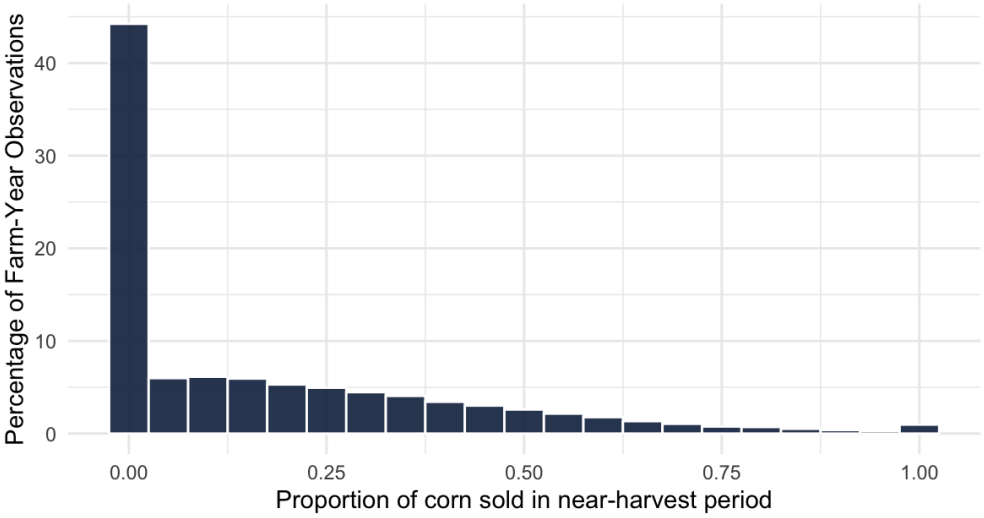


to August 31st of the following calendar year. Sales recorded as new crop must be realized between September 1 and December 31, since the grain must be physically delivered for a sale to be realized. These new crop sales can also be referred to as the "near-harvest" sales, because the sales are realized 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.

FBFM crop sales data are an incomplete picture of farmer marketing; they are not

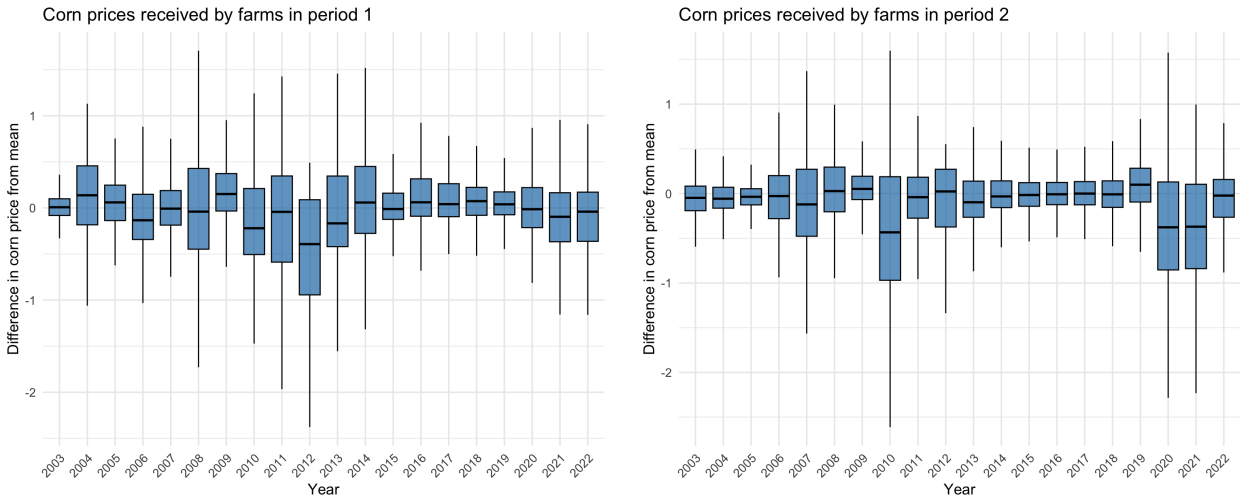
Figure 2: Proportion of corn sold in near harvest period



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)



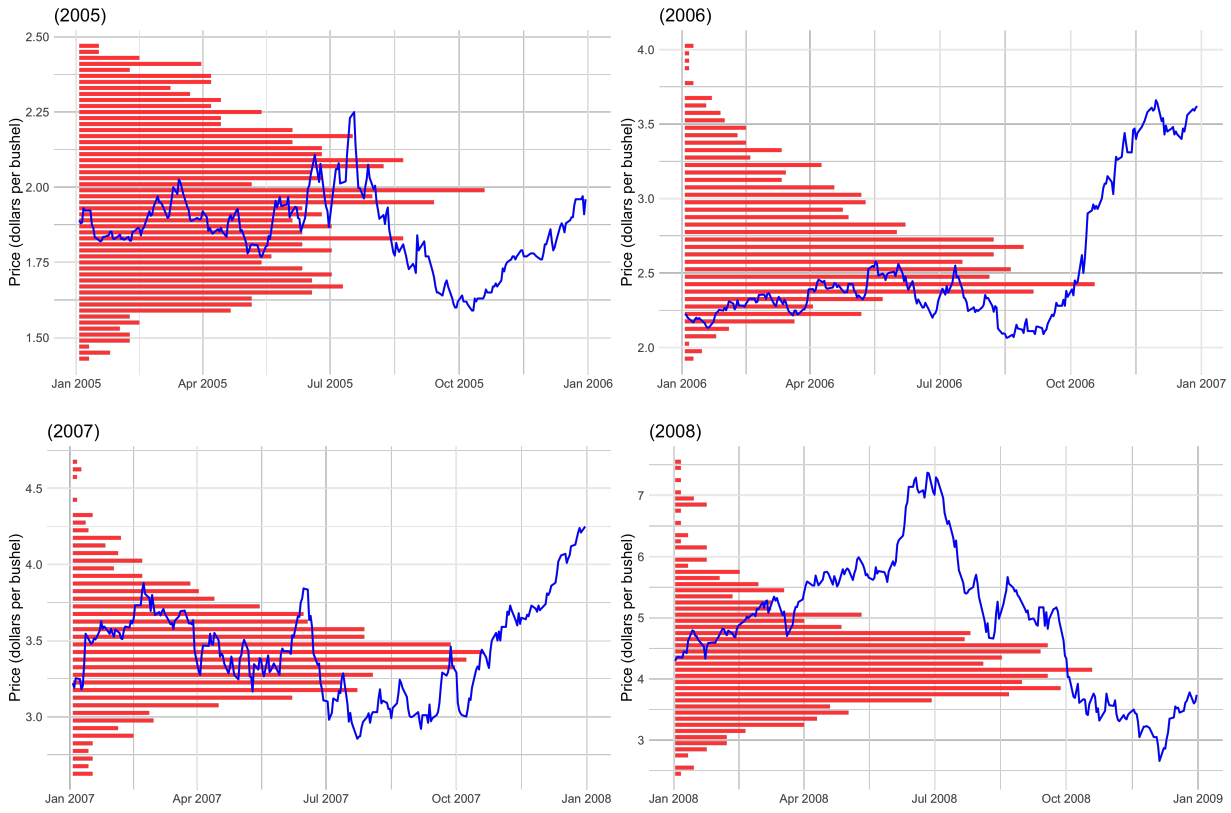
(a) Price received by farms in period 1

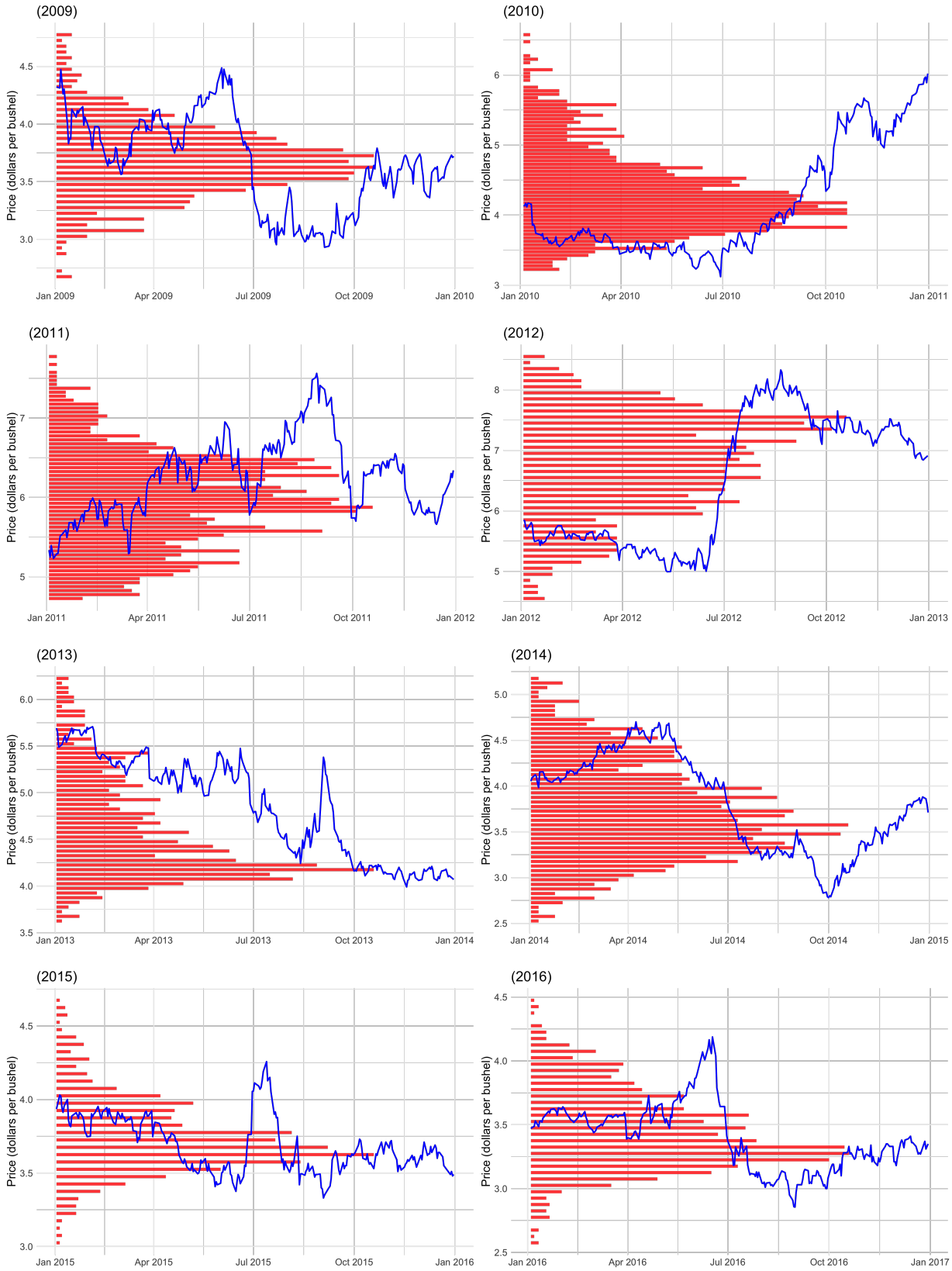
(b) Price received by farms in period 2

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 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 comes from the differences in the market conditions of each year, but variation within a year between farmers suggests that farmers do perform quite differently from each other even under the same market conditions. These differences in price received largely affect the profitability of farmers and create differences when compared to their better-performing 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. But we also need to consider the possibility of forward contracting by the farmers, which results in a 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; 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 4: Corn Market Prices and Farmers' Realized Price Distribution by Year




(2009)
Price (dollars per bushel)
4.5
4.0
3.5
3.0
Jan 2009
Apr 2009
Jul 2009
Oct 2009
Jan 2010
(2010)
Price (dollars per bushel)
6
5
4
3
Jan 2010
Apr 2010
Jul 2010
Oct 2010
Jan 2011
(2011)
Price (dollars per bushel)
7
6
5
Jan 2011
Apr 2011
Jul 2011
Oct 2011
Jan 2012
(2012)
Price (dollars per bushel)
8
7
6
5
Jan 2012
Apr 2012
Jul 2012
Oct 2012
Jan 2013
(2013)
Price (dollars per bushel)
6.0
5.5
5.0
4.5
4.0
3.5
Jan 2013
Apr 2013
Jul 2013
Oct 2013
Jan 2014
(2014)
Price (dollars per bushel)
5.0
4.5
4.0
3.5
3.0
2.5
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
(2015)
Price (dollars per bushel)
4.5
4.0
3.5
3.0
Jan 2015
Apr 2015
Jul 2015
Oct 2015
Jan 2016
(2016)
Price (dollars per bushel)
4.5
4.0
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3.0
2.5
Jan 2016
Apr 2016
Jul 2016
Oct 2016
Jan 2017

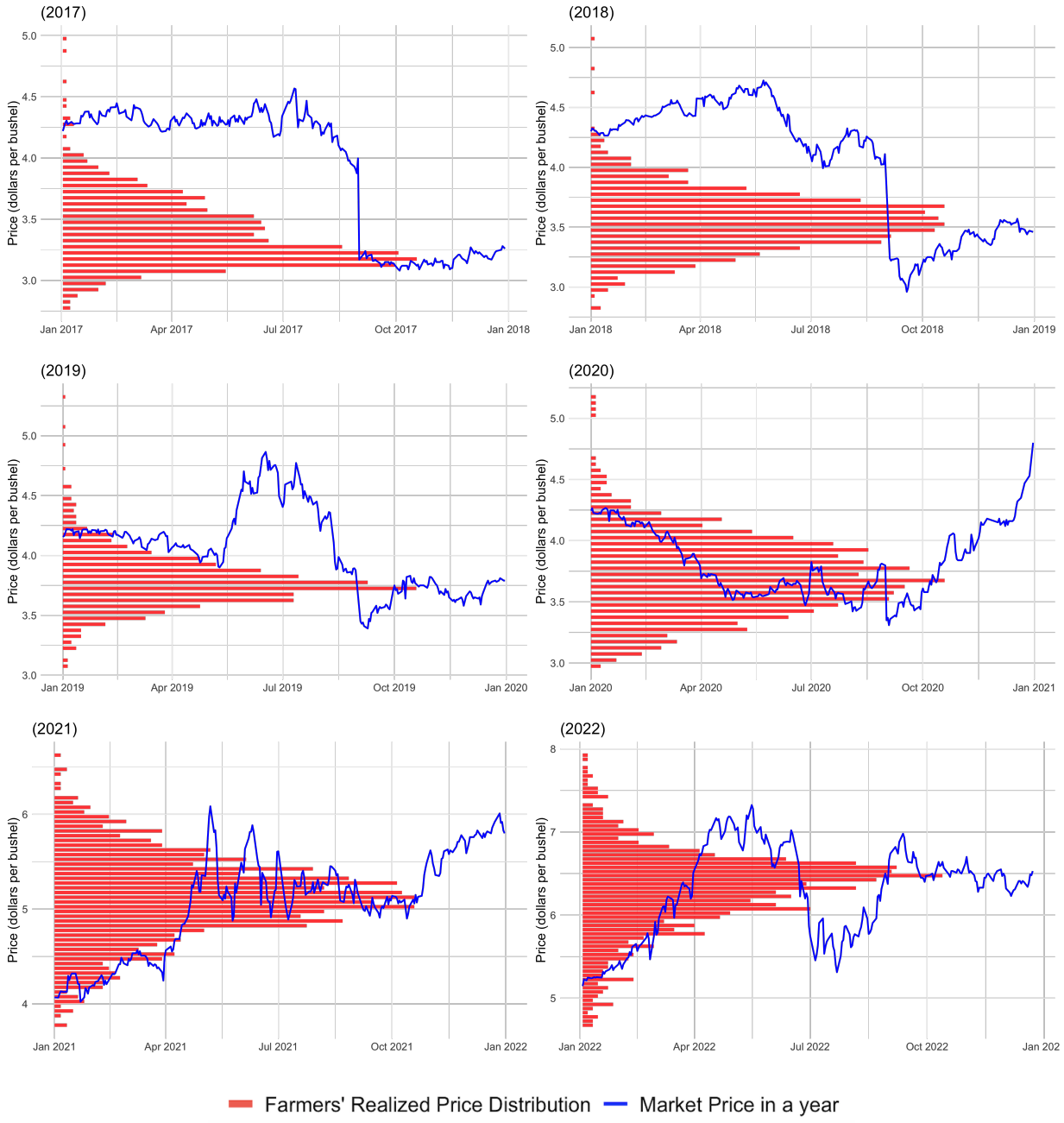


Figure 4 illustrates the available prices for farmers in each year, along with the distribution of prices realized by farmers each year from 2005 to 2022. The blue line represents the daily price in a given year that a farmer could potentially time their sales at, whereas the red histogram shows the distribution of the prices realized by all farmers in that year. Realized

prices shown 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, the highest distribution of farmers is 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, and two, the expectation of the prices might not be the only thing driving sales decisions.

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.

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

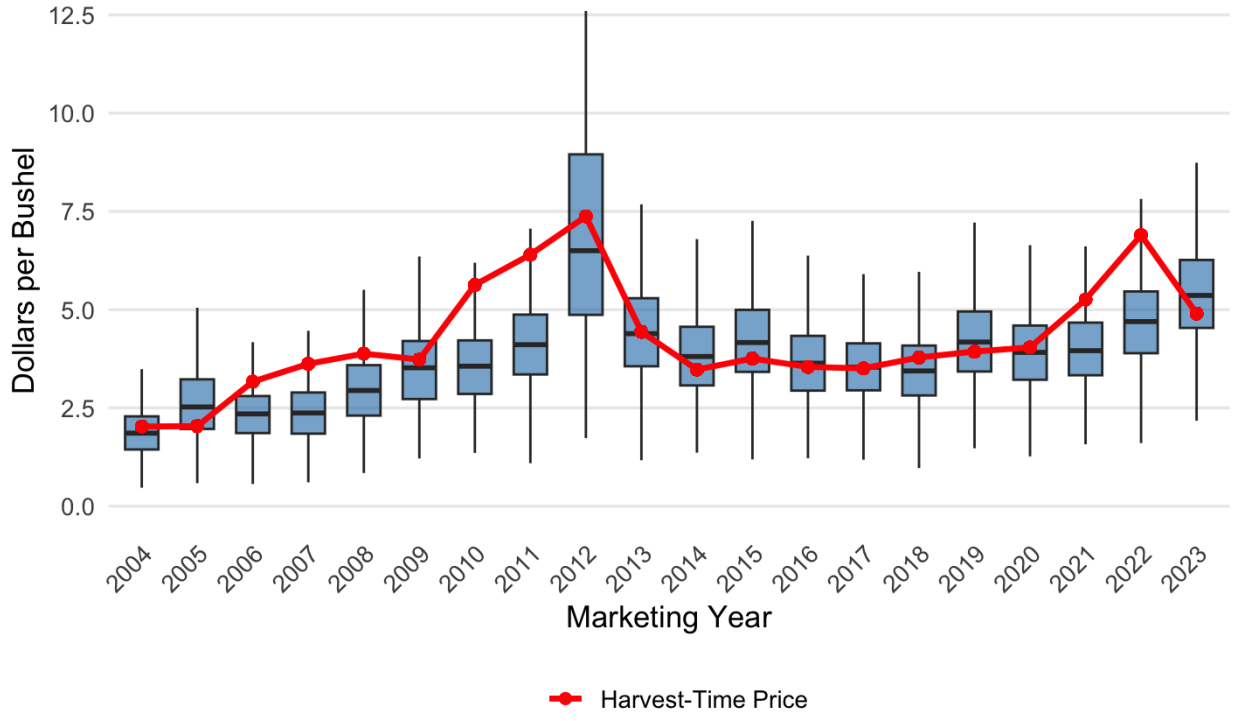


Figure 5 illustrates the variation in per-bushel production costs for corn, as shown by the box plots, alongside the mid-October futures price, indicated by the red line. We see there is substantial variation both between farmers and between years. Market conditions primarily drive year-to-year variation, 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.

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:

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

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.

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, farmers are generally less inclined to hedge when the futures price is below the reference price. In such cases, they may choose not to hedge at all unless they firmly believe that prices will fall even more. 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 4, 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 literature, 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, $\phi_{it,w}$ 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 Results

First, we present the results for corn marketing, followed by soybeans marketing. We then examine whether farmers substitute between corn and soybeans as a marketing strategy, offsetting losses in one crop with increased sales of the other.

5.1 Corn

Preliminary results for regression equations 4 and 5 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 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

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**	**Class 1**	**Class 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

(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, proxied by their per bushel cost of production. The estimation results for this analysis, corresponding to equation 6, 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), 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. Model 3 and 4 further add interaction terms to better understand the heterogeneity and differences in marketing strategies in different price environment. 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 signal. Model using within-transformed variables also yields qualitatively similar results.

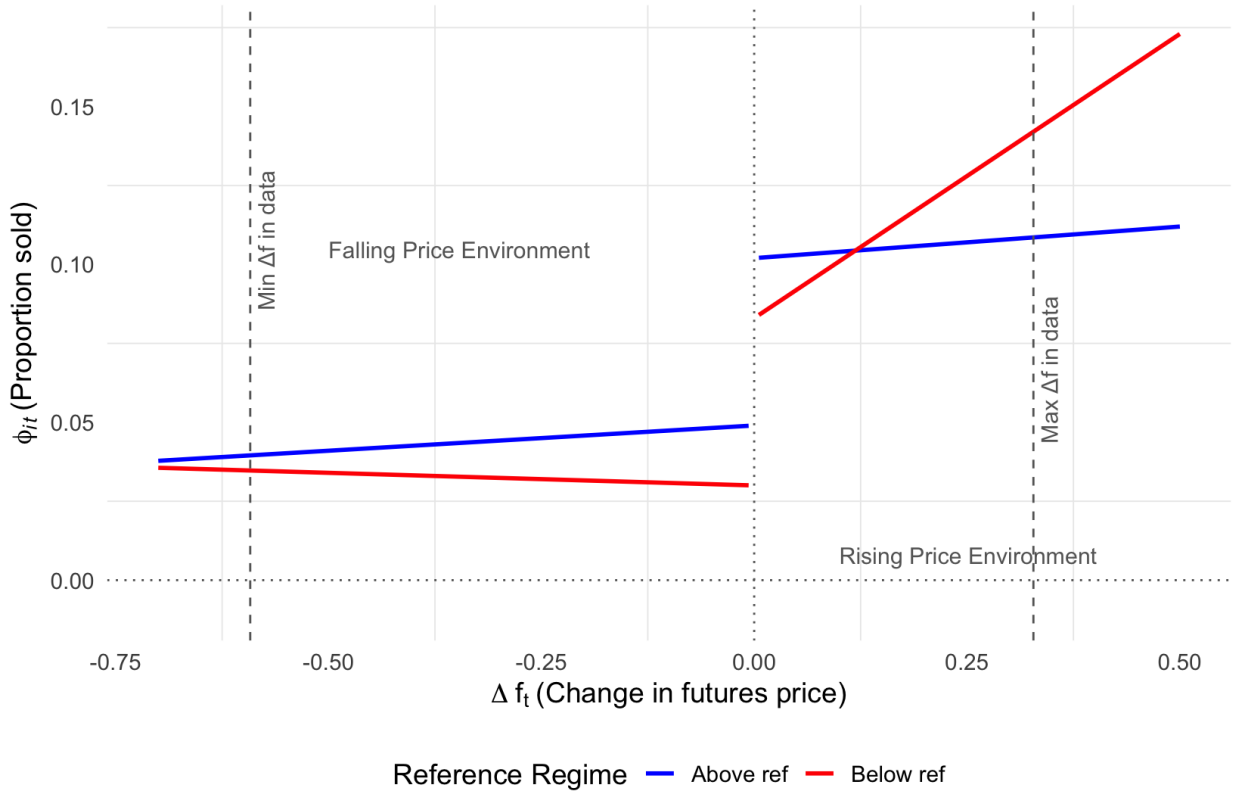
To understand whether farmers in different behavioral classes respond differently in the same market conditions, we include the class assignments predicted by the finite mixture model in model 3. We see that the less responsive group sells, on average, 18.2 percentage

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 (Futures price < Reference Point)	−0.007**	−0.014***	−0.019***	−0.019***
	(0.003)	(0.004)	(0.005)	(0.005)
Change in price (Δf_t)	0.087***	0.095***	0.095***	0.020
	(0.005)	(0.006)	(0.006)	(0.017)
Interaction between indicator and price change ($\Delta f_t \cdot I_{F_t<R_{it}}$)	0.035***	0.052***	0.052***	0.160***
	(0.012)	(0.015)	(0.015)	(0.034)
Indicator for Class 1 (Less responsive Group)			−0.182*	
			(0.097)	
Interaction between reference indicator and class 1 ($I_{F_t<R_{it}} \cdot I_{Class1}$)			0.018***	
			(0.006)	
Indicator for direction of price change ($I_{\Delta f_t<0}$)				−0.053***
				(0.005)
Interaction between price change and direction of change ($\Delta f_t \cdot I_{\Delta f_t<0}$)				−0.004
				(0.021)
Triple interaction: $\Delta f_t \cdot I_{F_t<R_{it}} \cdot I_{\Delta f_t<0}$				−0.184***
				(0.047)
Constant	0.010***	0.064***	0.234***	0.102***
	(0.001)	(0.004)	(0.097)	(0.011)
Farm FE	-	Yes	Yes	Yes
Observations	17,131	17,131	17,131	17,131
Note:				*p<0.1; **p<0.05; ***p<0.01

points less than the more responsive group, holding market conditions constant. Moreover, this group of farmer exhibits markedly weaker reference dependence. When the futures price falls below the reference point, they decrease their sales only by 0.1 percentage point, com-

Figure 6: Reference and Price Direction Effects on Outcome



pared to a 1.9 percentage point decline for more responsive group. This near-zero adjustment in marketing behavior reinforces the classification of these farmers as relatively less responsive to market signals and provides the evidence that reference dependence is not a uniform reaction among all farmers.

Further, Model 4 explores whether farmers' reaction to price change signals varies depending 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 strong positive price signal. The results provide evidence of further asymmetry in farmers behavior when the market price is below the reference price.

5.2 Soybeans

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 3 presents the results of equations 4 and 5 for soybeans.

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

Table 3: 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**	**Class 1**	**Class 2**
	(1)	(2)	(3)	(4)
Intercept (α)	0.471***	0.0019	0.0006	0.0024
	(0.001)	(0.0015)	(0.0012)	(0.0019)
Change in Price (Δf_t)	0.185***	0.1389 ***	0.0357***	0.17511***
	(0.013)	(0.0094)	(0.0091)	(0.0125)
Interaction between current price signal and past responsiveness	-0.732***	-1.349***	-0.4277	-1.5099***
	(0.152)	(0.2627)	(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

production as a proxy for the reference price, yields results broadly consistent with corn, though with some differences in magnitude (table 4). 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 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 price is above the reference price, represented by blue line, farmers increase soybeans

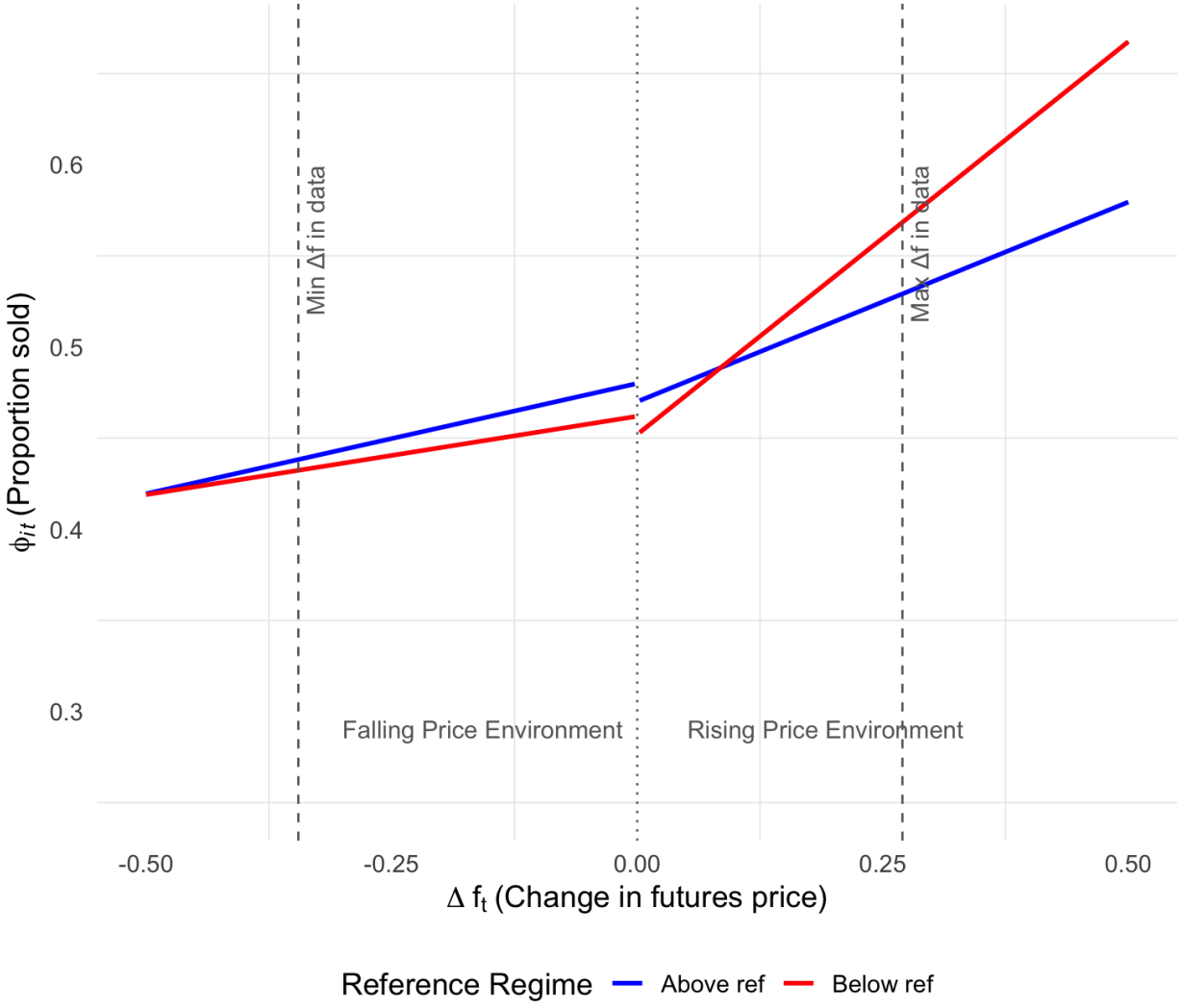
Table 4: OLS estimates exploring asymmetric response around reference point and behavioral heterogeneity across classes (Soybeans)

	Dependent variable: Proportion Sold			
	$\phi_{it,w}$	ϕ_{it}		
	(1)	(2)	(3)	(4)
Indicator (Futures price < Reference Point)	−0.005	−0.011**	−0.012*	−0.018**
	(0.003)	(0.005)	(0.007)	(0.007)
Change in price (Δf_t)	0.126***	0.143***	0.143***	0.219***
	(0.010)	(0.013)	(0.013)	(0.030)
Interaction between indicator and price change ($\Delta f_t \cdot I_{F_t<R_{it}}$)	0.016	0.030	0.030	0.212***
	(0.023)	(0.030)	(0.030)	(0.072)
Indicator for Class 1 (Less responsive Group)			0.106	
			(0.131)	
Interaction between reference indicator and class 1 ($I_{F_t<R_{it}} \cdot I_{Class1}$)			0.006	
			(0.008)	
Indicator for direction of price change ($I_{\Delta f_t<0}$)				0.010*
				(0.006)
Interaction between price change and direction of change ($\Delta f_t \cdot I_{\Delta f_t<0}$)				−0.098**
				(0.044)
Triple interaction: $\Delta f_t \cdot I_{F_t<R_{it}} \cdot I_{\Delta f_t<0}$				−0.247**
				(0.099)
Constant	0.004**	0.473***	0.366***	0.470***
	(0.002)	(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

sale steadily with more positive price signals, with only modest differences between rising and falling price environments. In contrast, when price is below the reference price, represented by red line, much sharper asymmetry in marketing is seen. Farmers are more reluctant to sell

in falling price environment, whereas in presence of upward trending price, farmers increase their sales sharply as seen in the case of corn. While qualitative results mirrors those found in corn marketing, soybean sales made when price is above reference price are higher on average and the slope is also steeper. This indicates that soybeans sales react more strongly to favorable price changes, adjusting sales more quickly than for corn when market signals improve.

Figure 7: Reference and Price Direction Effects on Outcome



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—but with notable differences in magnitude. 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 5: 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 $\times$ Loss domain	0.0333^{***}
	(0.00491)
Loss domain $\times$ 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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5 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 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. Further, marketing decisions of corn and soybeans are not disjoint since the same farmer is making simultaneous decisions for both crops.

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. The results hold for both corn and soybeans marketing strategies. However, we also find evidence of cross-crop substitution in grain marketing: when prices for one crop fall below the reference point, farmers tend to increase sales of the other crop, effectively using it to offset potential revenue losses. This behavior has important implications for price risk management, as it suggests that marketing decisions for multiple crops are often made jointly rather than independently.

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. Profitability, therefore, is not solely determined by external market conditions but also by farm-specific internal benchmarks. Our results show that effective price risk management must account for the fact that farmers respond differently to identical market signals. Moreover, portfolio-like substitution across crops—where sales of one crop are adjusted to offset potential losses in another—emerges as a complementary strategy for managing downside price risk. 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 under price risk.

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