Optimistic Price Expectations

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Abstract

Does optimism bias trigger unreasonable price predictions? Can decision noise be a mechanism manifesting optimistic price expectations? We conduct a laboratory-in-the-field experiment with producers to investigate the role of optimism bias in price expectations. We manipulate the ownership status by randomly assigning *seller* and *buyer* roles in different incentivized price prediction tasks. Exogenously varying the ownership status enables us to create a stake-based optimism bias and study its determinants and consequences. We find that price expectations significantly depend on the assigned roles. However, providing task-relevant information helps mitigate optimism bias suggesting uncertainty might be one of the primary sources for unrealistic high-price expectations. Finally, we show that the direction of expectation biases is sensitive to the decision context.

Keywords: Belief Distortions, Expectation, Optimism, Price, Risk.

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1 Introduction

Beliefs and expectations are at the core of economic activities. Goods are traded when buyers and sellers converge on a final transaction price, reconciling their pre-market expectations. A large gap between the price expectations of buyers and sellers can protract the bargaining process or even disrupt it leading to market inefficiencies.[1] Inter-disciplinary behavioral work, mostly by focusing on market transactions or trade situations, provides evidence that ownership status and endowment can create valuation differences between owners and non-owners.[2] Since market actions and the bargaining process are influenced by ex-ante price targets, investigating the determinants of pre-market expectations can improve our understanding of the sources of ownership-based valuation differences. Pre-market price expectations also influence important economic decisions, such as production volume or demand for risk-mitigating tools, and can potentially explain behavioral foundations of market dynamics.[3]

This article uses incentivized protocols to examine the causal relationship between ownership status and price expectations in a laboratory-in-the-field study with cattle producers. We find that ownership causally changes price expectations. Our findings indicate that producers exhibit *optimism bias* or stake-dependent expectations. Optimism bias is manifested in predicting higher future prices when an increase in prices positively affects prospective profits. Our results can be explained by *motivated reasoning* models predicting that decision-makers derive direct utility from their high-price expectations when those expectations are also associated with higher earnings (Kunda, 1990; Brunnermeier and Parker, 2005; Mayraz, 2011; Bracha and Brown, 2012; Bénabou and Tirole, 2016; Dillenberger et al., 2017).

We identify a crucial channel that triggers the optimism bias and leads to the price expectation

[1] Studies show that optimism and self-serving biases about one's future bargaining power can delay reaching a final agreement and completing market transactions (Babcock et al., 1995; Babcock and Loewenstein, 1997; Yildiz, 2011; Ortner, 2013).

[2] In their seminal work, Kahneman et al. (1991) link the gap between Willingness-to-pay (WTP) and Willingness-to-Accept (WTA) values to the ownership status. This endowment effect has been replicated in different decision domains (Plott and Zeiler, 2005; Marzilli Ericson and Fuster, 2014). Moreover, Fehr et al. (2015) show that the endowment effect is robust to procedural changes in experimental study protocols.

[3] Previous work showed that price expectations could affect production decisions and risk management practices. For instance, Deaton and Laroque (1996) demonstrate how price expectations can change market equilibrium dynamics through storage. Using data from cereal producers, Ricome and Reynaud (2022) found that price expectations are crucial in contract choices and risk management decisions.

gap between sellers and buyers. A higher uncertainty level due to the lack of product-specific objective quality measures manifests stake-dependent beliefs and widens the price expectation divide. We show that the provision of product-relevant objective information reduces the level of uncertainty and eliminates differences in price predictions of sellers and buyers.

Our results also show that one's confidence in price predictions has a moderate effect on the magnitude of stake-dependent expectations among producers. We also detect a positive correlation between high prediction confidence and higher risk tolerance.

We design price prediction scenarios to make experimental tasks more relevant to cattle producers and enhance our results' external validity. Therefore, our laboratory-in-the-field study with cattle producers enables us to investigate stake-dependent expectations with professionals and a set of price prediction tasks central to their job. In contrast, most laboratory studies in the literature focus on relevant groups but without constructing a natural decision-making environment (Mayraz, 2011; Coutts, 2019). Moreover, previous studies used the cattle industry and price expectations of cattle producers as case studies to understand the economic fundamentals of inventory dynamics (Foster and Burt, 1992), portfolio management (Jarvis, 1974), and market cycles (Chavas, 2000).

We focus on recent bull auctions and select 18 bull transactions where we have access to the videos and final sale prices of cattle. We generate 10-second short videos for each selected bull and incorporate them into our price prediction tasks. Producers predict the bull price in each task, and the prediction accuracy is measured with the range of $\pm$ of \$500 of the true market price.

In a between-subject design, we randomly assign cattle producers to the Buyers-No-Info, Sellers-No-Info, Buyers-Info, and Sellers-Info experimental conditions. In contrast to the No-Info conditions, the Buyers-Info and Sellers-Info conditions provide objective quality measures for the presented bulls. Thus, the provided information helps us reduce the uncertainty regarding the bulls' quality and test the relationship between product quality uncertainty and price expectations. We find that producers exhibit optimism bias in the Buyers-No-Info and Sellers-No-Info conditions. Buyers under-predict and sellers over-predict the prices of presented cattle. However, this disparity vanishes in the Buyers-Info and Sellers-Info treatments. Our findings identify product-related uncertainty as one of the potential mechanisms driving optimism bias.

We also design a follow-up online laboratory study with a general population sample to test the sensitivity of stake-dependent expectations to the decision context as the evidence about the optimism bias in the gain domain in the relevant literature is mixed at best (Mayraz, 2011; Coutts, 2019; Engelmann et al., 2019; Schwardmann, 2019; Bénabou and Tirole, 2016). We detect *pessimism bias*—systematically expecting lower prices when one profits from high prices—with our general population sample. We conclude that the direction of price expectation biases is sensitive to the decision setting and/or the nature of the price prediction task.

Previous studies have shown that optimism bias can affect individual investment decisions (Puri and Robinson, 2007), may increase the demand for short-term and expensive financing options (Landier and Thesmar, 2008), and can trigger over-reliance on positive information when making financial forecasts (Easterwood and Nutt, 1999). It has been empirically shown that high-price expectations can reduce the attractiveness of futures, and projecting lower price levels may decrease the production capacity (Woolverton and Sykuta, 2009; Deaton and Laroque, 1996). Holding unrealistic price expectations can also lead to substantial financial losses and bankruptcies. Recent decision theory models link upward price expectations to optimism bias when the decision-maker has a relevant stake (Bénabou and Tirole, 2016). Still, how different levels of uncertainty influence optimism bias and consequential decisions is unclear. This particular point is crucial because optimism bias and its negative consequences arise when individuals face decision uncertainties. Moreover, previous studies do not test optimism bias among professionals using externally valid tasks. Our paper fills the mentioned gaps by identifying product quality uncertainty as a crucial channel that triggers optimism bias. Finally, we provide evidence from a general population sample and producers showing the sensitivity of this behavioral anomaly to different decision domains. The systematic differences in behavioral biases of the general population and cattle producers encourage future studies to calibrate behavioral models with their target audience to ensure the external validity of their findings.

The rest of the manuscript proceeds as follows. The experimental study protocols for the laboratory-in-the-field studies are described in Section 2. We lay out our behavioral model deriving testable hypotheses in Section 3. We scrutinize and connect our study findings to the related studies in Section 4. Section 5 discusses our follow-up study with a general population sample. The final Section concludes. We provide additional information about our study design and results in Supplementary Materials.

2 Experimental Setup

We conducted our study at a regional producer meeting for the cattle industry in the Eastern region of the United States. This event was the primary annual event of cattle producers enabling them to connect with peer producers and learn about developments in the market. We held in-person sessions with cattle people recruiting them on a voluntary basis.

A total of 141 cattle producers participated in our study using provided tablets. Study participants were rewarded with a \$15.00 participation payment for their time in the study. We also granted a \$10.00 incentive for price prediction accuracy. Table S1 in Supplementary Materials provides a basic demographic profile of producer subjects. The average producer was a 50-year-old white male.[4]

Our study started with a consent screen that outlined the general rules and stages of the experiment. Consenting producers were presented with more detailed information about the stages of the study, incentives, and procedures. We designed price prediction tasks that were relevant to producers' business practices. We selected 18 recent bull transactions from cattle auctions representing different price ranges of market operations. The auction database also contained videos of the animals at the time of sale.

In the price prediction tasks, we presented a 10-second video of bulls and asked cattle producers to predict the price of the animal. The allowed price prediction deviation was $\pm$\$500.00. Before starting the main study, subjects went through three training tasks familiarizing them with the nature of prediction tasks.

After the training stage, we randomly introduced four between-subject treatments in the laboratory-in-the-field experiment: *Buyer-No-Info*, *Seller-No-Info*, *Buyer-Info*, and *Seller-Info*.[5] Figure 1 provides a snapshot of one of our price prediction tasks from the Buyer-Info experimental treatment. In the information conditions, we provided the Expected Progeny Differences (EPD) of the presented cattle. Previous research has demonstrated that EPD values play an important role in determining market values of bulls (Boyer et al., 2019). Producers use EPD measures in their valuation of cattle, and these values provide crucial knowledge about the animal's market price

[4]Only one subject was from a non-white ethnic background.

[5]Table S1 shows that subjects do not demonstrate statistically different bull price prediction behavior in the training tasks before the treatment assignment stage.

You are in the market and your role is **Buyer**. As Buyer, your goal is to buy a bull. Above you see a short video of a Charolais bull you consider for buying.

You are looking for a Charolais bull to put on your ~ 250 Angus x Hereford cows. You purchase replacement heifers annually and market all of your calves on a merit-based carcass grid.

Please see the EPD features of the bull below:

	CE	BW	WW	YW	Milk	MCE	MTL	SC	CW	REA	FAT	MB	TSI
EPD	10.1	o.3	69	127	23	9.2	58	1.2	33	0.74	-0.003	0.28	271.36
%	15	60	9	6	45	15	20	15	7	40	25	3	4

Figure 1: A snapshot from price prediction tasks in the laboratory-in-the-field experiment.

(Thompson et al., 2022; Boyer et al., 2019). However, in the *No-Info* treatments, we did not provide EPD values increasing uncertainty regarding the bulls' quality. This study design aims to investigate the impact of information (i.e., EPD values) on optimism bias. In the absence of EPD values, producers have to rely on visible phenotypic features of bulls to assess their market values which can yield noisy and imprecise price estimates (Thompson et al., 2022; Boyer et al., 2019).

We also provided a decision reference context to producers in both Seller and Buyer treatments to prevent potential confounding. Previous studies show that the existing herd's size and composition can affect producers' valuations of cattle in the marketplace (Boyer et al., 2020). For instance, as seen in Figure 1, producers considered buying a Charolais bull for their herd consisting of around 250 Angus and Hereford bulls. This design element allowed us to normalize decision reference contexts across our 18 bull price prediction tasks.

After concluding the 18 price prediction tasks, producers completed a brief demographic survey. The final step of the study was the determination of the binding task and calculating the final payoffs of participants based on their prediction accuracy performance in the randomly selected task.[6]

We elicited risk preferences using a survey-based instrument developed by Falk et al. (2022). Falk et al. (2022) show that reported risk preferences can provide truthful estimates of individuals' risk-seeking tendencies.[7] By not incentivizing the risk elicitation task, we aimed to prevent potential hedging concerns and improve the salience of the prediction accuracy bonus reward. Subjects were also required to provide their confidence in price predictions on a scale from 0 to 100.

3 Conceptual Framework

We build our model using the theoretical framework of Bracha and Brown (2012) with extensions. A decision-maker (DM) predicts future price points to earn the monetary reward M for their prediction accuracy. Predicting future prices also imposes a trade-off between the anticipated benefit M and the mental cost $C(\cdot) \geq 0$ of holding imprecise beliefs and making inaccurate predictions. The reward M is earned if the predicted $\hat{p} > 0$ satisfies $\hat{p} \in (p-k; p+k)$.

When making the prediction $\hat{p}$, the individual holds a perceived distance $\delta(\hat{p}, p) = |\hat{p} - p|$ between the true price $p > 0$ and the predicted $\hat{p}$. The DM strives to satisfy $|\delta| \leq k$ to earn the reward M. The probability of earning M can be described with the function $\pi(\delta)$ ($\pi \in [0,1]$), where $\frac{\partial \pi(\delta)}{\partial \delta} < 0$.

Having a prediction $\hat{p}$ that is different than the true price introduces a mental cost $C(\delta(\hat{p}, p), s)$, where s is the noise or decision uncertainty. The mental cost function is strictly convex, continuous and reaches its minimum value at p.[8]

[6] We replicated Seller-Info and Buyer-Info treatments in another regional producer meeting. Our second companion paper utilizes the data from Seller-Info, and Buyer-Info treatments and the replication study to investigate the impact of different producer characteristics and production features on price expectations. However, in this paper, we exclusively use Seller-No-Info, and Buyer-No-Info treatments and compare them to Seller-Info, and Buyer-Info treatments to scrutinize the role of optimism bias in future price expectations.

[7] Subjects reported their risk tolerance levels using a Likert scale ranging between 0 and 10.

[8] Although, predicting in $\pm k$ range, in other words, satisfying $\hat{p} \in (p-k; p+k)$ is satisfactory to earn the reward

Diminishing sensitivity: For different decision noise levels s_1 and s_2 in the decision environment, such that $s_1 < s_2$, then

$$C(\delta, s_1) > C(\delta, s_2). \tag{1}$$

The diminishing sensitivity property means that the mental cost of the prediction inaccuracy of $\hat{p}_i$ decreases if the decision noise s_i goes up.

The DM has a strictly increasing and strictly concave utility function $u(\cdot)$ of income over M. The expected utility maximization problem of the DM from making the price prediction $\hat{p}$ is represented as follows:

$$U(\hat{p}, s) := max_{\hat{p}}\{\pi u(M) - (1-\pi)C\}. \tag{2}$$

where $\pi = \pi(\delta(\hat{p}, p))$ and $C = C(\delta(\hat{p}, p), s)$. For the optimal price prediction $\hat{p}^*$, all else equal, $U(\hat{p}^*, s) > U(\hat{p}, s)$.

The DM's decision problem can be deduced as minimizing the mental cost coming from prediction inaccuracy since the cost minimization is also correlated with increasing the reward probability. Figure 2 displays the primary characteristics of our conceptual framework.

Intuition 1: The top panel of Figure 2 shows the relationship between the decision noise term s and the mental cost of prediction inaccuracy. For the same price prediction $\hat{p}$, the DM incurs a mental cost with a smaller magnitude when the decision noise is higher. A simple example can be the price predictions of a stock trader in two typical market conditions: a) extremely volatile, b) relatively stable. In the former case, having huge inaccuracies in price predictions might inflict negligible mental cost to the DM, as they can rationalize their imprecise predictions with market conditions. However, when the market is in a relatively stable condition, prediction inaccuracies cannot be downplayed. Therefore, we expect that the existence of noises in the decision environment will reduce the magnitude of mental cost for imprecise price predictions. As an example, the top panel of Figure 2 depicts the mental costs of over-predicting prices. For an over-prediction $\hat{p}_H$,

M, we assume that the DM receives an intrinsic utility as they reach closer to p with their prediction. This assumption helps us to avoid having a flat region and kinks in the mental cost function.

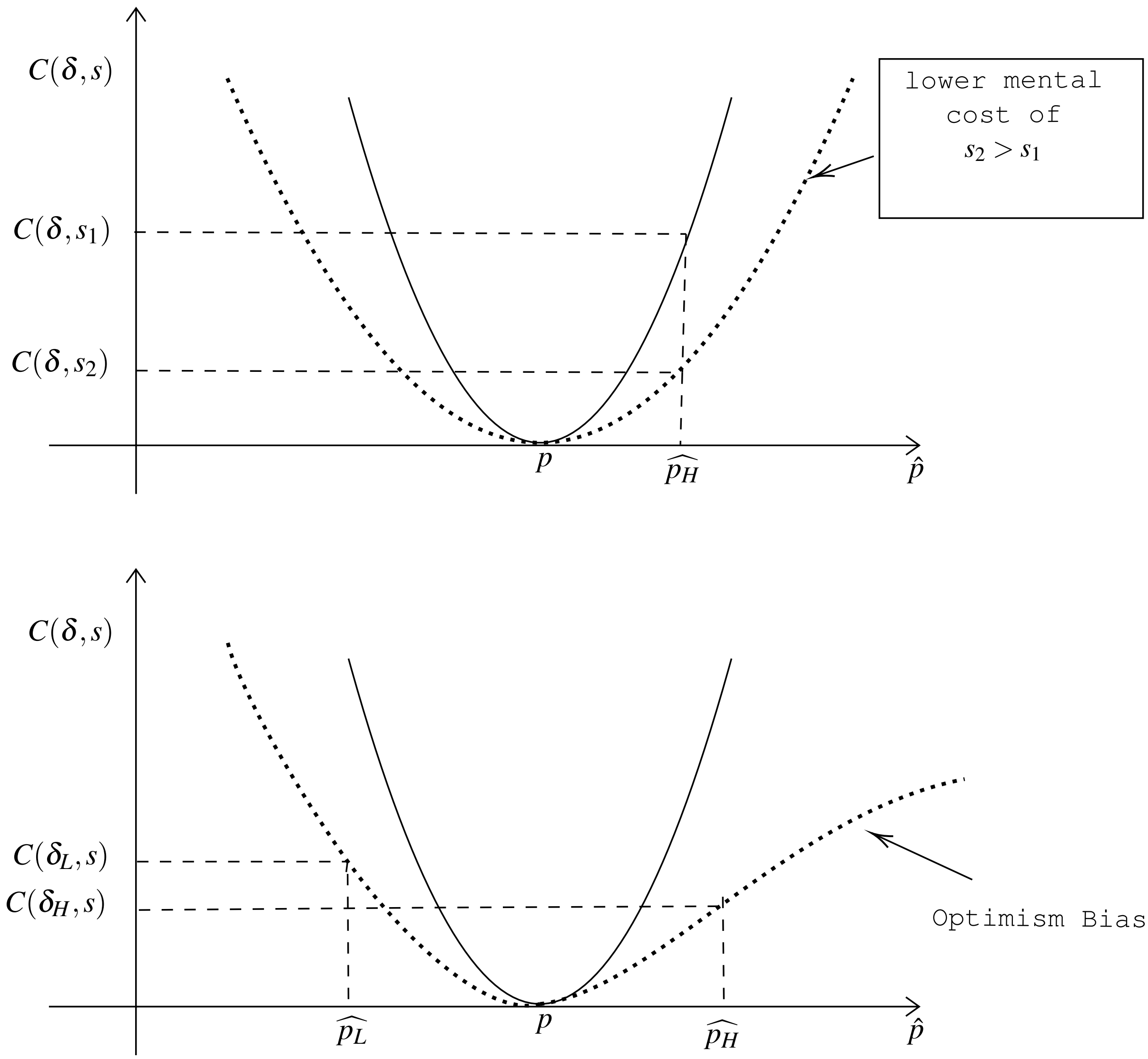


Figure 2: The relationship between Predictions and Optimism Bias.

$C(\delta,s_1) > C(\delta,s_2)$, when $s_1 < s_2$.

Lemma 1: A higher decision noise level will induce inaccurate price predictions.

Intuition 2: When there exists a noise in the decision environment, the decision-maker incurs a lower magnitude of mental costs stemming from imprecise price predictions. In this case, the emergence of stake-based expectations is more likely to occur. Put differently, owners (non-owners) are more likely to stake-based price predictions in the presence of a higher decision noise level. The bottom panel of Figure 2 displays this phenomenon. The dashed line is asymmetric, depicting the intuition that when stake-dependent expectations are active, the same magnitude of prediction inaccuracy can incur different mental cost levels depending on stakes. The bottom panel of Figure 2 describes this intuition with $\hat{p}_H = \hat{p}_L$, where high and low price predictions are equally imprecise with respect to the true price p (i.e., $\delta_L = \delta_H$). However, as the asymmetric shape of the dashed line shows, the DM incurs a lower mental cost level when they predict a high price level compared to the equally imprecise low price prediction (i.e., $C(\delta_L, s) > C(\delta_H, s)$).[9]

Lemma 2: The presence of a higher decision noise level will also induce asymmetric mental costs leading to stake-dependent price expectations.

We derive our testable hypotheses based on our lemmas.

Hypothesis 1: Owners (i.e., Farmers and Sellers) will over-predict, and non-owners (i.e., Bakers and Buyers) will under-predict future prices.

Hypothesis 2: The provision of product-related objective quality measures will reduce the noise in the decision environment and will close price expectation gaps between owners and non-owners.

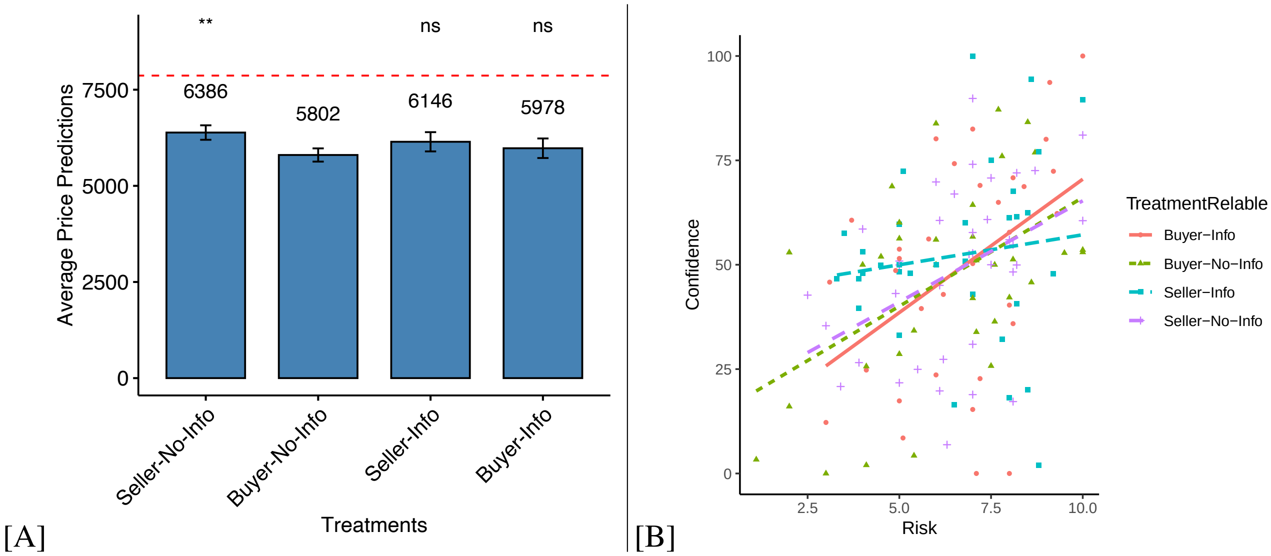
4 Results and Discussions

Result 1: *We find optimism bias in the laboratory-in-the-field study. On average, producers exhibit optimistic price expectations when there exists uncertainty about the product quality.*

We start scrutinizing the results of the laboratory-in-the-field study with producers by comparing average price expectations across experimental conditions. Figure 3, panel A, illustrates the average price predictions across experimental treatment conditions in the laboratory-in-the-field study. The results suggest that in the absence of product-related objective quality measures, Sellers (Seller-No-Info) tend to over-predict compared to Buyers (Buyer-No-Info) $(t-test, z-score = 1.95, p = 0.03)$. The average of predicted prices is \$6386 for the Seller-No-Info condition contrary to \$5802 in the Buyer-No-Info treatment.[10]

[9]For agents benefiting from lower price levels, the bottom panel of Figure 2 is asymmetric from the left side.

[10]We dropped four observations in which price predictions were above \$45,000. We also have 14 missing observations due to software glitches. The dropped observations constitute around 1% of our laboratory-in-the-field sample.



Panel A depicts the average price deviations (Predicted Price - True Price) in each treatment condition. The red dashed line indicates the average of true prices. Standard errors are clustered at the subject level. T-test p-values ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$) are shown comparing the treatment conditions. Panel B shows the association of risk preferences with confidence in price predictions. Each scatterplot point represents a decision-maker's tuple, consisting of risk preference and the average confidence in price predictions.

Figure 3: Price Predictions Across Treatments (Laboratory-in-the-field study)

This finding is further supported by the results presented in Table 1, which uses linear regressions to confirm this conclusion. Different model specifications in Table 1 robustly confirm that sellers over-predict than buyers when they do not have access to EPD measures. Our findings provide validation for Hypothesis 1.

Our findings are aligned with the literature showing that price expectations are influenced by *accuracy* concerns affecting the decision-maker's future material well-being, and also by *desirability* yielding instant gratifications. Bénabou and Tirole (2016) explain this tradeoff with holding inaccurate beliefs in the face of evidence and showing a preference for *wishful thinking*. Holding distorted beliefs increase first-order utility gains through increased anticipatory utility but also inflicts second-order costs due to suboptimal actions (Brunnermeier and Parker, 2005). This is such a widespread behavioral anomaly that psychologically healthy individuals are usually subject to the urge of being (unreasonably) optimistic regarding future events (Korn et al., 2014; Bénabou and Tirole, 2016). Studies also document optimistic expectations in industry-leading companies. Cowgill and Zitzewitz (2015) find that Google prediction markets exhibit optimism bias when employees expect high performance for projects and uncertain prospects in which they have relevant

Table 1: Determinants of Producer Prediction Behavior

	Dependent variable: Predicted Price		
	(1)	(2)	(3)
Buyer-Info	172.32	196.52	195.85
	(300.03)	(292.97)	(294.27)
Seller-No-Info	559.66**	575.15**	576.77**
	(248.54)	(247.33)	(248.43)
Seller-Info	319.90	366.41	369.07
	(297.83)	(301.59)	(302.90)
Prediction Confidence		−8.59*	−8.57*
		(4.46)	(4.48)
Constant	5,826.10***	6,225.99***	6,327.37***
	(164.36)	(284.13)	(345.36)
Task FE	*No*	*No*	*Yes*
Adj R-sqrd	0.01	0.01	0.02
N	2519	2519	2519

*p<0.1; **p<0.05; ***p<0.01

Note: The table shows the results of OLS regression analyses for the predicted bull prices across all experimental conditions in the laboratory-in-the-field experiment. Standard errors are clustered at the subject level.

stakes.

Stake-dependent expectations and ownership status have been shown to explain belief distortions leading to imprecise future expectations. Babcock et al. (1995) assigned plaintiff and defendant roles to law school students in 27 experimental legal cases and asked them to predict the fairness and severity of verdicts. The decisions were incentivized, and subjects were rewarded for their decision accuracy. Babcock et al. (1995) show that subjects, who knew their roles before reading case materials, exhibited more stake-dependent biases in estimating the magnitude of the judge's punishment/reward decision. However, this difference was mitigated when the experimenters assigned roles after the subjects concluded studying case materials. The results also suggest that stake-dependent expectations affect the length of the bargaining process and settlement success rates.

In a similar fashion, Hartzmark et al. (2021) randomly assign *owner* and *non-owner* roles in an asset valuation study and show that the ownership status can affect investors' valuations of financial instruments and their expectations about future earning performance. They also find that subjects symmetrically update their beliefs about owned goods in the face of positive and negative signals. Hartzmark et al. (2021) discuss that their findings contradict with *misattribution* and *loss aversion* models predicting more overreaction to negative signals compared to positive signals (Gagnon-Bartsch and Bushong, 2022). In contrast, motivated reasoning and stake-dependent expectation models predict that individuals overreact more to positive signals than negative signals (Kunda, 1990; Brunnermeier and Parker, 2005).

Result 2: *Decision noise contributes to optimism bias. The reduction of noise in the decision environment deactivates optimism bias.*

Figure 3, panel A, also shows the average price predictions in the Seller-Info and Buyer-Info conditions. These experimental treatments provide EPD values of bulls, and this information is very crucial for producers to assess the market price of cattle. Hypothesis 2 postulates that decision-makers are less likely to exhibit optimism bias when the uncertainty in the decision environment is reduced. The results in Figure 3, panel A, are consistent with this prediction, as the price predictions of Sellers and Buyers are not statistically different $(t-test, z-score = 0.35, p = 0.64)$.

Figure 3, panel B illustrates a positive correlation between prediction confidence and risk preferences in the laboratory-in-the-field studies with producers. Producers with higher risk tolerance also tend to exhibit high confidence in their price predictions. Interestingly, Table 1 presents a negative correlation between price prediction confidence and price prediction levels. However, this effect is moderately significant.

Our major contribution to the relevant literature is that we show the importance of objective information in bridging the gap between the price expectations of sellers and buyers. In a longitudinal study, Jones and Santos (2022) survey university graduates and elicit their future earning expectations. Graduates are assigned to a treatment containing information about the average earnings of peers. Jones and Santos (2022) find that information helps reduce the size of optimistic expectations regarding future labor market earnings but does not completely eliminate optimism bias. Previous work has also shown that decision-makers can self-select into an information source confirming their expectations or not challenging their beliefs (Castagnetti and Schmacker, 2022;

Akerlof and Dickens, 1982). It has also been shown that the ego-relevance, or the individual's belief and attitude towards the information, can mediate the effect of information (Castagnetti and Schmacker, 2022).

We use an information source that has high credibility among producers and provides objective quality assessments (Boyer et al., 2019, 2020). We show that information can eliminate optimism bias and converge price expectations of sellers and buyers when there are no controversies associated with the information source. Our findings offer a new perspective on how belief distortion can be avoided by increasing the reliability of the information.

5 Optimism Bias and Decision Context

One important criticism about our laboratory-in-the-field results might be the context effect. There is a lack of consensus on the determinants of stake-dependent expectations in the literature testing this phenomenon in different decision domains. For instance, Bénabou and Tirole (2016) discuss that students and athletes may develop "defensive pessimism" by downplaying their previous achievements and exaggerating their prospective challenges. Heller and Winter (2020) show that optimism bias and wishful thinking are frequently observed in strategic interaction games. However, pessimism can arise in games where the perceived opponent's strategy can lead to lower returns to the player relative to the real opponent's strategy across all strategy profiles. Moreover, pessimism can also arise in settings where the cost of preventive healthcare technologies is low, manifesting itself in the increase in the demand for such services in rich countries (Schwardmann, 2019).

To identify the role of the decision context on stake-dependent beliefs in price expectations, we design an incentivized follow-up study with a general population sample. Participants can earn a bonus payoff if they predict future price points of wheat with an allowed error margin in the presented 20 price scenarios. It must be noted that we do not incentivize the realized prices. Subjects only earn a bonus payoff for their price expectation accuracy. This design feature enables us to eliminate the potential contamination effects of hedging behavior.[11] Figure 4 provides a

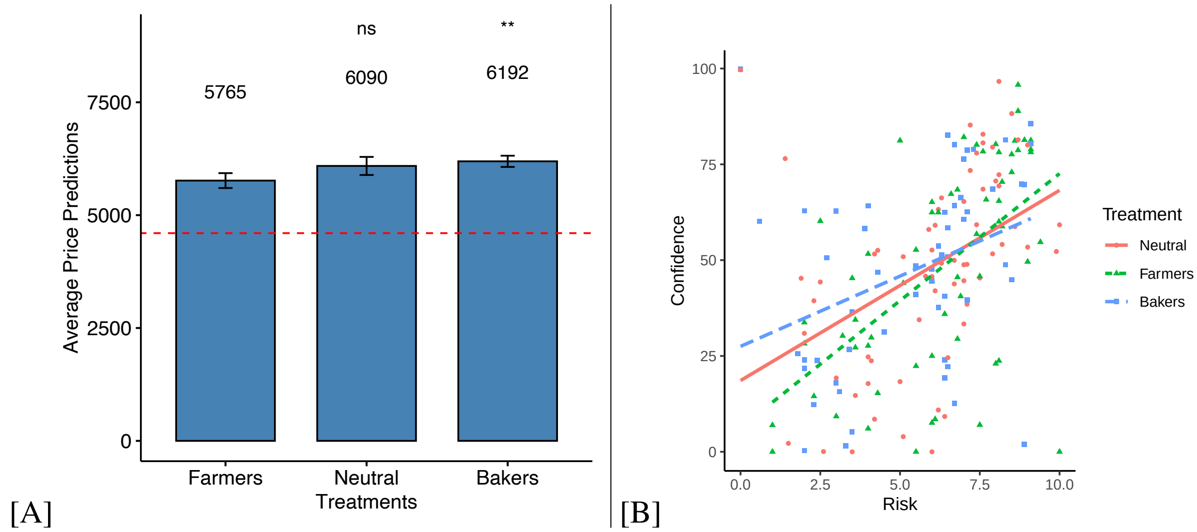
[11] Mayraz (2011) shows that incentivizing both the prediction accuracy and actual price levels creates hedging

Figure 4: A snapshot from price prediction tasks in the online laboratory experiment.

snapshot of one of the prediction tasks in the online study.

Our design is built on Mayraz (2011) with several extensions. We randomly assign *Farmer* (i.e., seller) and *Baker* (i.e., buyer) roles in a between-subject study design. According to the decision framing, Farmers are informed that they grow wheat to sell, and in each price scenario, they see constructed historical wheat prices over the last 365 days. Farmers are asked to predict the wheat price in ten days when they will be in the market to sell their products. Similarly, Bakers are instructed that they need to buy wheat for their production in ten days. Then Bakers predict future price points based on the constructed historical price information for the day they will be in the market to buy wheat. Unlike Mayraz (2011), we also include the Neutral treatment condition, where subjects do not have a decision framing. The Neutral condition allows us to detect the relative magnitude of the belief distortion induced by the Farmer and Baker conditions. Put differently, this treatment extension enables us to identify how much sellers and buyers individually contribute to the price expectation dispersion. For sellers, the optimism bias manifests in the gain domain by expecting higher prices for the goods they will sell. Contrarily, for buyers, the same

concerns.



This figure shows the association of risk preferences with confidence in price predictions. Each scatterplot point represents a decision-maker's tuple, consisting of risk preference and the average of price predictions.

Figure 5: Risk Preferences and Price Prediction Confidence Across Treatments in the Online Study

effect is in the cost domain in terms of price expectations about future costs. This design feature is suitable for identifying if belief distortions are asymmetric in gain and cost domains.

Figure 5, panel A, shows the average price predictions of subjects across the Farmers, Neutral, Bakers treatment conditions. Interestingly, we find *pessimism bias*—systematically expecting and predicting lower prices yielding lower profit levels—in our general population sample. Bakers over-predict, and Farmers under-predict relative to the Neutral treatment. Specifically, relative to the Neutral framing experimental treatment condition, Farmers under-predict relative to the Neutral condition by around \$375. Conversely, Bakers, on average, over-predict wheat prices compared to the Neutral framing by \$102. We conduct a t-test and confirm that the difference between Bakers and Farmers in terms of the average price predictions (clustered at the subject level) is statistically significant $(t-test, z-score = 1.73, p = 0.04)$. It is also interesting that the average price predictions of Bakers and Farmers are not statistically different than the Neutral condition.

Table 2 presents the results of regression analyses to scrutinize the price prediction behavior in the Bakers and Farmers treatments. Three model specifications robustly confirm our conclusion based on Figure 5, showing that Bakers over-predict relative to Farmers in our laboratory experiment. We do not detect any impact of prediction confidence on price predictions. Based on the

Table 2: Determinants of Price Prediction Behavior in the Laboratory Experiment

	Dependent variable: Predicted Price		
	(1)	(2)	(3)
Bakers	426.71**	425.64**	424.74**
	(205.88)	(204.78)	(205.64)
Prediction Confidence		−2.18	−4.00
		(4.47)	(4.35)
Constant	5,765.49***	5,867.05***	3,680.08***
	(164.59)	(174.34)	(283.96)
Task FE	*No*	*No*	*Yes*
Adj R-sqrd	0.00	0.00	0.60
N	2240	2240	2240

*p<0.1; **p<0.05; ***p<0.01

Note: The table shows the results of OLS regression analyses. Standard errors are clustered at the subject level.

entire sample of the laboratory experiment, we conclude that our results exhibit pessimism bias, which is the reverse of optimism bias.

We conclude that, in a similar price prediction task, our general population sample exhibits pessimism bias. Therefore, we warn future studies to consider the context effect in studying the determinants of wishful thinking.[12]

6 Conclusion

Decision-makers distort their expectations when facing uncertain prospects. Before the market, buyers and sellers of the same product may hold different price expectations aligning with their stakes. Having distorted and, at the same time, *favorable* beliefs about uncertain future prospects can be explained with *optimism bias* which is a self-deceptive act to inflate the expected utility of future events at the present (Coutts, 2019). This phenomenon has also been studied as a simple decision heuristic known as *wishful thinking* (Mayraz, 2011).

[12]Supplementary materials contain other details of this follow-up study.

This article uses incentivized protocols to examine the causal relationship between ownership status and price expectations in a laboratory-in-the-field study with cattle producers. We find that ownership causally changes price expectations. Our findings indicate that producers exhibit *optimism bias* or stake-dependent expectations. Optimism bias is manifested in predicting higher future prices when an increase in prices positively affects prospective profits. Our results can be explained by *motivated reasoning* models predicting that decision-makers derive direct utility from their high-price expectations when those expectations are also associated with higher earnings (Kunda, 1990; Brunnermeier and Parker, 2005; Mayraz, 2011; Bracha and Brown, 2012; Bénabou and Tirole, 2016; Dillenberger et al., 2017). We also show that an increase in uncertainty levels significantly elevates optimism bias. The provision of task-relevant objective information reduces the uncertainty, hence, eliminates the optimism bias.

Our finding about the role of prediction confidence in optimism bias is puzzling. We do not detect a consistent impact of prediction confidence on price expectation levels. Our conclusion does not overlap with studies showing a positive relationship between over-confidence and belief distortions (Möbius et al., 2022; Mayraz, 2011; Brunnermeier and Parker, 2005; Akerlof and Dickens, 1982). Nevertheless, the documented positive association between confidence and risk-seeking behavior has also been confirmed in empirical studies (Cowgill and Zitzewitz, 2015). Hirshleifer et al. (2012) show that CEOs with high confidence prefer risk-taking by investing more in research and development projects.

Our follow-up online laboratory study has provided evidence of pessimism bias, showing that the direction of stake-dependent expectations can be sensitive to the decision context. Future studies might benefit from exploring the relationship between the decision environment and motivated expectations.

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Supplementary Materials

Table S1: Balance Tests for Lab-in-the-field Study

Demographic Variables	N	Buyer-No-Info N = 35	Buyer-Info N = 34	Seller-No-Info N = 36	Seller-Info N = 34	p-value	p-value Adjusted
Age	139	47 (16)	51 (16)	52 (17)	50 (15)	0.72	0.72
Male	139	25 (71%)	23 (68%)	18 (50%)	23 (68%)	0.23	0.69
Income (Normalized)	139	61,699 (23,267)	61,494 (28,950)	71,340 (28,285)	59,050 (30,485)	0.08	0.50
Prediction in Training 1	139	3,041 (939)	3,587 (2,075)	3,897 (4,806)	3,936 (4,048)	0.65	0.72
Prediction in Training 2	139	4,590 (944)	4,604 (1,596)	4,869 (1,333)	5,373 (4,530)	0.42	0.72
Prediction in Training 3	139	3,362 (810)	3,491 (955)	3,703 (1,230)	3,737 (1,438)	0.68	0.72

Statistics: Mean (SD); n (%). Tests: Kruskal-Wallis rank sum test; Pearson's Chi-squared test; Fisher's exact test; Benjamini & Hochberg correction for multiple testing. Some demographic measures are missing for two subjects. Therefore, this table is based on the data from 139 subjects.

Online laboratory Study: We conducted the laboratory experiment using prolific.co, which offers country-based representative samples over different demographic features for online studies. Prolific has been widely used by recent economic studies to elicit the behavioral foundations of the economic decision-making process.[13] To ensure the quality of our sample, we restricted our recruitment to United States residents with a 95% approval rate and at least 10 study submissions. A total of 181 participants were recruited for the study out of 50,706 Prolific members who met these criteria. The recruitment process was conducted using the platform's survey prompts. The study recruitment prompt indicated that participants would have to spend around 45 minutes in the study, and they would be compensated with an $8.00 reward for complying with study rules and completing all study tasks. Participants had a chance to earn an additional $10.00 bonus payoff depending on their performance and luck. Interested platform members clicked on the study prompt to participate in tasks on a first-come-first-serve basis.

The first study screen explained the general rules and procedures of the experiment to the participants and asked them to indicate their consent to start the study. Participants were given more detailed information after expressing their consent. It was explained that they would have to submit their price predictions in 20 tasks, and their accuracy would be rewarded with a $10.00 additional bonus payoff. Subjects were first asked to complete three training tasks to obtain insights into the nature of the tasks. These three training tasks were similar to the 20 main study tasks.[14] Subjects predicted future price points in the training tasks and received immediate feedback about the accuracy of their price expectations.

After completing the training tasks, subjects were randomly assigned to experimental treatment conditions: *Neutral*, *Farmers*, and *Bakers*. Table S2 describes the primary demographic features and training task performance of treatment groups. The average participant was a 31-year-old college degree holder. The proportion of self-identified males was between 44%-53%. Conducted statistical tests comparing experimental treatment conditions did not reveal significant differences across primary demographic characteristics. Overall, Table S2 reports random treatment condition assignments generated statistically balanced sub-samples over collected key demographic features. We also do not find differences in training task performance across the treatment conditions.[15]

[13]For instance, see Brañas-Garza et al. (2022) and Butera et al. (2022).

[14]Figure S1 provides snapshots from 20 price scenarios.

[15]Nine subjects constantly submitted either the same price prediction and/or price prediction lower than $500.00,

In the Farmer (Baker) condition, subjects were presented with a profit function where wheat was the output (input) of the production, hence, representing the revenue (cost) level for the decision-maker. Higher price expectations promise higher revenues for Farmers and lower revenues for Bakers. In the Farmer and Baker treatments, study participants were shown a decision context with the following text, respectively:

Your role is Farmer across all tasks. Every day, you produce 1000 bushels of wheat. Your daily production cost is $500. At day 375, you will go to the market to sell 1000 bushels of wheat produced on that day. Buyers will pay the market price for that day to buy your 1000 bushels of wheat.

As Farmer, your profit at day 375 will be:

Profit = **True Wheat Price** (per 1000 bushels) **$500 The True Wheat price** will be the **revenue** in your profit function, and $500 will be deducted from it.

Your role is Baker across all tasks. Every day, you produce bread products using 1000 bushels of wheat. At day 375, you will have a buyer buying all of your products made on that day. The buyer will pay $16,000 for your bread products.

As Baker, your profit at day 375 will be:

Profit = **$16,000 True Wheat Price** (per 1000 bushels)

The **True Wheat price** will be the **cost** in your profit function, and it will be deducted from your $16,000.

We used 20 different agribusiness companies' stock market share prices to construct price scenarios. Specifically, we collected share prices of randomly selected 20 companies between June 2017 and June 2019.[16] Figure 1 presents a snapshot from one of the study tasks. Using real data allowed us to reflect real market price volatilities in our tasks, thus improving the external validity of our study tasks. We rescaled the collected data to limit prices between $500 and $16,000.

where true prices changed between $500.00 and $16,000. We dropped those nine participants' data from our final sample when conducting statistical analyses. Therefore, our results rely on 172 subjects: Farmers (59), Neutral (60), and Bakers (53).

[16]Selected companies: Adecoagro, Alico, Aqua Bounty Technologies, Fresh Del Monte Produce, Deere Co, Calavo Growers, Archer Daniels Midland, China Green Agriculture, Limoneira, Seaboard Corp, Andersons, Yara International, BRF S A, Bachoco, Bayer, Scotts Miracle-Gro Co, FMC Corp, Farmer Bros Co, Tyson Foods Inc, and Mosaic Co.

Table S2: Balance Tests for Online Lab Study

Demographic Variables	N	Neutral N = 64	Farmers N = 62	Bakers N = 55	p-value	p-value Adjusted
Age	181	32 (11)	31 (10)	31 (10)	0.95	1.00
Male	181	29 (45%)	27 (44%)	29 (53%)	0.58	0.98
Income (Normalized)	181	48,415 (31,896)	43,799 (26,593)	34,594 (19,935)	0.05	0.61
High-School grad	181	5 (7.8%)	5 (8.1%)	5 (9.1%)	1.00	1.00
Two-Year College grad	181	3 (4.7%)	1 (1.6%)	1 (1.8%)	0.62	0.98
Some College	181	8 (12%)	16 (26%)	13 (24%)	0.14	0.61
Four-Year College grad	181	13 (20%)	16 (26%)	12 (22%)	0.75	0.98
Some Graduate	181	5 (7.8%)	2 (3.2%)	0 (0%)	0.11	0.61
Masters Degree	181	27 (42%)	22 (35%)	23 (42%)	0.69	0.98
Doctorate Degree	181	2 (3.1%)	0 (0%)	0 (0%)	0.33	0.86
Prediction in Training 1	181	1,486 (567)	1,590 (834)	1,550 (488)	0.74	0.98
Prediction in Training 2	181	3,655 (1,448)	3,745 (1,312)	4,067 (1,140)	0.26	0.84
Prediction in Training 3	181	5,248 (7,922)	4,237 (1,407)	4,333 (1,176)	0.92	1.00

Statistics: Mean (SD); n (%). Tests: Kruskal-Wallis rank sum test; Pearson's Chi-squared test; Fisher's exact test; Benjamini & Hochberg correction for multiple testing.

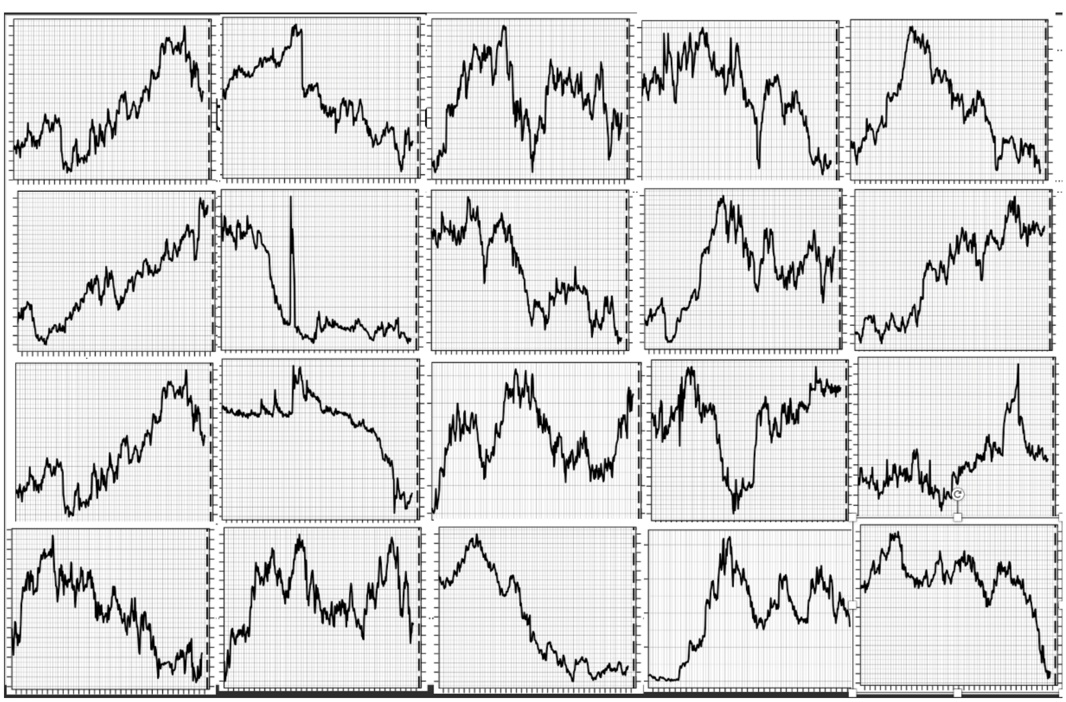

Figure S1: Constructed historical price information for 20 Price Prediction Tasks in the laboratory study.