The Role of Recency Bias and Price Salience in Insurance Take-up Decisions

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Abstract

Can learning from recent events impair the quality of risk management decisions? We conduct incentivized experiments using a dynamic decision-making setting with students and cattle producers to examine the role of real-life experience in demand for price insurance. Our controlled setting allows investigating if professionals exhibit different behavioral patterns in the face of risky prospects compared to educated but not experienced agents. Students and producers exhibit similar decisions at the extensive margin of risk-taking. However, on the intensive margin, students are more likely to opt in for the most expensive insurance coverage level that does not result in a loss compared to other insurance alternatives. Using eye-tracking technology, we identify that cattle producers with high-price salient behavior show *recency bias* and over-extrapolate from recent high-price events reducing their demand for insurance coverage. We discuss the policy implications of our findings with potential decision aids to improve the quality of risk management decisions in the agricultural industry.

Keywords: Expectation, Eye tracking, Learning, Producers, Risk.

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1 Introduction

When making decisions in the face of risky prospects, agents consider not only available incentives but also rely on accumulated knowledge from past experiences (Erev and Haruvy, 2013; Cai et al., 2020). However, the role of learning is often overlooked in mapping the determinants of the demand for insurance. This is because "positive" insurance experiences (receiving indemnities) only occur when there is a negative shock, which is not a frequent event (Cai et al., 2020). Studies demonstrate that insurance decisions are influenced by previous payout experiences (Karlan et al., 2014; Cai et al., 2020); thus, not accounting for learning can limit our understanding of economic behavior in the risk domain. Secondary data sources are often not rich enough to capture accumulated learning vis-à-vis recent insurance events. Experimental studies with granular data describing "decisions from experience" and "decisions from incentives" can provide valuable insights into well-known empirical puzzles, such as low take-up rates for subsidized insurances in both developed and developing countries (Finkelstein et al., 2019; Cole et al., 2013; Erev and Haruvy, 2013). This paper studies how accumulated real-life experiences, combined with recent and salient learning, impact the demand for price insurance.

We conducted an incentivized laboratory study with students and a laboratory-in-the-field experiment with cattle producers to investigate the determinants of insurance take-up behavior and the role of learning in risk management decisions. This setup allows us to observe dynamic differences in insurance take-up decisions between a set of agents with formal education but without real-life practice and a group of professionals possessing hands-on experience. Not having real-life experience induces students to act solely on financial incentives without the confounding effect of practice. However, producers usually operate based on the combined effect of incentives, gained experience, and practical as well as formal knowledge. We show that students and producers exhibit mostly indistinguishable behavioral patterns in their insurance decisions. Interestingly, these two groups also demonstrate the same degree of risk tolerance in the financial domain. However, producers are more likely to factor in their recent market experience compared to students. The effect of the recent learning is only limited to the first lag and does not stretch over distant previous learning experiences. This suggests that professionals may operate with a very short-term working memory triggering *recency bias* (i.e., over-weighing the information value of recent events).

We employ eye-tracking technology to uncover potential cognitive mechanisms behind producers' recency bias. We build the focus of our investigation on attribute salience and how it can lead to higher levels of risk-taking behavior. The seminal work of Bordalo et al. (2012) shows salient payoffs can distort decision weights of uncertain prospects. They also show decision-makers overweight the upside of lotteries and exhibit more risk-seeking behavior. The salience of decision attributes is very context-dependent, and there are different ways of identifying salient attributes (Bordalo et al., 2013a,b). Detecting the visual salience of different aspects of decision stimuli with eye-tracking technology can be a reliable method to pin down the salient attributes (Bordalo et al., 2022). Eye-tracking data enable us to identify two producer types: high and low-price salient producers. We find that high-price salient producers over-focus on the upside of uncertain prospects, and they are more likely to opt out of the insurance. Conversely, low-price salient producers are visually over-occupied with low-value outcomes of probable events, and they show more consistent insurance purchases. We also show a robust association between recency bias and salience in producers' risk-management decisions.

The incentivized laboratory-in-the-field experiment was conducted at a Beef Expo and Trade Show with 69 producers, each making 20 independent decisions yielding 1380 data points. We also employ eye trackers in the study, measuring the fixation time of producers on each decision attribute. This setup helps us obtain a granular picture of the decision-making process of producers. We designed a study where in each decision period, a random cattle price is determined from the known price distribution. The producers have the same decision context across periods, and their goal is to maximize their net price, which is the actual price received for their cattle minus the insurance premium plus the indemnity payment. Our design mimics the Livestock

Risk Protection (LRP) insurance program by allowing participants to insure a price level. We discuss the institutional features of the LRP policy program in the *Institutional Background* section of the manuscript and how our experiment varied from the actual LRP policy.

In each decision period, producers select a cattle price coverage level (no coverage or 0%, 90%, 95%, and 100%) to buy for the guaranteed price of $171 per cwt. The policy premiums increased with respect to the offered coverage percentages, while the 0% coverage was free. Designed coverage levels allow us to investigate the extensive and intensive margins of insurance decisions. For instance, the 0% coverage level means the decision-maker does not want to buy insurance, which enables us to observe the extensive margin of insurance demand (i.e., whether a decision-maker considers buying any non-zero insurance coverage level). On the other hand, with different coverage levels in this design, we can also measure the intensive margin of insurance decisions (i.e., if a decision-maker decides to buy insurance coverage, to what extent they reduce their uncertain prospects by choosing different coverage levels).

One can also translate these coverage levels into uncertain prospects, where the 0% coverage level offers a negative expected mean of potential cattle prices with the highest standard deviation. In contrast, the 100% coverage level is a lottery with the highest and "safest" average net price.[1] However, there is a small chance for agents to earn a higher net price with the 0% coverage level compared to the 100% coverage in high-price periods. Therefore, a risk-seeking agent will focus on this small-probability outcome and prefer lower coverage levels compared to a risk-averse decision-maker.

Participants receive an indemnity payment if and only if the realized market price is lower than the insured price level. After choosing the coverage level, the decision period's market price is realized, and subjects receive feedback on the realized market price, their indemnity payment if a non-zero coverage level was purchased before the realization, and their net price. At the end of the study, we randomly pick one decision period to be the binding decision, and the net price of that decision becomes a bonus

[1] We use the term "safe" to describe uncertain prospects with non-negative prices throughout the text.

payoff for our subjects in addition to their participation reward.

We conducted our laboratory study with 29 Agricultural Business and Economics undergraduate students (i.e., 580 decision data points) employing the same study protocols and incentives. The students were recruited from an Agricultural Business and Management course after they had been exposed to different risk management tools. We describe other details of our experimental protocols and measures in the *Experimental Participants, Procedures, and Design* section of this paper.

We focus on two outcome measures: a binary indicator for any non-zero coverage level purchases (i.e., the extensive margin of insurance demand) and specific non-zero coverage level choices (i.e., the intensive margin of insurance demand). We state our motivational model and testable hypotheses in the *Motivational Behavioral Model* section of the manuscript. Our analyses show that both students and producers buy the same proportion of 0%, 90%, and 95% coverages across 20 decision periods. However, the student sample is more likely to buy the 100% coverage level than producers. Therefore, our results reveal that producers and students show the same decision patterns on the extensive margin, but they differ in terms of the intensive margin of insurance decisions.

Study participants receive feedback after each decision period, and this design feature permits the investigation of the dynamics of the risk-management decision-making process. We find that only producers factor in their recent decision experience in their coverage level choices. Experiencing a high price in the previous period reduced the probability of buying a non-zero coverage level by seven (7) percentage points in the producer sample. We also report that a one-dollar increase in indemnity payments in the last decision period increases any non-zero LRP coverage level purchases by one (1) percentage point. However, the lag effect of high-price and indemnity payment experiences does not go beyond the first lag, suggesting that producers are mostly preoccupied with very recent market experiences, and they are prone to recency bias.

With the help of eye-tracking technology, we measure the fixation times of producers on insurance decision attributes. We construct a visual salience measure on the provided price distribution information. High-price salient producers exhibit a higher proportion of fixation time on the high prices of the price distribution information compared to low-price salient producers. Put differently, this measure allows us to identify a set of producers who show relatively higher visual attention to the upsides of uncertain prospects. Based on the prediction of Bordalo et al. (2012), high-price salient producers should demonstrate a relatively higher risk-seeking behavior than the low-price salient producers, which matches our findings. An average decision is to choose the 95% and 0% coverage levels in the low- and high-price salient producer subsamples, respectively. We also detect that only high-price salient producers buy lower coverage levels or opt out of the insurance after experiencing a high price in the previous decision period. We do not detect any correlation between salience and reported financial risk-taking preferences. The *Results* section of this manuscript discusses our analytical approaches and findings.

We connect our findings with relevant studies in the *Discussion* section. Our findings contribute to the literature investigating the behavioral foundation of insurance take-up decisions by comparing the decisions of formally educated agents (i.e., Ag Business students) without real-life exposure to professionals with extensive experience and heterogeneous educational achievements (i.e., cattle producers).[2] The inclusion of these groups provides us with a unique opportunity to understand the difference between learning-by-studying and learning-by-doing in the risk-management context. We show that professionals are more susceptible to recency bias by overextrapolating from the recent market experience, and salience can be a driving mechanism in the activation of this behavioral bias. In this regard, our study is related to Bellemare et al. (2020) investigating the production quantity decisions of Peruvian farmers and United States (US) students. Bellemare et al. (2020) show that farmers do not change their production choices when facing product price risk at extensive and intensive margins. However, they report that their student sample exhibits

[2]It must be noted that some of the producers in our study sample have advanced degrees. However, 47% of producers in the sample have education levels below a college degree.

downward changes in production quantities in the presence of product price risk at the intensive margin. Our paper also speaks to a broad literature examining the behavioral foundations of insurance take-ups. Cai et al. (2020) demonstrate that insufficient knowledge about the specifics of subsidized insurance policies leads to insurance choice decisions being made based on recent experiences. They show that having a recent indemnity payout experience permanently increases weather insurance take-up rates among Chinese rice producers. In our study, we also find that a one-dollar increase in recent indemnity payout pushes up the LRP insurance purchase probability by one (1) percentage point. Tonsor (2018) shows that US cattle producers use their best-experienced outcome as the reference point in production decisions. Using theoretical and empirical frameworks, Bordalo et al. (2022) discuss that salience can affect the decision reference point. In our experiment with producers, with the help of eye-tracking technology, we demonstrate that producers exhibiting high-price salience behavior are more likely to react to recent high prices by not buying any non-zero insurance coverage. Our results have policy relevance in terms of understanding decision failures leading to systemic risks in the agricultural industry. We show that agricultural producers are very vulnerable to abrupt changes in market dynamics as they mostly over-extrapolate from recent events (i.e., recency bias). Policies and extension education modules helping producers focus on long-term market forces can mitigate the negative consequences of recency bias. Designing behavioral decision aid tools can also improve risk management practices by increasing demand for subsidized insurance programs.

2 Institutional Background

Beef cattle production is susceptible to economic losses from uncontrollable events like drought and diseases, but price volatility has historically been the primary cause of losses to US cattle producers (Hart et al., 2001; Hall et al., 2003; Belasco et al., 2009; Tonsor and Schroeder, 2011). LRP insurance policy is one tool producers can use to reduce financial losses from price declines. The LRP program, which was introduced in 2003, is an insurance policy producers can purchase that guarantees a minimum price level for a certain period. Policyholders are paid an indemnity payment at the end of an insurance period if a cash price index is lower than the insured price. Our study designs an incentivized experiment for a price insurance policy like LRP but differs in two ways. First, we assume the coverage level to be either 90%, 95%, or 100%, but LRP offers coverage levels ranging from 70% to 100%. Also, LRP can be purchased daily for various insurance lengths ranging from 13 to 52 weeks.[3] In our experiment, we assume that the decision maker has equal insurance lengths for each coverage level.

While studies have shown that LRP policies are effective at protecting against price declines (Coelho et al., 2008; Feuz, 2009; Burdine and Halich, 2014; Merritt et al., 2017; Wei, 2019; Boyer and Griffith, 2023), LRP has not been widely used by US cattle producers (Hill, 2015; McKendree et al., 2021). There have been several hypothesized reasons for limited adoption, such as LRP being relatively expensive given protection costs (Burdine and Halich, 2014; Merritt et al., 2017). Indemnities are often time less than the cost of the LRP policy; thus, a producer might be better off taking the price loss in the market than buying the LRP policy and receiving the indemnity payment (Burdine and Halich, 2014; Merritt et al., 2017).

The USDA Risk Management Agency (RMA) increased the LRP premium subsidy from 13% of the total premium cost to 20% of the total premium cost in 2019 and then, further increased the subsidy rate in 2020. Studies have shown that these policy changes lowered the LRP cost of the premiums to producers and increased the likelihood of the indemnity being greater than the premium Boyer and Griffith (2023). These policy changes intend to improve incentives for producers to utilize the LRP program. Additionally, the amendments to this insurance policy can also potentially increase the likelihood of producers having a "positive" (i.e., receive a payout) experience from using LRP. Our experimental approach allows us to test if producers' learned experiences for price risk management can increase adoption.

[3]See https://www.rma.usda.gov/Policy-and-Procedure/Insurance-Plans/Livestock-Insurance-Plans for more details.

3 Experimental Participants, Procedures, and Design

We conducted the study with cattle producers and Agricultural Economics and Business undergraduate students. Our sample includes 98 participants. Since each study participant made 20 insurance purchase decisions, our analyses are based on 1968 data points. Our sample size is comparable with recent studies conducting experiments with students and professionals.[4]

A total of 69 producers were recruited for the study on a voluntary basis at a Beef Expo and Trade Show in the Eastern United States. The event targeted educating cattle producers on the best production and financial management practices. Therefore, our producer sample consists of professional producers who are the target audience of the LRP insurance program. We employed a lab-in-the-field setting and installed six computer stations with eye-tracking devices at the expo.

Our student sample is comprised of 29 Agricultural Economics juniors and seniors enrolled in an Agricultural Business Management course at a land-grant public university. The study with students was conducted during class time.

Table 1 shows the basic demographic features of our study participants. Table 1 Panel A lists important business characteristics of recruited professional cattle producers, ranging from their herd size to educational level. Around 89% of our producer sample possessed a cattle operation in 2021, and the average herd size was close to 81 head. Our data also contains beginning cattle producers (11% of the producer sample) who did not operate a cattle operation in 2021. An average cattle person in our study is a 50-year-old white male. The education level of our producer sample is diverse. Only 15% of the producers have a high school or lower education level. Interestingly, close to 52% of cattle people achieved a college degree or a higher level of education in our study sample.

Around 76% of the recruited producers indicated they had never used LRP insur-

[4] For instance, Bellemare et al. (2020) ran their study with 71 students and 48 producers.

Table 1: Basic Demographic Characteristics

	N	Mean	Min	Max
Panel A: Cattle Producers				
Had Cattle Operation in 2021	66	0.89	0	1
Herd Size	66	81.38	0	755
Never used LRP	66	0.76	0	1
LRP knowledge	66	3.08	1	7
Education: High School or less	66	0.15	0	1
Education: Some college	66	0.32	0	1
Education: College degree or more	66	0.52	0	1
Age	66	49.65	19	75
Male	66	0.67	0	1
White ethnicity	66	0.94	0	1
Panel B: Ag Business Students				
Age	29	22.1	19	26
Male	29	0.86	0	1
White ethnicity	29	0.97	0	1

Note: The table shows important demographic characteristics of recruited cattle producers and Ag Business students. Our dataset misses the demographic details of three producers.

ance. Hill (2015) shows the adoption rate of LRP insurance tools is 7% among US cattle producers. Therefore, our producer sample is reasonably representative of the US cattle producer population. Based on reported knowledge about the LRP insurance program, we can conclude that our sample has a moderate level (3 out of 7) of understanding of this risk management tool.

As Table 1 Panel B displays, the demographic features of our student participants are also homogeneous. An average student is a 22-year-old white male. Table 2 displays the relative comparison of reported risk preferences of the producer and student samples.[5] Students exhibit a statistically higher risk tolerance level in a general decision-making domain compared to cattle producers. However, these two samples report statistically indistinguishable financial risk preferences.

[5]We used stated risk preference measures. Falk et al. (2022) show that survey risk measures can efficiently measure risk preferences.

Table 2: Reported Risk Preferences of Study Participants

	N	Producers	Students	P-value
General Risk	95	5.3 (2.8)	6.5 (2.2)	0.06
Financial Risk	95	4.9 (2.7)	4.7 (2.3)	0.49

Note: The table shows the comparison of risk preferences of producer and student study participants. We use data from a survey question asking to report individual risk tolerance in general and financial risks. The survey question was worded as follows: “What is your willingness to take risks in the following activities, with 0 indicating 'not at all willing to take risks' and 10 indicating 'very willing to take risks'?" Mean (std. dev) and Wilcoxon test p-values are reported.

3.1 Experimental Procedures and Design

Producers: The study started with recruited participants reading the IRB-approved informed consent form describing the general rules and procedures of the experiment. Consenting producers proceeded to the instructions explaining study incentives, mechanisms, and payoff rules.[6] Participants were compensated with $10.00 for their time in the experiment, conditional on following and completing all the study protocols.[7] Participants were also informed they would have an opportunity to earn additional funds depending on their decisions and luck. The average earning from the lab-in-the-field study was $14.72 per respondent, with the maximum payoff being $26.00.

In the main stage of the study, participants made 20 insurance purchase decisions.[8] Before starting the decision stage, participants proceeded through the information screens detailing their decision context. The decision context described a typical case where a cattle producer is selling steer calves weighing an average of 650 pounds. The break-even price was determined to be $162.7 per cwt. Then participants were introduced to the LRP insurance policy that offered different coverage levels, guaranteed price minimums, and policy premium costs. Premium costs were set based on

[6] Only one producer stopped their participation at this stage of the study.

[7] On average, participants spent around 30 minutes completing the study.

[8] The half of producers and all students were shown a short instructional video after the first ten insurance decision periods. The video was narrated by one of the authors and summarized insurance decision instructions. Our intention was to mimic a typical extension education module. However, we did not detect any effect of this intervention. Therefore, we do not focus on this intervention in our results.

Table 3: Cattle Price Insurance Study Design Features

Price Probability Distribution Panel A		**Price Insurance** Panel B			
Prices	Probabilities	Coverage Level	Guaranteed Price	Premium Cost	Expected Marginal Net Price
$180	5%	100 %	$171.00	$5.40	$3.35
$171	50%	95 %	$162.45	$3.05	$1.85
$161	10%	90 %	$153.90	$1.77	$0.00
$151	10%	0 %	$0.00	$0.00	–$4.30
$141	10%				
$131	10%				
$110	5%				

Note: This table reports important design features of the LRP study. Panel A shows the price distribution and associated probabilities for each decision period. Panel B depicts LRP insurance coverages, expected marginal net price for each coverage level per period, and the premium cost.

historical LRP prices for various coverage levels.[9] The instructions also informed the participants that they would make 20 independent insurance purchase decisions. In each decision, the market price would be determined from a random realization of the given price distribution. We followed Hartzmark et al. (2021) and pre-realized a market price sequence from the specified distribution before the study.[10] Thus, all study participants proceeded with the same market price sequence. This allowed us to utilize between-subject comparisons in our data. Table 3 Panel A shows the presented market price distribution with associated probabilities. The additional payoff from the study was *Net Price* from a randomly selected binding decision, and it was calculated based on the formula as follows:

Net Price = Actual Market Price + LRP Indemnity – LRP Premium – Breakeven Price.

[9] It is worth it to reiterate that our study does not aim to recreate all potential LRP policy insurance tools and market consequences. We build on the LRP program but abstract away many details. Therefore, our study design captures the fundamental behavioral dynamics of insurance adoption decisions, and also offers a test-bed for understanding stylized decision patterns in the LRP program.

[10] Using randomly pre-determined price and incentive paths is a frequently used convention in experimental studies. For instance, see Fischbacher et al. (2017).

Table 4: Designed Price Insurance Prospects

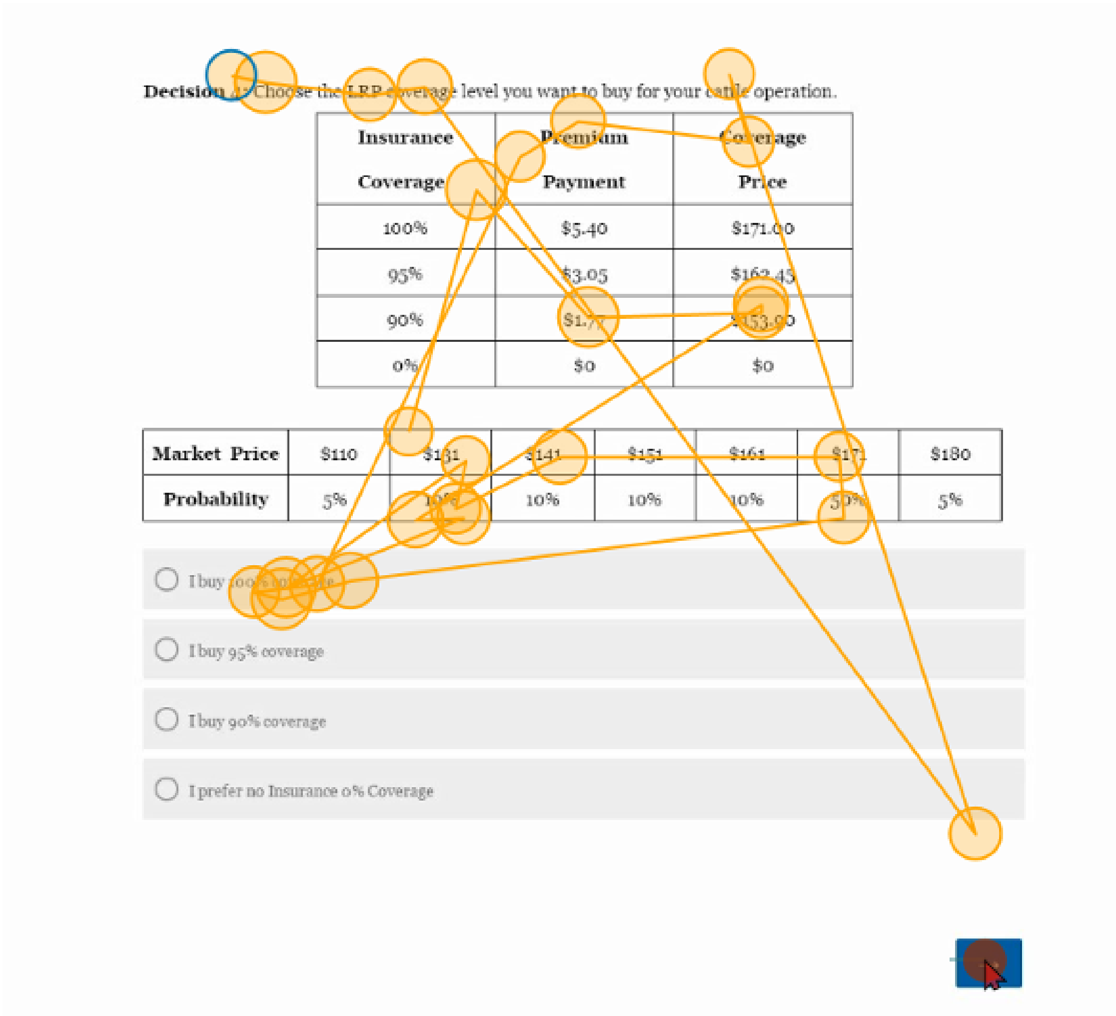
Coverage Level	$\triangle_1$ (π_1)	$\triangle_2$ (π_2)	$\triangle_3$ (π_3)	$\triangle_4$ (π_4)	$\triangle_5$ (π_5)	$\triangle_6$ (π_6)	$\triangle_7$ (π_7)	Expected Net Price	Std. Dev.
100 %	\$11.90 (5%)	\$2.90 (95%)						\$3.35	1.96
95 %	\$14.25 (5%)	\$5.25 (50%)	-\$3.30 (45%)					\$1.85	5.04
90 %	\$15.53 (5%)	\$6.53 (50%)	-\$3.47 (10%)	-\$10.57 (35%)				\$0.00	8.58
0 %	\$17.30 (5%)	\$8.30 (50%)	-\$1.70 (10%)	-\$11.70 (10%)	-\$21.70 (10%)	-\$31.70 (10%)	-\$52.70 (5%)	-\$4.30	18.20

Note: This table shows how each coverage level is translated into uncertain prospects. Prices are based on per cwt values.

Table 3 Panel B provides the details of each insurance coverage level, its guaranteed minimum price, premium cost, and expected net price. Figure 1 displays a decision screen from the insurance purchase decision stage of the study. For instance, buying the 90% coverage level provided the \$162.45 per cwt guaranteed price in exchange for \$3.05 per cwt premium cost. This insurance coverage yielded an indemnity payment if and only if the realized market price was lower than \$162.45 per cwt.

Buying the 100% coverage level had a \$3.35 per cwt expected marginal net price considering the market price distribution. The 90% coverage level had zero expected net price, meaning this was the break-even coverage level. Participants were not provided with the expected marginal net price information. Thus, our design is tuned to map a typical insurance purchase decision where producers have access to historical data and expected market price distribution.

Table 4 provides further details about our study design. Each price insurance coverage level can be transformed into uncertain prospects. For instance, the price insurance with 100% coverage level can be described as a lottery with two possible outcomes: \$11.90 (5%) and \$2.90 (95%) per cwt. The expected mean of this uncertain prospect is \$3.35 per cwt with a 1.96-standard-deviation. This is the safest lottery in our design. The 95% coverage level has a lower expected mean with a higher standard deviation. However, this insurance alternative also offers \$14.25 per cwt with a 5% probability.



This figure shows an exhibit from a decision stage (Decision 4) for one participant. The employed eye-tracking technology allows us to measure fixation points (represented with circles) and fixation times with a millisecond precision accuracy.

Figure 1: Screenshot from Decision Stage with Eye-Tracking (Producer Sample)

In comparison, the maximum possible payoff from the 100% insurance coverage level is $11.90 per cwt. Therefore, the 95% coverage level has a lower expected net price than the 100% coverage, but it also has a higher risk exposure. Not purchasing coverage (0% coverage) is the riskiest lottery in the design, at the same time, it also offers $17.30 per cwt payoff with a 5% probability.[11]

Students: We followed the same study protocols and incentive levels in the lab study

[11]Study participants earned $0 net price if the binding period's net price was negative.

Table 5: Key Experimental Measures

Variable and Its Type	Description	Range
Task: Integer	A trend that shows the decision period. This variable helps capture the potential learning effect	[1,20]
High-Price Dummy: Binary variable	Takes one (1) if the realized market price is $171 or $180	[0,1]
Net Price: Continuous	Shows the magnitude of net prices earned in insurance decisions	[-17.20,52.70]
Indemnity: Non-negative and Continuous	Shows the magnitude of indemnity payments in insurance decisions	[0,61]
High-Price Salient: Binary	It was constructed by finding the proportion of the fixation time on high prices ($171 and $180) relative to all prices for each study participant in the producer sample. The dummy variable was obtained by splitting the sample by the median point. This binary measure is one, if a participant fixation relatively more on the high-prices across all 20 periods. The Low-Price Salient dummy is the opposite of this measure.	[0,1]

with students. The average study earning was $12.86, with the maximum payoff being $22.00. Per IRB requirements, we also offered students an alternative non-experimental classwork. Only two students opted out of the study and completed the alternative assignment. The study with students was conducted without eye-tracking.

Table 5 describes key experimental measures. The eye-tracking technology and the fixation time measure are described in the Appendix.

4 Motivational Behavioral Model

Individual i chooses insurance coverage level $z \in \{1, 2, 3, 4\}$ at period $t-1$, maximizing the expected net price $\mathbb{E}[NetPrice_{i,z,t}]$ for period t. Each insurance coverage level has a different mean ($\mu_{z,t}$) and risk-premium ($\sigma_{z,t}$), such that:

$$\mu_{1,t} < \mu_{2,t} < \mu_{3,t} < \mu_{4,t}.$$

$$\sigma_{1,t} > \sigma_{2,t} > \sigma_{3,t} > \sigma_{4,t}.$$

The insurance coverage level $z = 1$ offers the lowest expected mean but also the highest risk premium. In contrast, the coverage level $z = 4$ has the highest expected mean with minimal risk exposure. A very risk-averse decision-maker will choose the coverage level $z = 4$, as it is the "safest" alternative. However, we hypothesized that a risk-loving decision-maker will choose $z = 1$ as this coverage level offers the highest risk exposure. The cost of each coverage level is inversely correlated with its risk exposure: $C_{1,t} < C_{2,t} < C_{3,t} < C_{4,t}$.

The expected net price is a function of the expected market price $\tilde{p}$ that is realized at period t from the known distribution F ($\tilde{p} \sim F$). For individual i, the expected net price from the coverage level z at period t is determined as follows:

$$\mathbb{E}[NetPrice_{i,z,t}] = \mathbb{E}[\tilde{p}_{i,z,t}] + I_{\mathbb{E}[\tilde{p}_{i,z,t}]<\hat{p}_{z,t}} |\hat{p}_{z,t} - \mathbb{E}[\tilde{p}_{i,z,t}]| - C_{z,t} - C_0. \tag{1}$$

where $\tilde{p}_{i,z,t} = g(\lambda_i, k_i\tilde{p}_{i,z,t-1}, \gamma_i\sigma_{z,t})$, the expected market price at period t, is a function of salience ($\lambda_i \in \{0, 1\}$), the previous period's market price ($\tilde{p}_{i,z,t-1}; k_i \in R$), and the attitude toward risk premium ($\gamma_i\sigma_{z,t}; \gamma_i \in R$).[12]

The salience parameter captures if the decision-maker chooses the insurance coverage when high prices are salient ($\lambda_i = 1$). Put differently, the salience parameter is one (1) if the decision-maker thinks about high prices and believes that they will get a higher price level at period t:

$$\mathbb{E}[\tilde{p}_{i,z,t}(\lambda_i = 1, k_i\tilde{p}_{i,z,t-1}, \gamma_i\sigma_{z,t})] > \mathbb{E}[\tilde{p}_{-i,z,t}(\lambda_{-i} = 0, k_{-i}\tilde{p}_{-i,z,t-1}, \gamma_{-i}\sigma_{z,t})].$$

The factor $k_i(k_i \in R)$ determines how much importance the decision-maker i assigns to the previous period's market price:

Case I: $k_i > 0$; In this case, if the decision-maker experiences a high price level at period $t-1$, they also expect a high price at period t. A larger $|k_i|$ value indicates a higher correlation between the experience at period $t-1$ and the price expectation for the period t.

[12] C_0 is a certain fixed cost and incurs independently of the chosen insurance coverage level.

Case II: $k_i = 0$; In this case, the decision-maker does not factor in their experience from the last period $t-1$ when forming price expectations for the period t.

Case III: $k_i < 0$; In this case, if the decision-maker experiences a high price level at period $t-1$, they expect a low price at period t. A larger $|k_i|$ value indicates a higher correlation between the experience at period $t-1$ and the price expectation for the period t.

The term $\sigma_{z,t}$ represents the associated risk-premium for each insurance coverage level. The parameter γ_i determines how the decision-maker i considers the risk-premium. For cases when $\gamma_i > 0$ ($\gamma_i < 0$), the decision-maker i expects a higher (lower) net price level by taking a higher risk. In its turn, $\gamma_i = 0$ indicates the decision-maker does not account for the risk exposure when buying an insurance coverage level.

4.1 Connecting Model to Experimental Design

In our study, participants receive feedback after each period and make an insurance purchase decision for the next period for a total of 20 times. The insurance coverage level $z = 1$ coincides with not-buying insurance and preferring the highest risk exposure in our study. Coverage levels $2, 3,$ and 4 represent the insurance coverage of $90\%, 95\%$, and 100%, respectively.

The realized market price $\tilde{p}$ is randomly drawn from the known distribution described in Table 3 Panel A. Since the market prices are independent, a participant should not factor the previous period's market price in their decision for the next period. Therefore, $k = 0$ for a bias-free decision-maker.

Remark 1: The recency bias emerges when $k_i \neq 0$. When $k_i > 0$, the decision-maker over-extrapolates from the recent experience. They expect a higher price level for period t, when a high price is experienced in period $t-1$.

Remark 2: A decision bias stems from the salience of high prices when $\lambda_i = 1$. The salience of high prices biases price expectations upward. Contrarily, the decision-maker does not have this bias when $\lambda_i = 0$.

Remark 3: A decision-maker will prefer the insurance coverage level $z = 1$ when they are not risk-averse. In that case, $\gamma_i > 0$ will lead to high price expectations.

4.2 Hypotheses

If individual i is less risk-averse than individual j ($\gamma_i > \gamma_j$), then, all else equal, individual i will have a higher price expectation level for period t compared to individual j:

$$\mathbb{E}[\tilde{p}_{i,z,t}(\overline{\lambda}, \overline{k}, \overline{p}_{z,t-1}, \gamma_i \sigma_{z,t})] > \mathbb{E}[\tilde{p}_{j,z,t}(\overline{\lambda}, \overline{k}, \overline{p}_{z,t-1}, \gamma_j \sigma_{z,t})].$$

Therefore, all else equal, individual i will be more likely to prefer the insurance coverage level $z = 1$.

Hypothesis 1: A lower degree of risk-aversion will lead to a higher probability of choosing the insurance coverage level $z = 1$: $Pr_i(z = 1|\gamma_i, \overline{\lambda}, \overline{k}, \overline{p}_{z,t-1}) > Pr_j(z = 1|\gamma_j, \overline{\lambda}, \overline{k}, \overline{p}_{z,t-1})$

Corollary 1: A lower degree of risk-aversion will also lead to a higher probability of choosing lower coverage levels. For instance, all else equal, individual i will be more (less) likely to prefer the insurance coverage level $z = 2$ ($z = 4$) than individual j when $\gamma_i > \gamma_j$.

Hypothesis 2: All else equal, individual i with a high-price-salience bias $\lambda_i = 1$, will be less likely to buy insurance compared to individual j with $\lambda_j = 0$: $Pr_i(z = 1|\overline{\gamma}, \lambda_i = 1, \overline{k}, \overline{p}_{z,t-1}) > Pr_j(z = 1|\overline{\gamma}, \lambda_i = 0, \overline{k}, \overline{p}_{z,t-1})$

Hypothesis 3: All else equal, individual i with a recent high-price experience bias $k_i > 0$ will be less likely to buy insurance compared to individual j with $k_i = 0$: $Pr_i(z = 1|\overline{\gamma}, \overline{\lambda}, k_i, \overline{p}_{z,t-1}) > Pr_j(z = 1|\overline{\gamma}, \overline{\lambda}, k_j, \overline{p}_{z,t-1})$

Corollary 2: Based on Hypotheses 2 and 3, we can conjecture that a higher price salience and/or degree of recency bias will lead to more frequent purchases of lower insurance coverage levels compared to higher coverage levels.

5 Results

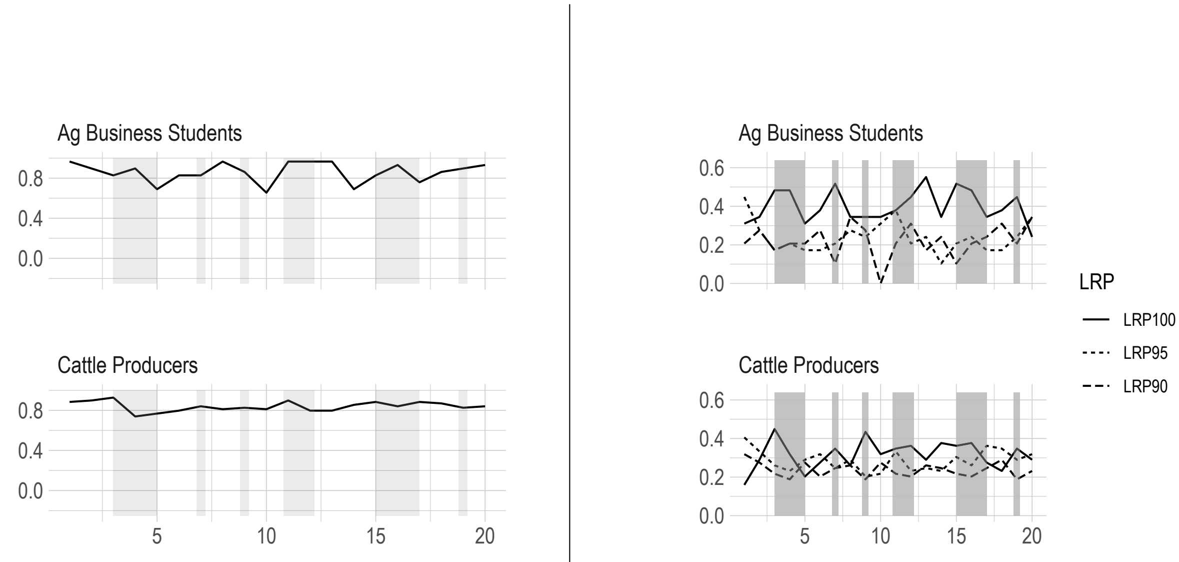
5.1 Preamble Findings A:

Both student and producer samples show statistically indistinguishable patterns in 0%, 90%, and 95% insurance coverage purchases. However, the student sample is more likely to purchase the 100% price coverage.

We start discussing our results by investigating the insurance purchase decisions of study participants. In this regard, the choice of price coverage levels in the first period presents a crucial insight into the pre-study preferences of participants. The proportion of subjects who bought a non-zero coverage level is 96% and 88% in the student and producer samples, respectively. A two-sided proportion test reveals that, although the proportion of non-zero insurance purchases is eight percentage points larger in the student sample compared to producers, this difference is not statistically significant.

Figure 2 Panel A shows the proportion of non-zero insurance coverage purchases in student and producer samples across all decision periods. We observe that the mean of insurance purchases is around 86% in both groups, but the student sample shows sharper changes around the mean compared to producers. However, the comparison of the sample means of proportions (clustered at the subject level) of non-zero purchase decisions across 20 periods shows that, overall, student and producer samples exhibit similar patterns ($(Wilcoxon, z-score = 0.43, p = 0.33)$).

Figure 2 Panel B shows the dynamics of 90%, 95%, and 100% price coverage purchases across the 20 decision periods. We observe that the student sample demonstrates a higher proportion of 100% coverage purchases across all decision periods than the producer group. The conducted Wilcoxon tests assert this observation as the overall mean of 100% coverage purchases (i.e., proportions clustered at the subject level) are statistically different between student and producer samples $(Wilcoxon, z-score = 1.61, p = 0.05)$. In contrast, both groups have the same sample means for 90% and 95% coverage purchases. We conclude that there are no statistically detectable group differ-



[A] [B]

Panel A shows sample means of insurance purchases across periods for producer and student samples. The figures show the proportion of participants who bought any non-zero insurance coverage level across periods. **Panel B** displays the dynamics of average insurance coverage purchases. Shaded periods indicate high-price periods in both panels.

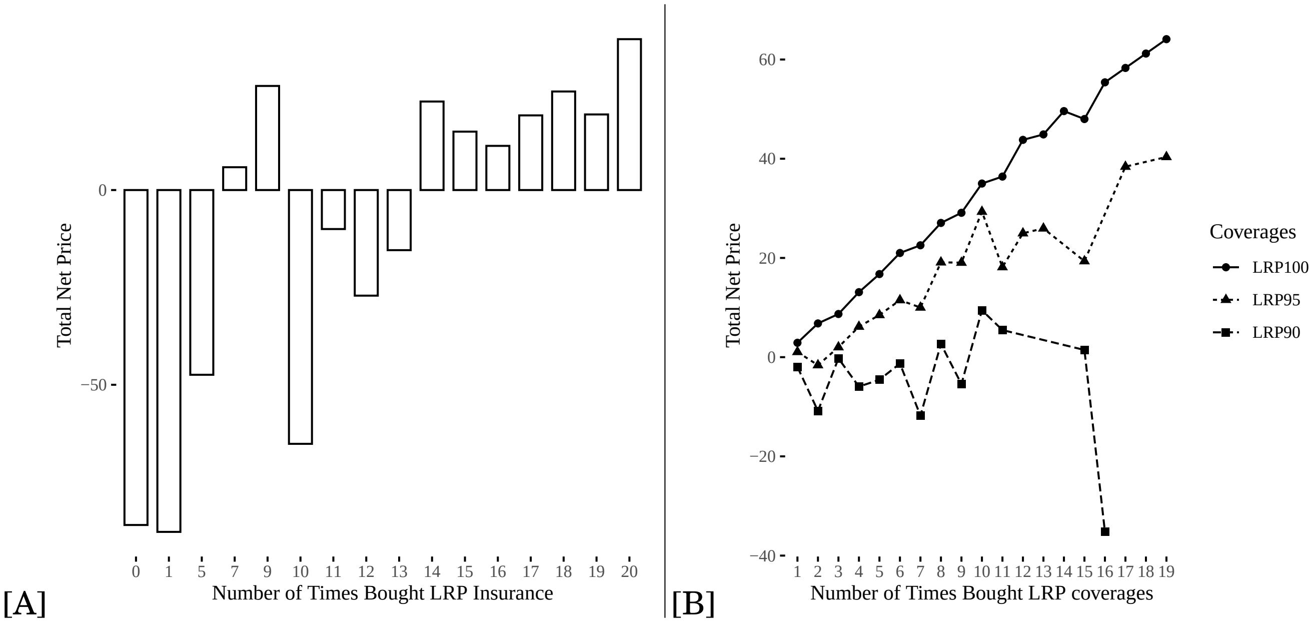
Figure 2: Dynamics of the Price Insurance purchases

ences in terms of purchasing 0%, 90%, and 95% insurance coverages between student and producer samples. However, the student sample is more likely to purchase the 100% coverage compared to producers.

5.2 Preamble Findings B:

Persistent non-zero coverage purchases yield a higher cumulative net price. The 100% coverage level returns a higher cumulative net price value compared to the 95% and 90% coverages. However, producers and students statistically have the same average earning levels.

Figure 3 Panel A displays the relationship between cumulative net price (clustered at the subject level) and the number of non-zero insurance coverage purchases. We observe a positive relationship between persistent non-zero coverage purchases and the cumulative net price. Figure 3 Panel B breaks down total net price earnings over



Panel A shows how average net prices change across the number of periods subjects purchased the insurance. Panel B depicts the relationship between average net prices and specific insurance coverage purchases.

Figure 3: Price Insurance Purchases and Total Net Price

each individual coverage level. It is noteworthy that persistent purchases of the 90% coverage level do not guarantee positive total net prices. However, the 95% and 100% coverage level purchases yield a higher level of total net price. Study participants who persistently purchased the 100% coverage level ended up receiving higher net prices compared to subjects preferring other coverage levels.

Our next query focuses on the average net price earned by the student and producer samples. Our Wilcoxon test results reveal that the average net returns of producers and students are not different $(Wilcoxon, z - score = 0.15, p = 0.55)$.

5.3 Finding 1:

Risk preferences do not affect insurance coverage purchases. The average decision is buying the 95% coverage level both in student and producer samples.

Table 6 shows regression analyses investigating the determinants of any non-zero LRP coverage level purchases. The first six columns test different model specifications via the step-wise inclusion of key experimental measures when the dependent variable is a binary indicator for any non-zero price coverage purchases. In Models 1-6, the Cattle Producer dummy is not significant. This result overlaps with our previous discussion and re-iterates that producer and student samples exhibit the same non-zero price insurance coverage purchasing patterns. The Task variable captures a learning effect, if any. The outcomes of regression analyses show there is no *trend* in purchase decisions from the first to the last decision period. We also find that risk preferences do not affect price insurance decisions as the Financial Risk Tolerance measure is not statistically different than zero in Model 6. Therefore, we cannot validate Hypothesis 1 with our findings.

Table 7 conducts similar analyses with a different dependent variable. The dependent variable is 1,2,3, and 4 for 0%, 90%, 95%, and 100% coverage levels, respectively. The core purpose of investigations in Table 7 is to understand how key experimental measures affect specific non-zero price coverage levels. The first column of Table 7 displays that risk preferences do not affect price coverage level purchases. As the regression constant shows, the mean decision is buying the 95% coverage in the entire sample. However, none of the tested measures has a significant impact on the dependent variable. Thus, based on our results, we also do not validate Corollary 1

5.4 Finding 2:

Price salience only affects non-zero price purchases after a high market price period. The average purchased insurance coverage level is 95% and 0% for low- and high-price salient producers, respectively.

Table 8 presents a set of regression analyses investigating the impact of Low Price Salience on non-zero insurance coverage purchases with a binary dependent variable. We focus on the producer sample since we only employed the eye-tracking technology in the lab-in-the-field study. The first four columns of Table 8 test different model specifications. The results show that price salience does not directly affect insurance purchases. Nevertheless, price salience exhibits an impact on insurance decisions af-

Table 6: Determinants of Insurance Purchases

	Dependent variable:Buy-Insurance Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cattle Producers	−0.02	−0.02	−0.02	0.02	0.02	0.02	−0.06	−0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Task		0.0004	0.002	0.002	0.003^{**}	0.003^{**}	0.004^{***}	0.001
		(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
High-Price Dummy (1st lag)			-0.04^{**}	0.01	0.01	0.01		
			(0.02)	(0.02)	(0.03)	(0.03)		
Cattle Producers*High-Price Dummy (1st lag)				-0.07^{**}	-0.07^{*}	-0.07^{*}		
				(0.03)	(0.03)	(0.04)		
High-Price Dummy (2nd lag)					−0.02	−0.02		
					(0.01)	(0.01)		
Financial Risk Tolerance						−0.01		
						(0.01)		
Indemnity (1st lag)							0.0000	
							(0.001)	
Cattle Producers*Indemnity (1st lag)							0.005^{***}	
							(0.001)	
Net price (1st lag)								0.0004
								(0.001)
Cattle Producers*Net price (1st lag)								0.0003
								(0.002)
Constant	0.86^{***}	0.86^{***}	0.85^{***}	0.83^{***}	0.82^{***}	0.86^{***}	0.81^{***}	0.84^{***}
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)
R-sqd	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.00
N	1960	1960	1862	1862	1764	1746	1862	1862

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

This table reports the results of OLS regression analyses. Robust standard errors are clustered at the participant level.

ter a period with high market prices. Decision-makers showing low-price salience behavior buy non-zero insurance coverage by eight percentage points less after a period with high market prices.

Table 7 Columns 3 and 4 present a similar analysis when the dependent variable is coded to represent each insurance coverage level: 1 (0%), 2 (90%), 3 (95%), and 4 (100%). The constant of Column 3 shows that the average purchased insurance coverage level is 95% when producers relatively over-fixate on low prices (low-price salience) of the market price distribution. In contrast, on average, producers with

Table 7: Regression Analyses of non-zero LRP Coverage Purchases

	Dependent variable: Insurance Coverage Levels			
	All	Producers	Producers Low-Price Salient	Producers High-Price Salient
Cattle Producers	−0.05 (0.13)			
High-Price Dummy (1st lag)	−0.06 (0.08)	-0.21^{***} (0.06)	−0.09 (0.08)	-0.10^{***} (0.03)
Task	0.004 (0.004)	0.01 (0.01)	0.003 (0.01)	0.005^{*} (0.003)
Financial Risk Tolerance	−0.03 (0.02)	−0.02 (0.03)		
Cattle Producers * High-Price Dummy (1st lag)	−0.15 (0.09)			
Constant	3.04^{***} (0.17)	2.93^{***} (0.17)	2.84^{***} (0.16)	0.82^{***} (0.05)
R-sqd	0.02	0.01	0.00	0.02
N	1843	1292	589	722

Robust standard errors are clustered at the participant level. *p<0.1; **p<0.05; ***p<0.01

high-price salience behavior buy the 0% coverage level.

We conclude that price salience does not directly affect non-zero coverage purchases but only changes the purchased coverage level after a market period with a high price experience. Therefore, our findings partially validate Corollary 2 but cannot substantiate Hypothesis 2.

5.5 Finding 3:

Experiencing a high price in the previous period decreases insurance purchase probability and also the likelihood of choosing higher coverage levels. But this effect is only detected in the producer sample. High-Price salience mediates the impact of this effect.

Table 6 Columns 3, 4, and 5 investigate the relationship between a high-price experience in the previous decision period on the current period's non-zero insurance coverage level choice. Although Column 3 shows a significant impact of *High-Price* dummy

Table 8: Salience and Insurance Purchases: Regression Analyses with Eye-Tracking Data

	Dependent variable:Buy-Insurance Dummy					
	All Producers	All Producers	All Producers	All Producers	Low-Price Salient Producers	High-Price Salient Producers
Low-Price Salient (Dummy)	0.05 (0.06)	0.05 (0.06)	0.05 (0.06)	0.003 (0.06)		
Task		0.0004 (0.001)	0.002 (0.002)	0.002 (0.002)	-0.001 (0.002)	0.005^{*} (0.003)
High-Price Dummy (1st lag)			-0.06^{***} (0.02)	-0.10^{***} (0.03)	-0.01 (0.03)	-0.10^{***} (0.03)
Low-Price Salient (Dummy)* High-Price Dummy (1st lag)				0.08^{**} (0.04)		
Constant	0.82^{***} (0.04)	0.81^{***} (0.04)	0.83^{***} (0.04)	0.85^{***} (0.04)	0.88^{***} (0.05)	0.82^{***} (0.05)
R-sqd	0.00	0.00	0.01	0.01	0.00	0.02
N	1380	1380	1311	1311	589	722

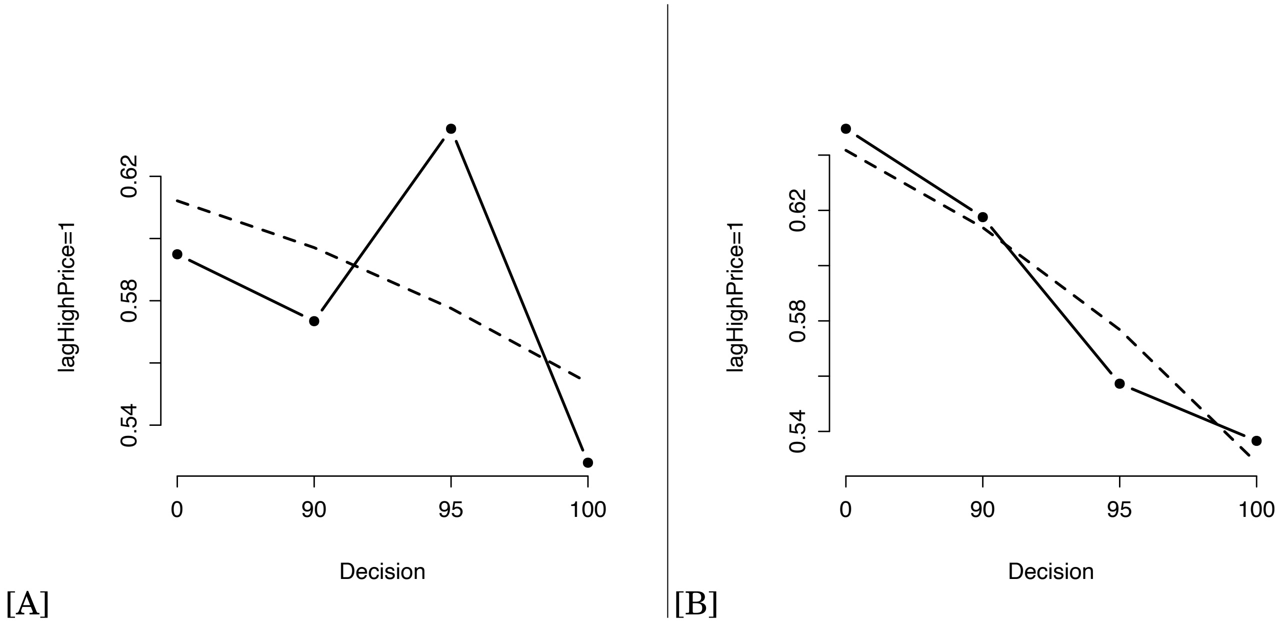
*p<0.1; **p<0.05; ***p<0.01

Standard errors are clustered at the participant level.

on the binary variable indicating a non-zero purchase decision, this effect disappears with the inclusion of other model variables. However, the effect of the high-price lag on insurance purchase is significant through the producer sample dummy. The sign of this effect is negative confirming Hypothesis 3. Overall, the results show that experiencing a high price in the previous decision period reduced the likelihood of buying insurance, and this effect is only observed in the producer sample.

Table 8 fifth and sixth columns show that the High-Price dummy is only significant and negative for producers who show High-Price Salience behavior, suggesting an association between salience and this effect. Table 7 provides evidence that the High-Price dummy is only significant for the producer sample in choosing a specific non-zero price coverage level. The last two columns of Table 7 reiterate that this effect is only statistically significant and negative for High-Price Salient producers.

We also conduct a multinomial logit regression analysis to investigate how the high-price dummy and high-price salience change specific insurance purchase probabilities. Figure 4 shows fitted insurance purchase probabilities after experiencing a



This figure shows fitted probabilities of insurance coverage purchases after a period with a high price. Panel A shows how relative purchase probabilities vary after a high-price period for participants who exhibit low-price salience behavior. Panel B shows the results of the same analysis for participants who exhibit high-price salience behavior.

Figure 4: Insurance Coverage Purchase Probabilities for Low- and High-Price Salient Participants

high price in the previous decision period for the low- and high-price salience samples. Figure 4 Panel A shows that producers showing low-price salience behavior are more likely to purchase the 90% coverage level after experiencing a high price in the last period. However, producers exhibiting high-price salience are more likely to not purchase insurance and not buy this insurance after a decision period with a high-price experience. Wilcoxon test results show that both high- and low-price salient producers possess not statistically different financial risk preferences $(Wilcoxon, z - score = 0.12, p = 0.55)$.

We conclude that a high-price experience only reduces the likelihood of insurance purchases for the producers, and this effect is mediated by high-price salience. Thus, we validate Hypothesis 3 and Corollary 3 for producers.

5.6 Post-hoc Findings

Table 6, Columns 7 and 8 investigate how the last decision period's indemnity payments and net price earnings affect non-zero price insurance purchases. We only detect a significant effect for the indemnity payments. A one-dollar increase in the last period's indemnity payment increases the insurance purchase probability by 1%. We do not detect any effect of the net price earning lag variable on insurance purchase decisions.

6 Discussion

Our study results reveal appealing differences between learning-by-studying and learning-by-doing behaviors. Although students and producers show similar patterns in their insurance coverage level choices, the producer sample is more susceptible to salience and recency bias. Bordalo et al. (2022) discuss that bottom-up salience (i.e., attention and salience without any goal) can function through *prominence*. In this context, prominence can stem from previous experiences. Thus, based on the behavioral framework of Bordalo et al. (2022), it is predictable that producers—who always seek high prices to make a living—will differently react to high prices compared to students. Huseynov et al. (2022) also show that producers might hold unreasonably high price expectations due to *optimism bias*. It is also possible that optimism bias is operational in our study, and optimistic producers tend to over-fixate on favorable prices leading to a reduction in the demand for cattle price insurance.

We also show that only producers react to the recent indemnity payout experiences. This finding is aligned with the results of Cai et al. (2020), as they show that farmers increase their insurance purchases after receiving indemnity payments. Michel-Kerjan and Kousky (2010) provide evidence that after a storm and flood, the demand for flood insurance policies goes up. These findings match recency bias which predicts that agents assign a higher weight to recent events in concluding decisions. Thus, our findings highlight the importance of considering knowledge and experience when investigating the demand for risk mitigation tools. This assertion also hints that improving the risk management practices of producers can be achieved by neutralizing recency bias.

The proportion of non-zero cattle price coverage choices is around 85% both in producer and student samples. This experimental result does not align with real-life LRP take-up rates among US cattle producers. One possible explanation for the continued limited adoption of LRP is that the policy choice structure is more complex compared to our study design. Per the LRP program, producers can purchase LRP daily for ten different insurance periods, and the coverage level is a continuous range between 70-100%. The combination of different coverage levels and insurance periods results in a lot of options for producers to choose from when purchasing LRP, which could be a choice overload issue. Choice overload is commonly defined as consumers making the wrong choice because they had an excessive number of unique choices to make (Chernev et al., 2015; Scheibehenne et al., 2010). A similar issue has been noted by Davidson and Goodrich (2021) for the pasture, rangeland, and forage insurance policy.

In our study, eye-tracking technology was utilized to understand how different fixation patterns on previous period outcomes impact their decision-making process in the current period. The results provide a foundation for future educational needs to producers in managing price risk and could have implications for policy adjustments in the future. This also extends the literature on how eye tracking can be used in understanding decision-making by producers.

7 Conclusion

This paper offers a detailed investigation of the role of “decisions from experience” and “decisions from incentives” in insurance take-up decisions. Conducting incentivized experimental studies with cattle producers and Ag Business students allows us to compare economic agents with formal education but without real-life experience to decision-makers with hands-on experience. Our experimental study protocols are tuned to measure both the extensive and intensive margins of cattle price insurance demand decisions, which were modeled after LRP. We leverage the eye-tracking technology in the laboratory-in-the-field setting with producers and offer behavioral mechanisms to explain the differential behavioral patterns of cattle producers.

Our findings bring a new angle into our understanding of how professional agents decide to employ risk mitigation tools in their market activities. We also show that the "decisions from experience" effect can reduce the insurance demand among producers. Producers and students show similar decisions at the extensive margin of insurance demand. However, on the intensive margin, Ag Business students are more likely to buy the 100 % coverage level, suggesting that producers are more likely to take a higher risk at the intensive margin. Recent experience and learning are crucial factors for insurance take-up decisions.

Eye-tracking technology reveals that producers are not demonstrating homogenous insurance choice decisions. The high-price (low-price) salient producer type overweighs high-value (low-value) outcomes of uncertain events. We show a robust association between high-price salience and recency bias. This finding suggests that cattle producers focusing on more favorable outcomes of probable future events are more likely to operate on short memory and reduce their insurance demand after seeing high prices. Put differently, producers tend not to buy the price insurance after good seasons, and this effect is associated with over-weighing favorable outcomes of uncertain prospects. We discuss that this result can be explained by *prominence* (i.e., agents always seek favorable information based on their past experiences) and *optimism bias* (i.e., always holding high price expectations) effects.

Our results suggest that identifying producer types and fine-tuning Extension education programming to address their biases can increase the demand for insurance. We also discuss that the current LRP program might overwhelm producers by offering a very complex decision environment. In our study, the average insurance take-up rates are around 85% both in producer and student samples. This take-up rate is higher than the observed market demand for the tools. Our study design presents a price insurance product for cattle producers, similar to LRP, in a less-crowded format reducing potential cognitive burden, and it might explain why producers are more inclined to buy any non-zero price coverage level in our study compared to real-life.

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Appendix

Robustness Check for Table 6

Table A1 presents a robustness analysis of our results presented in Table 6. We employ a panel probit model to investigate the determinants of any non-zero LRP insurance coverage level choices (i.e., the extensive margin of insurance take-up decisions). The results of Table A1 and Table 6 overlap. Using the panel probit regression estimation approach, we find that only producers are less likely to buy the LRP insurance after high-price decision periods. We also confirm that, unlike students, producers factor in indemnity payments in their insurance coverage level choices. An increase in indemnity payments also increases insurance purchase decisions.

The only difference between the results of Table 6 and Table A1 is the effect of risk preferences on the probability of insurance purchases. We detect a negative effect of the risk-tolerance variable on the extensive margin of insurance decisions in Table A1 when we use the panel probit estimation approach. It suggests that producers with a higher risk tolerance level are less likely to purchase any non-zero LRP insurance coverage level. However, this result has a moderate statistical significance. We conclude that Table A1 presents suggestive evidence about the negative relationship between risk tolerance and insurance purchase probability.

Table A1: Determinants of Insurance Purchases

	Dependent variable:Buy-Insurance Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cattle Producers	0.08	0.08	0.12	0.39	0.34	0.33	−0.05	0.14
	(0.25)	(0.25)	(0.26)	(0.29)	(0.30)	(0.30)	(0.26)	(0.27)
Task		0.003	0.01	0.01	0.02**	0.02**	0.02**	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High-Price Dummy (1st lag)			−0.24***	0.04	0.05	0.05		
			(0.09)	(0.15)	(0.16)	(0.16)		
Cattle Producers*High-Price Dummy (1st lag)				−0.44**	−0.43**	−0.44**		
				(0.18)	(0.19)	(0.19)		
High-Price Dummy (2nd lag)					−0.14	−0.14		
					(0.09)	(0.09)		
Financial Risk Tolerance						−0.08*		
						(0.05)		
Indemnity (1st lag)							−0.004	
							(0.005)	
Cattle Producers*Indemnity (1st lag)							0.03***	
							(0.01)	
Net price (1st lag)								−0.002
								(0.01)
Cattle Producers*Net price (1st lag)								−0.01
								(0.01)
								−0.01
								(0.01)
Observations	1,960	1,960	1,862	1,862	1,764	1,746	1,862	1,862
Log Likelihood	−669.89	−669.79	−636.06	−633.22	−607.72	−605.29	−628.36	−636.01
Akaike Inf. Crit.	1,345.79	1,347.58	1,282.12	1,278.44	1,229.43	1,226.57	1,268.71	1,284.01
Bayesian Inf. Crit.	1,362.53	1,369.90	1,309.77	1,311.61	1,267.76	1,270.29	1,301.89	1,317.19

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

This table reports panel probit regression results. Standard errors are clustered at the participant level.

Eye-Tracking Exhibits for Low-Price and High-Price Salient Producer Types

Figure A1 shows different eye fixation patterns using heatmaps over the provided price distribution information. The inspection of the presented heatmaps suggests that producers exhibit different fixation patterns over the price distribution information. In Figure A1 Panel A, eye fixations are more evenly distributed over potential price outcomes. However, in Panel B, fixations are mainly concentrated on high prices.

In a stylized fashion, Figure A1 exhibits how low-price and high-price salient producers show non-homogeneous attention to the potential outcomes of uncertain prospects. Our results demonstrate that these eye fixation differences are also associated with

[A] 

[B] 

Panel A and B show heatmap based on eye-tracking data from two different decision stages. Participants show different fixation patterns over the presented price distribution table.

Figure A1: LRP Insurance Purchases Decision Heatmaps

recency bias. Moreover, the average LRP insurance coverage choice is 0% and 95% for high-price and low-price salient producers, respectively. This suggests that salience can also be predictive of risk-taking behavior among producers in the marketplace.

Online Appendix

Thank you for participating in our study.

As part of the study, you will make 20 independent decisions related to Livestock Risk Protection (LRP) insurance. It means LRP decisions are unrealted to one another.

LRP decisions will also give you a chance to earn a bonus payoff. So, it is in your best interest to carefully consider each LRP decision.

You will receive **$10.00 guaranteed compensation** for participating in the study. You can also earn **up to a $17.00 bonus payoff depending on** your LRP decisions. You will receive rewards in cash today after the completion of the study.

This study will have three parts:
Part 1: 10 decisions related to LRP insurance.
Part 2: 10 decisions related to LRP insurance.
Part 3: Brief demographic survey.

Please click next to receive more information about LRP insurance decisions.

→

You are selling steer calves weighing an average of 650 pounds around December 15th, 2022. You have calculated that you need to sell these cattle for $162.7 per cwt to breakeven.

Livestock Risk Protection (LRP) is an insurance policy producers can buy to "lock in" a guaranteed price minimum. Below is an example of how this product works.

Currently, LRP policies that have an expected ending price for December 15, 2022 of $171/cwt for 650 pound feeder cattle. Looking at the table below, an LRP policy with 95% coverage could be purchased for $3.05/cwt. If the actual feeder cattle price is lower than the "coverage price" of $162.45 when the policy expires (December 15th), the LRP policy would pay an indemnity. The payment is the difference in the actual ending price and the coverage price. If the actual feeder cattle price was $161/cwt on December 15th, you'd receive a payment of $1.45/cwt ($162.45 - $161.00).

Insurance Coverage	Premium Payment	Coverage Price
100%	$5.40	$171.00
95%	$3.05	$162.45
90%	$1.77	$153.90

→

Starting next screen, you will be shown 20 price scenarios. In each price scenario, you will have to choose if you want to buy an LRP insurance plan. You will also have an opportunity to choose your LRP insurance coverage level if you decide to protect your cattle.

After finishing 20 decisions, we will randomly select one decision case, and your net price in that case will be your bonus payoff in addition to your participation reward. A negative net price is $0 bonus payoff.

Since each decision is independent, it is in your best interest to try to maximize your net price in LRP decision each case.

Your net price is calculated as:
Net Price = Actual market price + LRP Indemnity – LRP Premium – Breakeven Price

Remember LRP insurance Indemnity payment occurs if the Market Price is less than the Coverage Price. Remember your breakeven price is $162.7/cwt.

In each decision case, the market price will be randomly selected based on the shown probabilities below.

Market Price	$110	$131	$141	$151	$161	$171	$180
Probability	5%	10%	10%	10%	10%	50%	5%

→

Decision 4: Choose the LRP coverage level you want to buy for your cattle operation.

Insurance Coverage	Premium Payment	Coverage Price
100%	$5.40	$171.00
95%	$3.05	$162.45
90%	$1.77	$153.90
0%	$0	$0

Market Price	$110	$131	$141	$151	$161	$171	$180
Probability	5%	10%	10%	10%	10%	50%	5%

- [ ] I buy 100% coverage
- [x] I buy 95% coverage
- [ ] I buy 90% coverage
- [ ] I prefer no Insurance 0% Coverage

→

Random Market Price for this scenario is $171.

Since you preferred 95 percent coverage, the Coverage Price for your cattle operation is $162.45 for $3.05 premium payment.

You will receive $0.00 indemnity payment from LRP insurance.

Your net price is calculated as:

Net Price = Actual market price + LRP Indemnity – LRP Premium – Breakeven Price

Now Let's calculate your Net Price for this case:

Your Net Price= $171 + $0.00 - $3.05 - $162.7 = 5.25

Reminder: At the end of the study, if this decision is randomly selected, you will only receive a positive net price as a bonus payoff.

→

You have successfully completed the study!

Now the computer will randomly select one of the 20 LRP decisions you made, and the net price from the selected decision will be your bonus payoff.

Please click the next button to see your bonus payoff.

→

Random Market Price for this scenario is $131.

Since you preferred 95 percent coverage, the Coverage Price for your cattle operation is $162.45 for $3.05 premium payment.

You will receive $31.45 indemnity payment from LRP insurance.

Your net price is calculated as:
Net Price = Actual market price + LRP Indemnity – LRP Premium – Breakeven Price

Now Let's calculate your Net Price for this case:
Your Net Price= $131 + $31.45 - $3.05 - $162.7 = -3.30

Reminder: At the end of the study, if this decision is randomly selected, you will only receive a positive net price as a bonus payoff.

→

The computer randomly selected **Task 2**.

Your Net Price was **-10**. Therefore, your **bonus payoff is $0**. Your total payment from study is **$10**.

Please raise your hand and DO NOT click the next button.

→