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

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Can learning from recent events impair the quality of risk management decisions? We conduct incentivized experiments with agribusiness students and cattle producers to examine the role of real-life experience in demand for price insurance. Students and producers exhibit similar decisions at the extensive margin of risk-taking. However, on the intensive margin, students are more likely to opt for the most expensive insurance coverage than other alternatives. Using eye-tracking technology, we identify that cattle producers with high-price-salient behavior show recency bias and overextrapolate from recent high-price events, reducing their demand for insurance coverage.

Key words: expectation, eye tracking, learning, producers, risk

Introduction

When managing risk in the face of uncertain prospects, agents not only consider available incentives but also rely on accumulated knowledge from past experiences (Erev and Haruvy, 2013; Cai, De Janvry, and Sadoulet, 2020). However, the role of previously gained knowledge is often overlooked when mapping the determinants of insurance demand. This limitation occurs because "positive" insurance experiences (i.e., receiving indemnities) happen only after a negative shock, which is an infrequent event (Cai, De Janvry, and Sadoulet, 2020). Studies demonstrate that insurance decisions are influenced by previous payout experiences (Karlan et al., 2014; Cai, De Janvry, and Sadoulet, 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 more detailed 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 insurance in both developed and developing countries (Cole et al., 2013; Erev and Haruvy, 2013; Finkelstein, Hendren, and Luttmer, 2019).

This paper studies how accumulated real-life experiences, combined with recent and salient learning, impact demand for price insurance among cattle producers. Specifically, our focus is on the Livestock Risk Protection (LRP) insurance, one of the primary risk management tools to protect against unexpected price drops in the US beef cattle industry (Merritt et al., 2017). Beef cattle production is susceptible to economic losses from uncontrollable events like drought and

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diseases, but price volatility has historically been the primary cause of losses to US cattle producers (Hart, Babcock, and Hayes, 2001; Hall et al., 2003; Belasco et al., 2009; Tonsor and Schroeder, 2011). The LRP program, which was introduced in 2003, is an insurance policy 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.

While studies have shown that LRP policies are effective at protecting against price declines (Coelho, Mark, and Azzam, 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, Tonsor, and Schulz, 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 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). In 2019, the US Department of Agriculture (USDA) restructured the LRP program and expanded its coverage to 50 states (McKendree, Tonsor, and Schulz, 2021). Research shows that with enhanced subsidy components, LRP policies became very effective in stabilizing net prices with lower premium costs (Boyer and Griffith, 2022). However, the primary determinants of LRP enrollment decisions and the behavioral biases that reduce demand for this insurance remain unclear.

We conducted an incentivized laboratory study with agribusiness 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 agents with formal education but no real-life practice and a group of professionals possessing hands-on experience. We designed a study in which a random cattle price is determined from the known price distribution in each decision period. Study participants 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.

In each decision period, participants selected a cattle price coverage level (no coverage or 0%, 90%, 95%, and 100%) to buy for the guaranteed price of $171/ cwt.[1] 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 nonzero 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, the extent to which they reduce their uncertain prospects by choosing different coverage levels).

We 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.[2] 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.

Our analysis shows that, in terms of overall nonzero insurance coverage take-up decisions (i.e., the extensive margin), students and producers exhibit very similar behaviors across 20 decision periods. However, the student sample is more likely to buy the 100% coverage level compared to producers. We conclude that while producers and students show the same decision patterns on the extensive margin, they differ in terms of the intensive margin of insurance decisions.

[1] We use "guaranteed price" and "coverage price" interchangeably throughout the text.
[2] We use the term "safe" to describe uncertain prospects with nonnegative prices throughout the text.

Interestingly, producers are more likely to factor in their recent market experiences compared to students. We find that the effect of the recent learning is limited to only the first lag and does not include distant previous learning experiences. This finding suggests that professionals may operate with a very short-term working memory triggering *recency bias* (i.e., overweighing the information value of recent events).

We employ eye-tracking technology to uncover potential cognitive mechanisms behind producers' recency bias. We focus our investigation on attribute salience and how it can lead to higher levels of risk-taking behavior. The seminal work of Bordalo, Gennaioli, and Shleifer (2012) shows that salient payoffs can distort decision weights of uncertain prospects. With the help of eye-tracking technology, we measure producers' fixation times on insurance decision attributes. We construct a visual salience measure over 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 exhibit relatively higher visual attention to the upsides of uncertain prospects. Based on the prediction of Bordalo, Gennaioli, and Shleifer, high-price-salient producers should demonstrate relatively higher risk-seeking behavior than 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.

Overall, we show that professionals are more susceptible to recency bias by overextrapolating from the recent market experience and that salience can be a driving mechanism in the activation of this behavioral bias. In this regard, our study is related to that of Bellemare, Lee, and Just (2020), who investigate the production quantity decisions of Peruvian farmers and US students. Bellemare, Lee, and Just show that farmers do not change their production choices when facing product price risk at the extensive and intensive margins. However, they report that their student sample exhibits downward changes in production quantities in the presence of product price risk at the intensive margin.

Cai, De Janvry, and Sadoulet (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 $1 increase in recent indemnity payout pushes up the LRP insurance purchase probability by 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, Gennaioli, and Shleifer (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 nonzero insurance coverage.

Our findings also indicate that agricultural producers are highly vulnerable to abrupt changes in market dynamics. This tendency predicts that, in sudden economic downturns following high-price years, the pool of uninsured production units could be substantially large. If an overwhelmingly large proportion of cattle production remains uninsured during economic contractions, we can expect elevated bankruptcy instances across the industry. Consequently, the federal government may be compelled to issue relief funds, burdening the public budget (Url, Sinabell, and Heinschink, 2018). In the absence of government support, producers would likely face bankruptcy, potentially creating supply shocks and manifesting as food security issues for the entire populace. Thus, we posit that the documented behavioral biases could either burden public budgets if the government elects to assist uninsured producers or lead to negative supply shocks. Policies and extension education modules designed to help producers focus on long-term market forces can mitigate the negative consequences

Table 1. Cattle Price Insurance Study Design Features

Panel A. Price Probability Distribution		Panel B. Price Insurance			
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				

Notes: Table 1 reports important design features of the Livestock Risk Protection (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 premium costs.

of recency bias. Additionally, designing behavioral decision aids can improve risk management practices by increasing the demand for subsidized insurance programs.

Experimental Design and Procedures

We conducted the study with cattle producers and undergraduate students majoring in Agricultural Economics and Business. Our sample includes 143 participants. Since each study participant made 20 insurance purchase decisions, our analyses are based on 2,860 data points. Our sample size is comparable with recent studies conducting experiments with students and professionals.[3]

A total of 69 producers were recruited for the study on a voluntary basis at the 2022 Beef Expo and Trade Show in Tennessee. The event was targeted at 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 comprises 74 juniors and seniors enrolled in an Agricultural Business Management course at a land-grant public university in 2022 and 2023. The experiments with students were conducted during class time.

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.[4] Participants were compensated with $10.00 for their time in the experiment, conditional on following and completing all the study protocols.[5] 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 a maximum payoff of $26.00.

[3] For instance, Bellemare, Lee, and Just (2020) ran their study with 71 students and 48 producers.

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

[5] We compiled study instruments in Qualtrics and used the iMotions platform and Tobii equipment for collecting eye-tracking data. On average, participants spent around 30 minutes completing the study.

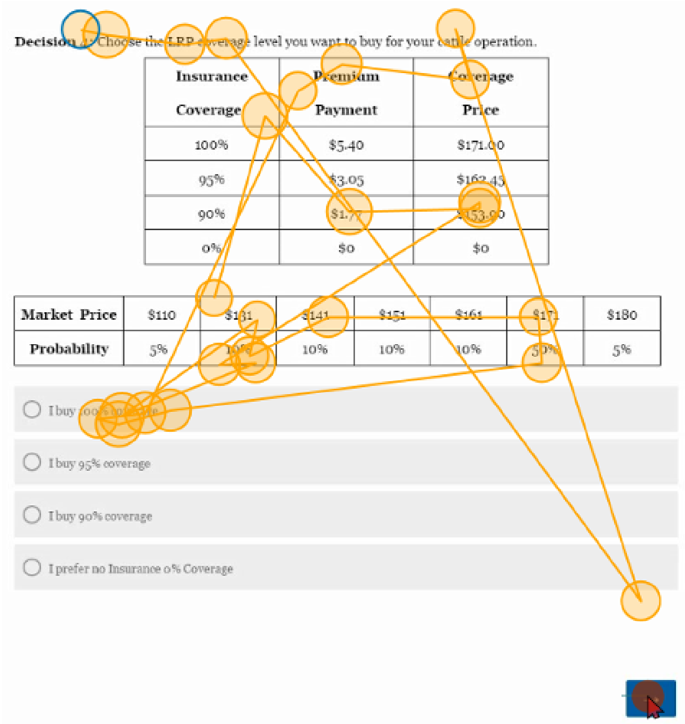

Figure 1. Screenshot from Decision Stage with Eye Tracking (producer sample)

Notes: Figure 1 depicts a decision stage (Decision 4) for one participant. The eye-tracking technology allows us to accurately measure fixation points (represented with circles) and fixation times with a millisecond precision.

In the main stage of the study, participants made 20 insurance purchase decisions.[6] The study concluded with a brief demographic survey. Before starting the decision stage, participants proceeded through the information screens detailing their decision context. The decision context described a typical case in which a cattle producer is selling steer calves weighing an average of 650 lb. The break-even price was determined to be \$162.7/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 historical LRP prices for various coverage levels.[7] The instructions also informed 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, Hirshman, and Imas (2021) and prerealized a market price sequence from the specified distribution before the study.[8] Thus, all study participants proceeded with the same market price sequence. This allowed us to utilize between-subject comparisons in our data. Panel A of Table 1 shows the presented market price distribution with associated probabilities. The additional payoff from the study was *Net Price* from a randomly

[6] 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 from this intervention. Therefore, we do not focus on this intervention in our results.

[7] It is worth reiterating 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 offers a test bed for understanding stylized decision patterns in the LRP program.

[8] Using randomly predetermined price and incentive paths is a frequently used convention in experimental studies. For instance, see Fischbacher, Hoffmann, and Schudy (2017).

Table 2. Designed Price Insurance Prospects

Coverage Level	Δ_1 (π_1)	Δ_2 (π_2)	Δ_3 (π_3)	Δ_4 (π_4)	Δ_5 (π_5)	Δ_6 (π_6)	Δ_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

Notes: Table 2 shows how each coverage level is translated into uncertain prospects. Prices are based on per cwt values.

selected binding decision, and it was calculated as

(1) $$\textit{Net Price} = \textit{Actual Market Price} + \textit{LRP Indemnity} - \textit{LRP Premium} - \textit{Breakeven Price}.$$

Panel B of Table 1 provides the details of each insurance coverage level and 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/cwt guaranteed price in exchange for \$3.05/cwt premium cost. This insurance coverage yielded an indemnity payment if and only if the realized market price was lower than \$162.45/cwt. Buying the 100% coverage level had a \$3.35/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 2 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/cwt (5%) and \$2.90/cwt (95%). The expected mean of this uncertain prospect is \$3.35/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/cwt with a 5% probability. In comparison, the maximum possible payoff from the 100% insurance coverage level is \$11.90/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/cwt payoff with a 5% probability.[9]

Our design is grounded in the literature on salience (e.g., Bordalo, Gennaioli, and Shleifer, 2012) and examines how decision makers can distort decision weights (i.e., probabilities, in our context) of uncertain prospects. According to this framework, decision makers tend to overweigh the upside of lotteries, thereby exhibiting more risk-seeking behavior.

We present the price distribution and measure individual visual attention to each price and probability pair in the producer sample. We posit that risk-taking decisions are influenced by the relative salience of price–probability pairs. Although the 0% coverage level is dominated in terms of variance, the salience of the highest upside prospect (\$17.30) might lead to a preference for the no-coverage option. Similarly, the salience of downside prospects may lead to a preference for the 100% coverage level.

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

Table 3. 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 a value of 1 if the realized market price is \$171 or \$180, and \$0 otherwise	[0, 1]
Net Price: Continuous	Shows the magnitude of net prices earned in insurance decisions	[-52.70, 17.30]
Indemnity: Nonnegative and continuous	Shows the magnitude of indemnity payments in insurance decisions	[0, 61]
High-Price Salient: Binary	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 1 if a participant fixation relatively more on the high-prices across all 20 periods, and 0 otherwise. The *Low-Price-Salient* dummy is the opposite of this measure.	[0,1]

Students

We followed the same study protocols and incentive levels in the lab study with students. The average study earning was \$12.86, with a maximum payoff of \$22.00. Per IRB requirements, we also offered students alternative, nonexperimental classwork. Only two students opted out of the study and completed the alternative assignment. The study with students was conducted without eye-tracking. Table 3 describes key experimental measures. The eye-tracking technology and fixation time measure are described in the online supplement (available online at www.jareonline.org).

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 expected mean ($\mu_{z,t}$) and risk-premium ($\sigma_{z,t}$), such that

$$\mu_{1,t} < \mu_{2,t} < \mu_{3,t} < \mu_{4,t}; \qquad (2)$$
$$\sigma_{1,t} > \sigma_{2,t} > \sigma_{3,t} > \sigma_{4,t}.$$

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:

$$\mathbb{E}[NetPrice_{i,z,t}] = \mathbb{E}[\tilde{p}_{i,z,t}] + I_{\mathbb{E}[\tilde{p}_{i,z,t}]<\hat{p}_{z,t}} |\hat{p}_{z,t} - \mathbb{E}[\tilde{p}_{i,z,t}]| - C_{z,t} - C_0. \qquad (3)$$

where $\tilde{p}_{i,z,t} = g(\lambda_i, k_i, \gamma_i)$, the expected market price at period t, is a function of salience ($\lambda_i \in \{0,1\}$), the correlation between the previous and current periods' market prices ($k_i \in \{-1,0,1\}$), and the risk aversion ($\gamma_i \in R$).[10]

The salience parameter captures whether the decision maker is preoccupied with high prices and overweighs experiencing high prices in general ($\lambda_i = 1$). Based on this approach, an individual with a price-salience behavior will expect higher prices compared to an individual without this bias:

$$\mathbb{E}[\tilde{p}_{i,z,t}(\lambda_i = 1, k_i, \gamma_i)] > \mathbb{E}[\tilde{p}_{-i,z,t}(\lambda_{-i} = 0, k_{-i}, \gamma_{-i})]. \tag{4}$$

The factor k_i shows the decision maker's belief about how previous and current market prices are correlated:

Case I: $k_i > 0$. If the decision maker experiences a high price level at period $t-1$, they also expect a high price at period t.

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

Case III: $k_i < 0$. If the decision maker experiences a high price level at period $t-1$, they expect a low price at period t.

When the decision maker is risk averse ($\gamma_i > 0$) (risk loving, $\gamma_i < 0$), they expect lower (higher) market prices and therefore choose higher (lower) coverage levels.

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 insurance coverage levels of 90%, 95%, and 100%, respectively.

The realized market price, $\tilde{p}$, is randomly drawn from the known distribution described in Panel A of Table 1. 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 overextrapolates 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. Conversely, 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 relatively risk loving. In that case, $\gamma_i < 0$ will lead to high price expectations.*

Hypotheses

If individual i is less risk averse than individual j ($\gamma_i < \gamma_j$), then, *ceteris paribus*, individual i will have a higher price expectation level for period t compared to individual j:

$$\mathbb{E}[\tilde{p}_{i,z,t}(\overline{\lambda}, \overline{k}, \overline{p}_{z,t-1}, \gamma_i \sigma_{z,t})] > \mathbb{E}[\tilde{p}_{j,z,t}(\overline{\lambda}, \overline{k}, \overline{p}_{z,t-1}, \gamma_j \sigma_{z,t})]. \tag{5}$$

Therefore, *ceteris paribus*, individual i will be more likely than individual j to prefer the insurance coverage level $z = 1$.

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

Table 4. Basic Demographic Characteristics

Panel A. Cattle Producers	*N*	Mean	Min.	Max.
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	***N***	**Mean**	**Min.**	**Max.**
Age	74	21.57	19	27
Male	74	0.76	0	1
White ethnicity	74	0.92	0	1

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

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, ceteris paribus, 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. *Ceteris paribus, 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. *Ceteris paribus, 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.*

Results

We begin by discussing the primary characteristics of our participants. Table 4 reports the basic demographic features of our study participants. 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 contain beginning cattle producers (11% of the producer sample) who did not operate a cattle operation in 2021. An average cattle producer 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 insurance. Previous studies also show that the adoption rate of LRP insurance tools is low among US cattle producers

Table 5. Reported Risk Preferences of Study Participants

	N	Producers	Students	*p*-Value
General risk	140	5.3 (2.8)	6.6 (2.6)	0.01
Financial Risk	140	4.9 (2.7)	5.5 (2.7)	0.37

Notes: The table shows the comparison of risk preferences of producer and student study participants. We use data from a survey question asking to report individuals to report their risk tolerance in general and for 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 and Wilcoxon test p-values are reported. Values in parentheses are standard deviations.

(Hill, 2015). 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.[11]

Panel B of Table 4 reports that the demographic features of our student participants are also homogeneous. An average student is a 22-year-old white male. Table 5 displays the relative comparison of reported risk preferences of the producer and student samples.[12] 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.

Preamble Findings A

At the extensive margin, both student and producer samples show statistically indistinguishable patterns. However, the student sample is more likely to purchase the 100% price coverage.

We first investigate study participants' insurance purchase decisions. The choice of price coverage levels in the first period presents a crucial insight into the prestudy preferences of participants. The proportion of subjects who bought a nonzero coverage level is 99% and 88% in the student and producer samples, respectively. A two-sided proportion test reveals that the proportion of nonzero insurance purchases is 11 percentage points larger in the student sample compared to producers; this difference is statistically significant ($p = 0.04$).

Figure 2a shows the proportion of nonzero 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 nonzero purchase decisions across 20 periods shows that, overall, student and producer samples exhibit similar patterns at the extensive margin (*Wilcoxon*, *z-score* $= 0.01, p = 0.50$).

Figure 2b 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 in most decision periods than the producer group. The Wilcoxon tests conducted 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* $= 1.66, /p = 0.05$). In contrast, both groups have the same sample means for 90% and 95% coverage purchases. We conclude that, at the intensive margin, the student sample is more likely to purchase the 100% coverage compared to producers.

[11] It must be considered that this is a reported knowledge measure, and individual perceived knowledge levels might be drastically different.

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

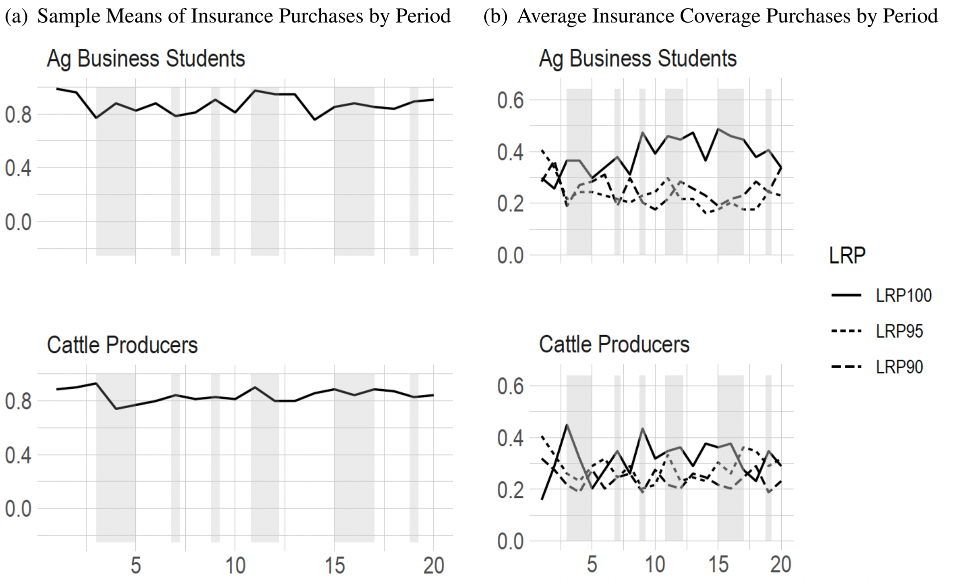

Figure 2. Dynamics of the Price Insurance purchases

Notes: The x-axis shows decision periods, while the y-axis represents proportions. Figure 2a shows sample means of insurance purchases across periods for producer and student samples. The figures show the proportion of participants who bought any nonzero insurance coverage level across periods. Figure 2b displays the dynamics of average insurance coverage purchases. Shaded periods indicate high-price periods in both panels.

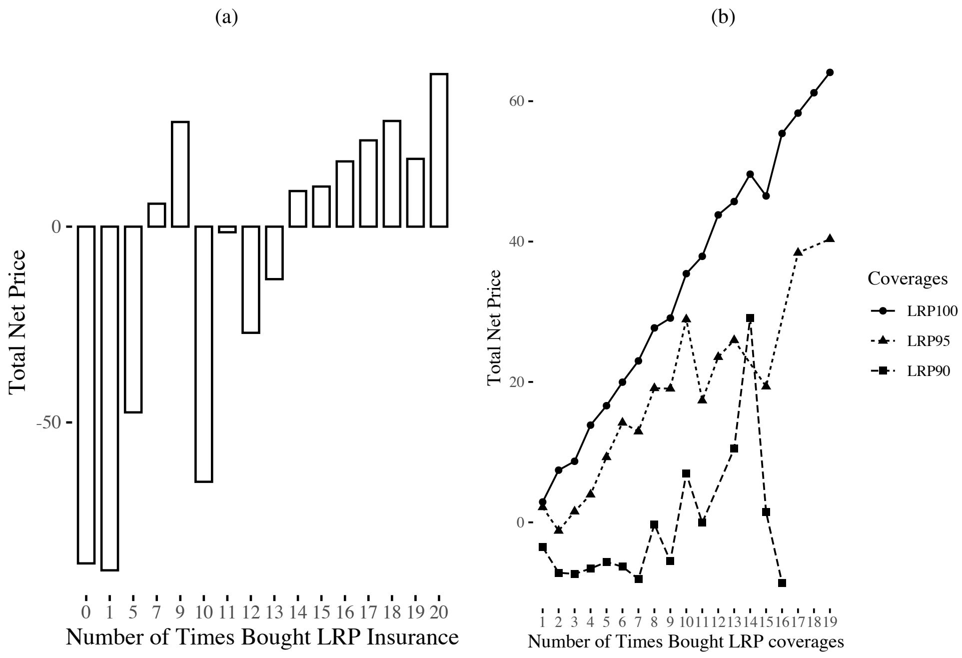

Figure 3. Price Insurance Purchases and Total Net Price

Notes: Figure 3a shows how average net prices change across the number of periods subjects purchased the insurance. Figure 3b depicts the relationship between average net prices and specific insurance coverage purchases.

Preamble Findings B

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

Figure 3a displays the relationship between cumulative net price (clustered at the subject level) and the number of nonzero insurance coverage purchases. We observe a positive relationship between persistent nonzero coverage purchases and the cumulative net price. Figure 3b breaks down total net price earnings over each individual coverage level. It is noteworthy that persistent purchases of the 90% coverage level do not guarantee positive total net prices. However, purchases of the 95% and 100% coverage level 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* $= 0.12$, $p = 0.55$).

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 ordinary least squares (OLS) regression analyses of the determinants of any nonzero LRP coverage level purchases. Columns 1–6 test different model specifications via the stepwise inclusion of key experimental measures when the dependent variable is a binary indicator for any nonzero price coverage purchases. In Models 1–6, the *Cattle Producer* dummy is not significant. This result overlaps with our previous discussion and reiterates that producer and student samples exhibit the same nonzero price insurance coverage purchasing patterns. The *Task* variable captures a learning effect, if any exists. The outcomes of regression analyses show there is a weak *trend* in purchase decisions from the first to the last decision period (*Task* $= 0.003$, p-value < 0.05). This result suggests that study participants were slightly more inclined to buy insurance coverage towards the end of the study, indicating a weak learning effect. We also find that risk preferences do not affect price insurance decisions as the *Financial Risk Tolerance* measure is not statistically different from 0 in Model 6. Therefore, we cannot validate Hypothesis 1 with our findings.

Columns 7 and 8 of Table 6 investigate how the last decision period's indemnity payments and net price earnings affect nonzero price insurance purchases. We detect a significant effect for the indemnity payments for cattle producers. A \$1 increase in the last period's indemnity payment increases the insurance purchase probability by 1% (p-value < 0.01). We do not detect any effect of the net price earning lag variable on insurance purchase decisions.

Table 7 conducts similar analyses with a different dependent variable: 1, 2, 3, and 4 for 0%, 90%, 95%, and 100% coverage levels, respectively. The core purpose of the analyses in Table 7 is to understand how key experimental measures affect specific nonzero price coverage levels. Column 1 of Table 7 reports that risk preferences do not affect price coverage level purchases. Thus, based on our results, we also do not validate Corollary 1.

As the regression constant shows, the mean decision is buying the 95% coverage in the entire sample. We also find that in later decision periods, study participants are more likely to buy higher insurance coverage levels (*Task* $= 0.01$, p-value < 0.1). Moreover, the occurrence of a high-price event in the last period induces only cattle producers to downgrade their insurance coverage level.

Table 6. Determinants of Insurance Purchases

Dependent Variable: Buy-Insurance Dummy								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Cattle Producers	−0.03 (0.03)	−0.03 (0.03)	−0.03 (0.03)	0.01 (0.04)	0.02 (0.04)	0.01 (0.04)	−0.07* (0.04)	−0.03 (0.03)
Task		−0.0001 (0.001)	0.002 (0.001)	0.002 (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.001 (0.001)
High-Price Dummy (1st lag)			−0.03* (0.01)	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)		
Cattle Producers × High-Price Dummy (1st lag)				−0.06** (0.03)	−0.07*** (0.03)	−0.07*** (0.03)		
High-Price Dummy (2nd lag)					0.0002 (0.01)	0.0002 (0.01)		
Financial Risk Tolerance						−0.01 (0.01)		
Indemnity (1st lag)							−0.0002 (0.001)	
Cattle Producers × Indemnity (1st lag)							0.005*** (0.001)	
Net price (1st lag)								0.0003 (0.001)
Cattle Producers × Net price (1st lag)								0.0005 (0.002)
Constant	0.87*** (0.01)	0.87*** (0.02)	0.86*** (0.02)	0.85*** (0.02)	0.81*** (0.03)	0.85*** (0.04)	0.83*** (0.02)	0.85*** (0.02)
R^2	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.00
No. of obs.	2,860	2,860	2,717	2,717	2,574	2,556	2,717	2,717

Notes: Table 6 reports the results of ordinary least squares (OLS) regression analyses for both producer and student samples. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level. Values in parentheses are heteroskedasticity-consistent robust standard errors clustered at the participant level.

Finding 2

Price salience affects only nonzero 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.

We calculate the total fixation time duration each subject spends, focusing on the high prices across all their decisions. We then find this duration's proportion in the total fixation time spent observing all price points in the provided price information for all decisions made. We use the median split of the distribution of individual proportions to classify producers as low-price salient (high-price salient) if their high-price fixation time proportion is less than or equal to (greater than) the median value of the distribution.

Table 8 presents a set of regression analyses investigating the impact of *Low-Price Salience* on nonzero 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. Columns 1–4 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 after a period with high market prices. Decision makers showing high-price-salience

Table 7. Regression Analyses of Nonzero LRP Coverage Purchases

Dependent Variable: Insurance Coverage Levels	**All**	**Producers**	**Low-Price-Salient Producers**	**High-Price-Salient Producers**
	1	**2**	**3**	**4**
Cattle Producers	−0.04			
	(0.11)			
High-Price Dummy (1st lag)	−0.05	−0.21***	−0.09	−0.10***
	(0.05)	(0.06)	(0.08)	(0.03)
Task	0.01*	0.01	0.003	0.005*
	(0.004)	(0.01)	(0.01)	(0.003)
Financial Risk Tolerance	−0.03	−0.02		
	(0.02)	(0.03)		
Cattle Producers × High-Price Dummy (1st lag)	−0.17**			
	(0.07)			
Constant	2.97***	2.93***	2.84***	0.82***
	(0.14)	(0.17)	(0.16)	(0.05)
R^2	0.01	0.01	0.00	0.02
No. of obs.	2,698	1,292	589	722

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Values in parentheses are robust standard errors clustered at the participant level.

behavior buy nonzero insurance coverage by 8 percentage points less (p-value < 0.05) after a period with high market prices.

Columns 3 and 4 of Table 7 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 overfixate on low prices (low-price salience) of the market price distribution. In contrast producers with high-price-salience behavior buy the 0% coverage level on average.

We conclude that price salience does not directly affect nonzero 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.

Finding 3

Experiencing a high price in the previous period decreases insurance purchase probability as well as the likelihood of choosing higher coverage levels, but this effect is detected only in the producer sample. High-price salience mediates the impact of this effect.

Columns 3–5 in Table 6 investigate the relationship between a high-price experience in the previous decision period and the current period's nonzero insurance coverage level choice. Although column 3 shows a significant impact of the *High-Price Dummy* on the binary variable, indicating a nonzero purchase decision (−0.03, p-value < 0.1), this effect disappears when other model variables are included. However, the effect of the high-price lag on insurance purchases is significant through the producer sample dummy. The sign of this effect is negative, confirming Hypothesis 3. The second lag of the *High-Price Dummy* is not statistically significant, showing that participants do not factor relatively distant price changes into their decisions. Overall, the results show that experiencing a high price in the previous decision period reduces the likelihood of buying insurance, and this effect is observed only in the producer sample.

Columns 5 and 6 of Table 8 show that the High-Price dummy is significant and negative only for producers who exhibit high-price-salience behavior (−0.10, p-value < 0.01), suggesting an

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
	1	**2**	**3**	**4**	**5**	**6**
High-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)
High-Price Salient (Dummy) × High-Price Dummy (1st lag)				−0.08** (0.04)		
Constant	0.87*** (0.04)	0.86*** (0.04)	0.88*** (0.04)	0.85*** (0.04)	0.88*** (0.05)	0.82*** (0.05)
R^2	0.00	0.00	0.01	0.01	0.00	0.02
No. of obs.	1,380	1,380	1,311	1,311	589	722

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Values in parentheses are heteroskedasticity-consistent robust standard errors clustered at the participant level.

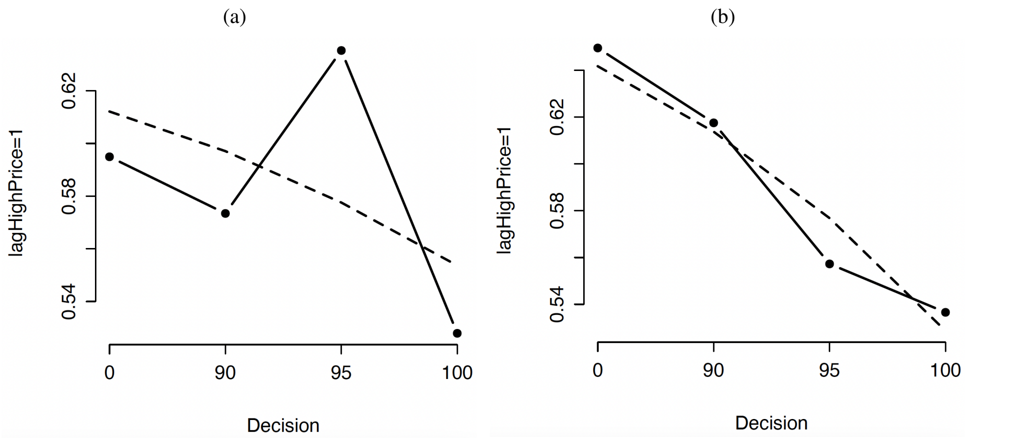

Figure 4. Insurance Coverage Purchase Probabilities for Low- and High-Price-Salient Participants

Notes: This figure shows fitted probabilities of insurance coverage purchases after a period with a high price. Figure 4a shows how relative purchase probabilities vary after a high-price period for participants who exhibit low-price-salience behavior. Figure 4b shows the results of the same analysis for participants who exhibit high-price-salience behavior. The solid line represents sample estimates, while the dashed line shows the trend in estimated sample values.

association between salience and the recency bias. Table 7 provides evidence that the *High-Price Dummy* is significant only for the producer sample in choosing a specific nonzero price coverage level. Columns 3 and 4 of Table 7 reiterate that this effect is statistically significant and negative only 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 high price in the previous decision period for the low- and high-price-salience samples. Figure 4a 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 not to purchase 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.

Discussion and 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 study results reveal appealing differences between learning-by-studying and learning-by-doing behaviors. 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. Although students and producers show similar patterns in their insurance decisions at the extensive margin, the producer sample is more susceptible to salience and recency biases. Bordalo, Gennaioli, and Shleifer (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, Gennaioli, and Shleifer (2022), it is predictable that producers—who always seek high prices to make a living—will react differently to high prices compared to students. Huseynov, Taylor, and Martinez (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 overfixate on favorable prices, leading to a reduction in the demand for cattle price insurance.

We also show that only producers react to recent indemnity payout experiences. This finding is aligned with the results of Cai, De Janvry, and Sadoulet (2020), who show that farmers increase their insurance purchases after receiving indemnity payments. Michel-Kerjan and Kousky (2010) provide evidence that after a storm and flood, demand for flood insurance policies goes up. These findings align with recency bias, which predicts that agents assign a higher weight to recent events in making 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 producers' risk management practices can be achieved by neutralizing recency bias.

The proportion of nonzero cattle price coverage choices is around 85% in both the producer and the 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% and 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 indicate choice overload, commonly defined as consumers making the wrong choice because they had an excessive number of unique choices to make (Chernev, Böckenholt, and Goodman, 2015; Scheibehenne, Greifeneder, and Todd, 2010). A similar issue has been noted by

Davidson and Goodrich (2023) for the pasture, rangeland, and forage insurance policy. Our results suggest that identifying producer types and fine-tuning Extension education programs to address their biases can increase the demand for insurance.

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

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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.

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 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.

Table S1. Determinants of Insurance Purchases

	Dependent variable:Buy-Insurance Dummy							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Cattle Producers	−0.03	−0.03	0.01	0.26	0.28	0.22	−0.16	0.02
	(0.17)	(0.17)	(0.18)	(0.20)	(0.21)	(0.21)	(0.18)	(0.18)
Task		−0.0004	0.01	0.01	0.02**	0.02**	0.01	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High-Price Dummy (1st lag)			−0.15**	0.03	0.10	0.10		
			(0.07)	(0.09)	(0.10)	(0.10)		
Cattle Producers*High-Price Dummy (1st lag)				−0.41***	−0.44***	−0.45***		
				(0.14)	(0.15)	(0.15)		
High-Price Dummy (2nd lag)					−0.003	−0.003		
					(0.07)	(0.07)		
Financial Risk Tolerance						−0.07**		
						(0.03)		
Indemnity (1st lag)							−0.005	
							(0.003)	
Cattle Producers* Indemnity (1st lag)							0.03***	
							(0.01)	
Net price (1st lag)								−0.003
								(0.01)
Cattle Producers* Net price (1st lag)								−0.01
								(0.01)
Constant	1.41***	1.42***	1.38***	1.28***	1.13***	1.52***	1.32***	1.30***
	(0.12)	(0.14)	(0.15)	(0.15)	(0.16)	(0.26)	(0.15)	(0.14)
Observations	2,860	2,860	2,717	2,717	2,574	2,556	2,717	2,717
Log Likelihood	−984.46	−984.46	−946.13	−942.02	−909.12	−905.92	−936.30	−944.84
Akaike Inf. Crit.	1,974.92	1,976.92	1,902.25	1,896.04	1,832.24	1,827.84	1,884.60	1,901.69
Bayesian Inf. Crit.	1,992.80	2,000.75	1,931.79	1,931.48	1,873.21	1,874.61	1,920.04	1,937.13
						*p<0.1; **p<0.05; ***p<0.01		

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

Table S2. Determinants of non-zero LRP Coverage Purchases

	Dependent variable: Insurance Coverage Levels			
	All	**Producers**	**Producers Low-Price Salient**	**Producers High-Price Salient**
	(1)	**(2)**	**(3)**	**(4)**
Cattle Producers	−0.095			
	(0.108)			
High-Price Dummy (1st lag)	−0.094	-0.355^{***}	−0.172	-0.512^{***}
	(0.099)	(0.103)	(0.153)	(0.139)
Task	0.014^{**}	0.009	0.007	0.011
	(0.006)	(0.009)	(0.014)	(0.012)
Financial Risk Tolerance	-0.047^{***}	-0.038^{**}		
	(0.013)	(0.018)		
Cattle Producers * High-Price Dummy (1st lag)	-0.261^{*}			
	(0.141)			
Prob of 90% coverage level or above	2.027^{***}	1.925^{***}	1.896^{***}	1.668^{***}
	(0.130)	(0.162)	(0.202)	(0.175)
Prob of 95% coverage level or above	0.707^{***}	0.691^{***}	0.533^{***}	0.531^{***}
	(0.124)	(0.153)	(0.184)	(0.164)
Prob of 100% coverage level or above	-0.332^{***}	-0.484^{***}	-0.660^{***}	-0.616^{***}
	(0.123)	(0.152)	(0.185)	(0.164)
Observations	2,698	1,292	589	722
R^2	0.015	0.013	0.002	0.020
				*p<0.1; **p<0.05; ***p<0.01

Notes: This table reports ordered logit regression results.

Table S3. Determinants of Indemnity Earnings

	Dependent variable: Indemnity Earnings		
	All	**All**	**All**
	(1)	**(2)**	**(3)**
Task		-0.45^{***}	-0.45^{***}
		(0.02)	(0.02)
High-Price Dummy (1st lag)	-3.45^{***}	-2.67^{***}	-2.67^{***}
	(0.25)	(0.24)	(0.25)
Constant	9.35^{***}	13.89^{***}	16.29^{***}
	(0.25)	(0.37)	(0.29)
Subject Fixed Effect	No	No	Yes
Observations	2,717	2,717	2,717
R^2	0.02	0.05	0.07
			*p<0.1; **p<0.05; ***p<0.01

Notes: This table reports OLS regression results.

(a)

(b)

Figure S1. LRP Insurance Purchases Decision Heatmaps

Notes: 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.

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 coverageprice. 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 inthat case will be your bonus payoff in addition to your participation reward. A negative netprice 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.I

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
- ◉ 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.

→