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Farmers and Bakers: The role of Optimism Bias in Price Expectations

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Abstract

Recent decision theory models link upward price expectations to optimism bias when the decision-maker has a relevant stake. We conduct incentivized online and lab-in-the-field experiments. In the online experiment, we construct 20 price-prediction tasks. In the Farmer (Baker) condition, subjects are presented with a profit function where wheat is the output (input) of the production. Farmers and Bakers exhibit pessimism bias (under-predicting future price points). Only risk-tolerant Farmers are prone to optimism bias and demonstrate higher price expectations.

We also conduct a lab-in-the-field experiment with cattle producers. We design 18 bull-price prediction tasks based on actual market transactions. We have Buyers, Sellers, Buyers with Info, and Sellers with info conditions where producers predict the market price of the bull. We find that cattle producers exhibit optimism bias. But the bias disappears when we introduce additional information (EPD measures).

Commodity price expectations significantly influence the demand for hedging instruments and risk management tools and preference for insurance plans (Ricome and Reynaud, 2021). It has been empirically shown that high-price expectations can reduce the attractiveness of futures, and,

projecting lower price levels may decrease the production capacity (Woolverton and Sykuta, 2009; Deaton and Laroque, 1996). Holding unrealistic price expectations can also lead to substantial financial losses and bankruptcies. Recent decision theory models link upward price expectations to optimism bias when the decision-maker has a relevant stake (Bénabou and Tirole, 2016). There is also experimental evidence that price expectations can be inflated due to optimism bias (Mayraz, 2011).

We conduct a series of incentivized online and lab-in-the-field between-subject experiments, randomly assigning *Farmer* and *Baker* roles. Our design resembles Mayraz (2011) with several extensions. We construct 20 price-prediction scenarios using stock market data of leading agribusiness firms in the period 2017-2019. Our scenarios represent different price trends and movements in agricultural markets and, thus, are indirectly related to commodities. In the Farmer (Baker) condition, subjects are presented with a profit function where wheat is the output (input) of the production, hence, representing the revenue (cost) level for the decision-maker. Higher price expectations promise higher (lower) revenues for Farmers (Bakers). We also employ the Neutral condition without imposing any decision context.

In different scenarios, participants predict future wheat price points based on the presented historical information. In each price task, we show price trends over 365 days and ask subjects to predict the market price at Day 375. At the end of the study, we randomly select one task to be binding. Participants earn a \$10 reward for accurately predicting price points (with up to \$50.00 error) and the \$8 participation compensation.

We design forward contracts for the Farmer experimental condition in follow-up studies and offer subjects lock-in prices. Subjects can accept our offers and realize the contract (sell their wheat products) at predetermined prices. Participants who do not accept our price offers wait and sell their wheat at the spot market prices.

Our findings reveal that contrary to the prediction of optimism bias, Farmers and Bakers exhibit pessimism bias (under-predicting future price points). Only risk-tolerant Farmers are prone to optimism bias and exhibit inflated price expectations. We also find that high-risk tolerant subjects

show higher degrees of confidence in their decisions, and this leads to an increase in inflated expectations. Interestingly, Bakers do not show any biases, suggesting that biases are the product of revenue items and the cost domain imposes a minimal bias on decisions.

The outcomes of the follow-up studies reveal that holding high price expectations also reduce the probability of accepting forward contracts, thus, increasing exposure to higher risk levels. We conclude that the risk-taking behavior of farmers can explain optimistic price expectations in the actual marketplace.

Our study also speaks to a vast behavioral economics literature that has extensively scrutinized the determinants of the Willingness-to-Pay (WTP) and Willingness-to-Accept (WTA) values in different domains of agricultural production. WTP and WTA measures capture various aspects of market transactions and are being shaped by several factors, including irrational pre-market price expectations (Isoni, 2011). Therefore, understanding the behavioral underpinnings of agricultural transactions necessitates explicitly investigating price expectations.

Experimental Design

Experiment 1

We conducted an online study using the Prolific.co survey platform. Our first and primary goal was to replicate the results of Mayraz (2018) and gain further insights on how and through which channels the optimism bias might influence the price expectations. Although this study was a replication effort, we modified a number of aspects of the original experiment.

We collected stock price data of leading North American and European Agribusiness firms from the period of 2017 to 2019. We selected this time period to avoid any major financial crises that might introduce very unusual patterns into price trends. Moreover, focusing on the prices of

Agribusiness firms enabled us to align price trends in our scenarios with the Agricultural context of our study. We re-scaled the collected stock price data to the \$500 and \$16,000 intervals. In line with Mayraz (2018), this procedure ensured that all price scenarios had trends within the same range.

We also introduced the Neutral treatment, which was not tested in Mayraz (2018). The purpose of the treatment was to document whether Farmers or Bakers or both demonstrate the optimism bias in price predictions. The Neutral treatment does not introduce any decision context and, therefore, can serve as a baseline for Farmers and Bakers treatments. We are interested in seeing which role (i.e., Baker and Farmer) triggers a higher magnitude of price expectation deviations from the Neutral condition.

Another difference in our study was eliciting risk preferences. We intend to connect confidence levels to risk attitudes to portray a more detailed picture of the price prediction behavior.

Experiment 2

Our primary goal was to investigate the role of optimism bias in demand for risk-mitigating tools. In particular, we designed forward contracts. We used price prediction tasks from Experiment 1. Subjects predicted future price points similar to Experiment 1. But the major difference was that price expectations were not incentivized. Moreover, all participants were assigned to a Farmer role. After entering their guesses about future prices, participants were offered a forward contract deal. The deal was about selling their wheat products at the price indicated in the offer. Participants had two options: a) Accepting the offer and selling their product at the specified price points, or b) waiting until the spot market and selling their products for the price that would come out from the presented price chart. We introduced three treatments. We sampled three price points from future prices and provided them to subjects. In Ascending (Descending) Treatment, price points were introduced in increasing (decreasing) order. No price points from future prices were provided in the control condition.

Experiment 3

Experiment 3 was conducted among cattle producers. Producers were assigned to Buyer and Seller roles. They were shown 18 tasks. Tasks provided different bull videos and asked participants to predict the market prices of the presented bull. Participants who correctly predicted prices (up to \$500 error) earned \$10.00 reward. All subjects were compensated with \$15.00 participation compensation. We had four treatments: Sellers, Sellers with Info, Buyers and Buyers with Info. Information contained EPD measures about the presented bulls.

Results

Experiment 1

Figure 1 shows boxplots of predictions across tasks and treatments. Treatment condition differences are noticeable for some tasks. Figure 1 reveals that task fixed effects can affect predictions and have to be controlled for in analyses.

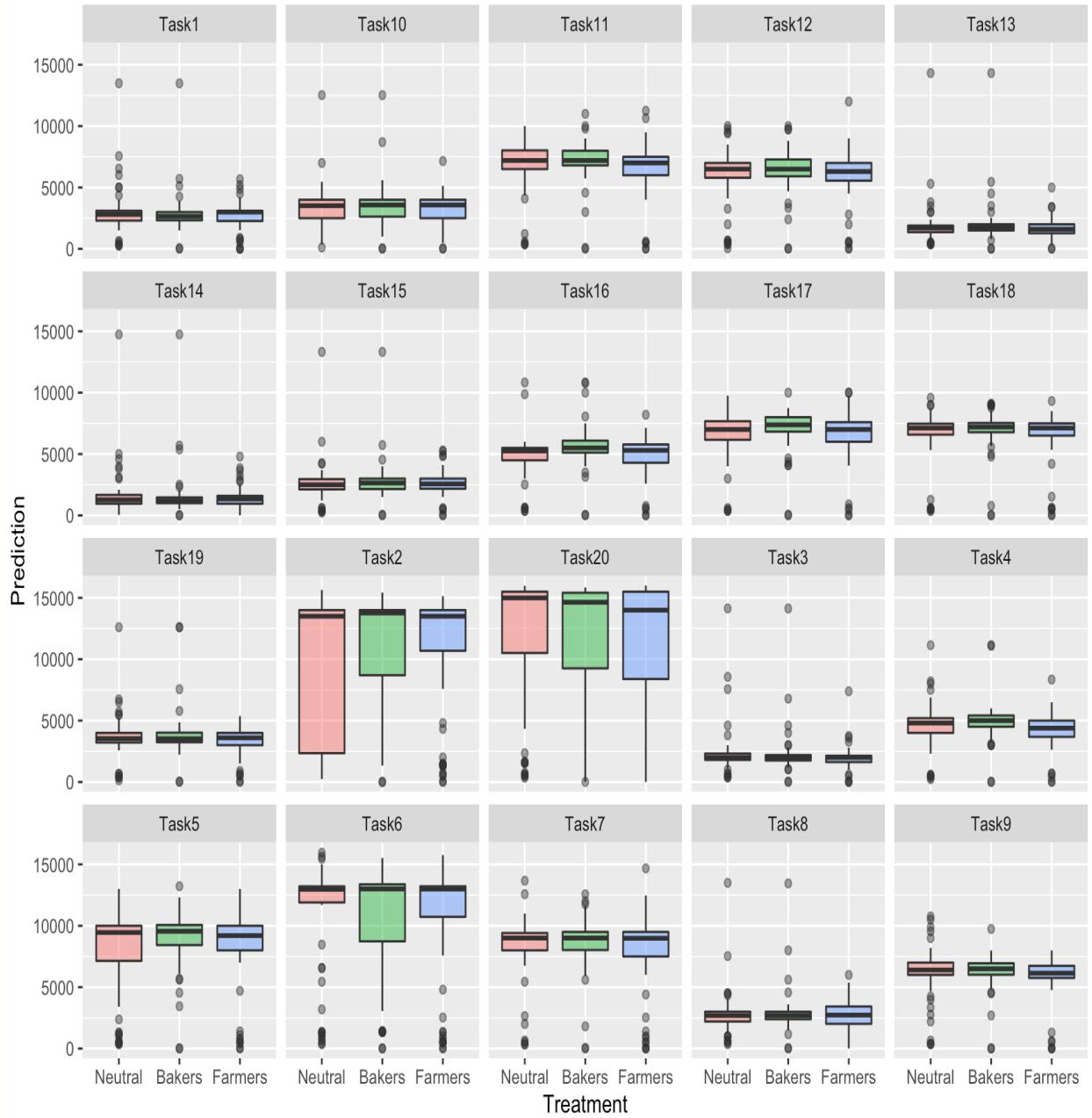


Figure 1: Predictions across Tasks

Figure 2 depicts average predictions across treatments. Contrary to Mayraz (2018), we find that on average, Bakers overestimate their wheat price predictions in the magnitude of \$427 compared to Farmers. Mayraz (2018) reports that Farmers overestimated wheat prices by £452 than Bakers. We also detect that the average value of wheat price predictions of Bakers is \$189 higher than the Neutral condition. The mean of Farmers' price expectations is \$238 smaller than the Neutral condition. The difference between the predictions of Farmers and bakers is

statistically significant when we conduct a simple mean difference test. The main outcome of Figure 2 is that we observe Pessimism Bias instead of Optimism bias in our full sample. IF Optimism bias predicts the overestimation of future profit levels, the pessimism bias operates in the reverse direction and underestimates the expected profits.

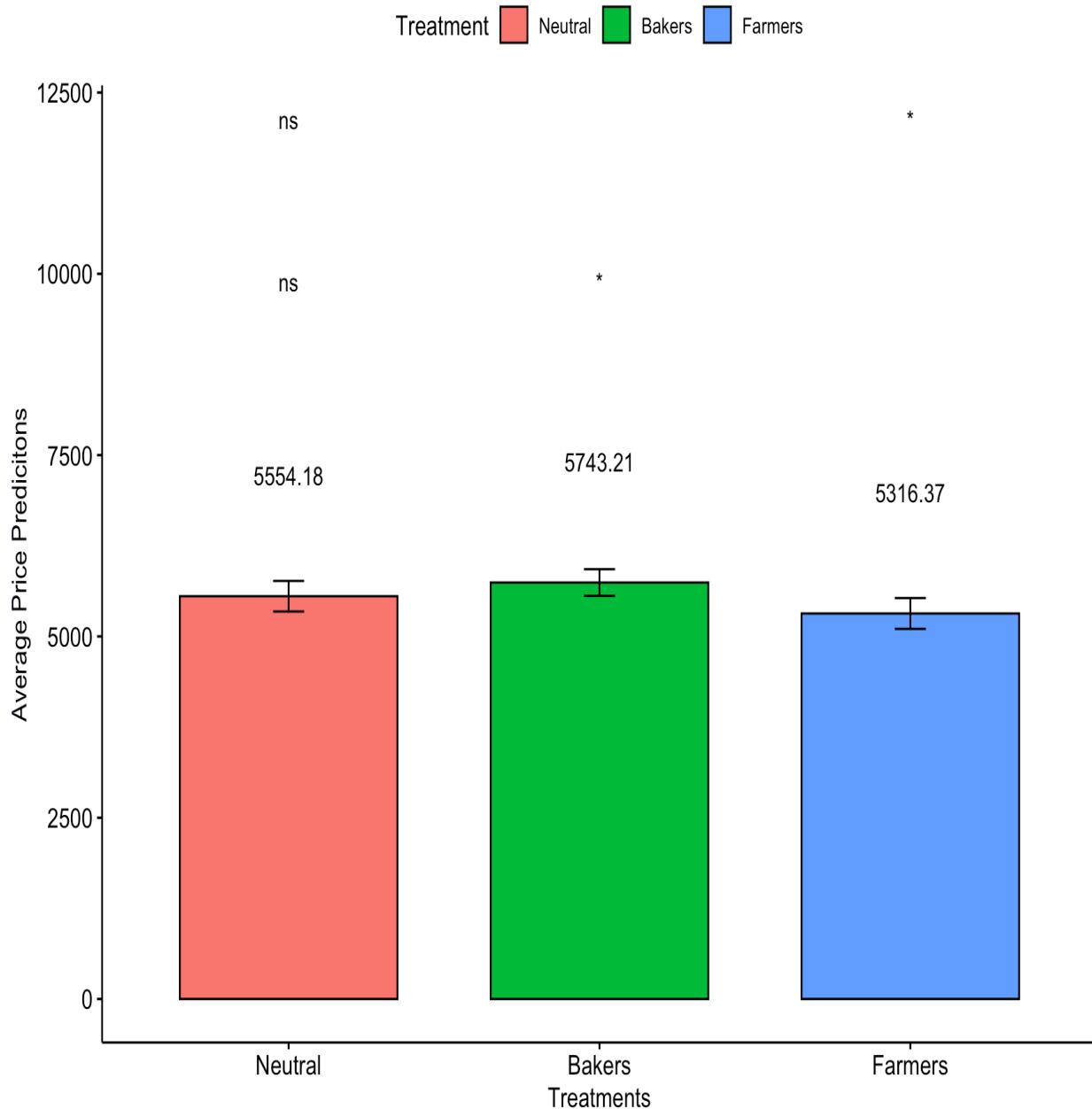


Figure 2: Average Predictions across Treatments

Table 2 presents regression analysis for the entire sample of our data and for sub-samples. Column (1) confirms our findings for Bakers (Farmers), revealing that subjects overestimate (underestimate) future prices compared to the Neutral condition when wheat is the input (output) of the production process. However, Column (2) reveals that when we control the confidence level only the effect for Farmers persist. It means the pessimism bias is robust in the income domain not in the cost domain.

Table 2: OLS Regression Analysis of Predictions

	Dependent variable:			
	Wheat Price Prediction			
	All (1)	All (2)	Low-Risk (3)	HighRisk (4)
Bakers	243.2*** (0.0)	503.2 (711.9)	722.4 (856.7)	1,905.5 (1,723.4)
Farmers	-147.7*** (0.0)	-1,286.8** (517.2)	-1,432.8* (750.7)	2,755.5** (1,224.8)
Confidence Degree		-0.7 (9.4)	21.4* (12.2)	-16.2 (12.7)
Bakers*Confidence Degree		-5.0 (17.3)	-23.4 (21.2)	1.6 (29.8)
Farmers*Confidence Degree		23.5* (13.6)	-3.4 (20.4)	42.4** (17.5)
Constant	6,020.0*** (0.0)	6,033.3*** (166.7)	5,639.7*** (216.9)	3,884.5*** (1,224.8)

Note:

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

Regressions control for subject and task fixed effects. Standard errors are clustered at subject level. Columns (2) and (3) represent sub-sample analysis for Up To College Degree and College Degree and More education levels. Columns (4) and (5) show Low- and High-Confidence levels. Columns (6) and (7) present regression results for Low- and High-Risk sub-samples.

Columns (3) and (4) portray sub-sample analysis based on risk tolerance levels. We find that relatively low-risk-tolerant participants demonstrate pessimism bias. However, relatively high-risk-tolerant participants are prone to optimism bias.

Table 3

Decision Characteristics	N	Neutral, N =	Bakers, N =	Farmers, N =	p-value	q-value
Prediction Confidence	181	48 (26)	47 (25)	48 (27)	0.97	0.97
Time to First Click (seconds)	181	21 (20)	25 (22)	23 (24)	0.66	0.87
Number of Clicks	181	3.50 (2.50)	4.06 (4.09)	4.90 (4.37)	0.17	0.57

Table 3

<i>Decision Characteristics</i>	N	Neutral, N = 64	Bakers, N = 55	Farmers, N = 62	p-value	q-value
Time Spent on tasks (seconds)	181	36 (31)	40 (25)	37 (26)	0.70	0.87
General Confidence	181	70 (21)	71 (22)	72 (20)	0.56	0.87
Financial Confidence	181	63 (26)	58 (27)	63 (23)	0.59	0.87
Risk Taking	181	6.01 (2.24)	5.42 (2.39)	6.30 (2.31)	0.12	0.57
Time Preference	181	7.05 (1.81)	6.60 (2.22)	6.76 (1.99)	0.67	0.87
Trust	181	6.58 (2.27)	5.80 (2.51)	6.33 (2.21)	0.14	0.57
Crytpo share in portfolio	181	36 (24)	36 (26)	34 (25)	0.80	0.89

¹ Mean (SD)² Kruskal-Wallis rank sum test³ Benjamini & Hochberg correction for multiple testing

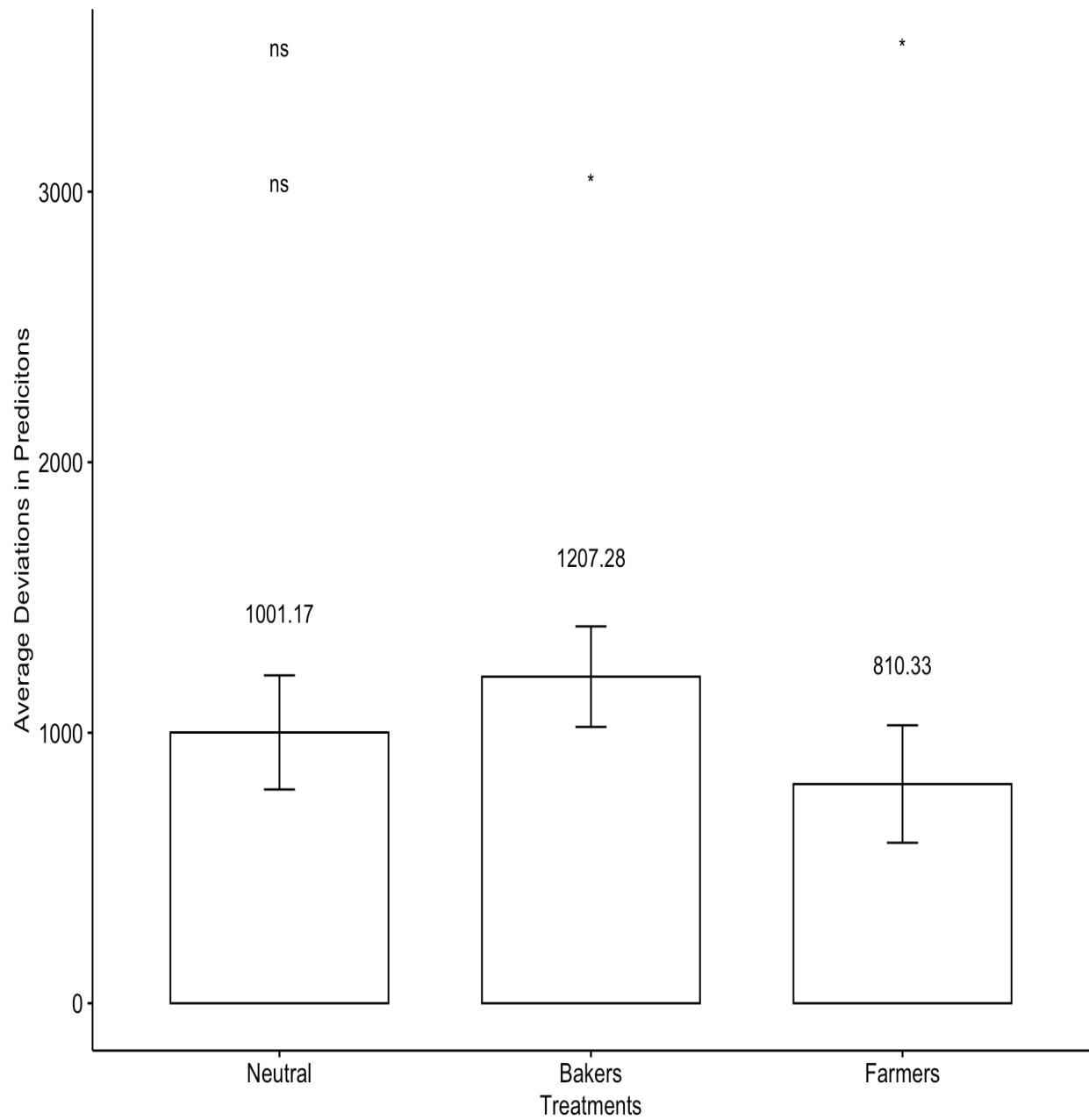


Figure 3: The relationship between Risk Taking Behavior and Task Confidence across Education dimension.

Table 3 depicts decision-making characteristics of subjects across treatments. We detect no differences among treatments indicating our experimental conditions do not affect decision variables.

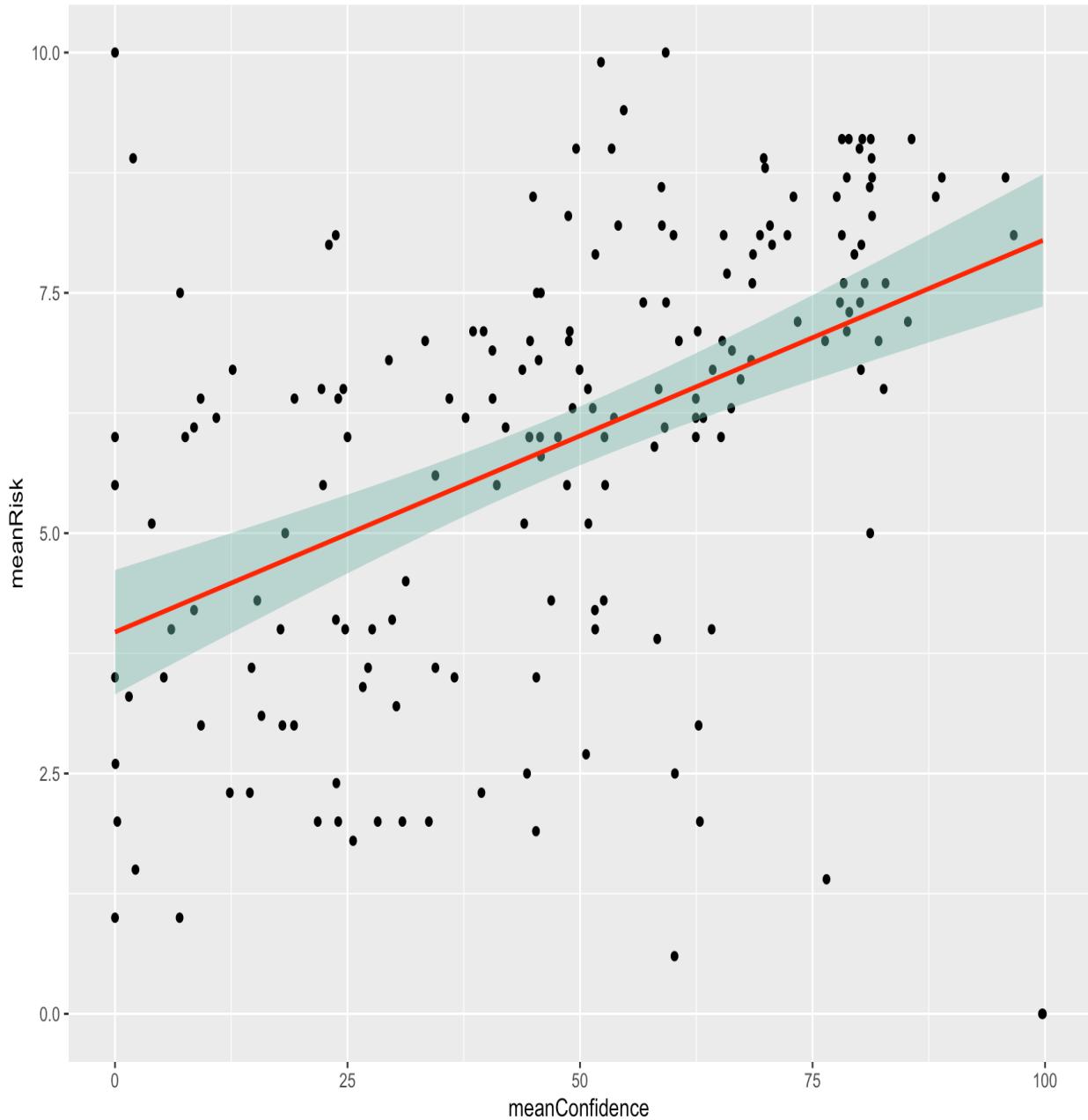


Figure 4: The relationship between Risk Taking Behavior and Task Confidence across Education dimension.

Figure 4 shows the correlation between risk tolerance and prediction confidence levels across Education dimensions. Confidence and Risk are positively correlated for both relatively higher and lower educated groups. However, an increase in confidence levels is associated with a higher magnitude hike in Risk tolerance in the relatively higher educated group compared to the lower educated sub-sample.

Experiment 2

We start examining demographic and decision-making characteristics that are not expected to be affected by assigned treatment conditions. Table 4 shows cross-treatment comparisons of key variables presenting pairwise statistical test p-values and multiple-testing-corrected q-values. Income averages show statistically significant differences across experimental treatment conditions. But controlling for the multiple testing reveals that the difference is not statistically meaningful. We conclude that our random treatment assignments are not contaminated with participant characteristics.

Table 4

Demographic Variables	N	Ascending, N = 40	Control, N = 41	Descending, N = 41	p-value	q-value
Age	122	33 (12)	37 (12)	33 (12)	0.18	0.70
Male	122	18 (45%)	22 (54%)	20 (49%)	0.74	0.94
IncomeNormalized	122	42,799 (26,373)	38,776 (23,184)	40,534 (22,470)	0.82	0.94
HighSchooGraduate	122	6 (15%)	6 (15%)	3 (7.3%)	0.52	0.78
TwoYearCollege	122	1 (2.5%)	4 (9.8%)	1 (2.4%)	0.36	0.73
SomeCollege	122	13 (32%)	12 (29%)	12 (29%)	0.94	0.94
FourYearCollege	122	14 (35%)	10 (24%)	16 (39%)	0.35	0.73
SomeGraduate	122	2 (5.0%)	1 (2.4%)	2 (4.9%)	0.87	0.94
MastersDegree	122	4 (10%)	8 (20%)	6 (15%)	0.48	0.78
Prediction in Train 1	122	1,741 (376)	2,050 (2,269)	1,646 (361)	0.31	0.73
Prediction in Train 2	122	4,079 (652)	4,252 (731)	4,376 (605)	0.03	0.19
Prediction in Train 3	122	4,674 (843)	4,406 (790)	4,050 (959)	0.02	0.19

¹ Mean (SD); n (%)

² Kruskal-Wallis rank sum test; Pearson's Chi-squared test; Fisher's exact test

³ Benjamini & Hochberg correction for multiple testing

Table 5: OLS Regression Analysis of Accept Probabilities

	Dependent variable:						
	Offer Accept						
	All (1)	All (2)	All (3)	All (4)	All (5)	(6)	(7)
Ascending	-0.0 (0.0)	0.01*** (0.003)	-0.03*** (0.01)	-0.1 (0.1)	-0.2 (0.2)	-0.4 (0.3)	0.1 (0.2)
Descending	-0.1*** (0.0)	-0.1*** (0.000)	-0.3*** (0.1)	-0.4*** (0.1)	-0.5** (0.2)	-0.7*** (0.2)	-0.3* (0.2)
Prediction Price		-0.01***	-0.01***	-0.01***	-0.01	-0.01	-0.01

	(0.003)	(0.003)	(0.004)	(0.01)	(0.01)	(0.01)	
Confidence Degree		-0.05*** (0.01)	-0.1*** (0.02)	-0.1* (0.03)	-0.04 (0.04)	-0.1* (0.03)	
Ascending*Prediction Price			0.002 (0.01)	-0.002 (0.01)	0.000 (0.01)	-0.000 (0.01)	
Ascending*Prediction Confidence			0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	
Descending*Prediction Price			0.01 (0.03)	0.02 (0.05)	-0.1 (0.1)	0.04 (0.04)	
Descending*Prediction Confidence			0.01 (0.02)	0.05 (0.04)	-0.005 (0.1)	0.02 (0.04)	
Constant	0.4*** (0.0)	0.5*** (0.01)	0.7*** (0.1)	0.8*** (0.1)	0.8*** (0.2)	1.3*** (0.2)	0.6*** (0.2)

Note:

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

Regressions control for subject and task fixed effects. Standard errors are clustered at subject level.

Figure 1 shows boxplots of predictions across tasks and treatments. Treatment condition differences are noticeable for some tasks. Figure 1 reveals that task fixed effects can affect predictions and have to be controlled for in analyses.

Experiment 3

<i>Demographic Variables</i>	N	Buyer, N = 35	BuyerEPD, N = 34	Seller, N = 36	SellerEPD, N = 34	p-value	q-value
Male	139	25 (71%)	23 (68%)	18 (50%)	23 (68%)	0.23	1.00
White	139	35 (100%)	34 (100%)	35 (97%)	34 (100%)	1.00	1.00
Less60000USD	139	6 (17%)	4 (12%)	3 (8.3%)	8 (24%)	0.31	1.00
FullTime	139	12 (34%)	11 (32%)	12 (33%)	15 (44%)	0.72	1.00
HighSchoolOrLess	139	2 (5.7%)	2 (5.9%)	4 (11%)	2 (5.9%)	0.84	1.00
Train1Pred	139	3,041 (939)	3,587 (2,075)	3,897 (4,806)	3,936 (4,048)	0.65	1.00
Train2Pred	139	4,590 (944)	4,604 (1,596)	4,869 (1,333)	5,373 (4,530)	0.42	1.00
Train3Pred	139	3,362 (810)	3,491 (955)	3,703 (1,230)	3,737 (1,438)	0.68	1.00
Train1Conf	139	57 (25)	62 (27)	60 (21)	59 (24)	0.82	1.00
Train2Conf	139	58 (23)	61 (28)	58 (20)	56 (22)	0.55	1.00
Train3Conf	139	49 (24)	55 (28)	52 (22)	53 (22)	0.68	1.00
FarmIncome%	139	27 (24)	28 (18)	36 (29)	41 (35)	0.43	1.00
Angus	139	23 (66%)	27 (79%)	25 (69%)	29 (85%)	0.22	1.00
Simmental	139	4 (11%)	12 (35%)	10 (28%)	8 (24%)	0.13	1.00
Charolais	139	4 (11%)	7 (21%)	9 (25%)	7 (21%)	0.53	1.00
EPD	139	24 (69%)	27 (79%)	26 (72%)	26 (76%)	0.75	1.00
GEEPDI	139	20 (57%)	19 (56%)	19 (53%)	15 (44%)	0.70	1.00
EPDRank	139	22 (63%)	17 (50%)	22 (61%)	19 (56%)	0.70	1.00
Phenotype	139	32 (91%)	33 (97%)	34 (94%)	33 (97%)	0.81	1.00
GeneralConf	139	79 (20)	79 (14)	78 (17)	76 (20)	0.88	1.00
FinancialConf	139	77 (19)	77 (18)	78 (16)	77 (21)	0.99	1.00
RiskPreference	139	6.23 (2.26)	6.69 (1.82)	6.51 (1.79)	6.49 (1.93)	0.91	1.00
TimePreference	139	7.50 (1.36)	7.23 (1.73)	7.18 (1.92)	7.24 (1.77)	0.95	1.00
Trust	139	5.89 (2.54)	6.36 (2.05)	6.89 (2.07)	6.31 (2.07)	0.33	1.00

¹ n (%); Mean (SD)

² Pearson's Chi-squared test; Fisher's exact test; Kruskal-Wallis rank sum test

³ Benjamini & Hochberg correction for multiple testing

Table 6

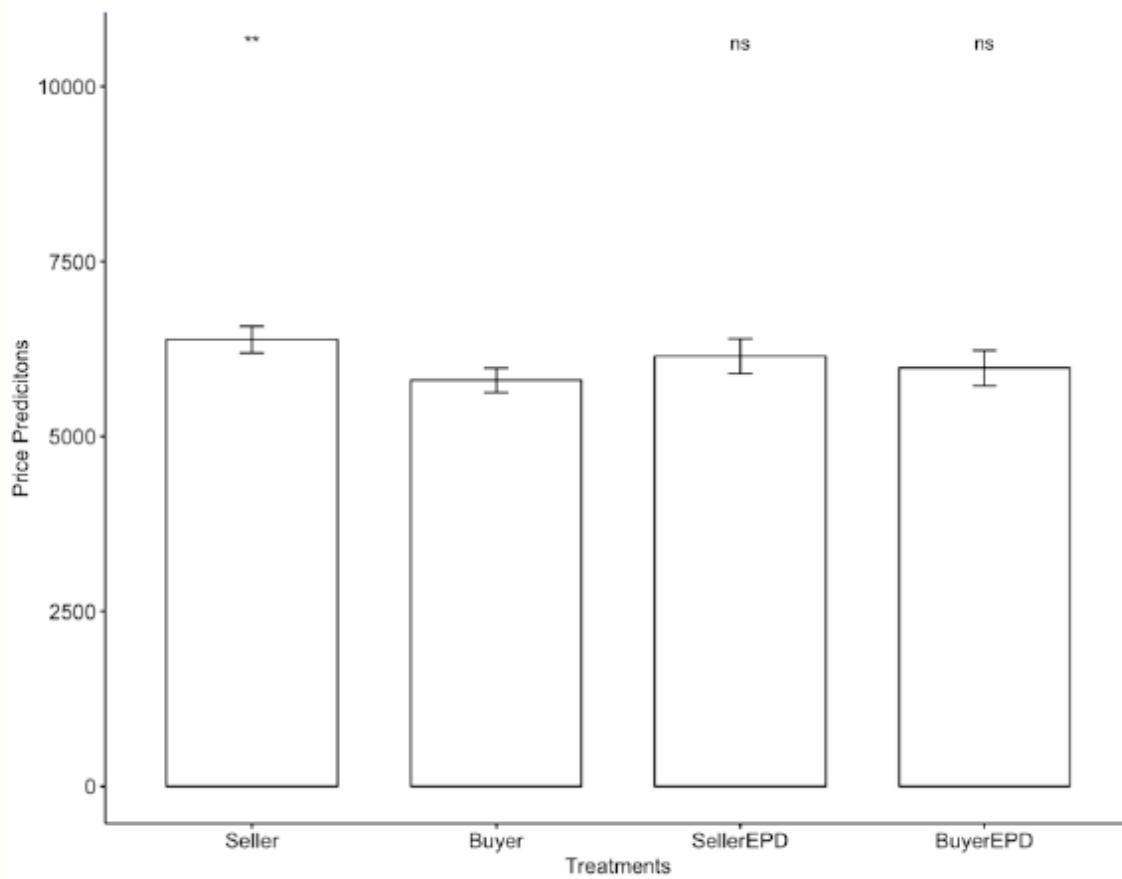


Figure 6

Conclusion

Our study and examination of the results reveal that the optimism bias is prevalent for participants with high risk tolerance behavior. Contrarily, the low risk tolerance group exhibits the pessimism bias. We also find that observed risks and confidence levels are positively correlated. We conjecture that agribusiness owners and farmers can be potentially more likely to be vulnerable to optimism bias if risk-seeking individuals self-select to the Ag sector.

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