Are experts overoptimistic about the success of market labeling information?

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Abstract

Being able to accurately predict the marketing effectiveness of product labels is critical for business profitability. Do industry experts (e.g., domain-specific and domain-general marketers) understand and accurately predict which messages appeal most to consumers? There is limited knowledge in this area, specifically around two essential food attributes: *health* and *taste*. Consumers perceive health and taste as trade-offs, which makes their reaction to such marketing information challenging to forecast. This study is the first to quantify the extent to which domain-general vs domain-specific experts can accurately predict consumer responses to health and taste information via marketing labels. We conducted three incentivized studies: Study 1 investigated consumer preferences for simple health versus taste labeling messages with actual consumers. Study 2 uncovered industry domain-specific 'industry experts' predictions for average consumers' willingness-to-pay (WTP) for the messages providing incentives for accuracy. Study 3 employs domain-general 'marketing experts' (cross-industry) and evaluates the role of market intelligence in improving consumer valuation forecasts. We found that while both expert types made optimistic predictions that marketing health-related information would effectively increase consumer valuations, consumers did not respond to such information. Moreover, despite exhibiting greater confidence in their predictions than domain-general experts (63% vs 70%), domain-specific industry experts overestimated consumer valuations by 33% relative to the average consumer WTP of $6.80 for an 8 oz. bag of pecans. In contrast, domain-general experts overestimated consumer valuations by only 5%, suggesting possible motivated reasoning among industry-specific experts. Releasing market intelligence to domain-general experts for the baseline valuation (control) improved the accuracy of the forecast for the control, but forecasting inaccuracies for specific labeling messages prevailed.

Keywords: BDM; forecasting; information nudges; overconfidence; overoptimism; willingness-to-pay.

JEL classification : D12, D83, C90, D90

1. Introduction

Industry experts and marketers emphasize the importance of effectively communicating with consumers to highlight product value, particularly for food—a category highly sensitive to consumer perceptions. Marketing messages often focus on health and taste, but consumer priorities vary by food type, with some favoring taste over health and others prioritizing health (Jo et al. 2016; Lusk and Briggeman 2009; Melo, Zhen, and Colson 2019; A. Drichoutis, Lazaridis, and Nayga 2006; T. Smith 2004; Papoutsi, Klonaris, and Drichoutis 2019; Nystrand and Olsen 2020).

The inherent tension between health and taste values (Papoutsi, Klonaris, and Drichoutis 2019; Ballco, Caputo, and de-Magistris 2020; Verbeke 2006) complicates accurate forecasting of consumer responses to labeling, marketing, and promotional strategies. Misjudging the economic impact of such efforts can harm businesses: overpredictions result in higher costs and potential losses from unfulfilled expectations (Abraham and Lodish 1990), while underpredictions lead to missed profitability opportunities due to underinvestment in promotion and advertising.

There is an important gap in the literature of information provision. Despite the vast literature on taste and health trade-offs (Ballco, Caputo, and de-Magistris 2020; Verbeke 2006; Luomala et al. 2015; Jo and Lusk 2018), our understanding of industry experts' ability to correctly predict and adjust consumer preferences for taste and health information is limited. Specifically, it is unclear whether the predictions of domain-specific experts, such as sellers and marketers within a particular industry, are more accurate given their industry knowledge than those of domain-general experts, like marketers across various industries. This discrepancy may arise because, compared to the latter, the former group tends to have a narrower focus, lacks a cross-industry perspective, has limited experience with diverse information strategies, and may be more prone to biases, including overconfidence, wishful thinking, and motivated beliefs (Caplin and Leahy 2019; Zimmermann 2020), therefore favoring information strategies prevalent within their own industry (e.g., those related to taste and health). To address this gap in the existing literature. We aim to determine whether experts anticipate that consumers will react differently to such messages and whether market intelligence can increase the forecast accuracy of experts.

We conducted three incentivized online studies with consumers (Study 1), domain-specific industry (Study 2), and domain-general marketing experts (Study 3). In Study 1, we quantified consumers' willingness to pay (WTP) for an 8 oz. bag of pecans using a between-subject design where consumers are randomly assigned to only one of five labeling conditions: four types of marketing messages frequently used in food markets (two health-related and two taste-related messages) and a control (neutral "pecan" message with no message). Consumers' valuations were incentivized using the Becker-DeGroot-Marschak (BDM) valuation mechanism (Becker, Degroot, and Marschak 1964).

In Study 2, we captured insights from domain-specific industry experts, specifically pecan experts, including producers and pecan marketers. While these experts bring specialized knowledge and deep expertise within their field, their perspective tends to be narrowly focused and lacks the broader, cross-industry viewpoint. Pecan experts submitted their forecasts of consumers' valuation for each of the five pecan products (one for each information condition). To determine experts' accuracy of predictions for each condition, we calculated the forecast error as the absolute difference between the expert predictions and the average consumer valuations

(Fischer and Harvey 1999). Accurate experts' predictions were incentivized with a monetary reward and public recognition in a popular press magazine.

In Study 3, we captured insights from domain-general marketing experts with diverse expertise and experience spanning multiple industries but without specialized knowledge of the pecan industry. Marketing experts submitted their forecasts of consumers' valuation for each of the five pecan products following the same approach as in Study 2. To assess whether marketing intelligence improves forecast accuracy, Study 3 differed from Study 2 in a key aspect. While participants in Study 2 submitted forecasts without any information on baseline consumer valuation, marketing experts in Study 3 provided forecasts in two rounds: first, without additional information, and then after receiving marketing intelligence data, including the mean and standard deviation of baseline consumer valuation (i.e., valuation of the product without health or taste information).

Our study contributes to two key areas of literature. First, it advances research on information asymmetry in food markets by evaluating whether experts have overly optimistic expectations about consumers' valuations of products with health and taste information. Additionally, it examines whether experts exhibit overconfidence in their forecasts, irrespective of their accuracy. While overconfidence has been well-documented in various fields such as economics, finance, entrepreneurship, advertising, and marketing (Abraham and Lodish 1990; Fellner and Krügel 2012; Invernizzi et al. 2017; Proeger and Meub 2014; Mahajan 1992; Kaplan, Sørensen, and Zakolyukina 2022; Shipman and Mumford 2011; Veress and Kaiser 2017), its impact on domain-general and domain-specific expert assessments remains unexplored. This is critical for practitioners and policymakers, as inaccurate and overconfident food information forecasts can influence business (Bohm, Lindén, and Sonnegård 1997; Gracia, Loureiro, and Nayga 2011) profitability and the effectiveness of information conveyed to consumers through food labels.

In the following section, we describe the factors influencing consumers and experts' assessments of pecans, our testable hypotheses, and our overall methodological approach. Then, we describe the three experimental studies, including how we analyzed the collected experimental data, and present the results. We discuss the results and implications in the last section.

2. Consumer and experts' assessments

Industry experts' ability to infer what attributes consumers value and, specifically, how health and taste labeling impact their food purchasing behavior is challenging for several reasons. First, consumers face health and taste trade-offs (Grunert and Wills 2007; Papoutsi, Klonaris, and Drichoutis 2019; Berning, Chouinard, and McCluskey 2011), which are linked to neurobiological processes underpinning food choice and control of eating behaviors (Lowe and Butryn 2007; Palma 2022). For instance, health information could serve as a cue for low taste and higher prices (Jo and Lusk 2018; Wardle 2000). At the same time, taste information can contradict a person's need for a healthy diet (Lowe and Butryn 2007), especially among consumers of value-added products (Campbell and Shonkwiler 2020).

Moreover, consumers' response to information is influenced by several factors, including whether information is hedonic or health-related (Ares et al. 2018), their level of familiarity with the product (Johnson and Russo 1984; C. W. Park and Lessig 1981), the relevance of product attributes such as health vs taste (Lusk and Briggeman 2009; Nystrand and Olsen 2020), and consumers' eating motivations and their food values (Hung et al. 2017; Luomala et al. 2015; Choi, Jessica Li, and Samper 2019).

Experts' predictions depend on their own biases or assumptions (Fages 2024). Overconfidence can be a critical behavioral bias associated with forecasting the effectiveness of marketing efforts on consumer demand responses. Overconfidence can be associated with experts' detrimental decision-making, including firm failure (Invernizzi et al. 2017). It could also be associated with significant spending in promotional efforts despite low returns (Abraham and Lodish 1990; Lovallo and Kahneman 2003) and less time invested in learning and planning (Shipman and Mumford 2011).

Several factors can significantly influence expert predictions. The presence (or lack) of similar peers and the observation of other decisions and actions (Proeger and Meub 2014) can influence the confidence level of one's own ability (W. P. Smith and Sachs 1997), which can vary across professional roles or contexts (Huseynov, Taylor, and Martinez 2024). In particular, expert interactions with diverse industry stakeholders, such as producers and managers, and their engagement with consumers can contribute to the explanation behind experts' overconfidence (Proeger and Meub 2014).

Experts' experience accumulation or role can serve as valuable proxies for their comprehension of market dynamics (Aharoni, Tihanyi, and Connelly 2011) and, therefore, their awareness of consumer preferences. At the same time, these two measurable characteristics are correlated with experts' cognitive biases. For instance, in a non-monetary study, investment experience and age were negatively correlated with overconfidence bias in stock markets (Menkhoff, Schmeling, and Schmidt 2013).

To assess experts' overconfidence in predicting consumer response to marketing information, our study focuses on the pecan market for two main reasons. First, pecan consumption has been associated with health benefits, including preventing obesity-related diseases (Delgadillo-Puga et al. 2023), and pecans are a tasty food (Du et al. 2022; Magnuson et al. 2016), making it an ideal food product to investigate consumer responses to health and taste information. Second, despite the rising demand for other specialty nuts, the pecan industry has experienced stagnant product demand (Campbell and Shonkwiler 2020; T. A. Park and Florkowski 2003). One potential reason could be the small investment in marketing strategies experts adopt compared to other tree nuts (Moore et al. 2009).

Hypotheses and approach

Our main hypotheses to test were whether both expert types overpredict consumer valuation response to marketing messages (main hypothesis 1) and whether providing domain-general experts with market intelligence for consumer baseline valuation improves experts' accuracy of predictions (main hypothesis 2). To test these hypotheses, we conducted three incentivized studies with a total of 718 participants.

In Study 1, we obtained consumers' valuation for pecan products under two rules to set the market price: a fixed price rule and the uniform distribution used in the conventional BDM. A secondary hypothesis posits that valuations derived from the fixed price rule may differ from those obtained via the BDM mechanism. Additionally, since Study 1 involved eliciting consumer responses to information, another secondary hypothesis examines whether providing health and taste information increases consumers' WTP for pecan products.

In Study 2, domain-specific pecan industry experts were asked to forecast consumers' valuation for pecan products displaying marketing messages. In Study 3, domain-general marketing experts (cross-industry) were asked to forecast consumers' valuation for the pecan products before and after receiving baseline consumer valuations for pecans.

The incentivized studies were pre-registered in the AEA RCT Registry (AEARCTR-0010789) and conducted online using the Qualtrics platform.[1] Online studies have an advantage in that they exhibit similar characteristics of a framed field experiment and more external validity because of the diversity in the sample (Harrison and List 2004). In each study, we evaluated five information treatments for the pecan products, including a baseline control (T_0) with no marketing message on the pecan product and four labeling information treatments with marketing messages: two health- and two taste-related marketing messages (T_1, T_2, T_3, and T_4).

Figure 1 displays each of the labeling information treatments: two health-related messages ("weight management pecans" and "controls cravings pecans"), two taste-related messages ("indulgently delicious pecans" and "great flavor pecans"), and a baseline control ("pecans"). The treatments were developed with the assistance of a marketing consultant based on marketing messages considered by the pecan industry (Federal and State Marketing Orders) and popular marketing claims considered by the tree nut industry. To create the health messages, we also consulted scientific evidence regarding the health benefits of pecans, particularly prevention of excessive weight and fat mass accumulation (Delgadillo-Puga et al. 2023; Cisneros-Zevallos et al. 2023) as well as "bad" cholesterol reduction (Morgan and Clayshulte 2000).

[1] The original pre-registration covered only Studies 1 and 2. Following feedback received after presenting the paper, we incorporated suggestions to include domain-general experts in a new experiment, Study 3.

3. Study 1 with consumers

Procedures

Recruitment

Study 1 was conducted online in April 2023 with Forthright panelists to obtain geographically-dispersed consumer WTP estimates in the United States. Forthright, a marketing company, recruits U.S. respondents through diverse online and offline advertising channels to obtain a nationally representative panel of the U.S. population over 18 years old. Our inclusion criteria required participants to be responsible for at least half of the grocery shopping for the household, have bought and eaten tree nut products at least once in the previous three months, not have a history of any eating disorders, not have any special dietary restrictions, and not be allergic to tree nut products. The final sample consists of 466 individuals, from 504 respondents, who initiated the survey and qualified for Study 1.[2]

Set up

At the beginning of Study 1, subjects were informed that they will receive $2.67 for their participation in the study that took approximately 10 minutes (about $16.02 hourly compensation). They were also told that they will receive an additional monetary compensation

[2] We excluded respondents who participated more than once with the same IP address (*n*=9), those who failed the first attention check question (*n*=9), those who entered implausible values to the reference price question (*n*=1), and those who took less than 5 minutes (1% percentile of duration distribution) answering the survey or more than 143 min (99% percentile of the distribution; *n*=19). We also excluded a few respondents (n=4) who answered that they buy less than half of the groceries in the exit questionnaire despite answering the initial (inclusion) question that they buy at least half of the groceries. Overall, conclusions hold including this last group of respondents. As a reviewer pointed out, it is possible that excluding respondents who are not primary shoppers may overlook valuable insights from irregular shoppers who might purchase pecan products as a special or occasional item.

of $15 or a food product if the elicitation task was selected for realization, based on the market realization procedure described later, and any remaining cash balance that resulted after subtracting the price paid from their $15 compensation.

The participants were asked to provide the maximum amount of money they were WTP for an 8 oz. bag of pecans labeled with only one of the five randomly assigned predetermined labeling messages (Figure 1). The labeling messages were designed to be simple and persuasive in nature, similar to existing claims in food labeling. Participants were asked their WTP in two similar, non-hypothetical, incentive-compatible elicitation stages using a within-subject design. Subjects were informed they would go through two stages in which they had to provide their WTP for a product with a predetermined marketing message (T_i), and the only difference between the two stages was the rule by which the market price was determined.

In the BDM price stage (S_1), subjects were informed that the market price would be randomly selected and that it would be equally likely to be a number ranging from $0 to $15. In the seller's fixed price stage (S_2), subjects were informed that a U.S. pecan producer determines the market price. Before launching the online survey and in order to avoid deception and make it a real market price, we partnered with a U.S. pecan producer-retailer and asked for the minimum amount of money the producer-retailer would be willing to accept (WTA) to sell the 8 oz. pecan products corresponding to each marketing message.[3] In this stage, consumers were told that the fixed price was the U.S. producer's minimum WTA. The U.S. producer minimum WTA was $10 for each of the five pecan products shown in Figure 1, which was not revealed to the respondents

[3] In Study 1, we compared a simpler rule to set the experimental price, potentially perceived as less ambiguous compared with the BDM. The rule is based on a fixed price obtained by asking the WTA of a single U.S. producer. As suggested by a reviewer, including responses from multiple producers could be a valuable research extension that keeps the simplicity in the instructions compared to drawing the price from a uniform distribution.

until the bidding concluded. Figure 2 (a) displays an example of the experimental procedures. The range of prices for an 8 oz. bag of pecans in the market during Spring 2024 was from $6 to $12. On Amazon.com, prices ranged from $4 to $13, with most products costing at least $10. Thus, the fixed price in the study (i.e., seller's WTA) falls within the range of regular retail.[4]

If the fixed seller price, perceived as more market-intuitive and transparent, produces similar valuations to the BDM mechanism, it could offer a simplified alternative for valuation studies, reducing game form recognition failures associated with BDM (Cason and Plott 2014a). To minimize ambiguity and avoid deception, we anchored the fixed price to the reservation selling price of a U.S. pecan producer, linking our work to the reference price literature (Bohm, Lindén, and Sonnegård 1997; Gracia, Loureiro, and Nayga 2011; Kilders and Caputo 2023; Ladenburg and Olsen 2006; Lemos, Halstead, and Huang 2022; A. C. Drichoutis, Lazaridis, and Nayga 2008).[5]

Monetary incentive approach

Prior to valuations, the market realization procedure was carefully described to the subjects as follows. First, subjects were informed if the bid is higher or the same as the market price, the subjects can buy the pecan product and pay the market price, and the market price would be subtracted from the fifteen-dollar participant endowment if the participant is selected for implementation. Second, subjects were told they had a 10% chance that their responses would be implemented, in which case they would pay the market price and receive the pecan product via

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[4] Compared to the BDM price, the proposed simpler price rule involves lower ambiguity about the payoff function and reduces participants' cognitive effort in understanding the incentive compatibility of valuation studies.

[5] This literature indicates that respondents often make choices based on reference prices. Thus, presenting respondents with a price rule they can relate to can reduce uncertainty about the payoff function.

priority mail shipping. To reduce the administrative and logistical costs of incentivizing all buying decisions, we used a lottery incentive payment mechanism with a 10% likelihood of being selected as a buyer, which yields valuations that are not statistically different from incentivizing all participants (Ahles, Palma, and Drichoutis 2024). Finally, subjects were instructed that if selected as a buyer (based on the lottery incentive payment), only one of the valuation stages would be randomly chosen for realization.

Figure 2 (b) illustrates the market realization procedure in Study 1 implemented based on the lottery payment mechanism. After responding to both stages (step 3), the participant was asked to choose a number from 1 to 10, which was then compared to a random number generated by the computer. If the number selected by the participant matched the randomly generated number (step 4), the participant's decision was implemented. Under this procedure, a participant had a 10% chance of being selected as a buyer for the market realization procedure. In the illustrative example provided in Figure 2 (b), S_1 was randomly selected for implementation (step 5) for the buyer. Since the subject's WTP was higher than the market price (\$8.00 > \$7.50), the subject paid for the product and the product was shipped to the home address via priority shipping (step 6). It is important to note that if S_2 had been randomly selected instead of S_1 since the WTP is less than the market price (\$8.50 < \$10.00), the subject would not have purchased the 8 oz. bag of pecans, in this case.

To elicit consumer emotional connection to the health- and taste-related messages, participants were asked the following after each market scenario: "Which of the statements below reflect your feelings toward the pecan product?" To answer, participants could select one of the following options: Love it!, Enjoyed it, Neutral, Did not like it, and Hate it, each represented with an emoji. Emoji-based questions have been implemented to elicit individuals' food preferences and emotions (Sick et al. 2023; Jaeger, Vidal, and Ares 2021).

After completing the two elicitation stages, respondents were asked to answer a brief survey that included questions about their purchasing habits and their expected market price for the pecan product. Participants were also asked about their overall health and taste preferences and food values (Lusk and Briggeman 2009).

Statistical Analyses

Unconditional analyses

To analyze consumer bids from Study 1, we employed non-parametric tests. The tests included the Wilcoxon signed-rank (WSR) test for matched data (within-subject comparisons of uniform price BDM versus producer set market price) and the Mann-Whitney (M.W.) test for unmatched data. That is, between-subject comparisons of each information condition (i.e., two health-related and two taste-related treatments) vs control (i.e., no information; Wilcoxon 1992). Finally, we adjusted *p*-values to account for multiple hypothesis testing using a bootstrap-based procedure (List, Shaikh, and Xu 2019).

Regression analyses

To control the potential effect of observable characteristics of the subjects on their bids, we regressed participants' bids on sociodemographic controls. This also controls for any imbalance of exogenous covariates (Appendix Table A1). We considered the following pooled OLS specification:

$$bid_{is} = \alpha_0 + \sum_{j=1}^{4} \alpha_{1j}\, T_j + \alpha_2\, S_2 + \sum_{j=1}^{4} \alpha_{3j}\, T_j\, S_2 + \gamma' Z_i + \varepsilon_{is} \tag{1}$$

where bid_{is} is the bid submitted by subject i in stage *s* ($s = 1,2$), T_j denotes the assignation of information treatment j ($j = 0,1,2,3,4$), S_2 is 1 when the subject submitted a bid when the market price is the seller's minimum willingness to accept to sell the product and 0 otherwise. Z is a vector of controls, including sociodemographic variables (i.e., age, region, sex, income, education, and marital and employment status), shopping behaviors, and food values. The terms α_k $(k = 0, \dots, 3)$ and γ are model parameters.

Data and Results

Summary statistics of respondents' characteristics in Study 1 are reported in Appendix Table A1. About half of respondents are female, half reported having a partner, very few attended graduate school (12%), had an annual income greater than $100,000 in 2022 (24%), or live in a rural area (23%). The majority have no children (65%) or work either full- or part-time (61%). A nontrivial proportion of respondents identify themselves as liberal (40%). The average respondent age is 47 years old. Note that this sample is based on the inclusion criteria for consuming pecan products in the previous three months.

We assessed the balance of participant samples across information treatments concerning observable characteristics. We reported standardized differences in Appendix Table A2 (Imbens and Rubin 2015). A standardized difference of less than 0.25 is considered acceptable (Cochran and Rubin 1973). Overall, we found none of the variables demonstrates significant imbalance, indicating an adequate randomization of subjects across treatments with a few exceptions. About 7 out of 111 differences show imbalances associated particularly with liberal ideology.[6] These differences are controlled in the regressions.

[6] Comparable results are reported based on balance tests. That is, results show no significant differences in these covariates between the control and treatment groups, except for one covariate (i.e., liberal) that was not balanced in one out of five comparisons (columns 7-10). These results suggest that the sample is fairly balanced across treatments.

In Study 1, we asked respondents to indicate the level of importance of each of eight food values when buying pecan products using a 5-point Likert scale (ranging from 1=Not important to 5=Very important). Most respondents (73%) indicated that taste was a very important attribute, followed by price (40%), processing level (34%), nutrition (32%), and visual appearance (31%). While the least important values were location (12%), production practice (19%), and convenience (21%; Appendix Figure A3, a).

Unconditional results

Table 1 (column 1) reports consumers' bids for each information condition under the two price rules from Study 1. For each condition, we fail to reject the hypothesis that consumer bids are different between the two price rule elicitation stages ($p>0.05$). This result suggests that a simpler elicitation mechanism based on a fixed price (i.e., a U.S. seller price) induces valuations statistically indistinguishable from the uniform price BDM. This finding implies that both approaches share similar limitations in capturing true preferences. Thus, while the fixed-price mechanism simplifies the process, it does not improve the reliability of elicited valuations compared to the BDM.

Furthermore, results in column 1 indicate that for each of the two elicitation tasks, there were no statistical differences in consumers' WTP between each treatment group and control ($p>0.05$). These results suggest that none of the health and taste-related information employed in this study affected respondents' WTP. On average, consumers were willing to pay $6.77 for an 8 oz. bag of pecans (with their assigned budget of $15.00). In the baseline control for the BDM task, the average consumer WTP was $6.85 and a standard deviation of $3.67. This data is relevant as it serves as the market intelligence information provided to domain-general experts in their second round in Study 3.

We conducted subsample analyses to assess whether participants' bids varied across their characteristics, including their attitudes and food values. Regarding key consumer food values (i.e., price, taste, processing level, and nutrition; as shown in Figure A3, a), we found no evidence of heterogeneity in consumer response to the marketing messages (Appendix Table A3, columns 1- 4).

We also explored valuation heterogeneity regarding health beliefs and weight status. Results indicate that respondents' beliefs in the health benefits of pecans or being overweight were not a determinant explaining valuation response (Appendix Table A4, columns 1 and 2). This is consistent with previous findings showing that nutrition is not important in explaining valuations (Appendix Table A3, column 1).

Finally, we considered consumer preferences' heterogeneity due to shopping behaviors and conducted subsample analyses based on shopping frequency (at least once a week vs less often) and shopping volume (buy all the groceries vs buy most groceries or at least half of groceries). We found no heterogeneous effects of marketing information due to these dimensions (Appendix Table A4, columns 3 and 4).

Regression results

Table 2 shows the results of OLS regressions of consumer WTP elicited in Study 1 based on equation (1) for different specifications: one excluding controls (column 1) and other specifications varying by the set of control variables we included in (1): sociodemographic information (column 2), shopping behavior (column 3), food values (column 4), and emotions and expected price (column 5). Across specifications, results confirmed the unconditional analysis results (Table 1). That is, β_j is not statistically significant, indicating that information treatment j does not increase consumer preferences for pecan products. Similarly, δ is not statistically significant, which indicates that subjects' bids under a fixed price are not statistically different from subject's bids under the BDM price. Finally, τ_j is not statistically significant, suggesting that bids do not vary due to the fixed price evaluation task across treatments.

In addition to pooled OLS, we considered alternative specifications, including quantile regressions that capture heterogeneity across different quantiles of the nonzero bid's distribution and random effects Tobit regressions that capture the panel nature of the data and the mass of zero bids. In none of these specifications, the parameter corresponding to treatment j was statistically significant, confirming the unconditional results in Table 1 that the marketing message has no effect on consumer valuation for pecans (Appendix Table A4).

Regression results in Table 2 reveal interesting aspects of consumer valuations for pecans. For instance, those who buy all groceries and those who buy tree nuts at least once a week have a greater WTP compared to those who are not primary shoppers and those who are not frequent buyers of tree nut products (columns 3-5). Finally, presumed positive feelings toward the product (with the randomly selected message) and expected market price are positively associated with respondents' valuations (column 5). When asked about their feelings upon seeing the pecan product, 72% of respondents, on average, indicated they "Love it!" or "Enjoyed it" when they were shown the product with taste- or health-related information, while only 28% were neutral or did not like it (Appendix Figure A1).

Information could have affected participants' bids through their expected market price or self-reported emotional connection to the marketing messages. To evaluate these effects, we regressed feelings and expected price on the set of controls and treatment variables used in equation (1). Results are shown in Appendix Table A5, which indicates that only the "indulgently delicious pecans" label was associated with a higher expected market price. The lack of emotional responses from consumers to marketing messages might explain the lack of consumer WTP response (Table 1) as well as why results remain the same when adding consumers' emotions in equation (1), shown in Table 2.

4. Study 2 with domain-specific pecan industry experts

Procedures

Recruitment

Study 2 was conducted online between April and July 2023 via Qualtrics and administered to experts in the pecan industry (i.e., producers, marketers, and sellers) across the United States. The five information treatments in Figure 1 and the two elicitation stages were presented to all participants. To qualify for the study, participants needed to be in the U.S., be over 18 years old, and have a role in the U.S. pecan industry (e.g., grower, handler, retailer, owner, marketer, etc.).

The responses were collected by sending email invitations to potential expert participants, with up to four periodic reminders sent biweekly. Email invitations to pecan experts were sent through pecan associations, and direct email was sent using experts' contact information obtained from extension specialists. Only the responses that had engaged with at least one of the ten market forecasting scenarios presented were included. The final sample consists of 51 domain-specific experts who completed the valuation tasks from a total of 91 respondents who initiated the survey.

Set up

Study 2 consisted of two similar, non-hypothetical, incentive-compatible elicitation stages based on a within-subject design to align the industry expert responses to the consumer valuations

(Fellner and Krügel 2012).[7] More specifically, subjects faced all market scenarios we presented to consumers in Study 1. Participants were asked to provide their best forecast estimate of the average bid a consumer is willing to pay for the pecan product for each of the four treatment conditions (T_1, T_2, T_3, and T_4) and control (T_0) in each of the two stages in randomized order (differing, as in Study 1, in how the market price is determined). Thus, experts faced a total of ten market scenarios. As in Study 1, stages were presented in random order to account for ordering effects. Within stages, treatments were also randomized. Figure 3 shows the experimental design in Study 2 with pecan industry experts.

The study began by explaining that before the survey, U.S. consumers were asked to provide their maximum WTP for pecan products for one of the five market scenarios (each showing a pecan product with a different marketing message) based on the two elicitation stages. After each of the ten market scenarios, the subject was asked to provide their best guess of the average consumer WTP for the pecan product in each scenario and the confidence level of their guess response. The confidence level question was as follows: "How certain are you of your response, on a scale from 0% to 100%?"[8]

Monetary incentive approach

To incentivize the repetitive signal-based prediction task, subjects were informed that the top ten respondents with the most accurate assessments would be rewarded. Participants were informed that the ten participants with the highest overall accuracy (lowest forecast prediction error aggregated over all products) would receive a monetary reward of $250. This approach

[7] Our approach is equivalent to studying experts' predictions, given different signal-based tasks.

[8] This question was also elicited in the study with domain-general experts (Study 3) to compare whether forecast confidence levels vary by expert type.

incentivizes participants to prioritize accuracy in their forecasting efforts (Fages 2024; Laster, Bennett, and Geoum 1999). To identify the top ten participants, we considered overall forecast accuracy, calculated by aggregating absolute differences between forecasts and average consumer bids across the ten conditions. Additionally, participants were told that their names would be publicly recognized and featured in the popular Pecan South Magazine as a reward for their accuracy in predicting consumer responses to the marketing messages (Appendix Figure A2; see the announcement of winners). Finally, subjects were told that the total earnings would be evenly distributed among the tied winners in the event of ties. There were no ties in this study.

Following the completion of the elicitation stages, we conducted further inquiries to gather comprehensive information that could explain responses. We asked about various aspects to infer their level of expertise, such as the participants' years of experience in the pecan industry, any additional employment they hold outside the pecan industry, the distribution channels they presently utilize for pecan sales, and their overall sales figures for 2022.

Statistical Analyses

Unconditional analyses

We conducted the same statistical tests from Study 1 to analyze experts' forecasts in Study 2. First, we used the WSR test for within-subject comparisons of experts' forecasts of consumer bids between each information condition and control. This comparison evaluates whether experts were less or more optimistic toward consumer responses when a marketing message was displayed compared to the control. Second, we compared means between consumer and expert assessments for each information condition and control, using M.W. for unmatched data.

In addition, we compared the distributions of consumer bids and expert forecasts by testing for stochastic dominance. First, we defined the two distributions of WTP with cumulative distribution functions (CDFs) as C(x) and E(x) for consumers and experts' valuations, respectively. E(x) first-order stochastically dominates C(x) if D ≡E(x) − C(x) ≥ 0 ∀x. Under first-order stochastic dominance, the distributions cannot cross. Under second-order stochastic dominance, there can be crossovers of the distributions. Thus, we tested (1) if there are statistical differences in distributions based on the two-sample Kolmogorov-Smirnov (K.S.) test (Smirnov 1948) and (2) if there are crossovers of the distributions, where they occur. For the last test, we employed the Goldman-Kaplan (G.K.) test (Goldman and Kaplan 2018), which determines specific ranges across the distribution for which equality is rejected.

To better understand experts' predictions, we calculated the accuracy of predictions for each of the ten market scenarios at the subject level. Table 3 reports the following measures: (i) *overprediction*, a binary variable equal to 1 whenever experts' guess is greater than average consumer WTP for a given condition and zero otherwise (column 1) and (ii) *deviation,* calculated as the absolute difference between the guess and average consumer bid for each of the ten conditions (Fischer and Harvey 1999). For *overprediction*, we used the McNemar's test (McNemar 1947), while for *deviation,* we used the M.W. test. In all unconditional analyses, we adjusted p values to account for multiple hypothesis testing using a bootstrap-based procedure (List, Shaikh, and Xu 2019).

Regression analyses

We considered the following specification to analyze the determinants of the accuracy of the experts' forecasts:

$$y_{ijt} = \beta_0 + \sum_{j=1}^{4} \beta_{1j} T_j + \beta_2 S_2 + \sum_{j=1}^{4} \beta_{3j} T_j * S_2 + \gamma' Z_i + \varepsilon_{ijt} \qquad (2)$$

where y_{ijt} is an accuracy measure for domain-specific experts' forecasts of WTP corresponding to subject i for treatment j and period t. Specifically, we use the *deviation* of expert forecast from the consumer WTP as the accuracy measure (Fischer and Harvey 1999). The remaining independent variables are similar to equation (1). One exception is that Z_i includes different factors that can be indirectly associated with forecasting accuracy, including respondents' sociodemographic factors (i.e., sex, age, marital status) and other factors that can be directly associated, such as years of experience, interaction with consumer, role, self-reported acknowledgment of the industry, and experts' certainty level of their response. The terms β_k $(k = 0, \ldots, 3)$ and γ are model parameters.

Data and Results

Appendix Table A5 reports summary statistics of pecan industry domain-specific expert characteristics in Study 2. Regarding knowledge and experience in the pecan industry and with consumers, few reported not having knowledge about the pecan market (28%) or having less than five years of experience (30%). About half of respondents sell pecans directly to consumers, including those who are growers only (41%) or retailers (26%). Comparison of sociodemographic characteristics between samples, industry experts vs consumers (Tables A1 and Table A3), reveals a few key differences. Respondents in Study 2 are older (average age 57 vs 47), mainly male (74% vs 50%), and more educated (35% vs 12% attended graduate school).

We asked industry experts to forecast consumers' pecan values in Study 2. Domain-specific experts indicated that most consumers consider taste to be very important (60%), followed by visual appearance (44%), processing level (31%), price (29%), and convenience (25%; Appendix Figure A3, b). The differences in the ranking of consumer food values between experts and consumer responses suggest misalignment, which may open the door for missing opportunities for the pecan industry. For instance, while experts forecasted appearance the second most important attribute, consumers ranked price as the second attribute. We also asked experts to indicate their own opinions about the importance of each food value for pecans. Overall, the ranking of experts' food values differs from that reported by consumers, except for the ranking of taste, which was the most important attribute (Appendix Figure A4, a vs b).

Unconditional results

Table 1 (column 2) reports subjects' forecasts of consumers' WTP from Study 2. In each stage, pecan experts' predictions of consumers' WTP for products with messages were only qualitatively higher than that of the control group (p>0.1). Yet, as shown earlier in Study 1 results (Table 1, column 1), consumers' WTP, on average, did not increase when marketing messages were employed (p>0.1).

When comparing the magnitude of pecan experts' forecasts and consumers' bids (column 1 vs column 2), there are statistical differences between consumer bids and expert forecasts for each condition (p<0.05, column 3). On average, pecan experts' overestimations of consumers' valuation across information conditions were quite significant, with an average of 33% overprediction. The average expert forecast was $8.99 compared to the average consumer WTP of $6.77.

Figure 4 illustrates the cumulative probabilities of consumers' WTP and experts' forecast of WTP across conditions. This figure shows that the CDF of experts' forecasts is to the right of the CDF of consumers' bids. Specifically, when the cumulative probability was 0.5, consumers' bids were up to $7, while experts' forecasts were up to $8, suggesting that experts' forecasts were always greater than actual consumer valuations for a given probability.

The results of the K.S. test for statistical differences in distributions rejected the combined hypothesis of equivalence (p<0.01). The results of G.K. test for crossovers of the distributions also rejected equality at all points between $1.99 and $14.00, which both lie outside the 10th and 90th quantiles for both groups. Results of this test also indicate that equality across the distributions is rejected at the 1% level, which is consistent with our finding using the K.S. test. Results from both tests provide evidence in support of first-order stochastic dominance by the pecan experts' distribution.

Table 3 shows the results for pecan experts' accuracy outcomes. Regarding the *overprediction* outcome, results indicate that experts' estimations, on average, surpassed the average consumer valuation in 80% of the tasks (Table 3 column 1). The results also indicate that the likelihood of overpredicting did not increase when a marketing message was employed (p>0.05).

Similarly, the *deviation* outcomes for marketing messages were not statistically different from the baseline control (p>0.05, Table 3 column 2). The greatest qualitative deviation to the consumer bid was associated with the "control cravings pecans" message. Experts overestimated consumers' valuation for this information condition by an average of 44%, which was the outcome average of the two elicitation stages (column 3). Average forecasts for the "control cravings pecans" message was at $9.17 compared to the average consumer bid of $6.39.

Results of subjects' self-reported confidence levels about their forecast for each condition are also reported in Table 3. Domain-specific experts were confident in the accuracy of their predictions in 70% of the tasks (column 3). Yet, they overpredicted average consumer valuations in 80% of the occasions (column 1). Compared to the control condition, experts were not less or more confident in their estimations when they were asked to predict consumer WTP for a message (p> 0.1; column 3).

Regression results

Table 4 reports estimation results for the OLS regression in equation (2) with and without different controls. Similar to unconditional results (Table 3), *deviation* of experts' forecast from consumer valuation is not statistically different between products displaying a marketing message and the control, which had no message ($p>0.05$; columns 1-3). One exception is that *deviation* is greater for products displaying the health-related information "weight management pecans" and "controls cravings pecans" ($p<0.01$). These results are robust to fixed effects and random effects model specifications (Appendix Table A8).

Table 4 results reveal that sociodemographic information was not associated with respondents' forecast accuracy ($p>0.1$). Similarly, there is no evidence that years of experience or confidence level of prediction was associated with *deviation* ($p>0.1$). Likewise, correlation analyses suggest a weak association ($\rho=0.0988$, $p=0.0262$) between *deviation* and confidence level on aggregate. This last result indicates that experts' perceived ability to predict the market success of health- and taste-related messages does not align with actual forecast accuracy.

Finally, there was weak evidence suggesting that respondents who perceived themselves as less knowledgeable about the pecan market were actually more accurate in their predictions (i.e., showed a smaller *deviation*, $p=0.07$) compared to those who claimed to be more knowledgeable. To evaluate whether experts' confidence level of predictions varies across conditions, we regressed confidence level on the set of controls and treatment variables used in (2). Results show that pecan industry experts showed similar levels of confidence (70%) across treatments in predicting consumers' WTP for a product with a marketing message (Appendix Table A9). There was one exception: experts were less confident in their predictions for "weight management pecans" ($p<0.05$).

5. Study 3 with domain-general marketing experts and the effect of market intelligence information

Study 2 has two main limitations: First, it elicits the forecasting accuracy of domain-specific experts, those in the pecan industry (including pecan growers, sellers, and marketers), who, despite having solid knowledge about pecan consumers, may not have a comprehensive understanding of consumer responses to marketing labels and may be more susceptible to biases, such as wishful thinking and motivated beliefs (Caplin and Leahy 2019; Zimmermann 2020). Second, Study 2 does not inform us whether experts can improve forecasting when receiving market intelligence information.[9] To address these shortcomings, we conducted Study 3 online in September 2024 to test (1) whether consumer valuations predicted by domain-general marketing experts are closer to actual valuations compared to those predicted by domain-specific experts (those in the pecan industry) and (2) whether domain-general experts (those with cross-industry marketing experience) improve the accuracy of their predictions when provided with marketing intelligence for the baseline consumer valuation (i.e., consumer valuation for the product without a marketing message).

Procedures

Recruitment

Marketing experts were recruited from Prolific, a subject pool for online experiments known for its quality of responses compared to other online panels (Douglas, Ewell, and Brauer 2023).

[9] We thank an anonymous reviewer for raising these two critical issues in Study 2 that prompted us to design and implement Study 3.

Prolific has a preset of screening questions. We used these questions to recruit only participants with marketing experience (i.e., those who work in marketing or sales/business and have a work role that includes marketing/sales/advertising development). In the online questionnaire, we also included a screening question. Those who noted no marketing experience in this question were screened out of the study. The final sample for Study 3 consists of 201 marketing experts who completed the valuation tasks.

Set up

Study 3 consisted of experts forecasting tasks under the BDM valuation task similar to Study 2. Contrary to Study 2, in which participants provided valuations only once with no information on actual consumer valuations, participants in Study 3 provided valuations before and after receiving market intelligence. There were two phases involved. In Phase 1 (pre-information phase), participants were asked to provide forecasting valuations for five pecan products (Figure 1). Similar to Study 2, we told participants that we previously asked 500 U.S. consumers for their valuations of an 8 oz. bag of pecan products and that the market price was randomly determined. After Phase 1, participants were provided with consumers' WTP mean and standard deviation for the pecan product with no marketing message (baseline control) elicited under the BDM task. Specifically, in Study 1 under this task, the average consumer value for the 8 oz. bag of pecans was \$6.85, with a standard deviation of \$3.67. Figure 5 illustrates market intelligence regarding consumer baseline valuation provided to domain-general marketing experts after Phase 1. In Phase 2 (post-information phase), participants provided their valuation forecasts again for the same five pecan products presented in Phase 1. The order of products was randomized in each phase.

Monetary incentive approach

Similar to Study 2, experts in Study 3 were incentivized with a monetary reward to provide the most accurate estimation in each of the five prediction tasks for each of the two phases. Participants were told that the ten experts with the highest overall accuracy (lowest forecast prediction error aggregated over all products) would receive a monetary reward of $20.

As in Study 2, following the completion of the prediction tasks, participants in Study 3 provided their confidence level of their predictions being correct. In Study 3, we also gathered information about participants' expertise, pecan preferences, and sociodemographic information.

Statistical Analyses

Unconditional analyses

Analyses in Study 3 were similar to those in Study 2 with pecan experts. We tested statistical differences of marketing experts' assessments between pre- and post- information disclosure using within-sample non-parametric tests proposed for Study 2.

Regression analyses

We considered the following specification to analyze the determinants of the accuracy of the domain-general marketing experts' forecasts:

$$y_{ijt} = \delta_0 + \sum_{j=1}^{4} \delta_{1j}\, T_j + \delta_2\, Post_t + \sum_{j=1}^{4} \delta_{3\mathrm{j}} T_j\, Post + \gamma' Z_i + \varepsilon_{ijt} \qquad (3)$$

where y_{ijt} is an accuracy measure (i.e., *deviation*) for domain-general experts' forecasts of WTP corresponding to subject *i* for treatment *j* and period *t*. *Post* is an indicator variable for post information disclosure (i.e., marketing intelligence). Z_i includes different factors that can be indirectly associated with forecasting accuracy of marketing experts, including respondents' sociodemographic factors (i.e., sex, age, and marital status) and other factors such as years of experience, role, self-reported acknowledgment of the industry as well as experts' certainty level of their response. The terms δ_k $(k = 0, \ldots, 3)$ and γ are model parameters.

Data and Results

Appendix Table A5 presents summary statistics of respondents' characteristics in Study 2 and Study 3, comparing domain-specific experts (Study 2) with domain-general marketing experts (Study 3). Respondents in Study 2 reported greater knowledge of pecans compared to those in Study 3 (28% vs 73% indicate a lack of knowledge). Additionally, respondents in Study 2 were older (57 vs 41 years), predominantly male (74% vs 48%), and more likely to have attended graduate school (35% vs 27%) than those in Study 3. Approximately the same proportion have less than five years of work experience (~30%).

Unconditional results

Table 5 reports respondents' WTP under the BDM task from Study 1 (column 1) and subjects' forecasts of consumers' WTP from Study 3 before (pre-information phase) and after providing market intelligence regarding consumer baseline valuation in the post-information phase (column 2). In both phases, marketing experts' predictions of consumers' WTP for products with messages were higher than that of the control group, particularly regarding health messages (i.e., the "weight management pecans" and "controls cravings pecans" messages; p <0.01). One exception was "great flavor pecans," with a valuation prediction that was not statistically different from that of the control in the pre-information stage (p=0.117, column 2). As shown earlier, consumers' WTP, on average, was not higher than the control for products with marketing messages (p>0.1, column 1). On average, domain-general experts' overestimations of consumers' valuation across information conditions were relatively small, with an average of 5%

overprediction. The average expert forecast pre-information was \$7.13 compared to the average consumer WTP of \$6.79.

Comparing the magnitude of domain-general experts' forecasts and consumers' bids (column 1 vs column 2) reveals that domain-general experts' estimations of consumers' valuation across information conditions are similar in the pre-information stage on average (p>0.05, column 3). In the post-information phase (i.e., after market intelligence information of consumer baseline valuation is disclosed), as expected, the average forecast of valuations for the control was slightly closer to the average consumer WTP. For the health messages, experts predicted significantly higher valuations than the actual consumer WTP ($p < 0.01$, column 3). This indicates that after correcting experts' beliefs about the control condition, experts expect that such health messages would influence consumer valuations despite evidence to the contrary.

Table 6 shows the results for domain-general experts' accuracy outcomes pre- and post-information phases. The results show the manipulation worked and market intelligence regarding consumer valuation for the control condition (with no marketing message) decreased the *deviation* outcome for this condition (p<0.001, column 1). In particular, in the pre-information phase, experts underestimated consumers' valuation by 8.0% for the control, with average forecasts at \$6.30 compared to the average consumer WTP of \$6.85, while in the post-information phase, they underestimated consumers' valuation by 7.8%, with average forecasts at \$6.31 compared to the average consumer bid of \$6.85 (Table 5). Market intelligence, however, did not change the confidence level (p=0.145) for the control.

Market intelligence reduced deviations for all message conditions (p<0.05), except for "weight management pecans" (p=0.471). However, it did not influence confidence levels of all message conditions. Overall, results suggest that the market intelligence decreased the deviation of predictions but had no effect on the expert's confidence.

Comparing the predictive abilities of the two expert groups without market intelligence (Table 3 vs Table 6) reveals that domain-general experts demonstrated a lower likelihood of overprediction (54% vs 80%) and smaller deviations in their predictions ($2.29 vs $2.78) compared to domain-specific experts. Notably, despite outperforming domain-specific experts in prediction tasks, domain-general experts reported lower confidence in their forecasts (63% vs 70%) and less knowledge of the pecan market (73% vs 28%; Appendix Table A5).

Results suggest that domain-general experts may be less susceptible to biases, such as wishful thinking and motivated beliefs (Caplin and Leahy 2019; Zimmermann 2020), prompting domain-specific experts to favor information strategies prevalent within their own industry, such as those emphasizing taste or health. This raises the possibility that excessive specialization may compromise accuracy by introducing industry-specific biases.

Regression results

Table 7 reports estimation results for equation (3) with and without different controls. Without market intelligence, *deviation* of experts' forecast from consumer valuation is not statistically different between products displaying a marketing message and no message for the control (p>0.05, columns 1-3). One exception is that *deviation* is greater for products displaying "controls cravings pecans" (p<0.05).

Similar to the unconditional results (Table 6), Table 7 results reveal that marketing intelligence decreased *deviation* (i.e., absolute difference between experts forecast and average consumer WTP) for the consumer baseline valuation (i.e., control condition). The *deviation* error decreased by almost half, by at least $0.99 (Table 6, column 1) from the average forecast of

$2.18, which was pre-information (Table 6, column 2). Interestingly, when providing baseline market intelligence, *deviation* for the two health messages, “weight management pecans” (p<0.001) and “controls cravings pecans” (p<0.05), increased.

Like in Study 2, sociodemographic information or years of experience were not associated with respondents’ forecast accuracy (p>0.05). There was weak evidence that domain-general experts’ greater confidence was associated with a greater *deviation* (p=0.07). This result provides suggestive evidence that domain-general experts’ perceived ability to predict the success of marketing messages does not align with actual forecast accuracy. Remarkably, in Study 2, confidence level was not associated with experts’ ability to correctly forecast consumer preferences (p=0.426).

To evaluate whether domain-general experts’ confidence level of predictions varies across conditions, we regressed confidence level on the set of controls and treatment variables used in (2). As anticipated, results show that marketing intelligence increased experts’ confidence regarding their predictions for baseline valuations (p<0.001). After information was provided, experts’ confidence in their predictions for taste messages was much lower than for that of the control (p<0.05; Appendix Table A10).

6. Discussion and implications

This three-part study analyzes consumers and experts’ assessments of pecan products displaying health- and taste-related information. Based on three sequential studies with U.S. consumers and domain-specific and domain-general experts, three main findings are revealed. First, despite taste and health being considered important consumer food values (Lusk and Briggeman 2009; Melo, Zhen, and Colson 2019), the inclusion of simple health and taste information—commonly used in snack product labeling—had no significant effect on consumers’ WTP for pecan products.

That is, we found no statistical differences in WTP between messages despite framing differences in the provided information. These results contrast previous work indicating that information framing influences how consumers perceive products (Yang and Hobbs 2020).

Three factors can explain the lack of effect of commonly used marketing messages on consumers' WTP. First, the information presented might not align with consumer values: those who value taste would overlook health-related information (Grunert and Wills 2007; Thunström 2019; Ballco, Caputo, and de-Magistris 2020). In our study, most consumers (73%) valued taste, while only one-third (32%) valued nutrition (Appendix, Figure A3), despite pecans being increasingly featured as a functional food (Nystrand and Olsen 2020). Second, as U.S. consumers may already expect pecans to be tasty and provide health benefits, health-related information is less salient (Charness, Oprea, and Yuksel 2021; Sharot and Sunstein 2020; Toney et al. 2023). In our study, provided marketing information had no influence on respondents' feelings (Appendix Table A7), potentially due to its low saliency. Third, information might convey a conflicting message, which could lead to no effects (Cheng, Chang, and Lee 2020; Cozzens and Contractor 1987; Goh and Balaji 2016; Santa and Drews 2023).

The overall insignificant effect of provided marketing information on consumer valuation in our study aligns with the growing literature on information nudges. Existing literature mainly focused on nutrition information suggests that evidence of the impact of food labeling information is inconclusive (Cecchini and Warin 2016). Concerning the broader influence of information nudges on non-food settings, consistently smaller effects compared to other nudges have been observed across various domains (Codagnone et al. 2016).

Second, despite consumers' lack of response to marketing information, experts, in particular domain-specific experts, were optimistic and overconfident about the effects of the provision of health and taste information on consumer valuations. That is, compared to domain-general experts, domain-specific experts were less accurate (greater *deviation*: $2.78 vs $2.29 with no information) and more confident (70% vs 67%). Evidence from other domains, including finance and investment, indicates that overconfidence is associated with overoptimistic forecasts (Invernizzi et al. 2017). Study 3 revealed that after phase 2, when market intelligence (i.e., baseline consumer valuations) was provided to domain-general marketing experts, they adjusted their forecasts to be more accurate for the control. It is reasonable to expect that providing marketing intelligence on actual consumer reactions to taste and health labels can also improve forecast accuracy.

Third, contrary to evidence indicating that educational attainment, experience, and age can be negatively associated with overconfidence bias and positively associated with accuracy (Aharoni, Tihanyi, and Connelly 2011; Invernizzi et al. 2017; Menkhoff, Schmeling, and Schmidt 2013), we found that experts' years of experience did not correlate with the accuracy of predicting consumer valuations. There was also no evidence that age or being a retailer were associated with accuracy. Interestingly, we found weak evidence that those domain-specific experts who see themselves as less knowledgeable had greater accuracy. Similarly, evidence indicates that expertise or self-assessed knowledge does not necessarily correlate with better forecasting or decision performance (Alevy, Haigh, and List 2007; Bodnaruk and Simonov 2015; Verma 2017; Mahajan 1992).

Lastly, to reduce the uncertainty of the payoff function associated with the BDM, we designed a simpler, auction-like valuation task based on a pre-set fixed price. Results show that the fixed seller price induced consumer valuations that are not statistically different from those elicited under the BDM. This suggests that, on average, the developed simpler valuation task suffers from the same limitations as the BDM. The lack of intuitiveness in the BDM mechanism has raised concerns regarding whether participants (i) fully understand its payoff structure (Asioli, Mignani, and Alfnes 2021; Cason and Plott 2014; Martin and Muñoz-Rodriguez 2022)[10], (ii) systematically misreport their preferences (Noussair, Robin, and Ruffieux 2004), and (iii) fail to identify the dominant bidding strategy (A. Drichoutis and Nayga 2022; Kendall and Chakraborty 2022)

Implications

This study is the first to compare average consumers' WTP for food products (from Study 1) with forecasts of consumer valuations made by domain-specific (pecan industry experts from Study 2) and domain-general experts (marketing experts from Study 3). Two key results regarding expert assessments are derived from these sequential studies. First, domain-specific industry experts significantly overestimate consumer valuations, and the magnitudes are quite large, with average overvaluations of 33%. In contrast, domain-general experts overestimated consumer valuations by 5% despite being slightly less confident in the predictions compared to domain-specific experts (63% vs 70%). Moreover, pecan and marketing experts tend to predict a positive impact of health information on consumer WTP; however, marketing information was ineffective at increasing consumers' WTP in our simple messages incorporated within the label. It is uncertain as to whether more complex information may also increase the degree of forecast

[10] Only around 16% of people offered a price to sell a two-dollar ticket they owned that was around its actual value of two dollars. One explanation is that subjects often confuse the BDM with a first-price auction (Cason and Plott 2014). In light of this, simpler incentive-compatible mechanisms perceived to be more transparent are considered by researchers instead, such as the multiple price list (MPL; Andersen et al. 2006; Asioli, Mignani, and Alfnes 2021; Morag and Loewenstein 2021). Asioli et al. (2021) found no differences in estimated WTP and response times between the BDM and static MPL. Yet, the MPL was perceived by respondents as simple to understand and decide on a response.

accuracy. Furthermore, all experts were not only optimistic about the impact of information on consumer demand, but they were also overconfident about their ability to predict the impact of that information. In other words, greater overprediction bias occurred whenever there was greater certainty about predictions. Similarly, those who self-described as less knowledgeable about the pecan industry exhibited a smaller overprediction bias and a lower probability of overpredicting consumer WTP (Table 4). Domain expertise exacerbates overconfidence because of lower cognitive effort, tunnel vision, and greater dependence on irrelevant cues presented in the decision context (Mahajan 1992; Dror 2011; Kaplan, Sørensen, and Zakolyukina 2022); thus, caution must be exercised when experts perceive that they have a high level of expertise in a given domain.

Second, market intelligence reduces the inaccuracy in marketing experts' forecasts by almost half. Literature indicates that experts' attention to market information can improve forecasting (Baghestani and AbuAl-Foul 2020). Our results suggest that facilitating market information to experts can decrease but not completely eliminate inaccuracies. To reduce expert bias, we suggest trying to assess expert forecasts of valuations of specific consumer groups or providing them with useful feedback on the source of the biases. More specifically, future work can test strategies that mitigate optimism bias, such as feedback (Mahajan 1992) or additional information on the decision context (Huseynov, Taylor, and Martinez 2024). For instance, experts' beliefs can be updated by learning or using a formal forecast system to reduce decision-making biases (Aharoni, Tihanyi, and Connelly 2011; Invernizzi et al. 2017).

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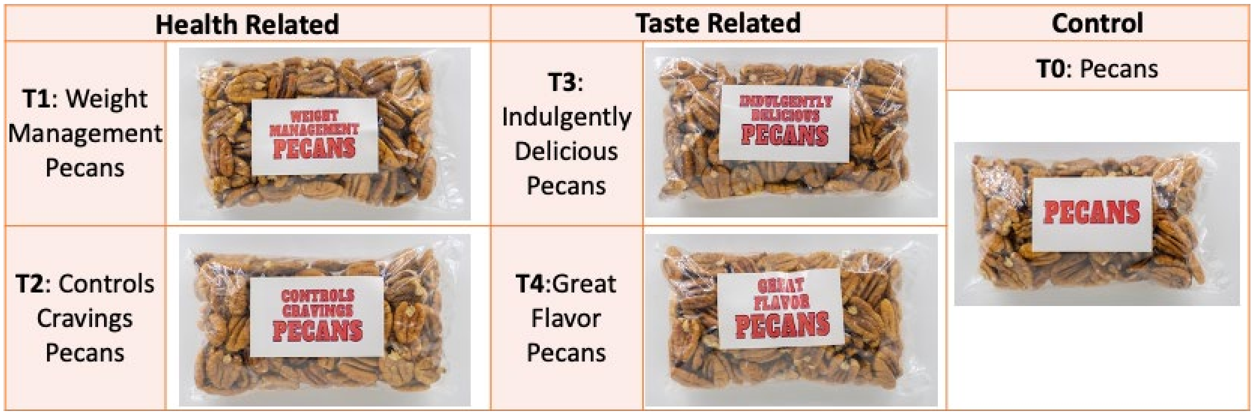
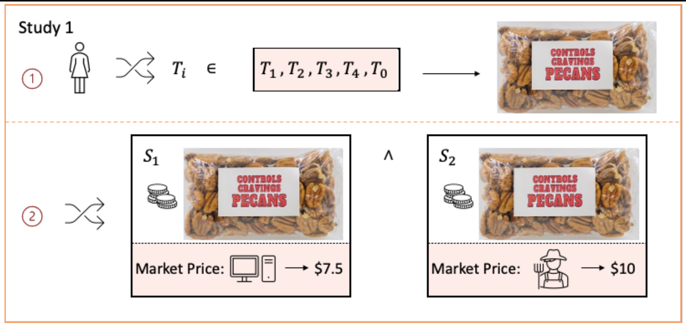
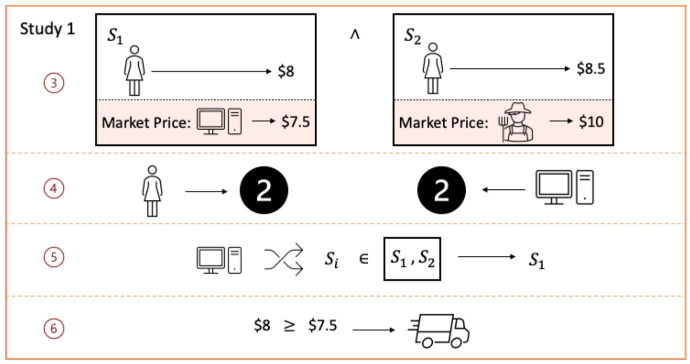


Figure 1. The five information treatments include four health- and taste-related marketing messages and a control. The treatment conditions were assigned randomly based on a between-subject design for Study 1 with consumers. A within-subject design with experts was conducted for Study 2 and Study 3.



(a) Experimental design for Study 1



(b) Market realization procedure for Study 1

Figure 2. Experimental design and monetary incentive approach for Study 1 with consumers. Figure 2(a) illustrates an example of the random assignation of a treatment to a subject in Study 1 with consumers. Each subject is involved in two WTP elicitation stages (S_1 and S_2). In this example, "controls cravings pecans" was the information treatment randomly assigned to the subject, $7.50 was the randomly chosen BDM price, and $10.00 was the seller price. The stages' order was randomly assigned, and the same information treatment was presented in the two stages (S_1 and S_2) the subject faces. Figure 2(b) illustrates the market realization procedure. A subject chooses a number from 1 to 10. If the chosen number matches the computer's randomly generated number, then one of the two elicitations is randomly chosen for implementation. In the example, the computer and subject select the same number (i.e., 2). In this case, S_1 is the randomly chosen stage. In this stage, the subject's WTP was greater than the market price (i.e., BDM price); therefore, the subject pays the market price, and the product is shipped to his US home mailing address provided at the end of the study.

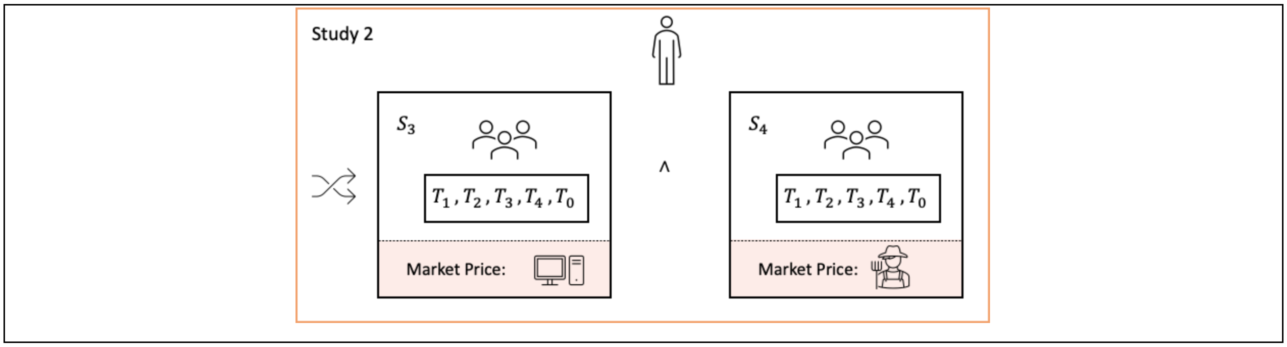


Figure 3. Experimental design for Study 2 with pecan experts. It shows the elicitation stages with experts. In Study 2, a pecan expert faces prediction tasks related to consumer valuations elicited under the two elicitation stages, BDM price (S_3) and seller price (S_4), each with the five different treatment conditions presented in Figure 1 (i.e., four information treatments and a control).

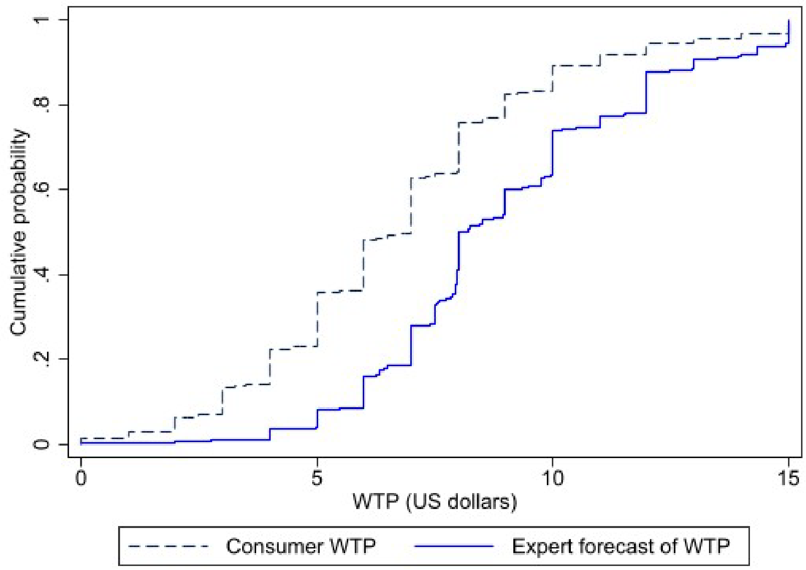


Figure 4. Cumulative distributions of consumer WTP (from Study 1) and pecan expert forecast of WTP (from Study 2). We rejected the hypothesis of equality of the distributions of the two samples ($p<0.01$, K.S. test).

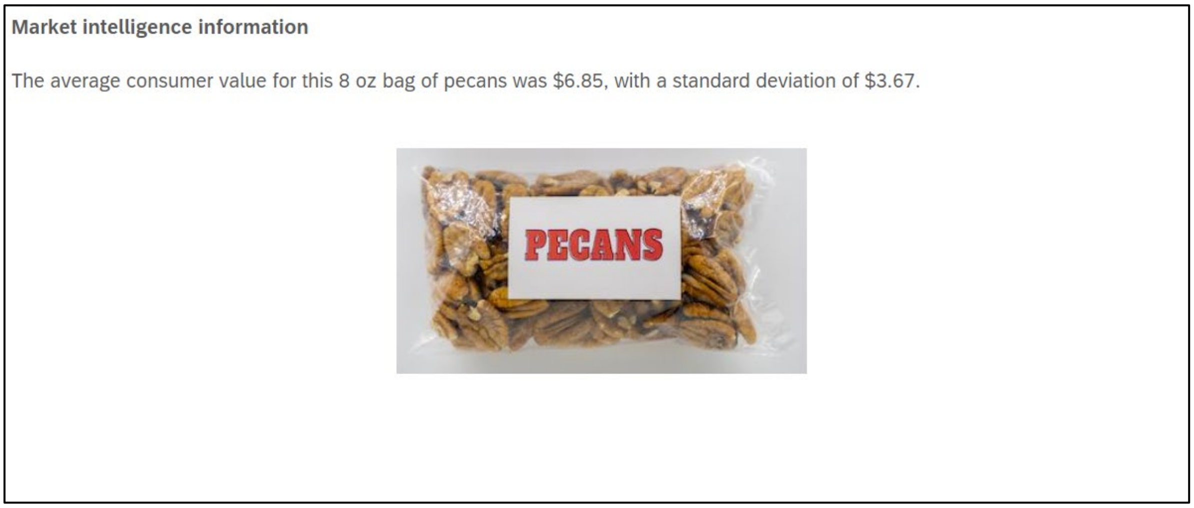


Figure 5. Market intelligence regarding baseline consumer valuation used in Study 3. We provided baseline consumer information (i.e., consumer valuation of the pecan product with no marketing message or control condition) elicited under the BDM task. In Study 3, a marketing expert faces prediction tasks related to consumer valuations in two phases: before and after marketing intelligence is provided, each phase with the five different treatment conditions presented in Figure 1 (i.e., four information treatments and a control).

Tables

Table 1. Consumers' WTP and pecan experts' forecast of consumers' WTP

Stage	Treatment	(1) Consumer bid			(2) Expert forecast			(3)
		N	Mean	Mktg. info. vs control *p* value	N	Mean	Mktg. info. vs control *p* value	Bid vs forecast
BDM price (S1)	Weight management pecans	100	6.933	0.813	51	9.310	0.742	<0.001
	Indulgently delicious pecans	85	7.162	0.834	51	9.194	0.819	0.001
	Great flavors pecans	92	6.547	0.901	51	8.870	0.822	<0.001
	Controls cravings pecans	94	6.458	0.864	51	9.235	0.809	<0.001
	Pecans (control)	95	6.853	-	51	8.446	-	0.003
Seller price (S2)	Weight management pecans	100	6.860	0.804	51	9.438	0.540	<0.001
	Indulgently delicious pecans	85	7.260	0.706	51	8.946	0.925	0.002
	Great flavors pecans	92	6.573	0.907	51	8.908	0.892	<0.001
	Controls cravings pecans	94	6.315	0.839	51	9.104	0.799	<0.001
	Pecans (control)	95	6.723	-	51	8.435	-	<0.001

Notes: The Mann-Whitney (M.W.) test was used for unmatched data (i.e., comparisons between marketing information treatments and the control for Study 1), while the Wilcoxon signed-rank (WSR) test was used for matched data (i.e., comparisons between BDM price and Seller price for each treatment for Study 1 and Study 2; comparisons between marketing information treatments and the control for Study 2, and comparisons between expert and consumer valuations). *p* values were adjusted to account for multiple hypothesis testing. Column 3 indicates that for each condition, we rejected the null hypothesis that the two samples (i.e., expert guess and consumer bids) are from populations with the same distribution. We could not reject the null hypothesis of differences between BDM price and Seller price comparisons (p>0.1).

Table 2. Pooled OLS estimation results of consumers' bids

Variables	Consumer bid				
	(1)	(2)	(3)	(4)	(5)
Weight management pecans	0.080	0.137	0.151	0.035	0.293
Indulgently delicious pecans	0.309	0.232	0.259	0.097	-0.464
Great flavors pecans	-0.305	-0.347	-0.268	-0.415	-0.319
Controls cravings pecans	-0.395	-0.364	-0.293	-0.466	-0.190
Seller price task (SPT)	-0.130	-0.130	-0.130	-0.111	-0.111
Weight management pecans x SPT	0.057	0.057	0.057	0.038	0.038
Indulgently delicious pecans x SPT	0.228	0.228	0.228	0.209	0.209
Great flavors pecans x SPT	0.156	0.156	0.156	0.177	0.177
Controls cravings pecans x SPT	-0.013	-0.013	-0.013	-0.032	-0.032
Age		0.041***	0.034***	0.034***	0.003
South		-0.220	-0.356	-0.529	-0.302
Midwest		-0.209	-0.211	-0.396	-0.301
Northeast		-0.475	-0.562	-0.599	0.106
Liberal ideology		-0.363	-0.416	-0.282	-0.050
Female		0.010	-0.088	-0.110	-0.526*
Graduate school education		0.350	0.273	0.312	0.313
Has a partner		-0.251	-0.134	-0.218	-0.057
Income greater than $100k		0.173	0.149	0.207	0.110
Non children		-0.038	0.060	0.009	0.148
Has a full- or part-time job		0.061	-0.213	-0.229	-0.257
Shop all groceries			0.521	0.494	0.399
Shop tree nuts at least once a week			1.145***	1.008***	0.645**
Price is important				-0.545	-0.339
Taste is important				0.478	0.395
Processing is important				0.423	0.177
Nutrition is important				0.092	0.022
Visual appearance is important				-0.116	-0.157
Convenience is important				0.420	0.030
Production practice is important				0.003	-0.055
Location is important				0.636	0.653
Positive feelings toward product: 'love it' or 'enjoy it'					1.229***
Expected price at a grocery store					0.655***
Constant	6.853***	5.345***	4.818***	4.725***	0.715
BIC	4834.640	4862.768	4837.281	4811.987	4309.633
N	932	932	932	924	924

Notes: ****p*<0.001 ***p*<0.01 **p*<0.05. Clustered standard errors were calculated. The consumer bid average (standard deviation) is $6.77 ($3.14).

Table 3. Pecan experts' predictions of consumer WTP

Stage	Treatment	(1) Overprediction I[Forecast-Bid>0]		(2) Deviation |Forecast-Bid|		(3) Certainty of forecast 0-100%	
		Mean	Mktg. info. vs control *p* value	Mean	Mktg. info. vs control *p* value	Mean	Mktg. info. vs control *p* value
BDM price	Weight management pecans	0.863	0.771	3.025	0.816	67.059	0.985
	Indulgently delicious pecans	0.725	1.000	2.758	0.982	70.000	1.000
	Great flavors pecans	0.824	0.983	2.600	0.998	70.400	1.000
	Controls cravings pecans	0.824	0.982	3.162	0.735	68.235	0.997
	Pecans (control)	0.725	-	2.293	-	70.784	-
Seller price	Weight management pecans	0.902	0.707	3.100	0.604	69.608	1.000
	Indulgently delicious pecans	0.765	1.000	2.691	0.981	70.000	0.999
	Great flavors pecans	0.804	1.000	2.742	0.985	71.176	1.000
	Controls cravings pecans	0.824	0.997	3.214	0.380	67.800	0.999
	Pecans (control)	0.765	-	2.215	-	70.000	-

Notes: For overprediction, we used McNemar's test, while for Deviation and Deviation to bid ratio, we used the WSR test. *p* values were adjusted to account for multiple hypothesis testing.

Table 4. OLS estimation results of pecan experts' accuracy of predictions of average consumers' bids

Variables	Deviation		
	(1)	(2)	(3)
Weight management pecans	0.732**	0.829**	0.853**
Indulgently delicious pecans	0.465	0.511	0.514
Great flavors pecans	0.307	0.341	0.257
Controls cravings pecans	0.868**	0.946***	0.962**
Seller price task (SPT)	-0.078	-0.076	-0.069
Weight management pecans x SPT	0.152	0.109	0.089
Indulgently delicious pecans x SPT	0.011	0.018	0.018
Great flavors pecans x SPT	0.220	0.210	0.285
Controls cravings pecans x SPT	0.131	0.119	0.191
Age		0.002	-0.010
Graduate school		-0.102	0.232
Female		-0.819	-1.005
Sales less than 50k		-0.389	0.189
Grower_only		0.999	0.830
Retailer		0.915	0.272
Married		0.888	0.716
Non children		-0.771	-0.563
Less knowledgeable			-1.234
Less than 5 years of experience			-0.305
Direct sales			0.381
Full time in the pecan industry			0.607
Certainty of forecast 0-100%			0.006
Constant	2.293***	1.958	1.891
BIC	2361.931	2222.664	2194.339
N	510	480	477

Notes: ****p*<0.001 ***p*<0.01 **p*<0.05. Clustered standard errors were calculated. The differences in observations (N) are due to missing information in some exit questions. The deviation average (standard deviation) is 2.78 (2.33).

Table 5. Consumers' WTP and marketing experts' forecast of consumers' WTP

Phase	Treatment	(1) Consumer bid under BDM			(2) Expert forecast			(3)
		N	Mean	Mktg. info. vs control *p* value	N	Mean	Mktg. info. vs control *p* value	Bid vs forecast
Pre info	Weight management pecans	100	6.933	0.812	201	7.827	<0.001	0.124
	Indulgently delicious pecans	85	7.162	0.358	201	7.115	0.016	0.911
	Great flavors pecans	92	6.547	0.327	201	6.892	0.117	0.664
	Controls cravings pecans	94	6.458	0.257	201	7.491	<0.001	0.063
	Pecans (control)	95	6.853	-	201	6.302	-	0.557
Post info	Weight management pecans	100	6.933	0.812	201	8.234	<0.001	<0.001
	Indulgently delicious pecans	85	7.162	0.358	201	7.455	<0.001	0.631
	Great flavors pecans	92	6.547	0.327	201	7.146	<0.001	0.263
	Controls cravings pecans	94	6.458	0.257	201	7.809	<0.001	0.003
	Pecans (control)	95	6.853	-	201	6.319	-	0.619

Notes: The Mann-Whitney (M.W.) test was used for unmatched data (i.e., comparisons between marketing information treatments and the control for Study 1), while the Wilcoxon signed-rank (WSR) test was used for matched data (i.e., comparisons between BDM price and Seller price for each treatment for Study 1 and Study 2; comparisons between marketing information treatments and the control for Study 2, and comparisons between expert and consumer valuations). We cannot reject the null hypothesis of differences for each condition between pre-and post-information stage comparisons (p>0.1). p values were adjusted to account for multiple hypothesis testing.

Table 6. Marketing experts' predictions of consumer WTP

Phase	Treatment	(1) Overprediction I[Forecast-Bid>0]		(2) Deviation |Forecast-Bid|		(3) Certainty of forecast 0-100%	
		Mean	Mktg. info. vs control *p* value	Mean	Mktg. info. vs control *p* value	Mean	Mktg. info. vs control *p* value
Pre info	Weight management pecans	0.677	<0.001	2.354	0.956	63.632	0.999
	Indulgently delicious pecans	0.438	0.999	2.181	0.995	62.090	0.977
	Great flavors pecans	0.552	0.085	2.163	1.000	63.035	0.999
	Controls cravings pecans	0.632	<0.001	2.548	0.440	62.587	0.997
	Pecans	0.418	-	2.180	-	63.700	-
Post info	Weight management pecans	0.771	<0.001	2.038	<0.001	67.214	0.978
	Indulgently delicious pecans	0.448	0.442	1.456	0.453	64.627	0.429
	Great flavors pecans	0.632	<0.001	1.372	0.802	64.899	0.485
	Controls cravings pecans	0.751	<0.001	2.013	<0.001	65.174	0.510
	Pecans	0.348	-	1.194	-	68.955	-

Notes: For overprediction, we used McNemar's test, while for Deviation and Deviation to bid ratio, we used the WSR test. *p* values were adjusted to account for multiple hypothesis testing. We could not reject the null hypothesis of no differences between pre-and post-information comparisons for overprediction and certainty of forecast ($p >$ 0.1). We rejected the null hypothesis of no differences between pre-and post-information comparisons for *deviation* for all message conditions (p<0.05) except for "weight management pecans" (p = 0.49).

Table 7. OLS estimation results of marketing experts' accuracy of predictions of average consumers' bids

Variables	Deviation		
	(1)	(2)	(3)
Weight management pecans	0.174	0.167	0.181
Indulgently delicious pecans	0.001	-0.039	-0.017
Great flavors pecans	-0.017	-0.020	-0.002
Controls cravings pecans	0.369*	0.390*	0.408*
Market intelligence (Post)	-0.986***	-1.007***	-1.027***
Weight management pecans x Post	0.670***	0.686***	0.682***
Indulgently delicious pecans x Post	0.261	0.275	0.282
Great flavors pecans x Post	0.195	0.196	0.212
Controls cravings pecans x Post	0.451*	0.435*	0.440*
Age		-0.000	-0.001
Graduate school		0.265	0.256
Female		0.197	0.173
Marketing analyst		-0.087	-0.138
Marketing manager		0.045	0.008
Married		0.084	0.066
Non children		-0.082	0.014
Less knowledgeable			-0.211
Less than 5 years of experience			0.065
Certainty of forecast 0-100%			0.006
Constant	2.180***	2.023***	1.766***
BIC	7806.563	7655.227	7642.019
N	2010	1960	1956

Notes: ***p<0.001 **p<0.01 *p<0.05. Clustered standard errors were calculated. The differences in observations (N) are due to missing information in some exit questions. The deviation average (standard deviation) is 1.96 (1.71).

Supplementary Figures

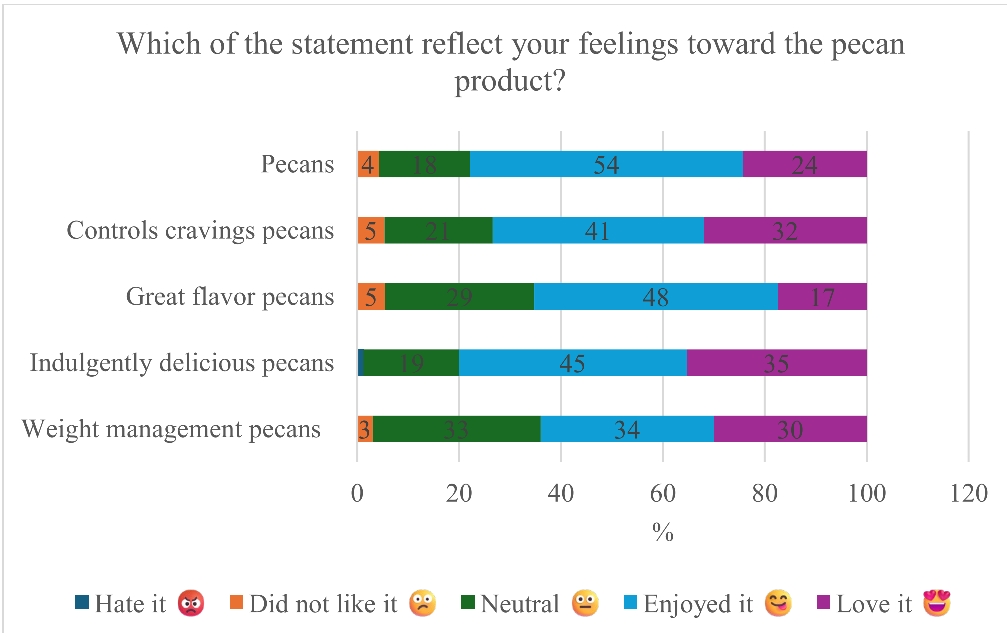


Figure A1. Emotional response scale for pecan products.

by Pecan South Staff / December 1, 2023 / Studies

Earlier this year, a team of researchers at Texas A&M University's Department of Agriculture and Life Sciences invited pecan industry members to participate in a study about consumer decision-making and consumer preferences for pecans. This research arose out of the belief that understanding an expert's ability to accurately forecast the effectiveness of marketing efforts to influence consumer valuations is critical for a firm's profit-maximizing decisions. In partnership with the Texas Pecan Growers Association, Texas A&M researchers conducted the study to determine to what extent pecan industry experts can accurately predict the success of marketing labeling messages.

In the study, they asked pecan producers to forecast the average consumer's willingness to pay for pecan products that displayed five different health and taste-related marketing messages. The marketing labeling messages included: a control message that read "pecans," health-related messages like "weight management" and "control cravings," and taste-related messages, including "indulgently delicious" and "great flavor." Participants with the top 10 most accurate predictions were selected as winners of a $250 gift card and, of course, bragging rights.

We thank all producers for participating in the study. Upon the completion of the study, the findings will inform stakeholders' decisions on the development of marketing efforts.

Here are the winners (in alphabetical order by last name). Each winner will be contacted via email about their prize.

Adam Green, Oak Jill, VA

Mark Hamilton, Coleman, OK

Karlene Hanf, Denair, CA

Darrel Jones, Iron City, TN

Monica Moran, Manor, TX

Ryan Mote, Graham, TX

Dena Purdy, Blackwell, OK

Phil Ricks, Oak Island, NC

Clay Robertson, Alexandria, LA

Aaron Steinle, Kerrville, TX

Figure A2. Announcement of winners in the Pecan South Magazine

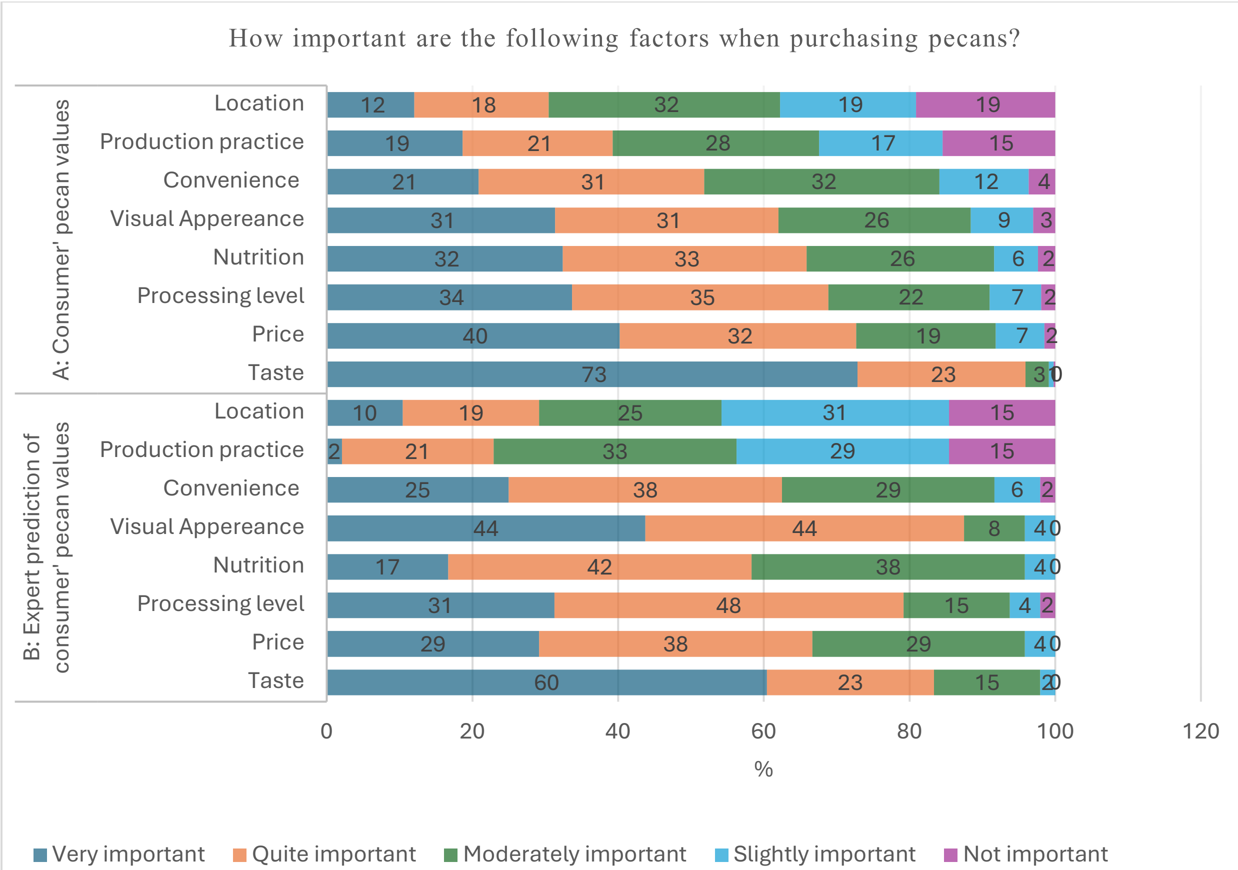


Figure A3. Consumer food values reported by consumers and forecasted by pecan experts. In Study 1, consumers were asked to indicate the level of importance of each of the eight food values using a 5-point Likert scale from 1 (not important) to (very important). In Study 2, pecan experts were asked to predict consumer pecan values using a scale similar to that in Study 1.

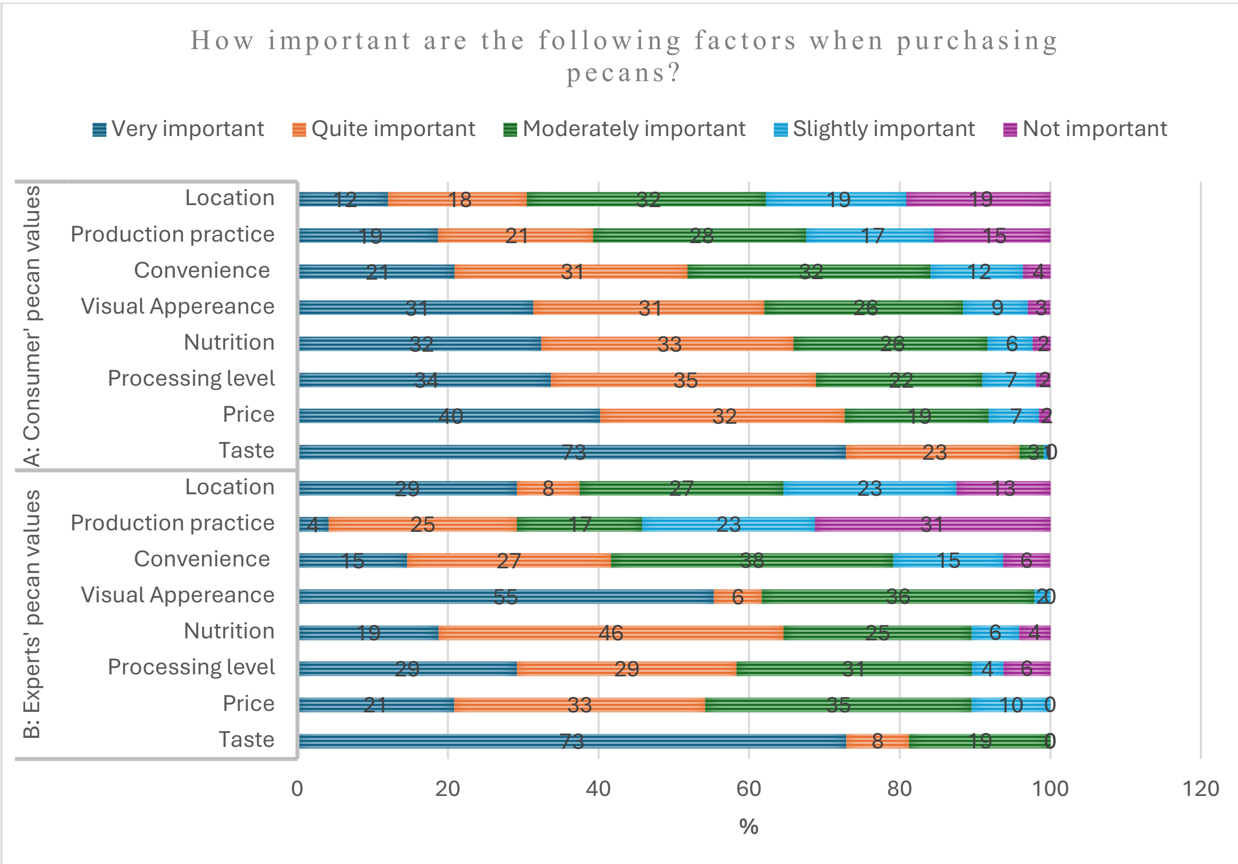


Figure A4. Consumer and pecan expert food values. In Study 2, pecan experts were asked to report their own pecan values using a scale similar to that in Study 1.

Supplementary Tables

Table A1. Respondents' characteristics in Study 1 for the full sample and each group.

Variable	(1) Full Sample	(2) Control	(3) T1	(4) T2	(5) T3	(6) T4	(7) Diff (2)-(3)	(8) Diff (2)-(4)	(9) Diff (2)-(5)	(10) Diff (2)-(6)
Age	47.43	47.99	46.66	47.15	47.84	47.54	0.58	0.35	0.07	0.20
South	0.44	0.47	0.34	0.45	0.39	0.54	1.91	0.36	1.13	-0.94
Midwest	0.22	0.22	0.21	0.18	0.30	0.20	0.19	0.74	-1.29	0.32
Northeast	0.17	0.15	0.25	0.18	0.13	0.16	-1.80	-0.53	0.33	-0.23
Liberal ideology	0.40	0.47	0.50	0.27	0.37	0.37	-0.37	2.85	1.44	1.41
Female	0.50	0.51	0.54	0.45	0.45	0.53	-0.48	0.78	0.81	-0.36
Graduate school education	0.12	0.09	0.13	0.16	0.10	0.11	-0.78	-1.40	-0.07	-0.26
Has a partner	0.55	0.55	0.53	0.54	0.52	0.63	0.24	0.08	0.35	-1.12
Income greater than $100k	0.24	0.23	0.29	0.29	0.23	0.17	-0.93	-0.95	0.05	1.05
Nonchildren	0.65	0.68	0.63	0.67	0.68	0.60	0.79	0.19	-0.01	1.27
Has a full- or part-time job	0.61	0.68	0.59	0.67	0.60	0.53	1.37	0.19	1.23	2.16
Shop all groceries	0.61	0.60	0.66	0.60	0.58	0.59	-0.86	0.00	0.33	0.21
Shop tree nuts at least once a week	0.61	0.66	0.60	0.62	0.57	0.57	0.91	0.55	1.38	1.25
N	466	95	100	85	92	94	195	180	187	189

Notes: Respondents in each group were assigned only one of the five treatment conditions. Columns 7-10 report *t*-values of two sample comparisons using parametric tests. T-test and chi-squared tests were conducted for continuous and categorical variables, respectively.

Table A2. Pairwise normalized differences between the information treatments for observable characteristics.

	T1 vs				T2 vs			T3 vs		T4 vs
Variable	T2	T3	T4	T5	T3	T4	T5	T4	T5	T5
Age	-0.031	-0.074	-0.058	-0.084	-0.043	-0.025	-0.053	0.019	-0.010	-0.030
South	-0.220	-0.106	**-0.416**	**-0.274**	0.113	-0.191	-0.053	**-0.306**	-0.166	0.138
Midwest	0.085	-0.217	0.019	-0.027	**-0.302**	-0.065	-0.112	0.236	0.190	-0.046
Northeast	0.180	**0.307**	0.225	**0.259**	0.128	0.045	0.079	-0.083	-0.049	0.034
Liberal ideology	**0.484**	**0.265**	0.259	0.053	-0.213	-0.219	**-0.429**	-0.006	-0.211	-0.206
Female	0.186	0.189	0.016	0.069	0.003	-0.170	-0.116	-0.173	-0.119	0.053
Graduate school education	-0.098	0.101	0.073	0.112	0.198	0.171	0.209	-0.028	0.010	0.039
Has a partner	-0.022	0.017	-0.198	-0.035	0.039	-0.176	-0.012	-0.215	-0.051	0.163
Income greater than $100k	-0.009	0.141	**0.287**	0.133	0.150	**0.296**	0.142	0.145	-0.008	-0.153
Non children	-0.085	-0.115	0.070	-0.114	-0.030	0.155	-0.029	0.186	0.001	-0.185
Has a full- or part-time job	-0.167	-0.016	0.117	-0.196	0.151	**0.285**	-0.029	0.133	-0.180	**-0.315**

Notes: T5 corresponds to control. We reported standardized differences (Imbens and Rubin 2015). A standardized difference of less than 0.25 is considered acceptable (Cochran and Rubin 1973). Differences greater than 0.25 in bold.

Table A3. Subsample analyses of consumers' bids by main consumer food values

Stage	Treatment	(1) Nutrition is important		(2) Price is important		(3) Taste is important		(4) Processing level is importamt	
		Yes	No	Yes	No	Yes	No	Yes	No
BDM price	Weight management	7.38	6.69	6.89	7.07	7.42	5.29	7.76	6.60
	Indulgently delicious	7.15	7.17	6.74	8.12	7.08	7.45	7.74	6.81
	Great flavors	6.68	6.51	6.41	6.80	6.76	6.17	6.67	6.50
	Controls cravings	7.00	6.06	6.35	6.84	6.47	6.38	6.66	6.28
	Pecans	8.15	6.42	6.91	6.76	7.14	6.31	7.90	6.46
Seller Price	Weight management	7.35	6.59	6.72	7.29	7.30	5.38	7.79	6.48
	Indulgently delicious	7.28	7.25	6.58	8.80	7.24	7.34	7.60	7.05
	Great flavors	7.00	6.47	6.50	6.70	6.81	6.26	7.05	6.39
	Controls cravings	6.61	6.09	6.10	7.05	6.31	6.35	6.35	6.28
	Pecans	8.19	6.23	6.83	6.48	7.07	6.14	8.00	6.24

Notes: A food value (e.g., taste) is important whenever the respondent indicates that it is "very important" based on a five-point Likert scale of importance level. None of the results of comparisons (between marketing message and control and between stages) were statistically significant at 5% level based on multiple hypothesis testing.

Table A4. Subsample analyses of consumers' bids by health beliefs, weight status, and shopping behaviors

Stage	Treatment	(1) Believe in health benefits of pecans		(2) Overweight		(3) Buy all the groceries		(4) Buy once a week	
		Yes	No	Yes	No	Yes	No	Yes	No
BDM price	Weight management	7.42	5.85	7.05	6.80	7.31	6.19	7.39	6.24
	Indulgently delicious	7.04	7.35	6.84	7.48	7.45	6.74	7.71	6.26
	Great flavors	7.07	5.76	7.01	6.18	6.35	6.82	6.90	6.09
	Controls cravings	6.82	5.84	6.32	6.64	7.12	5.53	6.89	5.87
	Pecans	7.13	6.39	6.46	7.35	7.15	6.41	7.38	5.81
Seller price	Weight management	7.21	6.08	6.86	6.86	7.23	6.14	7.29	6.21
	Indulgently delicious	7.07	7.56	7.25	7.27	7.39	7.06	7.92	6.16
	Great flavors	7.17	5.68	6.77	6.42	6.49	6.69	7.00	6.02
	Controls cravings	6.62	5.80	6.26	6.39	6.95	5.42	6.73	5.75

Notes: A food value (e.g., taste) is important whenever the respondent indicates that it is "very important" based on a five-point Likert scale of importance level. None of the results of comparisons (between marketing message and control and between stages) were statistically significant at 5% level based on multiple hypothesis testing.

Table A5. Respondents' characteristics in Study 2 and Study 3 with experts for the full sample

Variable	N	Mean (SD)
<u>Study 2. Pecan experts</u>		
Age	49	56.63 (16.60)
Graduate school	49	0.35
Female	50	0.26
Sales less than 50k	49	0.80
Grower only	51	0.41
Retailer	51	0.25
Married	49	0.84
Non children	50	0.64
Less knowledgeable	50	0.28
Less than 5 years of experience	51	0.29
Direct sales	50	0.52
Full time in the pecan industry	50	0.38
<u>Study 3. Marketing experts</u>		
Age	198	40.65 (12.30)
Graduate school	198	0.27
Female	199	0.52
Marketing analyst	201	0.16
Marketing manager	201	0.57
Married	201	0.43
Non children	201	0.51
Less knowledgeable	201	0.73
Less than 5 years of experience	201	0.26

Note: SD denotes standard deviation.

Table A6. Comparison of estimation results of consumers' bids across different specifications.

Variables	(1) Pooled OLS	(2) Random Effects Tobit	(3) Quantile
Weight management pecans	0.035	0.035	0.251
Indulgently delicious pecans	0.097	0.097	0.686
Great flavors pecans	-0.415	-0.415	0.429
Controls cravings pecans	-0.466	-0.466	-0.230
Seller price task (SPT)	-0.111	-0.111	0.005
Weight management pecans x SPT	0.038	0.038	-0.100
Indulgently delicious pecans x SPT	0.209	0.209	-0.005
Great flavors pecans x SPT	0.177	0.177	0.042
Controls cravings pecans x SPT	-0.032	-0.032	0.075
Age	0.034***	0.034***	0.025**
South	-0.529	-0.529	-0.669
Midwest	-0.396	-0.396	-0.204
Northeast	-0.599	-0.599	-0.833*
Liberal ideology	-0.282	-0.282	-0.495
Female	-0.110	-0.110	0.187
Graduate school education	0.312	0.312	0.054
Has a partner	-0.218	-0.218	-0.150
Income greater than $100k	0.207	0.207	0.098
Non children	0.009	0.009	0.240
Has a full- or part-time job	-0.229	-0.229	0.043
Shop all groceries	0.494	0.494	0.294
Shop tree nuts at least once a week	1.008***	1.008***	1.064***
Price is important	-0.545	-0.545	-0.173
Taste is important	0.478	0.478	0.563
Processing is important	0.423	0.423	0.162
Nutrition is important	0.092	0.092	0.180
Visual appearance is important	-0.116	-0.116	-0.102
Convenience is important	0.420	0.420	0.273
Production practice is important	0.003	0.003	0.043
Location is important	0.636	0.636	0.567
Constant	4.725***	4.725***	4.250***
sigma_u		2.740***	
sigma_e		1.000***	
BIC	4811.99	4128.95	.
N	924	924	924

Notes: ****p*<0.001 ***p*<0.01 **p*<0.05. Clustered standard errors were calculated.

Table A7. Pooled OLS estimation results of consumers' feelings and expected market price

Variables	Consumers' feelings toward the product: from 1 ("Hate it") to 5("Love it")	Consumers' expected market price
Weight management pecans	0.002	-0.134
Indulgently delicious pecans	0.154	0.893*
Great flavors pecans	-0.178	0.130
Controls cravings pecans	0.008	-0.197
Age	0.008**	0.039***
South	0.195*	-0.258
Midwest	0.085	-0.102
Northeast	-0.216	-0.756
Liberal ideology	-0.199*	-0.245
Female	0.174*	0.562*
Graduate school education	0.157	-0.206
Has a partner	-0.084	-0.155
Income greater than $100k	-0.166	0.154
Non children	-0.093	-0.112
Has a full- or part-time job	-0.025	0.011
Shop all groceries	0.115	0.102
Shop tree nuts at least once a week	0.367***	0.398
Constant	3.357***	5.249***
BIC	2216.16	4660.88
N	932	932

Notes: ****p*<0.001 ***p*<0.01 **p*<0.05. Clustered standard errors were calculated.

Table A8. Comparison of estimation results of experts' forecasts across different specifications.

	Pecan experts			Marketing experts		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	OLS	Fixed effects	Random effects	OLS	Fixed effects	Random effects
Weight management pecans	0.853**	0.921***	0.914***	0.181	0.180	0.180
Indulgently delicious pecans	0.514	0.533*	0.532*	-0.017	-0.016	-0.017
Great flavors pecans	0.257	0.324	0.322	-0.002	-0.002	-0.002
Controls cravings pecans	0.962**	1.010***	1.006***	0.408*	0.408*	0.408*
Seller price task (SPT)	-0.069	-0.049	-0.051	-1.037***	-1.043***	-1.040***
Weight management pecans x SPT	0.089	0.031	0.037	0.731***	0.733***	0.732***
Indulgently delicious pecans x SPT	0.018	0.005	0.006	0.304	0.308	0.306
Great flavors pecans x SPT	0.285	0.193	0.198	0.214	0.229	0.224
Controls cravings pecans x SPT	0.191	0.106	0.111	0.520**	0.523**	0.522**
Age	-0.010		-0.009	-0.001		-0.001
Graduate school	0.232		0.270	0.250		0.248
Female	-1.005		-1.072	0.175		0.173
Sales less than 50k	0.189		0.041			
Grower_only	0.830		0.865			
Retailer	0.272		0.089			
Married	0.716		0.786	0.070		0.071
Non children	-0.563		-0.386	0.014		0.016
Less knowledgeable	-1.234		-1.227	-0.207		-0.204
Less than 5 years of experience	-0.305		-0.180	0.055		0.051
Direct sales	0.381		0.343			
Full time in the pecan industry	0.607		0.535			
Certainty of forecast 0-100%	0.006		0.021	0.006	0.007	0.007*
Market analyst				-0.145		-0.151
Market management				-0.004		-0.006
Constant	1.891		0.812	1.777***	1.706***	1.754***
BIC	2194.339	1487.652	.	7638.211	6847.388	.
N	477	477	477	1956	1956	1956

Notes: ****p*<0.001 ***p*<0.01 **p*<0.05. Clustered standard errors were calculated.

Table A9. OLS estimation results of pecan experts' certainty of forecast

Variables	"How certain are you of your response, on a scale from 0% to 100%"
Weight management pecans	-4.167*
Indulgently delicious pecans	-0.710
Great flavors pecans	-0.471
Controls cravings pecans	-2.917
Seller price task (SPT)	-1.250
Weight management pecans x SPT	3.542
Indulgently delicious pecans x SPT	0.294
Great flavors pecans x SPT	1.930
Controls cravings pecans x SPT	1.255
Age	0.024
Graduate school	-1.370
Female	5.750
Sales less than 50k	8.459
Grower_only	-0.668
Retailer	10.747*
Married	-5.496
Non children	-12.794*
Less knowledgeable	-1.228
Less than 5 years of experience	-7.638
Direct sales	3.801
Full time in the pecan industry	2.855
Marketing analyst	
Marketing management	
Constant	71.545***
BIC	3981.795
N	477

Notes: ****p*<0.001 ***p*<0.01 **p*<0.05. Clustered standard errors were calculated.

Table A10. OLS estimation results of marketing experts' certainty of forecast

Variables	"How certain are you of your response, on a scale from 0% to 100%"
Weight management pecans	-0.034
Indulgently delicious pecans	-1.361
Great flavors pecans	-0.697
Controls cravings pecans	-0.799
Market intelligence (Post)	5.323***
Weight management pecans x Post	-1.547
Indulgently delicious pecans x Post	-3.231*
Great flavors pecans x Post	-3.423*
Controls cravings pecans x Post	-2.823
Age	0.100
Graduate school	1.295
Female	-0.254
Sales less than 50k	
Grower_only	
Retailer	
Married	0.486
Non children	-5.631*
Less knowledgeable	-11.544***
Less than 5 years of experience	4.965
Direct sales	
Full time in the pecan industry	
Marketing analyst	8.017**
Marketing management	3.503
Constant	66.038***
BIC	17401.762
N	1956

Notes: ***p<0.001 **p<0.01 *p<0.05. Clustered standard errors were calculated.