**Are experts overoptimistic about the success of food market labeling information?**

Grace Melo[1*], Marco Palma[2], Laura Chomali[3], Luis Ribera[4]

[1]Assistant Professor, Department of Agricultural Economics, Texas A&M, College Station, TX.
gmelo@tamu.edu
[2] Professor, Department of Agricultural Economics, Texas A&M, College Station, TX.
mpalma@tamu.edu
[3] Visiting Scholar, Department of Agricultural Economics, Texas A&M, College Station, TX.
[4] Professor, Department of Agricultural Economics, Texas A&M, College Station, TX.
lrivera@tamu.edu

*Corresponding author

[Preliminary Manuscript – Please Do Not Cite]

*Selected Paper prepared for presentation at the 2024 Agricultural and Applied Economics Association Annual Meeting, New Orleans, LA, July 28-July 30, 2024*

This research was supported by the Federal-State Marketing Program
(FSMIP21000033)

No financial disclosures were reported by the authors of this paper.

**Are experts overoptimistic about the success of food market labeling information?**


## Abstract

Being able to accurately predict the marketing effectiveness of product labels is critical for business profitability. Do experts (e.g., sellers) understand and accurately predict which messages appeal most to consumers? There is limited knowledge in this area, specifically around two essential food values: *health* and *taste*. Consumers perceive health and taste as tradeoffs, which makes their reaction to such information in marketing challenging to predict. This study is the first to quantify the extent to which experts can accurately predict consumer responses to health and taste information via marketing labels. We conducted two incentivized studies: Study 1 investigated consumers' value for "health" versus "taste" messaging, and Study 2 uncovered experts' predictions for average consumers' willingness-to-pay (WTP) for the messages. Study 1 assessed two price rules to set the market price in an experimental auction: a Seller's fixed price and the Becker-DeGroot-Marschak (BDM) price, which provides weak incentives for participants to reveal their truthful valuations. We found that experts optimistically predicted information would effectively increase consumer valuations when, in fact, consumers did not respond to such information. Moreover, experts inaccurately overestimated consumer valuations by 33% compared to the average consumer WTP of $6.8 for an 8 oz bag of pecans. We also found that the Seller price induces WTP valuations for pecan products that are not statistically different from those obtained from the BDM. This finding suggests that simplifying the price rule in non-strategic auction valuation studies could streamline the procedures while resulting in similar product valuations.



**Keywords:** BDM; forecasting; incentive compatibility; information nudges; overconfidence; overoptimistic; willingness-to-pay.

**JEL classification :** D12, D83, C90, D90

## 1. Introduction

Decision makers in supply chain and policy (hereinafter experts) have recognized the importance of providing information; thus, information is often used as a powerful tool to communicate critical aspects of food to consumers (Li, Liang, and Liu 2023; Boccia, Alvino, and Covino 2023), including *health* and *taste* values (Jo et al. 2016; Lusk and Briggeman 2009; Melo, Zhen, and Colson 2019). Striking a balance between offering health and taste information to consumers presents a challenge, as heterogenous preferences showcase that some consumers prioritize taste over health information (Jo et al. 2016) while others do the opposite (A. Drichoutis, Lazaridis, and Nayga 2006; T. G. Smith 2004; Papoutsi, Klonaris, and Drichoutis 2019). This significant individual heterogeneity in consumer preferences regarding health and taste-related information varies across products (Lusk and Briggeman 2009). For instance, health can be positively associated with consumers' attitudes toward functional foods, while taste can be negatively related (Nystrand and Olsen 2020).

Given the tension between health and taste attributes (Papoutsi, Klonaris, and Drichoutis 2019), experts face challenges in forecasting consumer responses to costly information labeling to increase consumer acceptance. Accurate predictions of consumers' responses to information are critical for labeling, marketing and promotion investments that influence profit maximization as inaccuracies are penalized in higher costs to the business and sustained inaccuracies may destroy the enterprise if the investments do not provide the anticipated returns (Abraham and Lodish 1990). In this article, we investigate (i) how consumers react to health versus taste information, (ii) how well experts can forecast consumer reactions to distinct types of health and taste information, and (iii) eliciting consumers and experts' assessments can be simplified, while prevailing incentive compatibility of the food valuation mechanisms.

This study first evaluates consumers' reaction to health versus taste information using pecans as a case study. We selected pecans because it is a food category that can be perceived as healthy, tasty, or both (Delgadillo-Puga et al. 2023; Du et al. 2022; Magnuson et al. 2016). This study is the first to quantify the extent to which industry experts, such as sellers, marketers, producers can accurately forecast consumer responses to such information. If experts are not able to accurately predict consumer reactions to health and taste messages, then information would be ineffective and costly to food businesses, and it could compromise policy decisions. Note that underpredicting consumer valuations may result in less profitability by under-investments in promotion and advertising. However, this scenario is less common[1] and potentially less harmful than overpredictions of ineffective consumer valuations that provide lower-than-expected returns for costly marketing messages.

We conducted two incentivized online studies with consumers and experts. 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 conditions, including four types of marketing messages (two health-related and two taste-related messages) and a control (neutral generic *pecan* message with no health or taste information). By considering both consumer and expert perspectives using incentive-compatible studies, we aim to identify

[1] Literature on forecasting consumer assessments mainly provides evidence of optimism bias and overestimation of returns of investments.

potential missing opportunities for the growth of food businesses as well as for developing effective information provision interventions.

In Study 1, consumers' actual valuations were incentivized using the Becker-DeGroot-Marschak (BDM) valuation mechanism. In the auction literature, the BDM is recognized as a strategy-proof elicitation mechanism that provides weak incentives to reveal valuations truthfully (Becker, Degroot, and Marschak 1964). The BDM, however, might not empirically recover the theoretical induced valuations, even when the item to be valued has a fixed induced value (Cason and Plott 2014a; Horowitz 2006). [2] Brown et al., (2023) compared the BDM with two recent strategic-proof elicitation mechanisms: game-structure obvious, which reassembles a Multiple Price list (MPL) (Kendall and Chakraborty 2022), and "contingent thinking" protocol, aimed to resolve uncertainty (Martin and Muñoz-Rodriguez 2022) and found that these mechanisms did not improve the overall accuracy of sellers' bids in a lab study.[3]

In the valuation literature, the BDM is appealing because of its simplicity as it requires no strategic group formation for its implementation. However, numerous studies in the consumer valuation literature indicate that people fail to bid optimally in BDM auctions (see Canavari et al. (2019) for a review). Because its format is not very intuitive, there are concerns about whether subjects (i) understand the mechanism's payoff function (Asioli, Mignani, and Alfnes 2021;

---

[2] This non-incentive-compatibility result also holds for the Vickrey auction and general nth-price auctions, even for non-random goods. In these auctions and the BDM, an individual's bid is potentially affected by the distribution of prices; therefore, elicited values differ across these auction mechanisms (Rutström 1998) and bids might not reflect the true cut-off price. For instance, (Bohm, Lindén, and Sonnegård 1997) find that bids in the BDM are sensitive to the choice of upper bound for the distribution of possible buyout prices.

[3] Accuracy of the seller's bids was measured as deviations from the weakly dominant optimal bids.

Cason and Plott 2014b; Martin and Muñoz-Rodriguez 2022)[4], (ii) systematically misreport preferences (Noussair, Robin, and Ruffieux 2004), and (iii) fail to recognize the dominant strategy (A. C. Drichoutis and Nayga 2022; Kendall and Chakraborty 2022). Practice rounds before actual valuations do not improve optimal bidding (Martin and Muñoz-Rodriguez 2022) and might increase participants' cognitive effort.

Therefore, to contribute to the valuation literature, we elicited consumer valuations using a valuation task similar to the BDM, but whose rule to set the market price is much simpler: the market price was determined by a seller prior to the implementation of the experiment (hereinafter the fixed price rule or Fixed Seller price). The intention of the Fixed Seller price is to reduce ambiguity and require less cognitive effort to understand the procedure. We compare the results of the fixed price rule with the BDM price using a within-subject design, randomizing the order of the tasks to account for possible ordering effects.

Because we elicited experts' forecasts of consumer valuations under the BDM and Fixed Seller price tasks, we can also compare experts' assessments of the BDM to the fixed price rule. Thus, another novel contribution of this study is to determine whether experts expect the two price rules associated with the BDM and the Fixed Seller's price to produce different consumer valuations. There are no differences in the consumer valuations ($p$=0.405) and the experts forecasts ($p$=0.486) across the two price rules. The comparisons of consumer and expert

---

[4] Only 16% of people offered a price to sell a \$2 ticket they owned that was around its actual value of \$2. One explanation is that subjects often confuse the BDM with a first-price auction (Cason and Plott 2014b). 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 etl 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.

assessment outcomes between the BDM and the fixed price rule have implications for studies that use regular consumers or participants who are unfamiliar with experimental auctions to simplify the instructions and obtain accurate value representations.

In Study 2, we adopted a within-subject experimental design to elicit experts' forecasts of consumers' valuation for pecan products for each of the five information groups and the two price rules (for ten forecasts per expert respondent) obtained from Study 1 with consumers. Accurate experts' predictions were incentivized with a monetary reward and a public recognition announcement in a popular press magazine. First, we compared the mean and distributions between consumer and expert assessments using nonparametric tests. To determine experts' accuracy of predictions for each of the ten conditions, we calculated the difference between the expert predictions and the average consumer valuations. Then, we evaluated whether experts were less (or more) accurate and confident in their forecast predictions compared to the control when a marketing message was displayed. In addition to the monetary rewards for accuracy, the winners were announced in Pecan South Magazine, a widely known and distributed popular press outlet throughout the pecan growing regions in the United States (Appendix Figure A2).

This study contributes to three strands of literature. First, we contribute to the literature on information asymmetry between consumers and producers in food markets. More specifically, we demonstrate that, on average, simple marketing labels conveying information regarding product health and taste did not increase the average consumers' WTP, yet experts were optimistic regarding consumers' valuations to both information types. Second, despite having inaccurate predictions, experts were overconfident about their forecasts. Overconfidence has been an important determinant in decision-making in various contexts (Grežo 2020). While it might be costly for entrepreneurship (Invernizzi et al. 2017), it might also have adverse financial impacts (Grežo 2020; Caplin and Dean 2015).

Our study also contributes to the literature on consumer food values. We found no statistically significant differences between the WTP elicited under the BDM and the fixed seller price across the five treatment groups (i.e., four health and taste messages and a control). This suggests that valuation studies might benefit from using a simplified fixed price rule, which respondents might perceive as more transparent, to simplify experimental procedures to avoid game form recognition failures associated with the BDM mechanism. To decrease perceived ambiguity of the payoff function and avoid deception, we used the reservation selling price of a U.S. pecan producer as the fixed price, which ties our work to the literature about reference prices (Bohm, Lindén, and Sonnegård 1997; Gracia, Loureiro, and Nayga Jr 2011; Kilders and Caputo 2023; Ladenburg and Olsen 2006; Lemos, Halstead, and Huang 2022; A. C. Drichoutis, Lazaridis, and Nayga 2008).

Finally, our study makes contributions to the literature on the effects of information on consumer behavior in two important ways. While we found that the marketing messages communicating taste and health values had no effect on average consumer valuations for pecans, it is possible that consumers are familiar with the taste and health benefits of pecans used in the labeling messages and hence did not respond to the marketing message information labels.

In the following section, we describe the factors influencing consumers and experts' assessments about pecans. Then, we describe the experimental studies, including how we analyzed the collected experimental data, and results are then presented. We discuss the results and implications in the last section.

## 2. Consumer and experts' assessments

Experts' ability to infer what consumers value and how health and taste labeling impact their food purchasing behavior is challenging for several reasons. First, consumers face health and taste tradeoffs (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). Depending on their food values and motivations, consumers can react to taste information but not to health information (or the opposite). Health information could serve as a cue for low taste and higher prices (Jo and Lusk 2018; Wardle 2000). For instance, some consumers with strong health motivations have a tendency to overweight health-related information (Choi, Jessica Li, and Samper 2019). 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' attention to information is influenced by several factors, including their level of familiarity with the product (Johnson and Russo 1984; C. W. Park and Lessig 1981), the relevance of product attributes (e.g., health vs taste) (Lusk and Briggeman 2009; Nystrand and Olsen 2020), consumers' healthy eating motivations (Hung et al. 2017), and whether the signal is hedonic or health-related (Ares et al. 2018).

Beyond experts' knowledge of consumer behavior, experts' predictions depend on their own biases or assumptions. Overconfidence can be an important 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 be associated with significant spending in promotional efforts despite low returns (Abraham and Lodish 1990; Lovallo and Kahneman 2003).

Overconfidence has been widely documented in different domains, including economics, investment, finance, entrepreneurship, advertising, and marketing (Abraham and Lodish 1990; Fellner and Krügel 2012; Invernizzi et al. 2017; Proeger and Meub 2014; Mahajan 1992) mainly in social settings (Proeger and Meub 2014). Yet, the extent to which this bias affects experts' assessments in food markets under the presence of information, particularly those related to taste versus health, has not been investigated.

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

Our study focuses on the pecan market to elicit experts' predictions for three primary reasons. First, pecan consumption has been associated with health benefits, including preventing obesity-related diseases (Delgadillo-Puga et al. 2023) and pecans are considered to have great taste (Du et al. 2022; Magnuson et al. 2016), making it an ideal food product to investigate consumer responses to health and taste information. Second, our research enables us to capture insights from experts with diverse expertise and roles, from producers to marketing experts. Lastly, despite the rising demand for other specialty crops, 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 adopted by experts (Moore et al. 2009).

## 3. Procedures

To elicit the ability of experts to forecast consumers' WTP, we conducted two online studies with U.S. pecan consumers and experts, pre-registered in the AEA RCT Registry (AEARCTR-0010789). Online studies exhibit similar characteristics of a framed field experiment (Harrison and List 2004)[5]; therefore, the two studies were conducted online using the Qualtrics platform. As explained later, the two studies were incentivized with monetary rewards and a lottery payment. In the two studies, we evaluated five information treatments. Particularly, we evaluated a control ($T_0$) with no marketing message on the pecan product and four information treatments with marketing messages (hereinafter marketing information treatments): two health- and two taste-related marketing messages ($T_1$, $T_2$, $T_3$, and $T_4$). Figure 1 displays the information treatments.

First, in Study 1, we obtained consumers' valuation for pecan products displaying health- and taste-related marketing messages. Second, in Study 2, experts were asked to forecast

[5] The online nature of our studies prevents us from controlling participants' attention to the information provided. While in a laboratory study one is able to control for attention and other factors, the framing and environment of a laboratory may distort behavior (List 2007). Furthermore, online studies outperform lab studies in obtaining a representative group of participants (Winston 2008).

consumers' valuation for the pecan products displaying each marketing message (Fellner and Krügel 2012).[6] We also asked experts to report their confidence in their forecasts. Next, we describe in detail the experimental procedures for each study. To incentivize the repetitive signal-based prediction task, subjects were informed that the top ten respondents with the most accurate assessments would receive a monetary reward and be showcased in a reputable, popular press magazine as described in the detailed procedures.

**Study 1**

*Recruitment*

Study 1 was conducted online in April 2023 with Forthright panelists to obtain geographically dispersed consumer WTP estimates in the United States Forthright Access, a marketing company, recruits U.S. respondents through a diverse set of 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 do at least half of the grocery shopping for the household, have bought tree nut products at least once in the last three months, have eaten tree nut products in the last 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 the study.[7]

---

[6] Our approach is equivalent to studying experts' predictions, given different signals.

[7] 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). Few respondents (n=4) 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. The results hold, excluding these respondents.

*Set up*

At the beginning of the study, subjects were informed that they will receive $2.67 for their participation.[8] They were also told that they will receive an additional monetary compensation of $15 or a food product if the elicitation task was selected for realization (based on the market realization procedure described later) and any 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 randomly assigned predetermined marketing messages (Figure 1). The marketing messages included two health-related messages (*weight management pecans, controls cravings pecans*), two taste-related messages (*indulgently delicious pecans, great flavor pecans*), and a control (*pecans*). Participants were asked their WTP in two similar, non-hypothetical, incentive-compatible elicitation stages based on a within-subject design. Subjects were informed they will 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. To avoid deception and make it a real market, before launching the online survey, we partnered with a U.S. based pecan producer and retailer and asked for the minimum amount of money the producer would be willing to accept (WTA) to sell the 8-oz pecan products

[8] The study took approximately 10 minutes.

corresponding to each marketing message. 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 until after bidding. Figure 2 (Panel a) displays an example of the experimental procedures.

*Monetary incentive approach*

Prior to valuations, the market realization procedure was carefully described to the subject 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 $15 participant endowment if the transaction 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 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 selected for realization.

Figure 2 (Panel b) illustrates the lottery payment procedure in Study 1. We conducted the lottery payment procedure following (Ahles, Palma, and Drichoutis 2024). 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.

Panel b also illustrates the market realization procedure. In this example, for this buyer, $S_1$ was randomly selected for implementation (step 5). Since the subject's WTP was higher than the market price ($8 > $7.5), the subject paid for the product and the product was shipped to home address via priority shipping (step 6). It is important to note that if $S_2$ had been selected, since the WTP is less than the market price ($8.5 < $10) in this case, the 8 oz package of pecans would not have been shipped to this buyer.

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 (Appendix Figure A1).

After the completion of 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. Additionally, participants were asked about their overall health and taste preferences and concerns.

## Study 2

### *Recruitment*

Study 2 was conducted online between May and July 2023 via Qualtrics and administered to experts in the pecan industry 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 participants (i.e., experts in the U.S. pecan industry) between April and July 2023, with up to four periodic reminders sent biweekly. Email invitations to experts were sent through Pecan Associations as well as direct email using producers' contact information obtained from extension specialists. Among these, only the responses that had engaged with at least one of the ten market scenarios were considered valid. Subsequently, a cleaning process was conducted to eliminate any unsuccessful attempts. The final sample consists of 51 pecan 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, $S_3$ and $S_4$ similar to Study 1. More specifically, a subject faced the market scenarios we presented to consumers in Study 1. Participants were asked to provide their best forecast estimate (i.e., guess) 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 the first study, in how the market price is determined). Thus, an expert participant faces a total of ten market scenarios. As performed in Study 1, $S_3$ and $S_4$ were presented in random order to participants. Within stages, treatments were also randomized. Figure 2 (Panel c) shows the experimental design in Study 2 with 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%?".

*Monetary incentive approach*

Similar to Study 1 with consumers, experts in Study 2 were incentivized to provide the most accurate estimation in each of the ten signal-based prediction tasks. Participants were told that the ten participants with the highest overall accuracy (lowest forecast prediction error aggregated over all products) would receive a monetary reward of $250. To identify the top ten participants, we considered overall guess accuracy, calculated by aggregating absolute differences between guesses and consumer bids across the ten conditions. Additionally, participants were told that their names would be featured in the popular Pecan South Magazine as a reward for their accuracy in predicting consumer responses to the marketing messages (Appendix Figure A2 shows the announcement of winners). Finally, subjects were told that in the event of ties, the total earnings would be evenly distributed among the tied winners.

Following the completion of the elicitation stages, we conducted further inquiries to gather comprehensive information that could explain responses. For instance, we asked about various aspects to infer their level of expertise, including 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 the year 2022.

## 4. Data and Results

### Samples

*Consumer sample*

Summary statistics of respondents' sociodemographic characteristics in Study 1 are reported in Appendix Table A1. Results indicate that the average age is 47, half are female, 40% identify themselves as liberal, 12% attended grad school, half had a partner, 24% had an annual income greater than $100,000 in 2022, 65% had no children living in the household, 23% live in a rural area, and 61% are working either full- or part-time (Table A1, column 1).

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 effective randomization of subjects across treatments with few exceptions. 7 out of 111 differences show imbalances associated particularly with liberal[9].

*Producer sample*

Appendix Table A3 reports summary statistics of respondents' characteristics in Study 2. Sample composition indicates that the average age is 57. About 41% are growers only and 26% are retailers. The majority of respondents are male (74%), married (84%), or reported less than $50,000 in pecans sales in 2022 (80%). About 64% had no children living in the household, and

[9] Similar 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.

a non-trivial proportion attended graduate school (35%). Regarding confidence and experience in the pecan industry, few reported less than five years of experience (30%), and about half (52%) sell pecans directly to consumers. Interestingly, a non-trivial proportion reported not having knowledge about pecan markets (28%).

**Pecan values**

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, Panel a).

Likewise, in Study 2, we asked experts to forecast consumers' pecan values. Experts indicate 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, Panel b). The differences in the ranking of consumer food values between experts and consumer responses suggest potential misalignment, which may open the door for missing opportunities for the pecan industry. For instance, while experts consider appearance the second most important attribute, price is the most important factor for consumers after taste. We also asked experts to indicate their own opinions about the importance of each pecan value. Overall, the ranking of experts' food values differs from that reported by consumers, except for the ranking of taste, which was forecasted as the most important attribute (Appendix Figure A4, Panel a vs Panel b).

**Unconditional analyses**

*Consumers' WTP*

Using nonparametric tests, we first compared consumer bids between each information condition (i.e., two health-related information treatments and two taste-related information treatments) and the control (i.e., no information). The tests included the Wilcoxon signed-rank (WSR) test for matched data (within-subject comparisons of BDM versus producer set market price) and the Mann-Whitney (M.W.) test for unmatched data (comparisons between subjects for the different information treatments) (Wilcoxon 1992). We calculated adjusted *p* values to account for multiple hypothesis testing (List, Shaikh, and Xu 2019).

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 BDM while significantly simplifying the instructions.

Furthermore, results in column 1 indicate that for each of the two elicitation tasks, there were no statistical differences in consumer' 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).

*Producers' guess of WTP*

Figure 3 illustrates the cumulative probabilities of consumers' WTP, and experts' forecast of WTP across conditions. The graph shows that experts' forecast cumulative distribution function (CDF) is to the right of consumers' bid CDF. Specifically, when the cumulative probability was

0.5, consumers' bids were up to \$7 while experts' forecasts were up to \$8, suggesting that for a given probability, experts' forecasts were always greater than actual consumer valuations.

We compared the distributions 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 $D \equiv E(x) - C(x) \geq 0 \; \forall x$. Under first-order stochastic dominance, the distributions cannot cross. Under second-order stochastic dominance, there can be cross-overs of the distributions. Thus, we tested (1) if there are statistical differences in distributions and (2) if there are cross-overs of the distributions, where they occur.

To conduct test (1), we conducted a two-sample Kolmogorov-Smirnov (K.S.) test (Smirnov 1948) and we rejected the combined hypothesis of equivalence ($p < 0.0001$). To conduct test (2), we employ the Goldman-Kaplan (G.K.) test (Goldman and Kaplan 2018), which determines specific ranges across the distribution for which equality is rejected. We rejected equality at the 1% level with a global test (consistent with our finding using the K.S. test). We also rejected equality at all points between \$1.99 and \$14, which both lie outside the 10*th* and 90*th* quantiles for both groups. Both tests provide evidence in support of first-order stochastic dominance by the experts' distribution.

Table 1 (column 2) reports subjects' forecasts of consumers WTP from Study 2. We compared experts' forecasts of consumer bids between each information condition and control using the WSR test. In each stage, experts' predictions of consumers' WTP for products with messages were higher than that of the control group ($p < 0.05$). These results suggest that producers predicted the health benefit marketing messages to effectively shift consumer valuations. In particular, experts predicted the *weight management pecans* and *controls cravings pecans* messages to induce the highest WTP. Yet, as shown earlier (Table 1, column 1), consumers WTP, on average, did not increase when marketing messages were employed ($p>0.05$).

When comparing the magnitude of experts' forecasts and consumers' bids (columns 1 and 2), it is shown that on average experts' overestimations of consumers valuation across information conditions are quite significant, with an average of 33% overprediction. The average expert forecast was $8.99 compared to consumer's WTP of $6.77. There are statistical differences in the means ($p<0.05$, column 3).

The valuations of consumers and experts were not in alignment. The results of Table 1 (columns 1 and 2) show that experts not only overpredict consumer valuations but were also unable to determine which marketing message, on average, is qualitatively the most and least effective among consumers. While *indulgently delicious pecans* induced the highest WTP among consumers, experts predicted that *weight management pecans* would induce the highest consumer valuation. Moreover, *controls cravings pecans* were predicted to increase consumers' WTP; however, consumers WTP for pecan products displaying this message was the lowest, being lower than the control.

Furthermore, similar to results in Study 1, with consumers showing no significant differences in WTP between elicitation stages ($p > 0.05$) (column 1), the results in Study 2 suggest that for each of the five conditions, we fail to reject the null hypothesis that experts' forecasts of consumers WTP are the same between the two elicitation stages (column 2).

To better understand experts' predictions, we calculated the accuracy of predictions for each of the ten market scenarios at the subject level. Table 2 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); (ii) *deviation,* calculated as the absolute difference between the guess and average consumer bid for each of the ten conditions; and (iii) *deviation to bid ratio*, computed as the proportion of deviation to the consumer's bid. For *overprediction*, we used the McNemar's test (McNemar 1947), while for *deviation* and *deviation to bid ratio,* we used the M.W. test.

Regarding the first outcome, results indicate that on average, in 80% of the tasks, experts' estimations surpassed the average consumer valuation (column 1). The results also indicate that the likelihood of overpredicting did not increase when a marketing message was employed ($p$>0.05).

Similarly, *deviation* and *deviation to bid ratio* for marketing message were not statistically different from control ($p$>0.05, columns 2 and 3). The greatest qualitative deviation to the consumer bid ratio was associated with the *control cravings pecans* message ($p$>0.05). On average, experts overestimate consumers' valuation for this information condition by an average of 44% (i.e., outcome average of the two stages) (column 3), with average forecasts at $9.17 compared to the average consumer bid of $6.39 (Table 1).

Study 2 elicited subjects' self-reported confidence levels about their forecasts. Experts were confident in the accuracy of their predictions in 70% of the tasks (column 4). Yet, they overpredicted average consumer valuations in 80% of the occasions (column 1). Compared to the control condition, experts were qualitatively less confident in their estimations when they were asked to predict consumer WTP for a health-related message (i.e., *weight management*) in the BDM price valuation stage (67% vs 68% $p$> 0.05, column 4).

**Conditional analyses**

*Consumers' WTP*

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:

$$bid_{is} = \alpha + \sum_{j=1}^{4} \beta_j T_j + \delta S_2 + \sum_{j=1}^{4} \tau_j T_j S_2 + \gamma' Z_i + \varepsilon_{is} \quad (1)$$

where $bid_{is}$ is the bid submitted by subject $i$ in stage $s$ ($s = 1,2$), $T_j$ denotes the assignation of information treatment $j$ ($j = 1,2,3,4$), $S_2$ 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 $\beta_j, \gamma, \tau$, and $\delta$ are model parameters.

Table 3 shows results 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), and food values (column 4). Across specifications, results confirmed the unconditional analysis results (Table 1). That is, $\beta_j$ is not statistically significant, indicating that information treatment $j$ does not increase consumer preferences for pecan products. Similarly, $\delta$ 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, $\tau_j$ 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 main results in Table 1 that the marketing message has no effect on consumer valuation for pecans (Appendix Table A4).

Regression results in Table 3 reveal interesting aspects of consumer demand 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 with those who are not primary shoppers and those who are not frequent buyers of tree nut products. Those who consider price a particularly crucial factor when buying pecan products tend to have, on average, a lower WTP, in contrast to those who think price is not very important. 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 when they were shown the pecan product, 72% of respondents, on average, indicated they "Love it!" or "Enjoyed it" when they were shown the product with a 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 and self-reported emotional connection to the marketing messages. To evaluate these hypotheses, we regressed feelings and expected price on the set of controls and treatment variables used in (1). Results indicate that only the *indulgently delicious pecans label* was associated with a higher expected market price (Appendix Table A5). The lack of emotional responses from consumers to marketing messages (Appendix Table A5) 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 3.

*Experts' forecasts of WTP*

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

$$y_{ijs} = \alpha + \beta_1 T_1 + \sum_{j=1}^{4} \beta_j T_j + \delta S_2 + \sum_{j=1}^{4} \tau_j T_j S_2 + \gamma' Z_i + \varepsilon_{ijs} \quad (2)$$

where $y_{ijs}$ is an accuracy measure for experts' forecasts of WTP corresponding to subject $i$ for treatment $j$ and valuation task $s$. Specifically, we use *deviation* of expert forecast from the consumer WTP as the accuracy measure. 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 as well as experts' certainty level of their response.

Table 4 reports estimation results for equation (2) without and with different controls. Similar to unconditional results (Table 2), *deviation* of experts' forecast from consumer valuation is not statistically different between products displaying a marketing message and a no message (control) (columns 4-6, $p$>0.05). One exception is that *deviation* is greater for products displaying *weight management pecans* and *controls cravings pecans* ($p$>0.05). These results are robust to fixed effects and random effects model specifications (Appendix Table A6).

Table 4 results further reveal heterogeneity based on sociodemographic information in estimation accuracy across respondents. For instance, results suggest that being female is associated with a lower deviation (columns 4 and 5). Being a pecan grower or working full-time in the pecan industry are both associated with a greater bias compared to their counterparts. On the contrary, years of experience (fewer than 5 years vs more than 5 years) and selling directly to consumers did not explain *deviation.*

Finally, those respondents who see themselves as less knowledgeable about the pecan market showed a smaller *deviation*. Certainty of predictions was uncorrelated with *deviation* (column 3). Similarly, correlation analyses suggest a weak association ($\rho$=0.0988, $p$=0.0262) between deviation and confidence level on aggregate. These results suggest that experts' perceived ability to predict the market success of health- and taste-related messages does not align with their actual forecast accuracy.

Information could have affected participants' accuracy through their confidence level. To evaluate these hypotheses, we regressed confidence levels on the set of controls and treatment variables used in (2). Results show that experts were not more or less confident than control in predicting consumers' WTP (Appendix Table A7). There was one exception: experts were less confident in their predictions for *weight management pecans* ($p$<0.05)

**Subsample analyses for heterogeneous responses**

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, Panel a), we found no evidence of heterogeneity in consumer response to marketing messages (Appendix Table A8, columns 1- 4).

We also explore valuation heterogeneity regarding health beliefs and conditions. Results indicate that respondents' beliefs in the health benefits of pecans or being overweight were not a determinant explaining valuation response (Appendix Table A9, columns 1 and 2). This is consistent with previous findings showing that nutrition is not important in explaining valuations (Appendix Table A8, column 1).

Finally, considering consumers preferences' heterogeneity due to shopping behaviors (Table 3), we 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 taste and health information due to these dimensions (Appendix Table A9, columns 3 and 4).

**Robustness checks**

We conducted three robustness checks to assess the validity of the results. First, consumers could have provided bids based on the perceived market price. To test for this, for each treatment condition, we asked participants: *What price would you expect a grocery store to charge for this pecan product?* Correlation analyses between consumer bids and expected prices indicate correlation values of $\rho =$0.47-0.73 ($p < 0.001$) for $S_1$ (the valuation stage with the BDM price) and $\rho = 0.67$- 0.70 ($p < 0.001$) for $S_2$ (the valuation stage with the Seller price). For *weight management pecans* in particular, there were no statistical differences between expected price and bid for both stages (Appendix Table A10).

These results suggest that there are some concerns that consumer bids are associated with expected market prices in both tasks. It is worth noting that, as shown earlier, whether we control or not for the potential effect of expected (or reference) price, the main conclusions regarding the effect of marketing messages on consumer preferences remain robust (Table 3, column 5).

More importantly, the findings suggest that, on average, individuals did not disclose their maximum WTP under the BDM price or the Seller price. The BDM method proved ineffective in eliciting optimal bidding even in the absence of uncertainty (Cason and Plott 2014b). Results suggest that the criteria individuals employ to choose bids under both approaches are similar: subjects, for instance, think of market prices when submitting bids. In both scenarios, the primary limitation is that respondents fail to provide their true values. Given the simplicity of the Seller price, one might consider using it instead of the BDM, with the acknowledgment of this limitation.

Second, the within-subject nature of the price rule could have induced order effects in the valuations across the two stages ($S_1$and $S_2$) each with a different price rule (i.e., anchoring effects due to order). As we randomized the sequence in which we presented the mechanisms, we can determine whether this possibility exists and whether anchoring effects affect the main conclusions.

We performed the analysis comparing valuations of the BDM stage $S_1$ with those of the Seller price $S_2$, using only the subset of responses from subjects who were presented with the valuation stage first. The results of consumer bids reported remain robust when using only these observations. (Appendix Table A11, column 2). That is, consumer valuations from the Seller price are not statistically different from valuations from the BDM price ($p$>0.05). Furthermore, results indicate that there are no statistical differences between valuations of products displaying health or taste-related information and the control ($p$>0.05).

Finally, we estimate a pooled regression analyses pooling consumer and expert valuations. Specifically, we estimate the following specification.

$$V_{is} = \alpha + \vartheta\ Expert + \sum_{j=1}^{4} \beta_j\, T_j + \delta\, S_2 + \sum_{j=1}^{4} \tau_j\, T_j\, S_2 + \gamma' Z_i + \varepsilon_{is} \qquad (3)$$

where $V_{is}$ is the bid submitted by subject $i$ in stage $s$ $(s = 1{,}2)$ for treatment $j$, $Expert$ is 1 if the valuation corresponds to that one submitted by the expert and 0 otherwise. The remaining independent variables are similar to equation (1). One exception is that $Z_i$includes key respondents' sociodemographic factors (i.e., sex, age, education) that can explain differences in valuations. The parameter of interest is $\vartheta$, which captures any difference between consumer and expert valuation. The terms $\beta_j, \gamma, \tau$, and $\delta$ are other model parameters.

The results indicate that being an expert yield higher valuations by $1.98 with a 95% confidence interval from $1.15 to $2.81 (Appendix Table A12, column 2). Given that consumer bid was on average $6.76 across conditions, our results suggest that after controlling for differences between consumers and experts in terms of key sociodemographic variables (e.g., education), a non-trivial overprediction rate of 29.29% [95% CI: 17.01%-41.42%] remains.

We estimate equation (3) interacting *Expert* with treatment *j* to test whether the expert forecast is greater when a marketing message is displayed (Appendix Table A12, column 3). The results indicate that experts predict *controls cravings pecans* to be effective at increasing consumer preferences, yet a marketing message had no effect on consumer valuations, as shown in Table 1.

## 5. Discussion and implication

### Discussion

This study analyzes consumers' and experts' assessments of pecan products displaying health- and taste-related information; Based on two sequential studies with U.S. consumers and producers, the study reveals three main findings. First, despite taste and health being considered important food values (Lusk and Briggeman 2009; Melo, Zhen, and Colson 2019), the provision of health and taste information about pecan products, through labels had no effect on consumer's WTP for pecans. Second, despite consumers' lack of response to information, experts (e.g., pecan growers) were optimistic and overconfident about the effects of the provision of health and taste information on consumer valuations. Third, a simpler, auction-like valuation task based on a (fixed) seller price-induced consumer valuations that are not statistically different to those elicited under the BDM.

Three factors can explain the first result, showing no effect of labels on consumers' WTP. First, the information presented might not align with consumer values or beliefs. For instance, those who value taste would overlook health-related information (Grunert and Wills 2007; Thunström 2019). In our study, most consumers (73%) valued taste, while only one-third valued nutrition (32%) (Appendix, Figure A3). Preference for hedonic benefits (e.g., taste) over utilitarian ones (e.g., nutrition) is surprising in our study, considering that pecans are being increasingly featured as a functional food (Nystrand and Olsen 2020), yet other attributes such as taste, price, and processing levels remain more critical than nutrition to the consumers in our study (Appendix, Figure A3).

Second, information that aligns with consumer values (e.g., taste) might not deliver additional value because consumers may already expect pecans to be tasty and provide health benefits (Charness, Oprea, and Yuksel 2021; Sharot and Sunstein 2020; Toney et al. 2023). In our study, marketing information had no influence on emotional responses (Appendix Table A4 indicates); potentially because it was not novel.

Third, information might convey a conflicting message, which could lead to skepticism and null or even unintended effects (Cheng, Chang, and Lee 2020; Cozzens and Contractor 1987; Goh and Balaji 2016; Santa and Drews 2023). For instance, consumers would ignore information if they do not trust that pecan products would taste good despite taste being a very important food value (Appendix Figure A3). Appendix Table A4 shows no emotional response from consumers to messages. This might suggest that they could have been perceived as ambiguous.

No significant effect of marketing information in our study overall aligns with the growing literature of information nudges. Existing literature in food markets, which is mainly focused on nutrition information, suggests that evidence of these nudges is inconclusive. A recent meta-analysis concluded that food labeling schemes led to a non-statistically significant decrease in calorie intake by approximately 3.6% (CI: -8.90% to +1.72%) (Cecchini and Warin 2016). Concerning the broader influence of information nudges, consistent smaller effects compared to other interventions have been observed across various domains (Codagnone et al. 2016).). An initial revision in non-food contexts highlighted "a paradigm for successful disclosure" yet acknowledged an early empirical study as "a model for successful disclosure."

To contribute to the consumer valuation literature, we also studied consumer valuations under two incentive-compatible elicitation stages differing only by the rule that determines the experimental market price: the BDM price and Seller's fixed price. The Seller's fixed price was the minimum willingness to accept a U.S. producer to sell pecan products (revealed to subjects at the end of the study). The Seller's Fixed price has the potential to simplify the procedures and might lead to a better understanding of the mechanism's incentives (Martin and Muñoz-Rodriguez 2022). We found no differences in valuations between the two stages in Study 1. Similarly, related studies (Bohm, Lindén, and Sonnegård 1997; Brown, Liu, and Tsoi 2023), which employed simpler incentive-compatible mechanisms that reduce the uncertainty of the payoff function, found that participants' reservation prices in simpler alternative mechanisms did not differ from those under the BDM. These results point out that misconceptions might not be the only factor driving WTP-WTA gaps, as suggested earlier (Plott and Zeiler 2005).

Furthermore, a fixed price might reduce the disconnection between subjects' reference price and an experimental price (e.g., BDM price) that potentially creates a source of uncertainty.

Respondents often make choices based on reference prices that are presented alongside (Gracia, Loureiro, and Nayga Jr 2011; Kilders and Caputo 2023; Ladenburg and Olsen 2006; Lemos, Halstead, and Huang 2022), thus reducing uncertainty about the payoff function can potentially induce true preferences.

Consumers are expected to have better intuition on how the payoff works under a fixed price compared to the BDM. Furthermore, a fixed price rule can be easily explained to participants and reduces uncertainty about the payoff function. Therefore, one could consider a fixed price valuation task for valuation studies with panelists who have little experience with the BDM.

This study is the first to compare average consumers' WTP for food products (from Study 1) with experts' forecasts of consumer valuations (from Study 2). Two key results are derived from this study. First, experts significantly overestimate consumer valuations, and the magnitudes are quite large, with average overvaluations of 33%. Moreover, experts tend to predict a positive impact of health and taste-related information on consumer WTP (Table 2). However, this information was ineffective at increasing consumers' WTP (Table 1).

Second, experts were not only optimistic about the impact of health and taste information on consumer demand, but they were also overconfident about their ability to predict the impact of that information. 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), suggesting caution must be exercised when experts perceive that they have a high level of expertise in a given domain

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). Contrary to these findings, we found that an expert's years of experience were not correlated with the accuracy of predicting consumer valuations. There was no evidence that age was associated with accuracy and that being a retailer was unrelated to accuracy. Interestingly, those who see themselves as less knowledgeable had greater accuracy. These results suggest that expertise does not improve the accuracy of predicting the success of marketing messages (Mahajan 1992), and it might decrease it.

**Implications**

Overall, these results have three primary implications for information provision management and policy. First, stakeholders and policymakers should carefully design information provision interventions because significant investments in "ineffective" information labels can be detrimental to business and even backfire with unintended consequences. Given that only a proportion of consumers respond to information, for instance, those who do not value nutrition respond to a particular taste-related message, resources could be better allocated to targeted efforts focusing on key food values (i.e., taste) and information consumers find relevant, new, and reliable. Experts' overconfidence in consumer reactions to information can be linked to prevailing low returns in business, as pointed out in other applications, including overinvesting (Mahajan 1992). Furthermore, we found weak evidence of negative impacts on purchases of health-related information in some consumer groups (those who considered nutrition an important food value); marketers might need to be cautious about using descriptions that might convey a negative signal to consumers (e.g., restrictions).[10] Unintended effects of information are not unique to health and taste information as these effects have been documented in green advertising (Goh and Balaji 2016), calorie labeling (Thunström 2019), and nutrition labeling (Melo, Zhen, and Colson 2019).

Second, to enhance sales, experts allocate substantial resources to communicate essential food characteristics, such as taste and health, to consumers, which might not have the expected effect. As information provision can be extremely costly, raising awareness of optimism bias and overconfidence among stakeholders and policymakers regarding the effectiveness of information provision interventions is critical. The findings affirm the ineffectiveness of nutrition or health information in motivating consumers toward healthier choices, suggesting the need to explore alternative market-driven strategies.

Third, a simple and intuitive rule to select a market price in induced-value studies could be considered instead of the BDM. The former might reduce complexity and cognitive effort, and increase transparency and participants' engagement, especially among consumers unfamiliar with the BDM. Subjects' decision-making process and optimal bidding behavior under a simplified auction-like mechanism (e.g., Seller fixed price) deserve further investigation. Our results suggest that simplifying the price rule in induced-value studies could potentially streamline the procedures while resulting in similar product valuations in non-strategic settings.

---

[10] After applying Bonferroni corrections to adjust for multiple hypotheses testing by manually applying a stricter threshold for the pairwise comparisons of treatments, there is no evidence of this.

**Limitations and future research**

Our study has limitations. First, when comparing valuations under the two similar auction-like mechanisms (the BDM and the Seller price), we did not elicit participants' understanding or strategic intention for each task. Further research could explore whether a simple price rule can induce valuations that represent optimal bidding using induced values (Brown, Liu, and Tsoi 2023) and whether such a price rule significantly reduces cognitive effort compared to the BDM.

We elicited self-reported emotional responses to information. Future research can benefit from exploring the behavioral aspects of consumers' reactions to this type of message beyond self-reported emotions, for example, attention span, attention focus, cognitive effort, and physiological reactions (Santa and Drews 2023). Promoting the taste of healthy food may lead to more successful health behaviors, which is essential considering the prevalence of obesity-related conditions in the U.S. (Petit et al. 2016). If nudges, however, are perceived to be paternalistic, consumers may make choices that contradict the intended objective of the intervention (Fang, Li, and Shen 2023; Thaler and Sunstein 2003).

Lastly, we found a significant level of optimism among experts regarding the effectiveness of marketing messages. Trying to identify expert forecasts for specific populations or providing them with useful feedback on the source of the biases may be useful for reducing the expert bias. 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).

**References**


Abraham, M M, and L M Lodish. 1990. "Getting the Most out of Advertising and Promotion." *Harvard Business Review* 68 (3): 50–51, 53, 56 passim.

Aharoni, Yair, Laszlo Tihanyi, and Brian L. Connelly. 2011. "Managerial Decision-Making in International Business: A Forty-Five-Year Retrospective." *Journal of World Business*, Managerial Decision Making in International Business, 46 (2): 135–42. https://doi.org/10.1016/j.jwb.2010.05.001.

Ahles, Amelia, Marco Palma, and Andreas Drichoutis. 2024. "Testing the Effectiveness of Lottery Incentives in Online Experiments." *American Journal of Agricultural Economics. (Forthcoming).*

Andersen, Steffen, Glenn W. Harrison, Morten Igel Lau, and E. Elisabet Rutström. 2006. "Elicitation Using Multiple Price List Formats." *Experimental Economics* 9 (4): 383–405. https://doi.org/10.1007/s10683-006-7055-6.

Ares, Gastón, Jessica Aschemann-Witzel, María Rosa Curutchet, Lucía Antúnez, Leandro Machín, Leticia Vidal, Joseline Martínez, and Ana Giménez. 2018. "Nutritional Warnings and Product Substitution or Abandonment: Policy Implications Derived from a Repeated Purchase Simulation." *Food Quality and Preference* 65 (April): 40–48. https://doi.org/10.1016/j.foodqual.2017.12.001.

Asioli, Daniele, Adriana Mignani, and Frode Alfnes. 2021. "Quick and Easy? Respondent Evaluations of the Becker–DeGroot–Marschak and Multiple Price List Valuation Mechanisms." *Agribusiness* 37 (2): 215–34. https://doi.org/10.1002/agr.21668.

Becker, Gordon M., Morris H. Degroot, and Jacob Marschak. 1964. "Measuring Utility by a Single-Response Sequential Method." *Behavioral Science* 9 (3): 226–32. https://doi.org/10.1002/bs.3830090304.

Berning, Joshua P., Hayley H. Chouinard, and Jill J. McCluskey. 2011. "Do Positive Nutrition Shelf Labels Affect Consumer Behavior? Findings from a Field Experiment with Scanner Data." *American Journal of Agricultural Economics* 93 (2): 364–69. https://doi.org/10.1093/ajae/aaq104.

Boccia, Flavio, Letizia Alvino, and Daniela Covino. 2023. "This Is Not My Jam: An Italian Choice Experiment on the Influence of Typical Product Attributes on Consumers' Willingness to Pay." *Nutrition & Food Science* ahead-of-print (ahead-of-print). https://doi.org/10.1108/NFS-04-2023-0076.

Bohm, Peter, Johan Lindén, and Joakin Sonnegård. 1997. "Eliciting Reservation Prices: Becker-DeGroot-Marschak Mechanisms vs. Markets." *The Economic Journal* 107 (443): 1079–89.

Brown, Alexander L., Jinliang Liu, and Michael Tsoi. 2023. "Is There a Better Way to Elicit Valuations than the BDM?" SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.4476764.

Campbell, Julie, and Vanessa Shonkwiler. 2020. "Pecan Preferences Associated with Mid-West Nut Buyers." *HortScience* 55 (10): 1662–69. https://doi.org/10.21273/HORTSCI15140-20.

Canavari, Maurizio, Andreas C Drichoutis, Jayson L Lusk, and Rodolfo M Nayga Jr. 2019. "How to Run an Experimental Auction: A Review of Recent Advances." *European Review of Agricultural Economics* 46 (5): 862–922. https://doi.org/10.1093/erae/jbz038.

Caplin, Andrew, and Mark Dean. 2015. "Revealed Preference, Rational Inattention, and Costly Information Acquisition." *American Economic Review* 105 (7): 2183–2203. https://doi.org/10.1257/aer.20140117.

Cason, Timothy N., and Charles R. Plott. 2014a. "Misconceptions and Game Form Recognition: Challenges to Theories of Revealed Preference and Framing." *Journal of Political Economy* 122 (6): 1235–70. https://doi.org/10.1086/677254.

———. 2014b. "Misconceptions and Game Form Recognition: Challenges to Theories of Revealed Preference and Framing." *Journal of Political Economy* 122 (6): 1235–70. https://doi.org/10.1086/677254.

Cecchini, M., and L. Warin. 2016. "Impact of Food Labelling Systems on Food Choices and Eating Behaviours: A Systematic Review and Meta-Analysis of Randomized Studies." *Obesity Reviews* 17 (3): 201–10. https://doi.org/10.1111/obr.12364.

Charness, Gary, Ryan Oprea, and Sevgi Yuksel. 2021. "How Do People Choose Between Biased Information Sources? Evidence from a Laboratory Experiment." *Journal of the European Economic Association* 19 (3): 1656–91. https://doi.org/10.1093/jeea/jvaa051.

Cheng, Zhao-Hong, Chun-Tuan Chang, and Yu-Kang Lee. 2020. "Linking Hedonic and Utilitarian Shopping Values to Consumer Skepticism and Green Consumption: The Roles of Environmental Involvement and Locus of Control." *Review of Managerial Science* 14 (1): 61–85. https://doi.org/10.1007/s11846-018-0286-z.

Choi, Jungsil, Yexin Jessica Li, and Adriana Samper. 2019. "The Influence of Health Motivation and Calorie Ending on Preferences for Indulgent Foods." *Journal of Consumer Research* 46 (3): 606–19. https://doi.org/10.1093/jcr/ucz002.

Cochran, William G., and Donald B. Rubin. 1973. "Controlling Bias in Observational Studies: A Review." *Sankhyā: The Indian Journal of Statistics, Series A (1961-2002)* 35 (4): 417–46.

Codagnone, Cristiano, Giuseppe Alessandro Veltri, Francesco Bogliacino, Francisco Lupiáñez-Villanueva, George Gaskell, Andriy Ivchenko, Pietro Ortoleva, and Francesco Mureddu. 2016. "Labels as Nudges? An Experimental Study of Car Eco-Labels." *Economia Politica* 33 (3): 403–32. https://doi.org/10.1007/s40888-016-0042-2.

Cozzens, Michael, and Noshir. Contractor. 1987. "The Effect of Conflicting Information on Media Skepticism." *Communication Research* 14 (4): 437–51. https://doi.org/10.1177/009365087014004004.

Delgadillo-Puga, Claudia, Ivan Torre-Villalvazo, Lilia G. Noriega, Leonardo A. Rodríguez-López, Gabriela Alemán, Erik A. Torre-Anaya, Yonatan Y. Cariño-Cervantes, et al. 2023. "Pecans and Its Polyphenols Prevent Obesity, Hepatic Steatosis and Diabetes by Reducing Dysbiosis, Inflammation, and Increasing Energy Expenditure in Mice Fed a High-Fat Diet." *Nutrients* 15 (11): 2591. https://doi.org/10.3390/nu15112591.

Drichoutis, Andreas C., Panagiotis Lazaridis, and Rodolfo M. Nayga. 2008. "The Role of Reference Prices in Experimental Auctions." *Economics Letters* 99 (3): 446–48. https://doi.org/10.1016/j.econlet.2007.09.010.

Drichoutis, Andreas C., and Rodolfo M. Nayga. 2022. "Game Form Recognition in Preference Elicitation, Cognitive Abilities, and Cognitive Load." *Journal of Economic Behavior & Organization* 193 (January): 49–65. https://doi.org/10.1016/j.jebo.2021.11.006.

Drichoutis, Andreas, Panagiotis Lazaridis, and Rodolfo Nayga. 2006. “Consumers’ Use of Nutritional Labels: A Review of Research Studies and Issues.” *Academy of Marketing Science Review* 10 (January).

Dror, Itiel E. 2011. “The Paradox of Human Expertise: Why Experts Get It Wrong.” In *The Paradoxical Brain*, by Alvaro Pascual-Leone, Vilayanur Ramachandran, Jonathan Cole, Sergio Della Sala, Tom Manly, Andrew Mayes, and Oliver Sacks, edited by Narinder Kapur, 1st ed., 177–88. Cambridge University Press. https://doi.org/10.1017/CBO9780511978098.011.

Du, Xiaofen, Xinwang Wang, Adriana Muniz, and Keith Kubenka. 2022. “Consumer Hedonic Ratings and Associated Sensory Characteristics and Emotional Responses to Fourteen Pecan Varieties Grown in Texas.” *Plants* 11 (14): 1814. https://doi.org/10.3390/plants11141814.

Fang, Hanming, King King Li, and Peiyao Shen. 2023. “To Go Electric or To Burn Coal? A Randomized Field Experiment of Informational Nudges.”

Fellner, Gerlinde, and Sebastian Krügel. 2012. “Judgmental Overconfidence: Three Measures, One Bias?” *Journal of Economic Psychology* 33 (1): 142–54. https://doi.org/10.1016/j.joep.2011.07.008.

Goh, See Kwong, and M. S. Balaji. 2016. “Linking Green Skepticism to Green Purchase Behavior.” *Journal of Cleaner Production* 131 (September): 629–38. https://doi.org/10.1016/j.jclepro.2016.04.122.

Goldman, Matt, and David M. Kaplan. 2018. “Comparing Distributions by Multiple Testing across Quantiles or CDF Values.” *Journal of Econometrics* 206 (1): 143–66. https://doi.org/10.1016/j.jeconom.2018.04.003.

Gracia, Azucena, Maria L. Loureiro, and Rodolfo M. Nayga Jr. 2011. “Are Valuations from Nonhypothetical Choice Experiments Different from Those of Experimental Auctions?” *American Journal of Agricultural Economics* 93 (5): 1358–73. https://doi.org/10.1093/ajae/aar054.

Grežo, Matúš. 2020. “Overconfidence and Financial Decision-Making: A Meta-Analysis.” *Review of Behavioral Finance* 13 (3): 276–96. https://doi.org/10.1108/RBF-01-2020-0020.

Grunert, Klaus G., and Josephine M. Wills. 2007. “A Review of European Research on Consumer Response to Nutrition Information on Food Labels.” *Journal of Public Health* 15 (5): 385–99. https://doi.org/10.1007/s10389-007-0101-9.

Harrison, Glenn W., and John A. List. 2004. “Field Experiments.” *Journal of Economic Literature* 42 (4): 1009–55. https://doi.org/10.1257/0022051043004577.

Horowitz, John K. 2006. “The Becker-DeGroot-Marschak Mechanism Is Not Necessarily Incentive Compatible, Even for Non-Random Goods.” *Economics Letters* 93 (1): 6–11. https://doi.org/10.1016/j.econlet.2006.03.033.

Hung, Yung, Klaus G. Grunert, Christine Hoefkens, Sophie Hieke, and Wim Verbeke. 2017. “Motivation Outweighs Ability in Explaining European Consumers’ Use of Health Claims.” *Food Quality and Preference* 58 (June): 34–44. https://doi.org/10.1016/j.foodqual.2017.01.001.

Huseynov, Samir, Mykel Taylor, and Charles Martinez. 2024. “Optimistic Price Expectations.”

Imbens, Guido W., and Donald B. Rubin. 2015. *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*. Causal Inference for Statistics, Social, and

Biomedical Sciences: An Introduction. New York, NY, US: Cambridge University Press. https://doi.org/10.1017/CBO9781139025751.

Invernizzi, Anna Chiara, Anna Menozzi, Diana Anna Passarani, Dean Patton, and Giampaolo Viglia. 2017. "Entrepreneurial Overconfidence and Its Impact upon Performance." *International Small Business Journal* 35 (6): 709–28. https://doi.org/10.1177/0266242616678445.

Jo, Jisung, and Jayson L. Lusk. 2018. "If It's Healthy, It's Tasty and Expensive: Effects of Nutritional Labels on Price and Taste Expectations." *Food Quality and Preference* 68 (September): 332–41. https://doi.org/10.1016/j.foodqual.2018.04.002.

Jo, Jisung, Jayson L. Lusk, Laurent Muller, and Bernard Ruffieux. 2016. "Value of Parsimonious Nutritional Information in a Framed Field Experiment." *Food Policy* 63 (August): 124–33. https://doi.org/10.1016/j.foodpol.2016.07.006.

Johnson, Eric J., and J. Edward Russo. 1984. "Product Familiarity and Learning New Information." *Journal of Consumer Research* 11 (1): 542–50. https://doi.org/10.1086/208990.

Kendall, Chad, and Anujit Chakraborty. 2022. "Future Self-Proof Elicitation Mechanisms." SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.4032946.

Kilders, Valerie, and Vincenzina Caputo. 2023. "A Reference-Price-Informed Experiment to Assess Consumer Demand for Beef with a Reduced Carbon Footprint." *American Journal of Agricultural Economics* n/a (n/a). https://doi.org/10.1111/ajae.12432.

Ladenburg, Jacob, and Søren Bøye Olsen. 2006. "Starting Point Anchoring Effects in Choice Experiments," IFRO Working Paper.

Lemos, Scott, John M. Halstead, and Ju-Chin Huang. 2022. "The Effects of Information about Price Anchoring: Evidence from a Choice Experiment." *Agricultural and Resource Economics Review* 51 (2): 240–65. https://doi.org/10.1017/age.2022.10.

Li, Xiaomei, Zhengbo Liang, and Yan Liu. 2023. "Information Provision and Consumer Search Behavior for Products with Asymmetric Uncertainty." *Journal of Management Science and Engineering* 8 (1): 49–82. https://doi.org/10.1016/j.jmse.2022.07.005.

List, John A. 2007. "Field Experiments: A Bridge between Lab and Naturally Occurring Data." *The B.E. Journal of Economic Analysis & Policy* 6 (2). https://doi.org/10.2202/1538-0637.1747.

List, John A., Azeem M. Shaikh, and Yang Xu. 2019. "Multiple Hypothesis Testing in Experimental Economics." *Experimental Economics* 22 (4): 773–93. https://doi.org/10.1007/s10683-018-09597-5.

Lovallo, Dan, and Daniel Kahneman. 2003. "How Optimism Undermines Executives' Decisions." *Harvard Business Review*.

Lowe, Michael R., and Meghan L. Butryn. 2007. "Hedonic Hunger: A New Dimension of Appetite?" *Physiology & Behavior* 91 (4): 432–39. https://doi.org/10.1016/j.physbeh.2007.04.006.

Lusk, Jayson L., and Brian C. Briggeman. 2009. "Food Values." *American Journal of Agricultural Economics* 91 (1): 184–96. https://doi.org/10.1111/j.1467-8276.2008.01175.x.

Magnuson, Shelby M., Brendan Kelly, Kadri Koppel, and William Reid. 2016. "A Comparison of Flavor Differences between Pecan Cultivars in Raw and Roasted Forms." *Journal of Food Science* 81 (5): S1243–53. https://doi.org/10.1111/1750-3841.13289.

Mahajan, Jayashree. 1992. “The Overconfidence Effect in Marketing Management Predictions.” *JOURNAL OF MARKETING RESEARCH*.

Martin, Daniel, and Edwin Muñoz-Rodriguez. 2022. “Cognitive Costs and Misperceived Incentives: Evidence from the BDM Mechanism.” *European Economic Review* 148 (September): 104197. https://doi.org/10.1016/j.euroecorev.2022.104197.

McNemar, Quinn. 1947. “Note on the Sampling Error of the Difference between Correlated Proportions or Percentages.” *Psychometrika* 12 (2): 153–57. https://doi.org/10.1007/BF02295996.

Melo, Grace, Chen Zhen, and Greg Colson. 2019. “Does Point-of-Sale Nutrition Information Improve the Nutritional Quality of Food Choices?” *Economics & Human Biology* 35 (December): 133–43. https://doi.org/10.1016/j.ehb.2019.07.001.

Menkhoff, Lukas, Maik Schmeling, and Ulrich Schmidt. 2013. “Overconfidence, Experience, and Professionalism: An Experimental Study.” *Journal of Economic Behavior & Organization* 86 (February): 92–101. https://doi.org/10.1016/j.jebo.2012.12.022.

Moore, Eli D., Gary W. Williams, Marco A. Palma, and Leonardo Lombardini. 2009. “Effectiveness of State-Level Pecan Promotion Programs: The Case of the Texas Pecan Checkoff Program.” *HortScience* 44 (7): 1914–20. https://doi.org/10.21273/HORTSCI.44.7.1914.

Morag, Dor, and George F. Loewenstein. 2021. “Narratives and Valuations.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3919471.

Noussair, Charles, Stephane Robin, and Bernard Ruffieux. 2004. “Revealing Consumers' Willingness-to-Pay: A Comparison of the BDM Mechanism and the Vickrey Auction.” *Journal of Economic Psychology* 25 (6): 725–41. https://doi.org/10.1016/j.joep.2003.06.004.

Nystrand, Bjørn Tore, and Svein Ottar Olsen. 2020. “Consumers' Attitudes and Intentions toward Consuming Functional Foods in Norway.” *Food Quality and Preference* 80 (March): 103827. https://doi.org/10.1016/j.foodqual.2019.103827.

Papoutsi, Georgia S., Stathis Klonaris, and Andreas Drichoutis. 2019. “The Health-Taste Trade-off in Consumer Decision Making for Functional Snacks: An Experimental Approach.” *British Food Journal* 123 (5): 1645–63. https://doi.org/10.1108/BFJ-10-2018-0694.

Park, C. Whan, and V. Parker Lessig. 1981. “Familiarity and Its Impact on Consumer Decision Biases and Heuristics.” *Journal of Consumer Research* 8 (2): 223–31.

Park, Timothy A., and Wojciech J. Florkowski. 2003. “Selection of Peach Varieties and the Role of Quality Attributes.” *Journal of Agricultural and Resource Economics* 28 (1): 138–51.

Petit, Olivia, Dwight Merunka, Jean-Luc Anton, Bruno Nazarian, Charles Spence, Adrian David Cheok, Denis Raccah, and Olivier Oullier. 2016. “Health and Pleasure in Consumers' Dietary Food Choices: Individual Differences in the Brain's Value System.” *PLOS ONE* 11 (7): e0156333. https://doi.org/10.1371/journal.pone.0156333.

Plott, Charles R., and Kathryn Zeiler. 2005. “The Willingness to Pay-Willingness to Accept Gap, the ‘Endowment Effect,’ Subject Misconceptions, and Experimental Procedures for Eliciting Valuations.” *The American Economic Review* 95 (3): 530–45.

Proeger, Till, and Lukas Meub. 2014. “Overconfidence as a Social Bias: Experimental Evidence.” *Economics Letters* 122 (2): 203–7. https://doi.org/10.1016/j.econlet.2013.11.027.

Rutström, E. Elisabet. 1998. “Home-Grown Values and Incentive Compatible Auction Design.” *International Journal of Game Theory* 27 (3): 427–41. https://doi.org/10.1007/s001820050082.
Santa, Juana Castro, and Stefan Drews. 2023. “Heuristic Processing of Green Advertising: Review and Policy Implications.” *Ecological Economics* 206 (April): 107760. https://doi.org/10.1016/j.ecolecon.2023.107760.
Sharot, Tali, and Cass R. Sunstein. 2020. “How People Decide What They Want to Know.” *Nature Human Behaviour* 4 (1): 14–19. https://doi.org/10.1038/s41562-019-0793-1.
Smirnov, N. 1948. “Table for Estimating the Goodness of Fit of Empirical Distributions.” *The Annals of Mathematical Statistics* 19 (2): 279–81.
Smith, Trenton G. 2004. “The McDonalds? Equilibrium. Advertising, Empty Calories, and the Endogenous Determination of Dietary Preferences.” *Social Choice and Welfare* 23 (3): 383–413. https://doi.org/10.1007/s00355-003-0265-3.
Smith, William P., and Paul R. Sachs. 1997. “Social Comparison and Task Prediction: Ability Similarity and the Use of a Proxy.” *British Journal of Social Psychology* 36 (4): 587–602. https://doi.org/10.1111/j.2044-8309.1997.tb01151.x.
Thaler, Richard H., and Cass R. Sunstein. 2003. “Libertarian Paternalism.” *The American Economic Review* 93 (2): 175–79.
Thunström, Linda. 2019. “Welfare Effects of Nudges: The Emotional Tax of Calorie Menu Labeling.” *Judgment and Decision Making* 14 (1): 11–25. https://doi.org/10.1017/S1930297500002874.
Toney, Brian, Marco A. Palma, Michelle Segovia, and Grace Melo. 2023. “The Instrumental Value of Calorie Information and Its Effect on Food Choices.” SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.4634107.
Wardle, J. 2000. “An Experimental Investigation of the Influence of Health Information on Children’s Taste Preferences.” *Health Education Research* 15 (1): 39–44. https://doi.org/10.1093/her/15.1.39.
Wilcoxon, Frank. 1992. “Individual Comparisons by Ranking Methods.” In *Breakthroughs in Statistics: Methodology and Distribution*, edited by Samuel Kotz and Norman L. Johnson, 196–202. Springer Series in Statistics. New York, NY: Springer. https://doi.org/10.1007/978-1-4612-4380-9_16.
Winston, Clifford. 2008. “The Efficacy of Information Policy: A Review of Archon Fung, Mary Graham, and David Weil’s ‘Full Disclosure: The Perils and Promise of Transparency.’” Edited by Archon Fung, Mary Graham, and David Weil. *Journal of Economic Literature* 46 (3): 704–17.

**Figures**

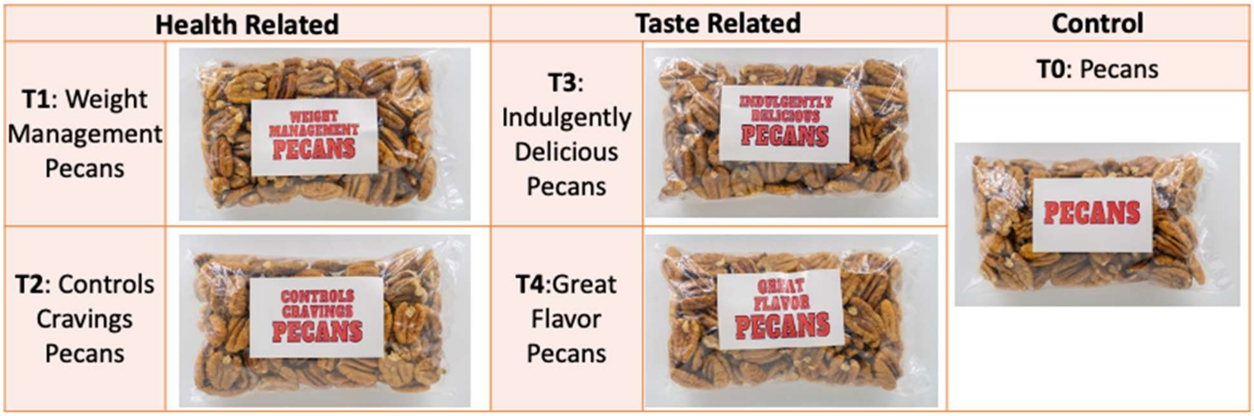
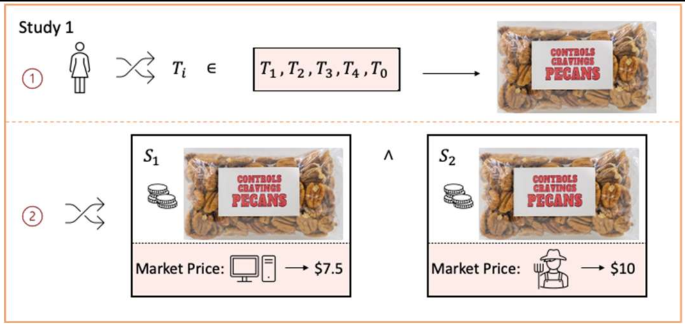
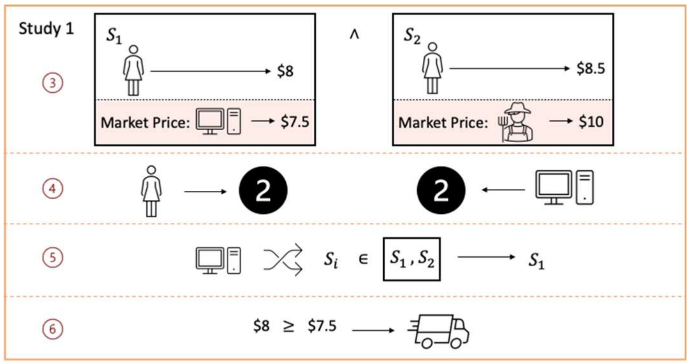


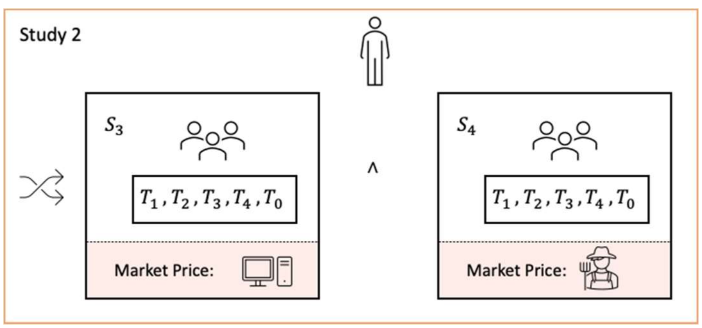

Figure 1. The five information treatments include four health- and taste-related marketing messages and a control. The treatment conditions were assigned randomly based on a between-subject design for Study 1 with consumers. A within-subject design with experts was conducted for Study 2.




Panel a. Experimental design Study 1




Panel b. Market realization procedure Study 1




Panel c. Experimental design Study 2

Figure 2. Experimental design and monetary incentive approach.

*Panel a* illustrates an example of a subject treatment assignation and involvement in the two WTP elicitation stages in Study 1 with consumers. In this example, *controls cravings pecans* was the treatment randomly assigned to the subject, $7.5 was the randomly chosen BDM price, and $10 was the seller price. The stages order was randomly assigned and the same information treatment was presented in both stages within the subject.

*Panel b* illustrates the market realization procedure for Study 1 with consumers. A subject chooses a number from 1 to 10. If the chosen number matches the computer's randomly generated number (i.e., 2), then one of the two elicitations is randomly chosen for implementation. In the example, $S_1$ 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.
*Panel c* shows the elicitation stages in Study 2 with experts. A subject faces the two elicitation stages, BDM price ($S_3$) and seller price ($S_4$), each with the five different treatment conditions presented in Figure 1.

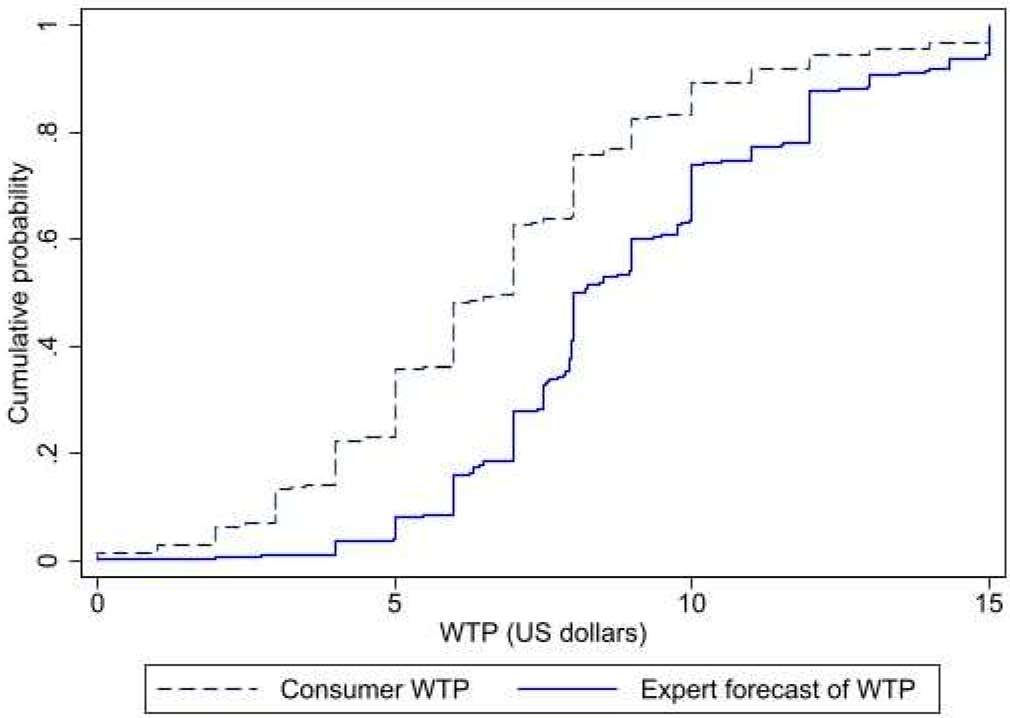



Figure 3. Cumulative distributions of consumer WTP (from Study 1) and experts forecast of WTP (from Study 2). We rejected the hypothesis of equality of the distributions of the two samples ($p$<0.01, K.S. test).

**Tables**

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

| Stage | Treatment | (1) Consumer bid | | | | (2) Expert forecast | | | | (3) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Mktg. info. vs control | S1 vs S2 | | | Mktg. info. vs control | S1 vs S2 | Bid vs forecast |
| | | N | Mean | *p* value | *p* value | N | Mean | *p* value | *p* value | *p* value |
| BDM Price (S1) | Weight management pecans | 100 | 6.933 | 0.813 | - | 51 | 9.310 | 0.777 | - | <0.001 |
| | Indulgently delicious pecans | 85 | 7.162 | 0.843 | - | 51 | 9.194 | 0.829 | - | <0.001 |
| | Great flavors pecans | 92 | 6.547 | 0.908 | - | 51 | 8.870 | 0.821 | - | <0.001 |
| | Controls cravings pecans | 94 | 6.458 | 0.873 | - | 51 | 9.235 | 0.813 | - | <0.001 |
| | Pecans (control) | 95 | 6.853 | - | - | 51 | 8.446 | - | - | 0.005 |
| Seller Price (S2) | Weight management pecans | 100 | 6.860 | 0.804 | 1.000 | 51 | 9.438 | 0.493 | 1.000 | <0.001 |
| | Indulgently delicious pecans | 85 | 7.260 | 0.704 | 1.000 | 51 | 8.946 | 0.933 | 1.000 | 0.004 |
| | Great flavors pecans | 92 | 6.573 | 0.907 | 1.000 | 51 | 8.908 | 0.901 | 0.997 | <0.001 |
| | Controls cravings pecans | 94 | 6.315 | 0.844 | 1.000 | 51 | 9.104 | 0.828 | 1.000 | <0.001 |
| | Pecans (control) | 95 | 6.723 | - | 1.000 | 51 | 8.435 | - | 0.985 | 0.003 |

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., experts' guess and consumer bids) are from populations with the same distribution.

Table 2. Experts' overprediction of consumer WTP

| Stage | Treatment | (1) Overprediction I[Forecast-Bid>0] | | (2) Deviation \|Forecast-Bid\| | | (3) Deviation to bid ratio Deviation/Consumer bid | | (4) Certainty of forecast 0-100% Self reported | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Mktg. info. vs control *p* value | 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 | 0.849 | 3.025 | 0.880 | 0.343 | 0.621 | 67.059 | 0.984 |
| | Indulgently delicious pecans | 0.725 | 1.000 | 2.758 | 0.987 | 0.284 | 0.985 | 70.000 | 1.000 |
| | Great flavors pecans | 0.824 | 0.982 | 2.600 | 1.000 | 0.355 | 0.983 | 70.400 | 1.000 |
| | Controls cravings pecans | 0.824 | 0.983 | 3.162 | 0.730 | 0.430 | 0.400 | 68.235 | 0.999 |
| | Pecans (control) | 0.725 | - | 2.293 | - | 0.233 | - | 70.784 | - |
| Seller price | Weight management pecans | 0.902 | 0.771 | 3.100 | 0.621 | 0.376 | 0.926 | 69.608 | 1.000 |
| | Indulgently delicious pecans | 0.765 | 1.000 | 2.691 | 0.985 | 0.232 | 1.000 | 70.000 | 0.997 |
| | Great flavors pecans | 0.804 | 1.000 | 2.742 | 0.983 | 0.355 | 0.980 | 71.176 | 1.000 |
| | Controls cravings pecans | 0.824 | 1.000 | 3.214 | 0.400 | 0.442 | 0.426 | 67.800 | 0.999 |
| | Pecans (control) | 0.765 | - | 2.215 | - | 0.255 | - | 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 3. 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.

Table 4. OLS estimation results of 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 guess 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.

**Supplementary Figures**

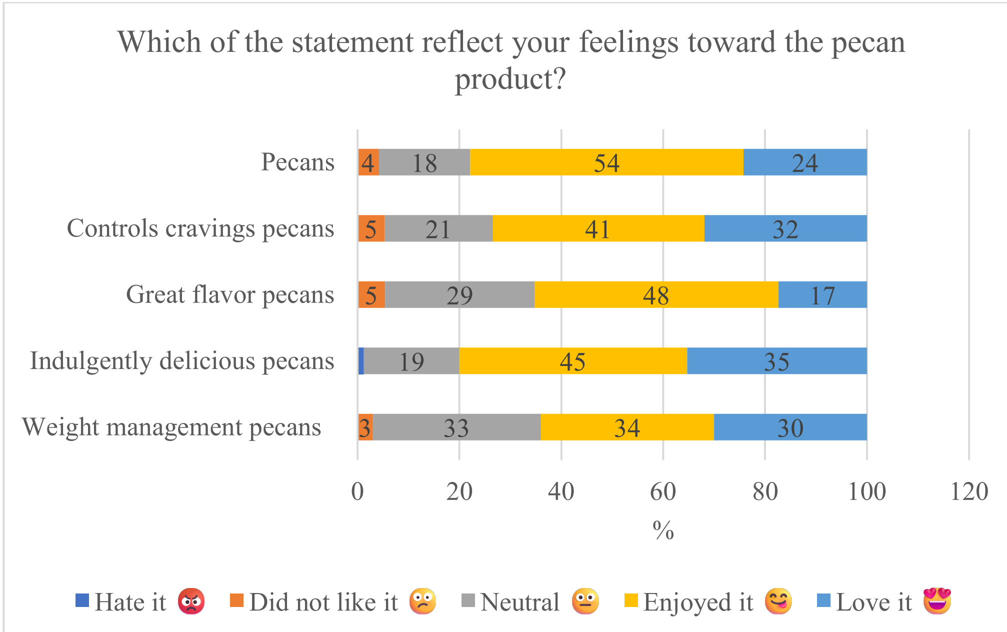



Figure A1. Emotional response scale for pecan products.

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

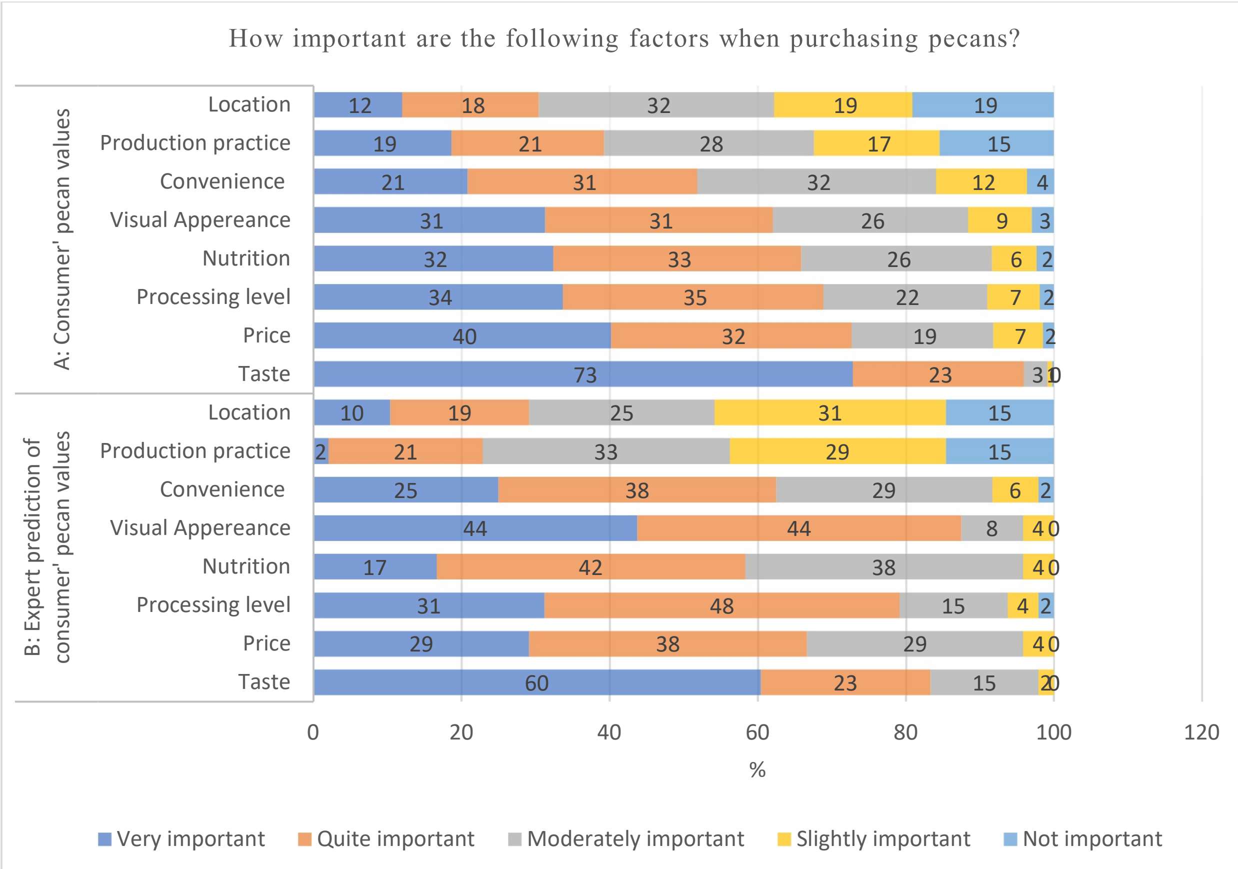



Figure A3. Consumer food values reported by consumers and experts

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, experts were asked to predict consumer pecan values using a similar scale as in Study 1.

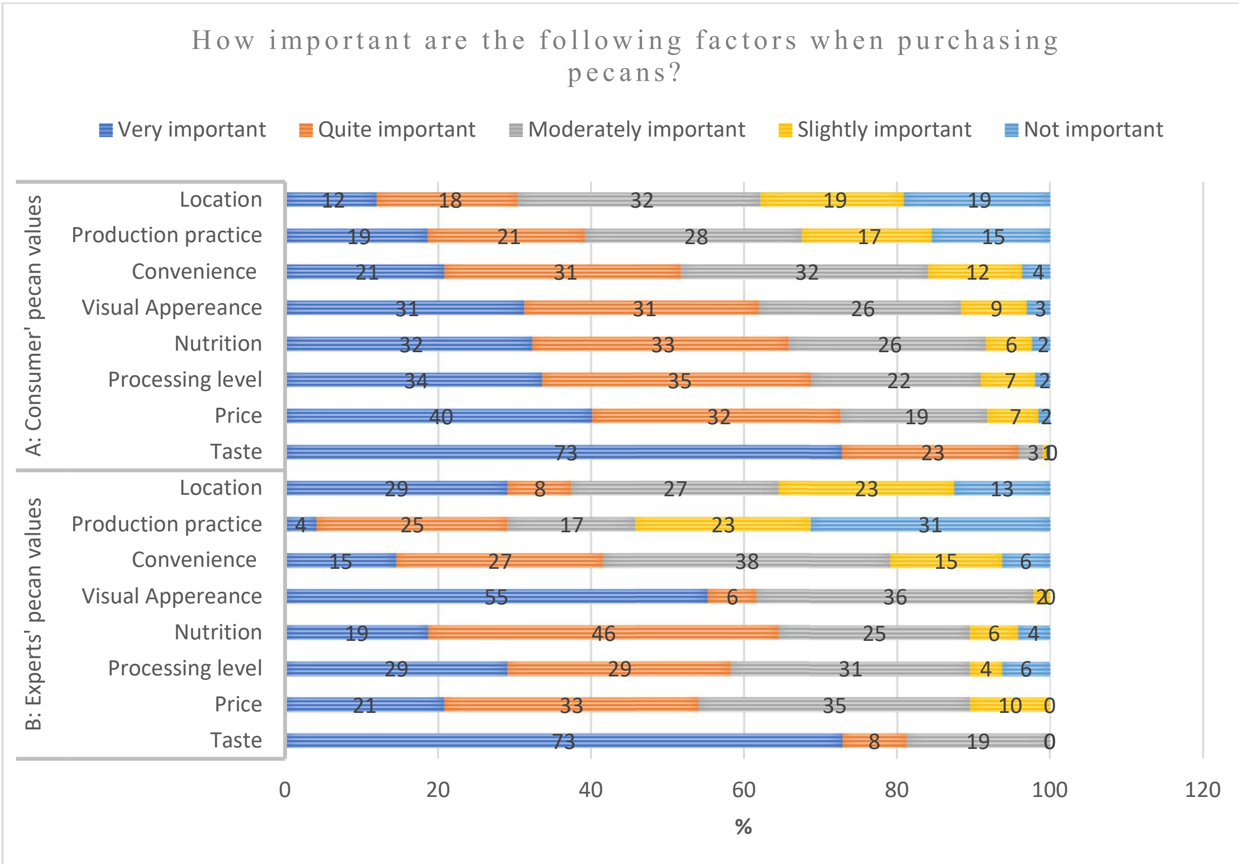



Figure A4. Consumer and expert food values

**Supplementary Tables**

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

| Variable | (1)<br>Full Sample | (2)<br>Control | (3)<br>T1 | (4)<br>T2 | (5)<br>T3 | (6)<br>T4 | (7)<br>Diff (2)-(3) | (8)<br>Diff (2)-(4) | (9)<br>Diff (2)-(5) | (10)<br>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 |
| Non children | 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 out of the five treatment conditions. Columns 7-10 report *p*-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 |

Table A3. Respondents' characteristics in Study 2 for the full sample

| Variable | N | Mean |
|---|---|---|
| Age | 49 | 56.63 |
| 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 |

Table A4. 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 |

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

Table A5. 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<0.05 ** p<0.01 *** p<0.001. Clustered standard errors were calculated.

Table A6. Comparison of estimation results of experts' forecasts across different specifications.

| Variables | (1) OLS | (2) Fixed effects | (3) Random effects |
|---|---|---|---|
| Weight management pecans | 0.853* | 0.921*** | 0.914*** |
| Indulgently delicious pecans | 0.514 | 0.533* | 0.532* |
| Great flavors pecans | 0.257 | 0.324 | 0.322 |
| Controls cravings pecans | 0.962* | 1.010*** | 1.006*** |
| Seller price task (SPT) | -0.069 | -0.049 | -0.051 |
| Weight management pecans x SPT | 0.089 | 0.031 | 0.037 |
| Indulgently delicious pecans x SPT | 0.018 | 0.005 | 0.006 |
| Great flavors pecans x SPT | 0.285 | 0.193 | 0.198 |
| Controls cravings pecans x SPT | 0.191 | 0.106 | 0.111 |
| Age | -0.010 | | -0.009 |
| Graduate school | 0.232 | | 0.270 |
| Female | -1.005*** | | -1.072 |
| Sales less than 50k | 0.189 | | 0.041 |
| Grower_only | 0.830*** | | 0.865 |
| Retailer | 0.272 | | 0.089 |
| Married | 0.716** | | 0.786 |
| Non children | -0.563 | | -0.386 |
| Less knowledgeable | -1.234*** | | -1.227 |
| Less than 5 years of experience | -0.305 | | -0.180 |
| Direct sales | 0.381 | | 0.343 |
| Full time in the pecan industry | 0.607* | | 0.535 |
| Certainty of guess 0-100% | 0.006 | | 0.021 |
| Constant | 1.891* | | 0.812 |
| BIC | 2194.339 | 1487.652 | . |
| N | 477 | 477 | 477 |

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

Table A7. OLS estimation results of experts' certainty level of predictions

| Variables | How certain are your from your response, 0-100% |
|---|---|
| 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 |
| Constant | 71.545*** |
| BIC | 3981.795 |
| N | 477 |

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

Table A8. 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 | 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 | 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 A9. Subsample analyses of consumers' bids by shopping behaviors and health beliefs and concerns

| 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 | 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 | 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 A10. Correlation between consumers' expected price and bids

| Stage | Treatment | Correlation coefficient | Expected Price vs bid *p*-value |
|---|---|---|---|
| BDM price | Weight management pecans | 0.60*** | 0.78 |
| | Indulgently delicious pecans | 0.73*** | 0.00 |
| | Great flavors pecans | 0.66*** | 0.00 |
| | Controls cravings pecans | 0.47*** | 0.08 |
| | Pecans | 0.64*** | 0.01 |
| Seller price | Weight management pecans | 0.70*** | 0.34 |
| | Indulgently delicious pecans | 0.67*** | 0.01 |
| | Great flavors pecans | 0.69*** | 0.00 |
| | Controls cravings pecans | 0.67*** | 0.00 |
| | Pecans | 0.67*** | 0.00 |

Note: Pearson correlation coefficients are reported. WSR test is for comparisons between a consumers' expected market price and bid. *** $p<0.001$.

Table A11. Consumers' WTP for the full sample and robust sample

| Stage | Treatment | (1) Consumer WTP Full sample | | (2) Consumer WTP Robust sample | |
|---|---|---|---|---|---|
| | | N | Mean | N | Mean |
| BDM price | Weight management pecans | 100 | 6.933 | 47 | 6.697 |
| | Indulgently delicious pecans | 85 | 7.162 | 46 | 7.022 |
| | Great flavors pecans | 92 | 6.547 | 44 | 6.290 |
| | Controls cravings pecans | 94 | 6.458 | 48 | 6.032 |
| | Pecans | 95 | 6.853 | 43 | 6.314 |
| Seller price | Weight management pecans | 100 | 6.860 | 53 | 6.726 |
| | Indulgently delicious pecans | 85 | 7.260 | 39 | 6.918 |
| | Great flavors pecans | 92 | 6.573 | 48 | 6.375 |
| | Controls cravings pecans | 94 | 6.315 | 46 | 6.426 |
| | Pecans | 95 | 6.723 | 52 | 6.692 |

Note: In the case of BDM price, the test is conducted only with observations where the BDM price was presented first. Similarly, for Seller price, the test is carried out solely with observations where the Seller price was presented first. There are no statistical differences between marketing information treatment and control and between stages. 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 A12. Pooled OLS estimation of consumer and expert valuations

| Variables | (1) | (2) | (3) |
|---|---|---|---|
| Expert | 2.223*** | 1.980*** | 1.393** |
| Weight management pecans | 0.352 | 0.381 | 0.108 |
| Indulgently delicious pecans | 0.457 | 0.463 | 0.390 |
| Great flavors pecans | -0.050 | -0.050 | -0.294 |
| Controls cravings pecans | 0.020 | 0.035 | -0.364 |
| Seller price task (SPT) | -0.089 | -0.104 | -0.104 |
| Weight management pecans x SPT | 0.084 | 0.085 | 0.085 |
| Indulgently delicious pecans x SPT | 0.057 | 0.075 | 0.075 |
| Great flavors pecans x SPT | 0.119 | 0.113 | 0.113 |
| Controls cravings pecans x SPT | -0.050 | -0.041 | -0.041 |
| Age | | 0.027** | 0.027** |
| Female | | -0.235 | -0.228 |
| Graduate school | | 0.076 | 0.073 |
| Weight management pecans x expert | | | 0.811 |
| Indulgently delicious pecans x expert | | | 0.243 |
| Great flavors pecans x expert | | | 0.714 |
| Controls cravings pecans x expert | | | 1.169* |
| Constant | 6.633*** | 5.442*** | 5.643*** |
| BIC | 7369.493 | 7269.107 | 7291.976 |
| N | 1442 | 1422 | 1422 |

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