



Peer feedback can decrease consumers' willingness to pay for food: Evidence from a field experiment

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ABSTRACT

The vast majority of consumer products fail to attract sufficient consumer demand. Word of mouth marketing and online feedback from other consumers have become focal marketing strategies for many products as social media has increased the size of networks and amplified the impact of messages from other consumers. The current literature on the influence that consumer feedback can have on consumers' willingness to pay (WTP) for food products is mixed and often draws upon studies with small samples and hypothetical situations. This study investigates how this feedback can impact other consumers' food preferences using an economic field experiment involving 1,068 adult consumers who make choices on oysters, mushrooms, and chocolate. Results suggest that knowledge of peer preferences, such as the willingness to pay for similar products and/or how often they consume these products, caused a decrease (5%–9%) in consumers' willingness to pay.

1. Introduction

Consumers often look to the decisions and recommendations of others to reduce uncertainty (Godes & Mayzlin, 2004), as more experienced individuals can serve as a guide for decision making (Iyengar et al., 2011; Narayan et al., 2011). Peer recommendations are often received as more authentic sources of information about products and services compared to sponsored or promotional advertisements (Reingen & Brown, 1987), and peer recommendations are particularly influential when mentioned amid conversations with social network members (Godes & Mayzlin, 2009). Fershtman and Segal (2017) posits that an individual is comprised of core and behavioral preferences, and behavioral preferences are constantly changing in response to social environments. In other words, consumer decision making is dynamic and responsive to cues from social environments.

Food choices are influenced by social frameworks and food context (Furst et al., 1996). Social modeling occurs when individuals use the choices of others to guide eating behavior. A review of almost 70 experiments from 1974 to 2014 concluded that the food choice of others can reduce uncertainty of unfamiliar foods and that social modeling increases when individuals perceived themselves, or desire to be affiliated, with those modeling food behavior (Cruwys et al., 2015). There is also evidence that social modeling can influence the selection and eating habits related to novel foods. An experiment among children examined

the effects of peer influence on the acceptability of healthy snacks colored blue – these snacks were not typically blue – and the results indicated that both positive modeling increased consumption and negative modeling decreased consumption of the novel snacks (Greenhalgh et al., 2009).

Many choices about food consumption occur away from the home. Food-away-from-home expenditures in the United States totaled \$969.4 billion in 2019, with 34.5% occurring at full-service restaurants (Economic Research Service (ERS), 2020). Since restaurant diners tend to gather in a social setting, with an average dining party of 3.7 individuals (Herring, 2005), food choices away from home are subject to social effects and peer influence (Ellison, 2014). In particular, the presence of peers affects dining behaviors such as meal duration (Bell & Pliner, 2003), the amount of food consumed (De Castro & Brewer, 1992; Herman et al., 2003), and the variety of food selected (Ariely & Levav, 2000). Peer influence can also affect consumer willingness to pay for food products (House et al., 2008; Richards et al., 2014) and peer recommendations are particularly influential among groups with strong social network ties (Iyengar et al., 2011; Richards et al., 2014).

This study aims to measure the influence of feedback from other consumers on the willingness to pay of other consumers.¹ We conduct a large field experiment with adult consumers making purchase decisions on three food products (i.e., raw oysters, white button mushrooms, and chocolate fondue with cookies for dipping), and hypothesized that

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¹ For simplicity, throughout the paper we refer to feedback from other adult consumers as peer influence. This definition is the word peer is simply referring to an adult who also attended the same public event and is not implying a close personal relationship.

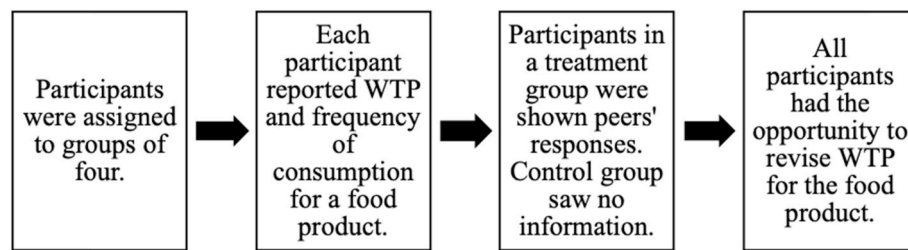


Fig. 1. Diagram of experimental flow.

individuals would revise the valuation of the products when informed about the willingness to pay of other consumers. We also hypothesized that revisions would particularly occur for foods that are more likely to be consumed in a social setting versus not (e.g. food away from home in a restaurant dining context). This study expands the economics, marketing, and eating habits literature on peer influence to include peers' measures of familiarity with the products. To our knowledge, no prior study has measured peer influence when consumers know both how much their peers are willing to pay for a food product and how frequently their peers have purchased the product. Thus, we investigate whether peers' level of familiarity with a product (frequency of consumption) increases their influence and how preference revisions vary across different types of food.

2. Methods

2.1. Statistical power analysis

This study was approved by the Institutional Review Board at the University of Delaware. The required sample size for this study was determined through a statistical power analysis conducted using pilot data from 52 participants. The pilot study was designed to be incentive compatible and conducted in the exact manner as the subsequent full experiment. The experiment used a combination of a within-subject design (one participant completed two rounds before and after treatment) and a between-subject design in which each participant was assigned to one of three treatments or a control. More details about the treatments are provided below.

Participants were assembled in groups of four, and the groups were randomized to either a treatment or the control (i.e. cluster-randomized). Thus, power was determined using a simulation for a cluster-randomized crossover study design (Reich et al., 2012). The regression defined by Eq. (1) below was used for the simulation; we hypothesized the minimum effect size using Cohen's F^2 that makes use of measures of variation in the outcome variable accounted for by explanatory variables in multivariate regression settings where multiple treatments are the multiple variables of interest. Cohen's F^2 implies the proportion of variations in outcomes explained by the treatments in multiple regression (treatments)². The `power.sim.normal()`³ code in the statistical program R was used to conduct the power analysis and to determine sample size.

Data collected in the pilot stage of the study were used to understand the extent to which the treatments in our study explained variation in the outcome variable (WTP). Based on regression analysis of the pilot data we assumed $R^2 = 0.45$. We assumed inter-cluster correlation (ICC) equal to 0.13, estimated from the pilot data using the "loneway" command in the statistical program Stata. At 5% level of significance (two-sided), 1,060 participants, or 265 groups with four members in each

cluster, was found to be required for a desired power of 0.80 of the study to be able to identify a statistically significant effect of at least one of the treatments. While a smaller effect size assumption would be more conservative, multiple restrictions from the design of our experiment – randomization by group with intra-and-between cluster variations, period effects, etc. – already necessitated a large sample (1,060) using statistics from the pilot data. Moreover, assuming a lower effect size would have necessitated an even larger sample size than 1,060. Conducting experiments among 1,060 adult consumers required large resources in a large number of field settings for data collection, and a more conservative effect size assumption would have demanded more resource-heavy settings.

2.2. Study participants

Purchase decisions, attitudes, and demographic information was collected from 1,068 adult participants during 56 field experiment sessions conducted between June and October 2019 in the Mid-Atlantic region of the United States. Participants were recruited through local media notifications (e.g. community flyers) and convenience sampling in person. The experiment was conducted at six locations: a local creamery, a state fair, a ferry terminal, a university campus laboratory, a lifelong learning institute, and a university-sponsored community event promoting coastal research. The variety of experiment locations allowed us to sample from a diverse population of adult consumers in public settings. These observations generated 2,136 WTP responses for each food product (1,068 pre-treatment and 1,068 post-treatment).

2.3. Experimental design and protocol

The diagram in Fig. 1 illustrates the experimental flow described in the following paragraphs. Initially, participants were assigned into groups of four members to mimic the average party size of a restaurant dining experience (Herring, 2005). Since groups were assigned at the start of the experimental session, some groups contained highly connected members while other groups were comprised of strangers. This diversity of natural peer connection amongst groups was intentionally designed to test the importance of peer information on consumer willingness to pay for food items. All four participants were seated at one table with mid-height privacy dividers to allow participants to privately respond to questions. Treatments (as described below) were randomly assigned by group, so different groups in the same room could have been assigned to different treatments or the control. The experiment setting was equipped with privacy dividers that sought to limit spillover effects. No discussion was permitted among participants during the experiment so that no information that was being verbally exchanged amongst or between the groups. Thus, the written descriptions of the treatments contained all of the information that was communicated amongst participants. Participants completed the experiment independently using

² Cohen's $F^2 = R^2 - R^2_{\text{null}}$ where R^2 is the measures of variation in outcome variables accounted for by explanatory variables. Independent variables in our case are the treatments in consideration.

³ See Reich et al., 2012 for more detail on the program, including R code.



Fig. 2. Display of food products used in the experiment: oysters (left), mushrooms (middle) and chocolate (right).

iPad tablets.⁴ Each participant was allowed as much time as needed to complete the process, and most groups finished within 30 min. Each participant was compensated \$10.

In the experiment, three food products were presented to participants in bundles: two shucked raw oysters, one pound of white button mushrooms, and three and a half ounces of milk chocolate fondue dessert with five pizzelle cookies for dipping (see Fig. 2). By comparing distinct food products, we aimed to investigate the role of peer influence for foods that are more or less likely to be consumed in group settings. Oysters were selected due to their recent emergence as a novel food product in local markets in the Mid-Atlantic of the U.S. (Kecinski et al., 2017) and the frequency by which they are associated with food ordered out of house at restaurants and bars (Meltzer, 2020). Raw white button mushrooms and chocolate fondue were selected as comparison products based on results of a focus group in which 40 participants were asked to identify foods they typically consume in a social group setting versus not. Based on the results of the focus group and the local availability of products⁵, we categorized raw mushrooms as a food that is not likely to be consumed in a group setting and chocolate fondue as a food that is highly likely to be consumed in a group setting.

During the experiment, participants were asked how often they consumed each food product and to indicate the amount of money they were willing to pay for each bundle.⁶ Participants could offer any amount between \$0 and \$10⁷. WTP from each participant was elicited twice during the experiment: *before* and *after* observing a peer influence treatment. The order of food products presented was held constant within a four-person group and randomized across groups to avoid potential order effects.

Figure A-1 in Appendix A shows a sample screenshot of where participants indicated their WTP and frequency of consumption for the respective food product. WTP for the three food products was measured using a Becker Degroot Marschak (BDM) mechanism to ensure incentive compatibility of the experiment (Becker et al., 1964). A key advantage of the BDM mechanism is that it is theoretically incentive compatible as the optimal strategy is for each participant to provide a point estimate of their highest amount that they would be willing to pay for a product.

Participants were informed that one of the purchasing decisions would be selected by random at the end of the experiment to determine

Table 1
Peer influence treatment descriptions.

		Peer's Baseline Willingness To Pay	
		No	Yes
Peer's Frequency of Consumption	No	Control	Treatment 1
	Yes	Treatment 2	Treatment 3

Notes: In all four conditions, participants were shown their own baseline WTP.

whether they purchased the item and the amount of cash they would take home. As is standard with the BDM mechanism, participants who submit a bid that is greater than or equal to the randomly selected price purchase the selected product, pay the price, and take home the money that remains from their initial balance. If a participant submitted a bid lower than the random price, then they did not purchase the selected product, did not pay the price, and just received their entire initial balance. The products were only made available to participants at the end of the study (i.e. participants were not asked to taste the products). The participant could choose whether they wanted the food item packaged “to go” or ready for consumption on-site (e.g. shucked or unshucked oysters).

2.4. Randomly assigned treatments

At the start of each session, participants were randomly assigned to one of three peer influence treatments or a control group shown in Table 1. The three peer influence treatments displayed the participant the responses reported by their peers in the first step of the experiment:

- (1) peers' reported WTP for each food product (*PeerWTP*),
- (2) peers' reported frequency of consumption for each food product (*PeerFreq*), and
- (3) peers' reported WTP and reported frequency of consumption for each product (*PeerWTP&Freq*).

The treatments were presented to participants in a table reporting the respective information (e.g. WTP and/or frequency of consumption) reported by each peer in the group. Fig. 3 shows a screenshot example of an individual assigned to treatment (3): peers' reported WTP and reported frequency of consumption for each product. On the same screen, along with the table of information, participants were prompted to enter their WTP for the food item for a second time thus, eliciting potential revisions in WTP. Participants in the control group received no information about their peers; nevertheless, WTP was elicited twice to control for potential order effects of bidding twice on the same products. All participants were reminded of their pre-treatment WTP to minimize variation in post-treatment WTP due to uncertainty about prior revealed

⁴ The experiment was programmed using SoPHIE, an online experimental platform. Full experiment instructions can be found in [supplemental Appendix A](#).

⁵ It was important that the products be available from local vendors since the experiment was non-hypothetical (i.e. products needed to be readily available) and the funding source for this project (NSF's EPSCoR program) has a strong interest in supporting research that could support the local economy.

⁶ Each product bundle had a market value of approximately \$5, though this was not told to the participants.

⁷ The upper bound of \$10 was determined based on the market value of the product bundle and the project budget for participant compensation.

Recall: You are Person B.

	Person A	Person B	Person C	Person D
Willingness to Pay	\$2.00	\$8.00	\$4.50	\$3.50
Frequency of Consumption	Almost never	Once every 6 months	Once every 6 months	Almost never

Please indicate below your current willingness to pay for 2 locally produced oysters:

\$

Fig. 3. Screenshot of peer information for an individual assigned to the peer WTP and reported frequency of consumption treatment.

WTP.⁸

We hypothesize that an individual will revise WTP based on information about peers' WTP (treatment 1) for oysters and chocolate fondue – foods that are more likely to be consumed in a social setting. We expect this to also hold true when the information about peers' WTP is combined with information about how frequently they consume the food item (treatment 3). Treatment 2 is included in the experiment to achieve a full factorial design, and we hypothesize there will be no revision of WTP when an individual is only presented with information about peers' frequency of consumption for a food item.

2.5. Data analysis

Peer influence on WTP were examined for each food and between foods products. The difference between post-treatment and pre-treatment WTP values were used as the dependent variable in all OLS estimations, which controls for variation across pre-treatment values to identify treatment effects on WTP.

Three OLS models were estimated to determine treatment effects for each food product, and the models can be specified by:

$$\Delta WTP_{if} = \alpha_{0f} + \beta_{1f}PeerWTP_i + \beta_{2f}PeerFreq_i + \beta_{3f}PeerWTP\&Freq_i + \beta_{4f}PreWTP_{if} + \beta_{5f}NoWTP_{if} + Consumption_{if}\beta_{6f} + X'_{if}\beta_{7f} + \varepsilon_f \quad (1)$$

where ΔWTP_{if} is the difference between post-treatment and pre-treatment WTP values for food participant i and product f . $PeerWTP_i$, $PeerFreq_i$, and $PeerWTP\&Freq_i$ are indicator variables equal to 1 if participant i was assigned to a treatment that received information about peer responses. $PreWTP_{if}$ is the pre-treatment WTP and $NoWTP_{if}$ is an indicator variable equal to 1 if a participant provided a WTP value of \$0 pre- and post-treatment for product f . $Consumption_{if}$ are factor variables for the stated consumption frequency of product f (daily to almost never), sociodemographic variables were controlled for by X'_i (gender, age, income, race, education, and political affiliation), and ε_f is an error term. The average change in WTP for the control group is estimated by α_{0f} and the average treatment effects are estimated by β_{1f} , β_{2f} , and β_{3f} .

To examine heterogeneity in treatment effects between the food products, the data were stacked so that there were two observations per

participant (e.g., one observation for oysters and one observation for mushrooms). Stacking the data allowed us to include interaction effects in a model similar to equation (1). Three interaction models were estimated to compare the three foods (i.e., oysters vs mushrooms, oysters vs chocolate, and chocolate vs mushrooms), and the models can be specified by:

$$\begin{aligned} \Delta WTP_{ijk} = & \alpha_{0fk} + \beta_{1fk}PeerWTP_i + \beta_{2fk}PeerFreq_i + \beta_{3fk}PeerWTP\&Freq_i \\ & + \beta_{4fk}F_f + \beta_{5fk}PeerWTP_iF_f + \beta_{6fk}PeerFreq_iF_f + \beta_{7fk}PeerWTP\&Freq_iF_f \\ & + \beta_{8fk}PreWTP_{ijk} + \beta_{9fk}NoWTP_{ijk} + Consumption_{ijk}\beta_{10fk} + X'_{ijk}\beta_{11fk} + \varepsilon_{fk} \end{aligned} \quad (2)$$

where ΔWTP_{ijk} is the difference between post-treatment and pre-treatment WTP values for food f or k for participant i , and F is an indicator value equal to 1 for food f . The coefficients α_{0fk} and β_{4fk} estimate the average WTP change in the control group for food k and f , respectively. Coefficient estimates for the interaction effects, β_{5fk} , β_{6fk} , and β_{7fk} , determine whether there were heterogeneous treatment effects across food products f and k .

Equations (1) and (2) were estimated using ordinary least squares (OLS) regression with clustered standard errors by group because treatments were randomly assigned by participant group. Sensitivity analyses are performed on equation (1) to evaluate whether results differ when non-consumers of the products are excluded from the analysis or when group average WTP is substituted for individual WTP. As an additional sensitivity analysis, we estimate an analysis of covariance (ANCOVA) specification where the dependent variable is equal to post-treatment WTP following McKenzie (2012).

3. Results

3.1. Descriptive statistics

Table 2 presents a summary of participants' demographic and socioeconomic characteristics. The average participant was approximately 43 years old. Approximately 76% of the participants were white, comparable with 74 percent of the average white population in the resident states for most of our participants (US Census Bureau, 2021). Our sample was slightly more representative of females, 60%, compared to 50% females in the population (US Census Bureau, 2021). The average household income of our participants was \$73,630, slightly higher than the median household income of \$64,994 in the resident states of our participants (US Census Bureau, 2021). Approximately 32% had obtained a bachelor's degree and 20% had obtained a Master's degree; this is slightly more educated sample than the population where 32% hold a Bachelor's degree or higher (US Census Bureau, 2021). Liberal,

⁸ Reference prices are often uncertain at the time of purchase (Caputo et al., 2020) and repetition in auction experiments can lead to affiliation or loss of a subject's initially formulated value, especially when a participant is not familiar with the product (Bernard, 2006). Therefore, our results should be interpreted as lower bounds for the amount of change that might be expected from this type of information.

Table 2
Summary of demographic and socioeconomic statistics.

Variable	Measure	Mean	Std. Dev.
Age	Years	43.73	17.518
Gender	% Male	39.79	0.490
	% Other Sex	0.66	0.081
Household Income	\$1,000	73.63	54.099
Race	% Asian	9.64	0.295
	% Black	5.34	0.225
	% Latino	3.84	0.192
	% Other Race	1.12	0.105
	% White	76.31	0.425
	% Less than High School	0.66	0.081
Education	% High School Diploma	11.05	0.314
	% Some College	17.60	0.381
	% Associate's	8.90	0.285
	% Bachelor's	31.74	0.466
	% Master's	19.94	0.400
	% Professional/Doctorate Degree	6.65	0.249
Political Affiliation	% Conservative	23.31	0.423
	% Moderate	21.25	0.409
	% Liberal	20.41	0.403
	% No Affiliation	31.74	0.466

moderate, and conservative political affiliations among participants were relatively evenly distributed (from 20% to 23%) and nearly one third (32%) reported having no political affiliation.

Table 3 presents pre-treatment and post-treatment WTP means, medians and size of the peer influence treatment sample for each food product. In every case, the average post-treatment WTP was less than the average pre-treatment WTP. We used T-tests to analyze statistical variation in mean WTP between treatment groups and for treatment groups versus the control group. We found, on average, that treated participants were willing to pay statistically significantly less for oysters after the peer influence treatment than participants in the control group whereas

Table 3
Mean and median pre- and post-treatment willingness to pay for oysters, mushrooms and chocolate for the whole sample.

Food Product by Treatment	Pre-Info Treatment		Post-Info Treatment		
	Mean	Median	Mean	Median	n
Oysters					
Control	\$3.31 (2.78)	\$3.00	\$3.05 (2.70)	\$2.50	244
Peer WTP	\$3.08 (2.61)	\$3.00	\$2.61 (2.32)	\$2.00	272
Peer Frequency	\$3.07 (2.76)	\$2.50	\$2.59 (2.62)	\$2.00	284
Peer WTP & Frequency	\$3.60 (3.03)	\$3.00	\$3.00 (2.73)	\$2.00	268
Mushrooms					
Control	\$3.38 (2.43)	\$3.00	\$3.17 (2.39)	\$3.00	244
Peer WTP	\$3.43 (2.04)	\$3.00	\$3.10 (1.84)	\$3.00	272
Peer Frequency	\$3.42 (2.24)	\$3.00	\$3.19 (2.28)	\$3.00	284
Peer WTP & Frequency	\$3.37 (2.20)	\$3.00	\$2.95 (1.89)	\$3.00	268
Chocolate					
Control	\$3.75 (2.28)	\$3.50	\$3.50 (2.17)	\$3.50	244
Peer WTP	\$3.56 (2.10)	\$3.50	\$3.27 (1.87)	\$3.00	272
Peer Frequency	\$3.64 (2.27)	\$3.00	\$3.30 (2.31)	\$3.00	284
Peer WTP & Frequency	\$3.88 (2.18)	\$4.00	\$3.44 (1.92)	\$3.00	268

Note: Standard errors in parentheses.

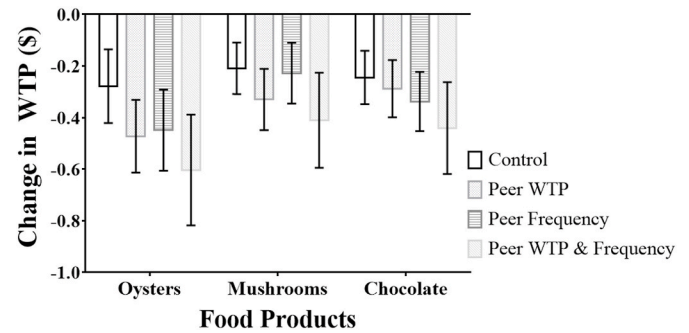


Fig. 4. Change in Willingness-To-Pay Between Pre-Treatment and Post-Treatment Note: The error bars represent upper and lower limits of a 95% confidence interval.

there was no statistically significant pre-treatment or post-treatment WTP compared to the control for mushrooms or chocolate. The T-test results are provided in Table B1 of Appendix B.

Fig. 4 and Table B1 in Appendix B show the mean change in WTP across each peer influence treatment along with standard error bars. In all cases, average WTP decreased post-treatment. The largest change in WTP was associated with the combined peer WTP and frequency peer influence treatment (*Peer WTP & Frequency*). In addition, change in WTP for oysters was statistically significantly different than that of the control group for the combined peer WTP and frequency peer influence treatment (*Peer WTP & Frequency*). There was no statistically significant decrease in WTP for mushrooms or chocolate among the peer WTP treatment (*Peer WTP*) or the peer frequency treatment (*Peer Frequency*).

3.2. Treatment effects on each food item

Table 4 reports the effects of the peer influence treatments for each food item estimated by equation (1)⁹. The coefficients measure the effect of each peer influence treatment for each food product relative to the pre-treatment WTP in the control group. For oysters, we found that mean post-treatment WTP treatment decreased \$0.26 on average (8% change from the mean control pre-treatment WTP) when participants were informed of their peers' WTP. When participants could view both peers' WTP and frequency of consumption for the food item (*Peer WTP & Frequency*) mean WTP for oysters decreased by \$0.27, on average (8% change from the mean control pre-treatment WTP).

For mushrooms, the results in Table 4 show modest evidence that mean post-treatment WTP decreased \$0.16 on average (5% change from the mean control pre-treatment WTP) when participants were informed of their peers' WTP (*Peer WTP*). In the *Peer WTP & Frequency* treatment, mean post-treatment WTP for mushrooms decreased by \$0.25 on average (7% change from the mean control pre-treatment WTP). Model 3 in Table 4 shows an absence of peer effects on WTP for chocolate when participants were informed of their peers' WTP (*Peer WTP*). However, there is modest evidence that mean post-treatment WTP for chocolate decreased by \$0.19 on average (5% change from the mean control pre-treatment WTP).

OLS results were robust to the exclusion of non-consumers of the products as well as the inclusion of a group average WTP instead of individual WTP (Table B3 and Table B4 in Appendix B). Estimating an analysis of covariance produces the same estimates (Table B5).

3.3. Heterogeneous treatment effects by food item

To understand how peer effects differ for foods that are more likely to

⁹ Tobit regressions produced the same estimates in a robustness check. See Table B2 in the appendix.

Table 4

OLS regression for change in willingness to pay for oysters, mushrooms and chocolate.

VARIABLES	Change in WTP		
	(1)	(2)	(3)
	Oysters	Mushrooms	Chocolate
Peer WTP	−0.263*** (0.094)	−0.163* (0.083)	−0.083 (0.076)
Peer Frequency	−0.220* (0.113)	−0.027 (0.087)	−0.105 (0.072)
Peer WTP & Frequency	−0.265** (0.129)	−0.255** (0.100)	−0.189* (0.106)
Consume Daily	0.700*** (0.163)	0.475*** (0.157)	0.014 (0.312)
Consume Weekly	0.570 (0.347)	0.437*** (0.127)	0.393* (0.213)
Consume Monthly	0.428*** (0.156)	0.505*** (0.124)	0.388** (0.165)
Consume in Last 6 Months	0.575*** (0.133)	0.263* (0.144)	0.260* (0.133)
Consume in Last Year	0.605*** (0.161)	0.587 (0.370)	0.285** (0.129)
Almost Never Consume	0.265** (0.113)	0.276** (0.118)	0.146 (0.105)
Pre-treatment WTP	−0.229*** (0.030)	−0.212*** (0.029)	−0.205*** (0.027)
Non-Consumers	−0.101 (0.088)	−0.227** (0.096)	−0.372*** (0.090)
Constant	6.943 (5.038)	4.197 (4.917)	8.307* (4.241)
Covariates	Yes	Yes	Yes
Observations	1,068	1,068	1,068
R-squared	0.216	0.186	0.169

Robust standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. Covariates included in analysis were age, gender, household income, race, education, and political affiliation.

be consumed in a group setting versus not we analyzed the interaction model in equation (2). Table 5 presents the effects of the peer influence treatments on changes in WTP for a comparison of two food products. Each model evaluates participant bids for two of the three food items: oysters vs. mushrooms, oysters vs. chocolate, and chocolate vs. mushrooms such that $N = 2,136$. The results for the *Peer WTP* for oysters versus the chocolate were similar; the *Peer WTP* treatment resulted in participants significantly reducing their average WTP for oysters by \$0.15 relative to chocolate. We found no statistically significant difference in changes in WTP for mushrooms when compared to oyster or chocolate. Thus, the results suggest peer effects do not vary by type of food item. The presence of an oyster non-consumer in the group did not statistically significantly impact the change in WTP (Table 5, models 1 and 2). However, when we accounted for the presence of non-consumers of chocolate in the group, the change in WTP was \$0.22 lower for chocolate than for mushrooms (Table 5, model 3).

4. Discussion

To understand how feedback from other consumers (aka. peer influence) affects consumer willingness to pay and eating habits for different food items, we designed and implemented a framed field experiment in which 1,068 adult participants were recruited from the public in the Mid-Atlantic of the United States. Participants were randomly assigned to treatments that presented information about their peers' (1) WTP for each food product, (2) frequency of consumption for each food product, and (3) WTP and frequency of consumption for each food product. Post-treatment WTP from groups that received treatment were compared to the post-treatment WTP of the control groups in which participants were not presented with information about their peers' preferences for the food products. The results suggest that

Table 5

Interaction Model Regression Results for Change in Willingness To Pay for Oysters v. Mushrooms, Oysters v. Chocolate, and Chocolate v. Mushrooms.

Variables	(1)	(2)	(3)
	Oysters vs. Mushrooms	Oysters vs. Chocolate	Chocolate vs. Mushrooms
Peer WTP	−0.183** (0.085)	−0.093 (0.081)	−0.164** (0.077)
Peer Frequency	−0.060 (0.091)	−0.125 (0.077)	−0.037 (0.088)
Peer WTP & Frequency	−0.166 (0.103)	−0.159 (0.106)	−0.209** (0.101)
Oyster	−0.069 (0.063)	−0.034 (0.061)	
Oyster X Peer WTP	−0.073 (0.089)	−0.151* (0.089)	
Oyster X Peer Frequency	−0.152 (0.101)	−0.078 (0.103)	
Oyster X Peer WTP & Frequency	−0.124 (0.106)	−0.129 (0.113)	
Oyster Pre-Treatment WTP	−0.154*** (0.023)	−0.155*** (0.021)	
Oyster Non-Consumer	−0.016 (0.072)	−0.117* (0.069)	
Chocolate			−0.035 (0.068)
Chocolate X Peer WTP			0.077 (0.094)
Chocolate X Peer Frequency			−0.075 (0.097)
Chocolate X Peer WTP & Frequency			0.005 (0.105)
Chocolate Pre-Treatment WTP			−0.153*** (0.024)
Chocolate Non-Consumer			−0.216*** (0.083)
Consume Daily	0.634*** (0.145)	0.611*** (0.125)	−0.207 (0.233)
Consume Weekly	0.545** (0.275)	0.291 (0.258)	0.142 (0.173)
Consume Monthly	0.288** (0.119)	0.150 (0.124)	0.327** (0.137)
Consume in Last 6 Months	0.401*** (0.105)	0.346*** (0.097)	0.182 (0.112)
Consume in Last Year	0.438*** (0.127)	0.468*** (0.099)	0.177 (0.111)
Almost Never Consume	0.161* (0.089)	0.208*** (0.079)	0.071 (0.095)
Constant	6.549 (4.473)	6.089* (3.684)	7.946** (3.880)
Covariates	Yes	Yes	Yes
Sample Size	2,136	2,136	2,136

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Covariates included age, gender, household income, race, education, and political affiliation. All models were estimated with 2,136 observations.

consumers did change their behavior in response to feedback about their peers' preferences.

Since a significant amount of food is consumed away from home, feedback from other consumers has the potential to influence food choices and eating habits. Previous studies on the effect of peer influence have produced mixed results in terms of the presence of an effect as well as the direction and magnitude of effects found (Godes & Mayzlin, 2004, 2009; House et al., 2008; Iyengar et al., 2011; Narayan et al., 2011; Richards et al., 2014). Most of this research was conducted with small samples or with hypothetical surveys and often with student participants. Larger sample observational studies on restaurant dining found evidence of peer effects on dining behavior and food choice, however the existing literature does not measure consumer WTP.

Our study using experimental data expands on the existing peer influence studies that used observational data to investigate peer influence and food preferences. Ariely and Levav (2000) studied 2,202 diners and

found that participants exhibited variety-seeking behavior when ordering food and beverages at restaurants with their peers. Yet a similar study by [Ellison \(2014\)](#), using a sample of 1,459 restaurant patrons, found individual utility increased when members of a dining party ordered products in a similar meal category, suggesting that those consumers valued individualism only to a small degree and instead perceived confirmation of their preferences when fellow members of their dining party ordered similar products. Our experiment compares consumer willingness to pay for foods likely to be consumed in a social setting versus not as previous research has shown social eating contexts can influence food choice ([Samson & Buijzen, 2021](#)). Our findings show no difference in peer influence across different food items and a general negative revision in willingness to pay when consumers are exposed to information about peers' willingness to pay.

Our finding that consumers negatively revise their preferences in response to peers adds important information to the literature. Previous experimental studies have found a positive increase in WTP for electronic book readers ([Narayan et al., 2011](#)), negative changes in WTP for fitness trackers ([Fang et al., 2019](#)) negligible changes in WTP for varieties of ice cream ([Richards et al., 2014](#)), and inconsistent influence across different food products when the setting and level of convenience varied ([House et al., 2008](#)). Notably these experimental studies relied on small sample sizes of college students; [Narayan et al. \(2011\)](#) analyzed behavior among 70 college students, [Fang et al. \(2019\)](#) experimented with 63 students, [Richards et al. \(2014\)](#) recruited samples of 34 and 73 students, and [House et al. \(2008\)](#) involved 22 students. Our study recruits 1,068 adult consumers.

Results within this study revealed that individuals tend to converge to the lowest WTP when they have information about other consumers' WTP, which may reflect a tendency among consumers to seek out the "better deal" for these food items or a tendency for negative reviews to be more influential than positive reviews ([Tiware & Richards, 2015](#)). Finding from previous studies have been mixed. Our results align with findings from [Richards et al. \(2014\)](#) that suggests social networks have more influence on subjective attributes of food such as taste rather than objective attributes such as price. Other studies where peer influence negatively impacted WTP include experiments on fitness trackers ([Fang et al. 2015](#)) and buns made from cricket flour ([Alemu & Olsen, 2020](#)). On the contrary, [Narayan et al. \(2011\)](#) found peer influence led to a positive increase in WTP; although, they examined WTP among electronic book readers. More closely related to food, a study of Norwegian wine consumers found that consumers prefer peer-recommended wines ([Thrane, 2019](#)). In a restaurant dining experiment [Tiware and Richards \(2015\)](#) found peer reviews to be three times more influential than anonymous reviews in determining consumer preference. Heterogeneity in peer effects on WTP across studies may indicate that the role of peer influence is dependent on context.

When comparing oysters versus chocolate, we find modest evidence of smaller negative changes in WTP for oysters (\$0.15) than for chocolate when participants were informed about peer WTP. However, there were no other observed treatment effects when comparing food items. Understanding how peer effects vary by food item is important as previous work has shown factors such as the purchase setting or convenience influence the choice of food products ([House et al., 2008](#)), and food decisions vary when the environment is framed in the context of a social setting ([Samson & Buijzen, 2021](#)). We find no evidence that peer influence differs by type of food item; however, this study was limited by the number of food items that could be presented in the field experimental context.

The foods included in this study could be considered superior goods and may not be reflective of staple foods or the typical food consumed in a restaurant. A meta-analysis exploring the literature of price and income elasticities concluded that demand for staple foods is less responsive to changes in prices and income compared to superior foods ([Femenia, 2019](#)). Thus, heterogeneity in results across foods may be driven by the types of food and by peer influence. Given findings from

the elasticity literature showing that consumers are more responsive to changes in price and income for superior foods, consumers in general may also be more responsive to peer effects for superior foods.

5. Conclusions

The findings from this study have important implications for current food markets where word-of-mouth marketing and on-line feedback from other consumers as recommendations can reduce uncertainty ([Godes & Mayzlin, 2004](#)). As with many products, food choice and eating habits are affected by engagement with food brands and online purchasing ([Baldwin et al., 2018](#)). Social media has increased the size of networks and amplified the impact of messages from other consumers. Recommendations from peers in a social network are often perceived as more "truthful" reviews than advertising claims or reviewers from anonymous or unknown people; and therefore, these peer recommendations seem more credible to consumers ([Reingen & Brown, 1987](#); [Tiware & Richards, 2015](#)). Eating habits and food choice will take on new trends as consumers continue to engage with food brands and marketing online and in social media platforms.

Similar to the conclusions about decreased consumptions arising from negative social modeling ([Greenhalgh et al., 2009](#)), our results indicate that peer influence about the demand for a good and how frequently it is consumed can lead to a decreased willingness to pay. Further, this finding held regardless of whether the food item is one that is more likely to be consumed in a social setting. Negative peer effects would be especially detrimental to profit margins for food retailers as peer preferences can create a follow-the-bandwagon effect, where individuals seek social acceptance by making similar purchasing decisions as their network ([Yang & Allenby, 2003](#)). Thus, food retailers and food service providers may need to employ positive marketing messages to offset negative feedback from other consumers.

This study contributes to the literature comparing food items that are more or less likely to be consumed in a social setting. However, we were limited in the number of food items we could evaluate. Further research could explore preferences for a menu or bundle of food items commonly consumed in a restaurant setting.

Ethical statement

This research was approved by the Institutional Review Board at the University of Delaware. This manuscript is not in review at any other journal. Data and replicable code are available upon request.

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Declaration of competing interest

To our knowledge, no conflicts of interest exist with any of the co-authors of this manuscript.

Data availability

Data will be made available on request.

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Appendix A. Experimental Protocol

A.1. Experiment Instructions to Participants

Welcome to the University of Delaware. Thank you for agreeing to participate in this research study about social networks and food choice.

Today you will be given \$10 to participate in this research study, and you will also have a chance to purchase one of several food items. You can think of this \$10 as funds in a bank account which you will use to purchase the food item.

Here's how it works. During the study, we will present you with three different food items. For each food item, you name your price – you tell us the maximum amount of money you would be willing to pay for it.

At the end of the study, we will pick one of the food items at random. For that food item, a sales price will be randomly generated. That sales price is the amount it will cost you to buy that food item.

If the maximum amount you stated that you would be willing to pay is **greater than or equal** to the sales price, you **will** pay the sales price to purchase the food item using funds from your \$10 bank account. You will receive the food item. Any remaining funds in your bank account will be paid out to you dollar-for-dollar in U.S. cash. If the maximum amount you stated that you would be willing to pay is **less than** the sales price, you will **not** purchase the food item and instead we will pay you the full \$10 remaining in your bank account, dollar-for-dollar in U.S. cash. In this case, you will not receive the food item.

You cannot influence the sales price. The computer chooses it at random. It could be high or it could be low. So, for each food item, your best strategy is to simply state the maximum amount of money you are willing to pay for it.

Let's look at an example.

Alex is participating in a special edition of this study and is given \$40 for participating. Only one product is offered: a fruit basket. Alex likes the fruit basket and would be willing to pay up to \$25 for it. So, when asked what he would be willing to pay for the fruit basket, Alex chooses \$25. Then the computer generates a random sales price for the fruit basket between \$0 and \$40. Let's say it turns out to be \$22. The maximum of \$25 that Alex said he would be willing to pay for the fruit basket was **greater than** the randomly drawn sales price of \$22, so Alex pays the sales price from his \$40 bank account to purchase the fruit basket. Alex will go home with the fruit basket and what is left of his \$40 bank account after buying the fruit basket, in this case \$18.

The equation below shows how Alex calculated how much money he will go home with. His original bank account was worth \$40. He bought the fruit basket at the sales price of \$22, that leaves \$18 for Alex to take home.

$$\$40 - \$22 = \$18$$

But let's suppose that instead of stating a \$25 willingness-to-pay, Alex thought he could do better by saying that he would only be willing to pay \$15. Alex thinks by doing this he can get a better deal on the fruit basket, but Alex is wrong. Let me explain why.

The computer randomly generates \$22 as the fruit basket's price. If Alex said he would only be willing to pay \$15, then his maximum willingness-to-pay would now be **lower than** the sales price and Alex would not purchase the fruit basket. Since Alex actually valued the fruit basket more than \$15, he is technically worse off than if he just stated his true willingness-to-pay of \$25 because he missed out on the opportunity to purchase the fruit basket.

The point here is that, when asked his value for the fruit basket, Alex should choose the maximum value that he is willing to pay for the fruit basket. Alex gains nothing by stating a different value because his choice does not affect the sales price. Alex's choice only affects whether he purchases the product or not.

Let's consider Alex's case again but imagine that the random sales price generated by the computer was \$30, rather than \$22. If Alex had stated his true willingness-to-pay of \$25 for the fruit basket, his willingness-to-pay would be **less than** the \$30 sales price. Alex **would not** purchase the fruit basket and would simply be paid his entire \$40 bank account.

Now suppose that instead of stating his true willingness-to-pay of \$25, Alex thought he could make it more likely that he would go home with the fruit basket by choosing a much higher value, like \$35. In this case, Alex's willingness-to-pay of \$35 would be **more than** the sales price of \$30, so Alex **would** purchase the fruit basket and pay \$30 from his original \$40 bank account. The problem is that Alex did not actually value the fruit basket that much, so Alex again ends up worse off than if he had just reported his true willingness-to-pay of \$25.

Here is the point of Alex's example: You cannot do any better by claiming to be willing to pay more or less than what you are truly willing to pay. Answer honestly to get your best deal.

As you go through the study, every group member will make an individual decision about the maximum amount he or she is willing to pay for a food item. All group members have equal opportunity to purchase the food item. For example, if all four members of the group are willing to pay more than the randomly drawn sales price, then all four members will purchase the food item.

We will begin the study momentarily, but first we would like to explain the participant letter and diagram on your desk. You should see a participant ticket on the desk in front of you that looks similar to the one shown. The ticket says **Person A, B, C or D**. That is your assigned participant letter for this study. At this time, please take a quick moment to look at your ticket and verify your participant letter.

You have been seated in a group of four. The three other participants that you are sitting with are your group members. It is very important that you know the participant letter for each of your group members. The diagram on your desk shows the seating arrangement and participant letters for your group members. You can refer to that diagram throughout the study. To help you identify your group members, we are going to go through a quick exercise to ensure that you know your other three group member's participant letters. We will call out each letter A through D, one by one. When **your** participant letter is called, please stand and quietly acknowledge your other 3 group members.

The figure shows two screenshots of a survey interface. The top screenshot is a text box asking participants to indicate the maximum amount they would be willing to pay for 2 locally produced oysters, with a dropdown menu for dollar amounts from \$0.00 to \$10.00. The bottom screenshot is a question about oyster consumption frequency with a list of options: Daily, Weekly, Monthly, Once every 6 months, Once per year, Almost never, and Never. The 'Daily' option is selected with a checkmark.

Fig. A1. Sample Screenshots Asking Participants to Indicate their WTP and Frequency of Consumption for Each of the Three Food Products

Appendix B. Supplemental Analyses

B.1. Differences in Means

Analyzing the *t*-test results for pre-treatment WTP values from Table B1, there were no statistically significant changes in WTP between control and any of the three peer influence treatments for oysters, mushrooms, or chocolate. When analyzing *t*-test results between peer influence treatments, for oysters, participants who were assigned to receive the combined information about their peers' pre-treatment WTP and frequency of consumption had a statistically significant higher difference in mean WTP by \$0.49, on average, compared to participants who were assigned to receive information about their peers' pre-treatment WTP (p -value < 0.05). Similarly, participants who were assigned to receive the combined information about their peers' pre-treatment WTP and frequency of consumption had a statistically significant higher difference in mean WTP for oysters by \$0.58, on average, compared to participants who were assigned to receive information about their peers' frequency of consumption (p -value < 0.05). There were no statistically significant *t*-test results between peer influence treatments for mushrooms or chocolate.

When analyzing the *t*-test results for post-treatment WTP values from Table B1 for oysters, participants who received information about their peers' pre-treatment WTP had a statistically significant lower difference in mean WTP by \$0.45, on average, compared to participants who were assigned to receive the control (p -value < 0.05). Similarly, participants who received information about their peers' frequency of consumption had a statistically significant lower difference in mean WTP for oysters by \$0.50, on average, compared to participants who were assigned to receive the control (p -value < 0.05). Analyzing the *t*-test results for post-treatment WTP values among mushrooms and chocolate, there were no statistically significant differences in WTP between control or any of the three peer influence treatments.

Analyzing the change in WTP from Table B1 for oysters, participants who were assigned to receive the combined information about their peers' pre-treatment WTP and frequency of consumption had a statistically significant lower change in mean WTP for oysters by \$0.33, on average, compared to participants who were assigned to receive the control (p -value < 0.05).

When analyzing the *t*-test results for change in WTP between pre- and post-treatment WTP for mushrooms, participants that were assigned to receive the combined information about their peers' pre-treatment WTP and frequency of consumption had a statistically significant lower change in mean WTP by \$0.20, on average, compared to participants who were assigned to receive the control (p -value < 0.01). When evaluating *t*-test results for change in WTP for chocolate, participants who were assigned to receive the combined information about their peers' pre-treatment WTP and frequency of consumption had a statistically significant lower change in WTP by \$0.20, on average, compared to participants who were assigned to receive the control (p -value < 0.01).

B.2. Sensitivity Analysis

Additional sensitivity analyses were performed to check whether the results differed between potential consumers and non-consumers of the products. Observations of "non-consumers" were dropped if the participants reported a WTP value of "\$0.00" both pre-treatment and post-treatment. In this way, observations of individuals who would not have participated in the market for that particular food product would be dropped and we then test if the results are sensitive to the inclusion of these participants. Results in Table B3 reveal that the analysis is not sensitive to the inclusion of non-consumers. The estimated coefficients are similar to those found in Table 4. The number of participants dropped for each food product was fewer than 200, so we assume that this would not have an outstanding weight effect on average change in WTP when there are over 1,000 sample participants. This indicates that participants who had an initial preference to not purchase the food product unrelated to the information supplied by their peers, overall did not statistically significant impact the results.

Another sensitivity analysis was performed to evaluate whether the results from equation (1) differed by controlling for group average pre-treatment WTP rather than by individual participant pre-treatment WTP. Table B4 shows the results of the sensitivity analysis, which estimates the same Ordinary Least Squares (OLS) regression from equation (1) with an indicator variable *AboveGroupAvgWTP* instead of *PreWTP_{if}*, which equals 1 when the participant indicated a pre-treatment WTP above the average group pre-treatment WTP. Results in Table B4 reveal that the analysis is not sensitive to the inclusion of the group average WTP rather than the individual's pre-treatment WTP. The estimated coefficients are similar to those found in Table 4, which indicate that participants likely took into account their WTP relative to the average of their group members when submitting their post-treatment WTP for each of the three food products.

As a final sensitivity analysis, we estimate an analysis of covariance (ANCOVA) model following McKenzie (2012) where the dependent variable in

equation (1) changes to post-treatment WTP rather than the difference in pre- and post-treatment. The results in Table B5 are equivalent to the results from our original model specification in Table 4.

Table B1
Difference in Means T-Test Results Between Peer Influence Treatments for Oysters, Mushrooms and Chocolate

	(1)Oysters			(2)Mushrooms			(3)Chocolate		
	Pre-Treatment	Post-Treatment	Change	Pre-Treatment	Post-Treatment	Change	Pre-Treatment	Post-Treatment	Change
Control v. Peer WTP	−0.251 (0.293)	−0.445** (0.044)	−0.194* (0.058)	0.056 (0.776)	−0.065 (0.729)	−0.121 (0.131)	−0.186 (0.336)	−0.229 (0.197)	−0.044 (0.575)
Control v. Peer Frequency	−0.332 (0.165)	−0.503** (0.029)	−0.171 (0.118)	0.041 (0.842)	0.022 (0.915)	−0.019 (0.815)	−0.109 (0.583)	−0.202 (0.302)	−0.093 (0.243)
Control v. Peer WTP & Frequency	0.242 (0.350)	−0.083 (0.728)	−0.325** (0.015)	−0.010 (0.962)	−0.211 (0.265)	−0.202* (0.066)	0.138 (0.486)	−0.059 (0.745)	−0.196* (0.068)
Peer WTP v. Peer Frequency	−0.082 (0.717)	−0.059 (0.779)	0.023 (0.831)	−0.016 (0.932)	0.087 (0.623)	0.102 (0.230)	0.077 (0.680)	0.027 (0.879)	−0.050 (0.542)
Peer WTP v. Peer WTP & Frequency	0.493** (0.044)	0.362* (0.097)	−0.131 (0.313)	−0.066 (0.719)	−0.147 (0.361)	−0.081 (0.467)	0.323* (0.079)	0.171 (0.297)	−0.153 (0.151)
Peer Frequency v. Peer WTP & Frequency	0.575** (0.019)	0.420* (0.064)	−0.154 (0.250)	−0.050 (0.791)	−0.233 (0.192)	−0.183* (0.097)	0.247 (0.194)	0.143 (0.429)	−0.103 (0.332)

***p < 0.01, **p < 0.05, and * p < 0.1.

Table B2
Tobit Regression for Change in Willingness to Pay with Exclusion of Non-Consumers for Oysters, Mushrooms and Chocolate

VARIABLES	Change in WTP		
	(1)Oysters	(2)Mushrooms	(3)Chocolate
Peer WTP	−0.264** (0.110)	−0.158* (0.0905)	−0.0828 (0.0889)
Peer Frequency	−0.219** (0.109)	−0.0226 (0.0896)	−0.104 (0.0885)
Peer WTP & Frequency	−0.264** (0.111)	−0.243*** (0.0909)	−0.187** (0.0895)
Consume Daily	0.722 (1.242)	0.524** (0.260)	0.0845 (0.456)
Consume Weekly	0.594 (0.423)	0.477*** (0.104)	0.419** (0.178)
Consume Monthly	0.447*** (0.155)	0.545*** (0.0951)	0.425*** (0.151)
Consume in Last 6 Months	0.593*** (0.118)	0.305** (0.124)	0.295*** (0.111)
Consume in Last Year	0.622*** (0.128)	0.608*** (0.196)	0.319*** (0.104)
Almost Never Consume	0.281** (0.111)	0.291** (0.120)	0.176** (0.0882)
Pre-treatment WTP	−0.223*** (0.0144)	−0.202*** (0.0146)	−0.193*** (0.0144)
Constant	7.276 (4.655)	4.382 (3.897)	8.499** (3.780)
Sigma	1.526*** (0.0662)	1.031*** (0.0447)	0.994*** (0.0431)
Covariates	Yes	Yes	Yes
Observations	1,068	1,068	1,068

Table B3
OLS Regression for Change in Willingness To Pay With Exclusion of Non-Consumers for Oysters, Mushrooms and Chocolate

VARIABLES	Change in WTP		
	(1)Oysters	(2)Mushrooms	(3)Chocolate
Peer WTP	−0.321*** (0.115)	−0.183** (0.092)	−0.085 (0.080)
Peer Frequency	−0.256* (0.140)	−0.037 (0.098)	−0.104 (0.074)
Peer WTP & Frequency	−0.320** (0.153)	−0.283** (0.110)	−0.192* (0.110)
Consume Daily	0.736***	0.513***	0.022

(continued on next page)

Table B3 (continued)

VARIABLES	Change in WTP		
	(1)Oysters	(2)Mushrooms	(3)Chocolate
	(0.190)	(0.166)	(0.313)
Consume Weekly	0.587*	0.479***	0.412*
	(0.354)	(0.138)	(0.224)
Consume Monthly	0.471***	0.550***	0.405**
	(0.169)	(0.135)	(0.171)
Consume in Last 6 Months	0.619***	0.308**	0.272*
	(0.141)	(0.154)	(0.139)
Consume in Last Year	0.646***	0.655	0.305**
	(0.172)	(0.410)	(0.138)
Almost Never Consume	0.313**	0.361**	0.163
	(0.125)	(0.145)	(0.115)
Pre-treatment WTP	−0.230***	−0.212***	−0.206***
	(0.030)	(0.029)	(0.027)
Non-Consumer	–	–	–
Constant	8.112	4.917	8.726**
	(5.957)	(5.169)	(4.429)
Covariates	Yes	Yes	Yes
Observations	899	985	1,019
R-squared	0.207	0.186	0.167

Robust standard errors are shown in parentheses. ***p < 0.01, **p < 0.05, and * p < 0.1. Covariates included in analysis were age, gender, household income, race, education, and political affiliation.

Table B4

OLS Regression for Change in Willingness To Pay Including Group Average Pre-Treatment WTP Opposed to Individual Pre-Treatment WTP for Oysters, Mushrooms and Chocolate

VARIABLES	Change in WTP		
	(1)Oysters	(2)Mushrooms	(3)Chocolate
Peer WTP	−0.222**	−0.163**	−0.072
	(0.088)	(0.076)	(0.075)
Peer Frequency	−0.200*	−0.033	−0.110
	(0.112)	(0.084)	(0.070)
Peer WTP & Frequency	−0.296**	−0.213**	−0.197*
	(0.134)	(0.101)	(0.111)
Consume Daily	0.405**	0.616***	0.181
	(0.172)	(0.179)	(0.325)
Consume Weekly	0.559	0.419***	0.203
	(0.350)	(0.133)	(0.213)
Consume Monthly	0.389**	0.484***	0.254
	(0.164)	(0.126)	(0.164)
Consume in Last 6 Months	0.477***	0.259*	0.191
	(0.133)	(0.148)	(0.136)
Consume in Last Year	0.477***	0.487	0.256*
	(0.157)	(0.391)	(0.132)
Almost Never Consume	0.204*	0.319**	0.155
	(0.116)	(0.124)	(0.109)
Above Group Avg WTP	−0.921***	−0.710***	−0.658***
	(0.101)	(0.076)	(0.069)
Non-Consumers	0.268***	0.185**	0.086
	(0.067)	(0.076)	(0.059)
Constant	8.430	3.871	8.146*
	(5.253)	(5.012)	(4.365)
Covariates	Yes	Yes	Yes
Observations	1,068	1,068	1,068
R-squared	0.159	0.139	0.111

Robust standard errors are shown in parentheses. ***p < 0.01, **p < 0.05, and * p < 0.1. Covariates included in analysis were age, gender, household income, race, education, and political affiliation.

Table B5
Analysis of Covariance (ANCOVA) on Post-Treatment Willingness To Pay for Oysters, Mushrooms and Chocolate

VARIABLES	Post-Treatment WTP		
	(1)	(2)	(3)
	Oysters	Mushrooms	Chocolate
Peer WTP	−0.264** (0.111)	−0.157* (0.0915)	−0.0827 (0.0898)
Peer Frequency	−0.220** (0.111)	−0.0226 (0.0906)	−0.103 (0.0894)
Peer WTP & Frequency	−0.265** (0.112)	−0.243*** (0.0920)	−0.188** (0.0904)
Consume Daily	0.723 (1.255)	0.523** (0.263)	0.0855 (0.461)
Consume Weekly	0.592 (0.427)	0.476*** (0.105)	0.419** (0.180)
Consume Monthly	0.445*** (0.157)	0.544*** (0.0962)	0.426*** (0.152)
Consume in Last 6 Months	0.591*** (0.119)	0.304** (0.125)	0.295*** (0.113)
Consume in Last Year	0.619*** (0.129)	0.603*** (0.199)	0.319*** (0.105)
Almost Never Consume	0.279** (0.112)	0.290** (0.122)	0.176** (0.0891)
Pre-treatment WTP	0.777*** (0.264**)	0.799*** (0.0148)	0.807*** (0.0145)
Constant	7.202 (4.703)	4.339 (3.941)	8.443** (3.820)
Covariates	Yes	Yes	Yes
Observations	1,068	1,068	1,068
R-squared	0.773	0.768	0.770

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