Future Foods 10 (2024) 100494

Contents lists available at ScienceDirect

Future Foods

journal homepage: www.elsevier.com/locate/fufo

Exploring the impact of ocean acidification information on consumers' preference for seafood

Manuel Barrientos [a,*], Moisés Carrasco-Garcés [b], Felipe Vásquez-Lavín [c,d,e], Roberto D. Ponce Oliva [c,d,e], Valeska A. San Martín [d,f], Stefan Gelcich [d,e,g]

[a] Business School, Universidad Católica de la Santísima Concepción, Concepción, Chile
[b] Departamento de Gestión Empresarial, Universidad de Concepción, Los Ángeles, Chile
[c] School of Business and Economics, Universidad del Desarrollo, Concepción, Chile
[d] Coastal Socio-Ecological Millennium Institute (SECOS), Chile
[e] Center of Applied Ecology and Sustainability (CAPES), Chile
[f] Centro de Investigaciones Costeras-Universidad de Atacama (CIC-UDA), Copiapó, Chile
[g] Facultad de Ciencias Biológicas, Pontificia Universidad Católica de Chile, Santiago, Chile

ARTICLE INFO

Keywords:
Information
Climate change
Choice experiment
Ocean acidification
Commercial attributes

ABSTRACT

We conducted a discrete choice experiment to explore whether providing information about a lesser-known issue related to climate change, ocean acidification (OA), affects consumers' preferences for seafood products in a middle-income country in the southern hemisphere. Our objective was to determine whether OA information affects consumer preferences for seafood using stated preference (SP) techniques. Seafood attributes include shell size and appearance, meat color, texture, taste, nutritional composition, product assortments, and price. We applied a split-sample approach to test for information effects, with one sample receiving information about OA while the other did not. We analyze the differences between samples using visual instruments and statistical tests. The results demonstrate that although the statistical test does not identify a difference between models, we did find that OA information increases the precision of 'consumers' responses. Moreover, using visual instruments, we found differences in specific parameters – not detected in the statistical analysis - which can lead to substantial differences in the willingness to pay for seafood attributes. The article is relevant as understanding these matters is essential when generating more effective communicational strategies regarding the impacts of global changes.

1. Introduction

Climate change has had multiple impacts, including changes to marine ecosystems (Chiabai et al., 2018), sea level rise (Solomon et al., 2009), extreme weather events (Mann et al., 2017), acceleration of some species' extinction risk (Urban, 2015), species migration (Reuveny, 2007), and ocean acidification (OA) (Hoegh-Guldberg et al., 2007). While sea level rise, extreme weather events, and species extinction are well known to the public due to direct observation and media coverage, OA remains a lesser-known issue, largely circumscribed to academic circles, as it is not directly observable or experienced by individuals (Capstick et al., 2016).

OA is generated by the addition and dissolution of (anthropogenic) CO_2 into seawater, increasing the concentration of hydrogen ions and decreasing ocean pH (Cao et al., 2007). This phenomenon hinders the growth of calcium carbonate skeletons and shells of many species of marine fauna (Cooley and Doney, 2009), and it will impact many industries, with aquaculture being one of the most affected (Ekstrom et al., 2015). The case of mussels is particularly interesting because OA affects their biological attributes by modifying survival, dissolution, and calcification rates (Cooley and Doney, 2009; Kroeker et al., 2013; Narita and Rehdanz, 2017). It also affects shell growth, ingestion, and respiration (Gazeau et al., 2013; Vargas et al., 2017) and increases vulnerability to diseases and parasites (Mackenzie et al., 2014; Thomsen et al., 2013).

These biological changes also affect commercial attributes associated with mussel quality, such as taste, appearance, and nutritional composition (Cardoso et al., 2013; Olsen, 2003; Sveinsdóttir et al., 2009). In

* Corresponding author at: Business School, Universidad Católica de la Santísima Concepción, Alonso de Ribera 2850, Concepción, Chile.
E-mail address: Manuel.barrientos@ucsc.cl (M. Barrientos).

https://doi.org/10.1016/j.fufo.2024.100494
Received 29 April 2024; Received in revised form 16 October 2024; Accepted 4 November 2024
Available online 9 November 2024

this regard, lab experiments conducted by San Martin et al. (2019) demonstrate the adverse effects of OA on physical (shell color, size) and nutritional attributes (i.e., vitamin B12, protein content, and fatty acid composition). These attributes are also relevant from a consumer perspective. For instance, shell appearance is relevant to consumers' choices (Daczkowska-Kozon and Pan, 2016), market prices (Brenner et al., 2012) and consumer demand (Ponce et al., 2019). Other additional attributes potentially affected by OA that could influence the consumer's food choice are flavor, nutritional value, quality, size, and freshness (Alfnes et al., 2006; Cardoso et al., 2013; Sveinsdóttir et al., 2009; Trondsen et al., 2004).

Therefore, previous results suggest that OA may affect different aquaculture product attributes. Yet, the evidence regarding the role of OA information disclosure on consumers' preferences is still in its infancy. The information consumers receive would be key to understanding their marginal willingness to pay, purchasing decisions, and preferences for a specific product with attributes that satisfy their needs. Thus, knowing whether disclosing information about OA affects consumer preferences could inform public and private policies to cope with, or even take advantage of, OA. This type of information is in some way brand new to consumers. Similar issues arise regarding information about the environmental and health effects of microplastics (Barrientos et al., 2024). Therefore, this article focuses on whether information about OA, a lesser-known global environmental problem, affects consumers' preferences for seafood using Stated Preference (SP) techniques.

While the role of information in potentially changing human attitudes, beliefs, and behavior has received considerable academic attention from multiple disciplines (e.g., Ankamah-Yeboah et al. (2020); Chen and Cho (2019); Kitano and Yamamoto (2020); Kulesz et al. (2019); McFadden and Huffman (2017); Petit et al. (2020); Tienhaara et al. (2021)), research assessing the role of information disclosure in climate-driven changes in food attributes is still scarce. Instead, the literature on climate change has explored the role of information in understanding broader topics, such as the general public engagement with climate change issues (e.g., Emberger-Klein and Menrad (2018), Greenhill et al. (2018), or Jones et al. (2017)).

Since many of the expected impacts of global and climate change have not yet been experienced, the most appropriate approach to gain insights into consumers' preferences over changing attributes is SP techniques (Bateman et al., 2002, 2001; Champ et al., 2003; Schläpfer et al., 2004), such as contingent valuation (CV) and Choice Experiment (CE). In SP, individuals face a series of hypothetical choices from which they must choose one alternative according to their preferences and restrictions. Commonly, the hypothetical scenarios provide information regarding the current situation (status quo) and one or several alternatives to this scenario (Fifer et al., 2014; Holmes et al., 2017; Louviere et al., 2008; Meenakshi et al., 2012). This information should be understandable and credible to interviewees (Johnston et al., 2017). SP methodologies shed light on consumer preferences by estimating willingness to pay (WTP) or willingness to accept for changes in the provision of a good or service or its attributes.

A common concern in SP applications is whether the information provided in the survey alters consumers' preferences (Ajzen et al., 1996; Mathews et al., 2006). Early SP research, primarily using CV, questioned how the quantity and quality of the information provided in surveys influence the mean and variance of WTP estimates; the results are mixed. Some studies show that increasing information does not affect the mean WTP but reduces its variance (Bergstrom et al., 1989; Boyle, 1989). Other studies indicate that providing more positive information[1] can increase WTP (Bergstrom et al., 1990); however, a saturation level emerges at which further new information no longer affects the estimates (Munro and Hanley, 2001).

More recently, Vásquez et al. (2016) demonstrated that tourists provided with ecological information regarding the negative impacts of human presence around penguins are willing to remain farther away from the nesting areas, although doing so reduces the quality of the tourism experience. Similarly, Jones et al. (2017) find that providing information about greenhouse gas emissions increases consumers' willingness to support the current situation instead of an alternative that increases greenhouse gas emissions. Furthermore, increased WTP based on information provided is demonstrated by Kulesz et al. (2019), who test whether the inclusion of biotechnology information modifies consumer preferences in a survey about sterilization techniques for salmonids. Other researchers find that additional information increases the willingness to support climate change mitigation efforts (Greenhill et al., 2018), or donor preferences for conservation projects (Curtin and Papworth, 2018), and decreases the likelihood of choosing the status quo alternatives (Tienhaara et al., 2021), and choice precision (Eppink et al., 2019).

In food-related studies, information is primarily presented through labels and certifications. Chalak and Abiad (2012) evaluate the effect of providing food security information through certification, finding that consumers' WTP increases with the addition of this source of information. Abiad and Chalak (2012) determine that food safety certificates increase purchase decision preferences and variance heterogeneity. Gracia et al. (2009) find that a more complex nutritional panel label is more valuable than simplified nutritional claims. Emberger-Klein and Menrad (2018) find a similar result. They investigated the effect of information provision on carbon labels used on food packaging. Related to meat products, Li et al. (2004) found an increase of 6 % in beef consumers' WTP when incorporating scientific information regarding genetically modified corn-fed beef. Caputo (2020) determines that providing information regarding the benefits of food irradiation increases the acceptance of irradiated beef, and Boncinelli et al. (2021) demonstrate that information about the benefits of omega-3 in animal welfare and the natural process of supplemental omega-3 in animals raises the likelihood of consumption of omega-3 enriched beef.

Conversely, Wang et al. (2011) find mixed results indicating that the provision of information affects purchase decisions but differs based on the meat type. Other studies evaluate the effects of health information on consumers' food purchase decisions. For instance, Bi et al. (2016) incorporate information about seafood's nutritional content and health benefits, finding that nutritional information increases WTP between 6 % to 17 %, but health information was less effective. Øvrum et al. (2012) determine that including healthy diet information increases consumers' WTP for semi-hard cheese. Closely related to our study, Barrientos et al. (2024) found that the information about microplastic's environmental and health effects could each individually impact consumers' WTP for mitigation technology, the probability of choosing not to purchase, and riskiness perception. However, when both information types are together, the combined impact decreases. Similarly, Chung et al. (2024) found that presenting calorie labelling and daily intake recommendations together in a restaurant canceled out the information effect on reducing calories consumption.

Admittedly, these mixed results are puzzling, suggesting that the results appear to be context-dependent. However, a closer look at the design of SP applications provides insight regarding whether we should expect any impact of information provision on consumer preferences. The impact depends on the information provided (price, income, quality, attributes, and levels) (Blomquist and Whitehead, 1998), the type of good under evaluation (private versus public goods) (Czajkowski et al., 2016), whether the payment is mandatory or voluntary (Hu et al., 2009), how the information is communicated (Eppink et al., 2019), and the objective of the study (Bateman and Mawby, 2004). For instance, in Vásquez et al. (2016), the objective of providing information regarding the detrimental effects of closeness to the penguin nesting area (sometimes unknown by the visitors) was to change tourists' behavior. Finding no effect would signal a biased survey design or that respondents do not

[1] Positive information refer to information that highlights the benefits over the drawbacks of the valuated good (Hu et al., 2009)

care about penguin conservation. Other studies also provide information aiming to highlight unfamiliar attributes for the respondents; therefore, they also aim to affect consumers' preferences (for instance, regarding the term "biotechnology" in Kulesz et al. (2019)). In other contexts, we might expect that the information does not affect consumers' preferences, as the provision of information merely seeks to create a context for respondents to reveal preferences. Subsequently, defining whether information provision generates biased responses is context-specific and should be explicitly addressed in each research plan and application (Johnston et al., 2017).

We explore whether providing neutral information regarding OA as a global driver affects consumers' preferences for seafood products. This issue is essential for developing strategies that enhance the sustainability of aquaculture products with a prominent role in food security (Willer and Aldridge, 2020). In general, the role of information could be to provide context or generate behavioral changes. Since the information we provide is just for contextualizing the OA problem and the reasons why the product will have changes in its attributes, we hypothesize that it should be neutral. If this is not satisfied, providing acidification information may change people's preferences and, therefore, we will observe significant differences in the coefficients associated with the model's attributes. To test this hypothesis, we conduct a CE to capture consumers' attribute preferences for mussels in Chile. We use a split-sample approach to disclose OA information to one group for comparison with a sample that does not receive the information and analyze the differences between samples using statistical and visual instruments. We find that incorporating OA neutral information does not produce differences in mean or standard deviation parameter estimates; however, differences emerge in the scale parameter. Specifically, consumers' choices in the information disclosure group were less precise (larger variance of the error term) than the without information group. Moreover, we visually identified variations in some mean parameters, which led to changes in attribute's WTP. Finally, this study provides novel evidence of the effect of information in a middle-income country in the southern hemisphere for seafood.

2. Materials and methods

2.1. Experimental design and survey

An in-person paper survey was conducted from October to December 2016 in the two largest Chilean cities (Santiago and Concepcion). The survey was co-designed with professionals in the aquaculture industry through implementing four focus groups and tested with 125 individuals in a pilot survey. We apply a split-sample approach with and without OA information. Both surveys follow a probabilistic multistage sampling approach in which we randomly selected the neighborhoods and blocks. The field strategy was to select one household in the northern corner of each block, and if there was no answer in the selected household, we skipped the next four houses and attempted to survey again in the fifth. Participants were informed about the study's objectives and could withdraw their participation at any stage. They gave informed consent, and we provided them with our contact details in case they wanted to delete their information or know the study results afterwards.

The survey contains four sections. The first section introduces the survey and information regarding mussels' characteristics. In the second section, we explain the relationships between mussels' production and environmental aspects, including specific information about OA in one of the samples. The third section presents an example of a choice to the respondent to ascertain their understanding of the experiment, after which we apply the CE. Finally, in the fourth section, we request socioeconomic characteristics, such as age, educational level, income, and household size.

In the CE, interviewees were presented nine main mussel attributes. These attributes and corresponding levels were identified through interviews, seminars, focus groups, pilots, and an extensive literature review on the effects of OA in mussels. These attributes include shell size, meat color, and shell appearance (physiological), texture and taste (organoleptic), nutritional composition, distance to salmon farms, product assortments (fresh, frozen, bagged, and dressed formats), and six price levels that vary according to the product assortment and were generated from actual market prices. It is worth mentioning that the product assortment attributes were the output of a co-construction approach with the industry. Physiological, organoleptic, and nutritional attributes are affected by OA (Ponce et al., 2019; San Martin et al., 2019). Table 1 summarizes the attributes and levels presented in the CE.

Each respondent was presented with six choice sets with three alternatives, including two mussel (new) profiles and one no-purchase alternative. We applied a d-efficient design (Street and Burgess, 2007) estimated in the software Ngene, considering 60 choice sets divided into ten blocks of six choice questions each. An example of a choice set is presented in Figure

Fig. 1

The only difference between the samples was the disclosure of OA information in one of them. We will refer to them as *survey 1* (without disclosure of climate change information) and *survey 2* (with disclosure of climate change information). Then, the OA information treatment was as follows:

> *(…) Another relevant effect of climate change is the increase of ocean acidification due to the rise of* $\mathrm{CO_2}$ *in the atmosphere when fossil fuels are used (burned). When these fuels are burned, as in automobiles or buses, greenhouse gases are released that raise the planet's temperature (including the ocean's temperature).*
>
> *The gas emissions have other effects in the ocean beyond the temperature increase. These gases raise seawater acidity.*

We compared this circumstance with human stomach acidity to provide a more familiar analogy of the problem. We asked: *Have you ever had* stomach acidity*? To mitigate this* stomach acidity*, some people drink an antacid containing sodium bicarbonate. This component helps to neutralize the acid. The excess carbon dioxide in the atmosphere is dissolved in the sea, causing an acidity increase that cannot be neutralized because there is not enough "sea-antacid" naturally available (called carbonic acid).*

Table 1
Attributes and levels presented in the discrete choice experiment.

Attributes	Levels
Shell size	Small (5 cm)
	Large (7 cm)
Meat color	Yellow
	White
Shell appearance	Acidified
	No acidified
Texture	Hard
	Soft
Taste	Moderate
	Intense
Nutritional composition	Low
	High
Distance to salmon farms	Low (Less than or equal to 1.5 kms)
	High (Greater than 1.5 kms)
Product assortment	Fresh with shell
	Fresh only meat
	Frozen with shell
	Frozen only meat
	Bagged with shell in butter and garlic dressing
	Bagged with shell in white wine dressing
	Bagged with shell in tomatoes dressing
	Canned in oil or water
	Canned in hot sauce
	Canned in green sauce
Price (250 g)	Six prices varying between US$1.3 – US$5 depending on product assortment

Note: We presented the price attribute in Chilean pesos. However, we used US$ in the estimations, using the conversion rate 1 US$ = 650 CLP.

	Alternative 1	**Alternative 2**	**No purchase**
Shell Size	Small (5 cm.)	Large (7 cm.)	
Texture	Hard	Soft	
Taste-sea scent	Moderate	Intense	
Nutritional Composition	High	Low	
Distance to salmon farms	Greater than 1.5 kilometers	Less than or equal to 1.5 kilometers	
Product assortment			
Shell Appearance			
Meat Color			
Price (250 gr) in US$	US$ 4.12	US$ 1.74	US$ 0
Your choice			

Fig. 1. Choice set examples.

This increases ocean acidity and affects many living beings that consume seawater, particularly the mussel. The DCE framing that was common between surveys 1 and 2 is included in Appendix A. Note that consumers from both samples were informed about environmental stressors that could affect mussels, though without detailed explanation. The information treatment focuses on one of these potential stressors, the OA.

We surveyed 627 individuals using survey 1 and 636 using survey 2. The entire sample includes 1263 individuals, and as each participant responded to six choice situations, 7578 observations were obtained. The descriptive statistics and statistical tests to compare sample distributions are presented in Appendix B.

2.2. Statistical modelling

Discrete choice experiments (DCEs) construct hypothetical choice scenarios in which individuals choose between several alternatives that differ in a set of attributes (Carlsson et al., 2003). In this context, the utility attained by individual n that chooses alternative i in choice scenario t is:

$$U_{nit} = V_{nit} + \varepsilon_{nit} \tag{1}$$

where V_{nit} represents the deterministic component of the utility function and could be defined as $V_{nit} = \lambda(\alpha_i + \beta_n x_{nit})$ if it is assumed linear-in-parameters, where α_i is an alternative specific constant, x_{nikt} is a set of explanatory variables such as levels of the attributes presented, and the respondents' characteristics, β_n is the vector of parameters to be estimated, and λ is a scale parameter. The variable ε_{nit} is the analyst-unobserved random component, which is assumed to be an independent and identically distributed (iid) type I extreme value, and its variance is $V(\varepsilon_{nit}) = \pi^2/6\lambda^2$, then the λ parameter is inversely related to the variance of the error term. However, this parameter is confounded with α_i and β_n then cannot be identified; consequently, it is arbitrarily set to one (Swait and Louviere, 1993; Train, 2009). This classic model is known as conditional logit; however, preference heterogeneity can be captured in a mixed logit (ML) model by using random parameters defined as $\beta_n = b + \sigma_\beta \eta_n$, where β_n is an individual parameter, b is the mean of the random parameter across all individuals, σ_β is the standard deviation of the parameter, and η_n is a random realization of the standard normal distribution. In that specification, $\sigma_\beta \eta_n$ represents the deviation of the population mean b. Now, the probability that individual n chooses alternative i in choice scenario t is given by:

$$P_{nit}(y = i | x_{nit}) = \frac{e^{\lambda(\alpha_i + \beta_n * x_{nit})}}{\sum_{j=1}^{J} e^{\lambda(\alpha_j + \beta_n * x_{njt})}} \tag{2}$$

We estimated the ML models assuming a normal distribution for random parameters, using 100 Halton sequence random draws,[2] and solving the log-likelihood with the BFGS optimization algorithm.[3]

To test whether the OA information treatment impacts any relevant outcome of our choice model, we followed the statistical procedure suggested in (Swait and Louviere, 1993), which we detailed in Appendix C. Basically, we need to test the hypothesis of the equality between the coefficients associated with sample 1 (without disclosure of information) and sample 2 (with disclosure), representing $H_0 : \beta_n^1 = \beta_n^2$ and $\lambda_1 = \lambda_2$. Therefore, we test $H_{0A} : \beta_n^1 = \beta_n^2$, allowing for different scale parameters. If we reject H_{0A}, H_0 is partially rejected, but the confoundness between the scale parameters and the coefficients do not allow us to claim that H_0 is rejected directly. When H_{0A} cannot be rejected, we then test $H_{0B} : \lambda_1 = \lambda_2 = \lambda$. If H_{0A} and H_{0B} cannot be rejected, we can say that both sets of parameters (b, σ_β, and λ) are the same.

After this statistical testing, we visually inspect whether any parameter difference was not detected in the Swait and Louviere (1993) procedure. Therefore, we place the estimated parameters into a cartesian plane where the coefficients from S_1 are on the y-axis and those from S_2 are on the x-axis. Then, we draw a 45-degree line as a reference to evaluate the equality between coefficients. The farther the coefficients are from the line, the likelier is that the coefficients are unequal. Next, we estimate a linear regression to quantify the linear relationship between both sets of estimated parameters.

Finally, if we visually detect coefficient differences, we will simulate the WTP by taking 100,000 random draws from the random parameter distribution and dividing this by the monetary parameter. We used the R programming language (R Core Team, 2022) to model estimation, hypothesis testing, and visualization.

3. Results

This section presents the estimation results for the samples with and without OA information. Table 2 presents the models estimated independently, while table 3 details the estimation using pooled data that permits the scale parameter to differ across samples (pooled model A) and the model fixing the scale parameter to $\theta = 1$ (pooled model B). We then visually inspect the differences between parameters. If we find some differences, we will calculate WTP for these attributes to measure the impact of information on mussel purchase decisions.

3.1. Separate estimations

In Table 2, we separately estimated the samples with and without information to check their results when scale differences are not considered. Regarding the estimated coefficients, the alternative specific constant for no purchase alternative is statistically significant, with a negative sign for both models. This implies that consumers' welfare increases when one of the mussels offered is selected. Among several sociodemographic variables, only trust in institutions and household size are statistically significantly different from zero (and negative) .[4] The higher the trust in institutions (or household size), the higher the probability of choosing an alternative other than the no-purchase option.

In terms of the attributes presented in the CE, price is negative and significant. The coefficients of the attributes, such as shell appearance, meat color, nutritional composition, frozen: with shells, canned hot sauce, bagged: with shell: butter and garlic, bagged tomato, and bagged white wine, are statistically significant through the models. Conversely, attributes such as texture, frozen-only meat, canned oil or water, canned green sauce, and fresh-only meat are statistically insignificant.

The disclosure of climate change information may affect the statistical significance of some attributes. For instance, shell size (large) is statistically significant in the case of information disclosure, and taste-sea scent and proximity to salmon farms (low distance) are statistically significant in the sample without information but not in the sample with information. In particular, assortment attributes, such as frozen, canned, or bagged products negatively affect consumer welfare when they are statistically significant. Respondents have a strong preference for the base category of fresh with shell.

Regarding the heterogeneity captured by the ML model, nearly every standard deviation parameter is statistically significant, suggesting considerable heterogeneity in consumers' preferences for mussels; however, some differences arise between models. For instance, the frozen–only meat standard deviation parameter is only statistically significant in the model with information disclosure. Similarly, bagged white wine and fresh- only meat has significant heterogeneity in the sample with information. Conversely, bagged with shell: butter and garlic has significant heterogeneity only in the estimation sample without the information.

3.2. Pooled estimations

Most results presented in the separate estimations remain in pooled estimations (table 3). Some minor differences arise in the mean parameter of shell size (large), which is statistically significant only in pooled model B, or the standard deviation parameter in frozen-only meat, which is only statistically significant in pooled model A.

Regarding the hypothesis testing, in pooled model A, we cannot reject H_{0A} at 5 % significance, which implies that the β_n of the ML model for different information treatments are the same. Next, in pooled model B, we rejected the H_{0B} null hypotheses. The latter indicates that although the information disclosure does not statistically impact β_n it does on the scale parameters. As the scale parameter is a function of the variance of the random term, it can be analyzed as a measure of the relationship between the deterministic and random components of the indirect utility function (Eppink et al., 2019); therefore, having different scale parameters could imply different choice precision among samples. Specifically, as the scale parameter is higher than 1 in pooled model A, we can suggest that the sample without information about OA makes more precise choices than the sample with OA information.

3.3. Visual inspection

Next, we want to explore whether the statistical tests could be hiding relevant parameter differences. In this regard, Fig. 2 presents the relationship between the model coefficients with and without information disclosure. This figure reveals the differences visually between the estimates of the models. The more dispersed shade of the 45° line, and the farther the parameters are from the 45° line, the less likely the parameters are equal. Fig. 2 is accompanied by a line for linear regression considering the estimator of ordinary least squares (OLS) among the coefficients. For example, attributes such as bagged - white wine are far from the 45° line and even outside the line for linear regression. Another

[2] We tested the stability of our estimations over a larger number of Halton draws (1000) and using a different algorithm (Modified Latin Hypercube Sampling, MLHS) and the main results were robust.

[3] We developed our own code to estimate ML models and used the R package numDeriv (Gilbert & Varadhan, 2016) to compute the Hessian.

[4] Income is an important sociodemographic variable to include in stated preference studies, which indicates the validity of the budget constraint. In our case, we got many missing values in this variable (i.e., respondents preferred not to answer this question), so including this variable would significantly reduce the number of observations in our estimations (from 7578 to 1969). Nevertheless, we tested this variable as an interaction with the status quo using the reduced sample, but it was not statistically significant. The results of this estimation are available upon request.

Table 2
DCE results separately estimating samples with and without information.

Coefficients	Without information disclosure				With information disclosure			
	Mean (b)	Std. Err	SD (σ_β)	Std. Err	Mean (b)	Std. Err	SD (σ_β)	Std. Err
ASC_nopurchase	−1.984***	(0.269)			−2.044***	(0.267)		
ASC_nopurchase*trust	−0.287*	(0.153)			−0.425***	(0.149)		
ASC_nopurchase*hh_size	−0.199***	(0.044)			−0.074*	(0.043)		
Price	−0.451***	(0.074)			−0.292***	(0.074)		
Shell size (large)	−0.040	(0.072)	0.697***	(0.113)	0.154**	(0.073)	0.598***	(0.141)
Shell appearance (not acidified)	−0.925***	(0.093)	1.289***	(0.114)	−1.095***	(0.103)	1.556***	(0.118)
Meat color (yellow)	0.235***	(0.088)	1.372***	(0.113)	0.387***	(0.088)	1.415***	(0.113)
Texture (soft)	−0.022	(0.066)	−0.336**	(0.161)	−0.050	(0.071)	−0.631***	(0.16)
Taste-sea scent (moderate)	0.208***	(0.073)	−0.613***	(0.146)	−0.041	(0.074)	−0.766***	(0.132)
Nutritional composition (high)	−0.359***	(0.08)	1.095***	(0.107)	−0.312***	(0.078)	−0.972***	(0.115)
Distance (low)	−0.178**	(0.076)	0.865***	(0.119)	−0.054	(0.076)	0.734***	(0.121)
Frozen - only meat	−0.193	(0.171)	0.418	(0.381)	−0.161	(0.184)	−0.793**	(0.326)
Frozen - with shells	−0.368**	(0.176)	1.188***	(0.309)	−0.650***	(0.183)	−1.210***	(0.297)
Canned - oil or water	0.162	(0.177)	1.676***	(0.336)	0.072	(0.187)	−1.885***	(0.319)
Canned - hot sauce	−0.538***	(0.192)	1.968***	(0.322)	−0.679***	(0.177)	1.109***	(0.279)
Canned - green sauce	−0.278	(0.194)	−1.667***	(0.345)	−0.075	(0.198)	1.916***	(0.332)
Bagged with shell - butter and garlic	−0.724***	(0.173)	−0.784*	(0.448)	−0.659***	(0.168)	−0.33	(0.477)
Bagged – tomato	−1.059***	(0.197)	1.116***	(0.388)	−0.990***	(0.183)	0.922***	(0.302)
Bagged – white wine	−0.467***	(0.168)	0.086	(0.459)	−0.918***	(0.186)	−0.844*	(0.445)
Fresh - only meat	−0.124	(0.165)	0.648	(0.414)	−0.096	(0.181)	1.389***	(0.298)
N	3762	3816						
log-likelihood	−3365.524	−3388.804						

Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.
As ML estimates a distribution of the parameters, we present the mean (b) and standard deviation (σ_β). Sociodemographic variables were interacted with the alternative specific constant of the no purchase alternative (ASC_nopurchase), and we only show those that are statistically significant (trust in institutions and household size).

Table 3
DCE results estimating pooled models.

Coefficients	Coefficients Pooled model A				Coefficients Pooled model B			
	Mean (b)	Std. Err	SD (σ_β)	Std. Err	Mean (b)	Std. Err	SD (σ_β)	Std. Err
ASC_nopurchase	−1.916***	(0.193)			−1.801***	(0.178)		
ASC_nopurchase*trust	−0.447***	(0.106)			−0.468***	(0.103)		
ASC_nopurchase*hh_size	−0.132***	(0.029)			−0.142***	(0.029)		
Price	−0.373***	(0.053)			−0.347***	(0.051)		
Shell size (large)	0.06	(0.049)	0.542***	(0.11)	0.102**	(0.048)	0.417***	(0.147)
Shell appearance (not acidified)	−0.926***	(0.072)	1.414***	(0.094)	−0.955***	(0.067)	1.450***	(0.084)
Meat color (yellow)	0.279***	(0.062)	1.360***	(0.089)	0.303***	(0.06)	1.355***	(0.076)
Texture (soft)	−0.054	(0.048)	−0.412***	(0.128)	−0.058	(0.047)	0.354**	(0.143)
Taste-sea scent (moderate)	0.08	(0.052)	0.749***	(0.097)	0.062	(0.051)	0.829***	(0.077)
Nutritional composition (high)	−0.343***	(0.055)	1.023***	(0.084)	−0.333***	(0.054)	0.991***	(0.075)
Distance (low)	−0.148***	(0.052)	0.720***	(0.091)	−0.143***	(0.052)	0.716***	(0.082)
Frozen - only meat	−0.11	(0.126)	0.924***	(0.213)	−0.073	(0.12)	−0.282	(0.389)
Frozen - with shells	−0.453***	(0.124)	−1.056***	(0.271)	−0.389***	(0.122)	−1.104***	(0.229)
Canned - oil or water	0.135	(0.125)	1.669***	(0.253)	0.183	(0.126)	−1.738***	(0.224)
Canned - hot sauce	−0.486***	(0.131)	−1.654***	(0.207)	−0.508***	(0.124)	−1.235***	(0.195)
Canned - green sauce	−0.115	(0.138)	1.809***	(0.234)	−0.083	(0.132)	1.670***	(0.228)
Bagged with shell - butter and garlic	−0.654***	(0.123)	−1.026***	(0.246)	−0.634***	(0.124)	1.186***	(0.283)
Bagged – tomato	−0.890***	(0.124)	−0.531*	(0.287)	−0.883***	(0.118)	−0.364	(0.291)
Bagged – white wine	−0.603***	(0.126)	0.776**	(0.364)	−0.592***	(0.123)	0.653**	(0.3)
Fresh - only meat	−0.083	(0.119)	0.890***	(0.213)	−0.076	(0.118)	−0.973***	(0.214)
Scale parameter	1.005***	(0.062)			1 (fixed)			
N	7578				7578			
log-likelihood	−6779.829				−6774.12			
P-value chi square for H0A	0.062							
P-value chi square for H0B					0.000			

Standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.
As ML estimates a distribution of the parameters, we present the mean (b) and standard deviation (σ_β). Sociodemographic variables were interacted with the alternative specific constant of the no purchase alternative (ASC_nopurchase), and we only show those that are statistically significant (trust in institutions and household size).

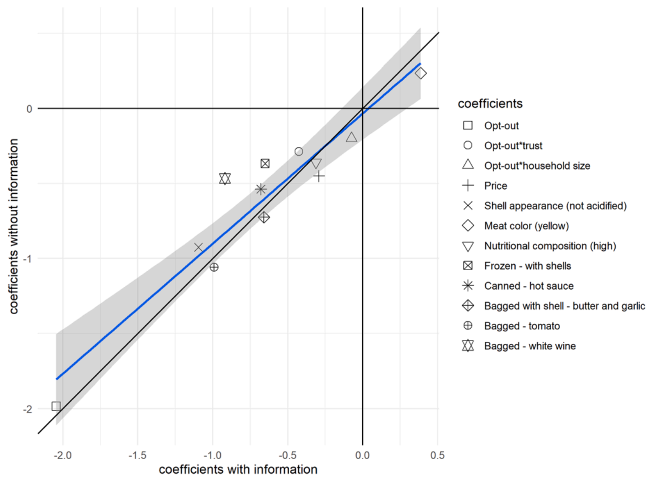

Fig. 2. Comparison of ML mean parameters: with and without disclosure information.
The more dispersed shade of the 45° line, and the farther the parameters are from the 45° line, the less likely the mean parameters are equal. This figure is accompanied by a linear regression line considering the estimator of ordinary least squares (OLS) among the coefficients.

relevant difference between parameters is the frozen–with shells format.[5] Both parameters present a larger negative effect on consumer welfare when OA information is presented. In the case of bagged - white wine, we hypothesize this effect is because consumers perceive white wine as less able to hide any potential flavour change produced by OA compared to hot sauce, butter and garlic or tomato (the other format attributes statistically significant in both samples). For frozen-with shells format, we hypothesize that consumers react to the change in shell appearance due to OA since this format presents a more evident impact of OA. In the margin, we observed that the cost parameter also presents differences between parameters, and the implications of these differences could seriously affect welfare measures.

In addition to the differences between mean parameters, information provision may generate differences in the heterogeneity of the attributes (see Fig. 3). As in Fig. 2, Fig. 3 considers both the line of 45° representing the equality of attributes and the line for linear regression considering the OLS estimator among the coefficients. First, there is a remarkable difference between the slopes of the regression line of Fig. 2 and Fig. 3. The latter shows greater differences to the 45° line slope. Besides, attributes such as canned hot sauce, and texture (soft) are farther from the 45° line and linear regression line.

This visual analysis indicates that almost every estimate is aligned with the 45-degree line; then, they are similar between samples, with few exceptions. Interestingly, they are not statistically different, but these differences could have an effect on welfare measures. Therefore, we calculate the WTP focusing on these differences, which include bagged white wine and frozen: with shells, as they visually demonstrate the most notable differences. Table 4 summarizes these calculations. Notably, the WTP with information is greater than the WTP without information.

4. Discussion and conclusions

We evaluated the effects of neutral information about OA using a split-sample approach in a CE conducted in Chile. To determine the effects of information disclosure, we used the statistical procedure proposed by Swait and Louviere (1993) to test differences between mean parameters, standard deviations, and scale parameter. A notable insight derived from our results is that the statistical procedure to identify differences between two SP models can conceal differences, which - although not statistically significantly different from each other - could still impact business or policymaker's decisions.

Our results demonstrate that incorporating OA information does not produce differences between mean parameters or standard deviations in the ML estimation in statistical terms; however, it does in the scale parameter. The choices made by respondents under the information disclosure treatment were less precise (larger variance of the error term) than the control group. This result is not unique in the literature (e.g., Eppink et al. (2019), Shr et al. (2019), or Czajkowski et al. (2016)). In our case, we believe that OA information makes consumers less likely to purchasing seafood, which can explain the lower choice precision in the treated sample. Although we frame the experiment in terms of OA, we argue that the setting could be insightful for other surveys covering less-known environmental or climate-driven issues.

Furthermore, using visual instruments, we reveal differences in some mean parameters, like bagged white wine, frozen: with shells, and price, and standard deviation parameters like canned - hot sauce and texture (soft). Interestingly, this visual analysis indicates that the impact of OA information provision is higher in the heterogeneity of consumer preferences than mean values.[6]

We also showed that these visual differences could imply large differences in WTP, even larger than differences previously observed in the literature; 204 % for bagged white wine and 173 % for frozen: with shells. In the SP food-related literature, using (health or nutritional) information disclosure demonstrates differences between 6 % and 17 % in the WTP for seafood (Bi et al., 2016), 6 % of the premium for genetically modified corn-fed beef (Li et al., 2004), a premium of 27.2 % for low-saturated-fat cheese (Øvrum et al., 2012), and near 100 % for healthy breakfast cookies (Gracia et al., 2009). We argue that these large differences are mainly explained by the role of price/cost parameters. Slight differences in these parameters (undetected by an overall statistical analysis) could generate considerable differences in WTP estimates. Therefore, providing a WTP confidence interval is vital to identify potential treatment effects not captured in statistical tests.

This finding is critical for empirical applications. Not all studies test different information treatments (or valuation questions framing); therefore, their results are conditional on the specific information provided. This often-overlooked detail could significantly impact decisions made by businesses or policymakers. Consequently, we emphasize the importance of transparency regarding the exact information presented in SP studies.

Additionally, our study provides new evidence of the effect of information in a middle-income country in the southern hemisphere for seafood. Most previous studies are conducted in high-income countries in the northern hemisphere (with Lebanon (Chalak and Abiad, 2012) as an exception). We also innovated in terms of the food product studied. The food products previously analyzed in the literature on information disclosure include breakfast cookies, shawarma sandwiches, cheese, fruit, vegetables, and meat. Only Bi et al. (2016) investigate the effect of information provision in seafood using SP methods.

Finally, understanding OA's impact on mussels' attributes that are relevant to consumers and identifying strategies to increase the acceptability of mussels affected by OA are critical gaps to inform the industries' capacity to adapt to these stressors. For instance, in this article, we show that disclosing OA information does not affect preferences for mussels in general terms, but it does in specific attributes and in the precision of consumer responses. Many factors can explain this

[5] We did not include coefficients that were not statistically significant in at least one of the samples.

[6] While this study does not focus on the difference in the scale parameter, Czajkowski et al. (2016) and Eppink et al. (2019) suggests a decomposition of the scale parameter that allows characterizing this heterogeneity and could provide a broader perspective on this difference.

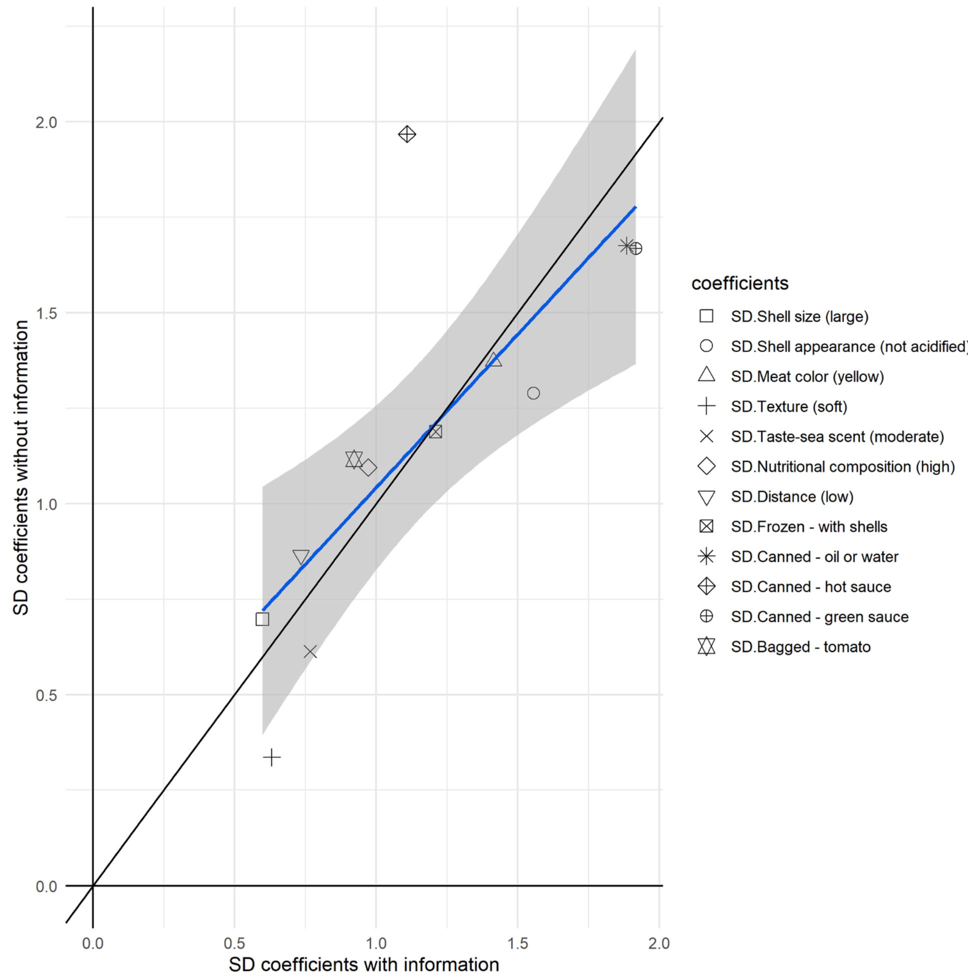

Fig. 3. Comparison of ML standard deviation parameters with and without disclosure information.
The more dispersed shade of the 45° line, and the farther the parameters are from the 45° line, the less likely the standard deviation parameters are equal. This figure is accompanied by a linear regression line considering the estimator of ordinary least squares (OLS) among the coefficients.

Table 4
Willingness to pay comparison between samples.

	WTP without information	WTP with information	WTP difference (increase)
Bagged (white wine) (in US$)	1.04	3.14	2.11 (204 %)
Frozen- with shells (in US$)	0.82	2.23	1.41 (173 %)

The willingness to pay (WTP) measure was calculated as the ratio between the attribute's parameter and the price parameter. In Fig. 2, we only calculated the WTP of attributes with relevant visual differences.

statistical insensitivity to OA. We believe that it could be explained by a strong preference for mussels in Chile. Hence, the demand for mussels is likely relatively inelastic to climate events and, additionally, due to a lower awareness about climate change in the year the survey was conducted. This raises an interesting question of how consumer preferences have evolved as the awareness of the climate change crisis has increased. However, we acknowledge that other design reasons can affect the results. For instance, we cannot ensure that every consumer interprets and internalizes information in the same manner, or how familiar they were with it before the CE.

Understanding the effect of information disclosure on SP is a complex issue. Despite myriad studies investigating how knowledge, familiarity, or fatigue affects the impact of information in SP (Hasselström and Håkansson, 2014; Needham et al., 2018; Tienhaara et al., 2021), a considerable amount of uncertainty remains regarding the impact of such information. We assert that there is a gap of a complete and detailed taxonomy of information treatments and goals in SP studies. In some cases, information affects choices. In other, it does not. The latter led to our conclusion that every SP study must clearly establish the expected intent of the information used. Some options are contextualization (not expecting a change in parameters) or generating behavioral changes (positive or negative). Subsequently, researchers must then prove that the treatment has the intended role.

Ethical statement

Participants were informed about the study's objectives and could withdraw their participation at any stage. They gave informed consent, and we provided them with our contact details in case they wanted to delete their information or know the study results afterward.

CRediT authorship contribution statement

Manuel Barrientos: Writing – review & editing, Writing – original draft, Visualization, Investigation, Data curation. **Moisés Carrasco-Garcés:** Software, Investigation, Formal analysis. **Felipe Vásquez-Lavín:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Roberto D. Ponce Oliva:** Writing – review & editing, Project administration, Conceptualization. **Valeska A. San Martín:**

Writing – original draft, Investigation. **Stefan Gelcich:** Writing – original draft, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledge

We acknowledge the financial support from the project AFB240003 (CAPES). Additional funding during the preparation of the manuscript and analysis is acknowledged to the coastal Social-Ecological Millenium Institute (SECOS), Millennium Science Initiative Program -code ICN 2019–015 and Fondecyt Postdoctoral Project N°3210219 supported to VASM during the edition of this manuscript. Special thanks to the Quillon Lab for support and inspiration.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.fufo.2024.100494.

Data availability

Data will be made available on request.

References

Abiad, M., Chalak, A., 2012. Unraveling mean and variance heterogeneity influences of information provision on safer food purchasing decisions: a heteroscedastic mixed logit approach. Food Econ. 9 (3), 135–144.
Ajzen, I., Brown, T.C., Rosenthal, L.H., 1996. Information bias in contingent valuation: effects of personal relevance, quality of information, and motivational orientation. J. Environ. Econ. Manage 30 (1), 43–57.
Alfnes, F., Guttormsen, A.G., Steine, G., Kolstad, K., 2006. Consumers' willingness to pay for the color of salmon: a choice experiment with real economic incentives. Am. J. Agric. Econ. 88 (4), 1050–1061.
Ankamah-Yeboah, I., Asche, F., Bronnmann, J., Nielsen, M., Nielsen, R., 2020. Consumer preference heterogeneity and preference segmentation: the case of ecolabeled salmon in danish retail sales. Marine Resour. Econ. 35 (2).
Barrientos, M., Lavín, F.V., Oliva, R.D.P., Nayga Jr, R.M., Gelcich, S, 2024. Microplastics in seafood: consumer preferences and valuation for mitigation technologies. Food Research International, 114342.
Bateman, I.J., Carson, R.T., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., Loomes, G., Mourato, S., Özdemiroglu, E., 2002. Economic valuation with stated preference techniques: a manual. Econ. Valuation with Stated Preference Tech. a Manual.
Bateman, I.J., Mawby, J., 2004. First impressions count: interviewer appearance and information effects in stated preference studies. Ecological Economics 49 (1), 47–55.
Bateman, I.J., Willis, K.G., Arrow, K.J., 2001. Valuing Environmental preferences: Theory and Practice of the Contingent Valuation Method in the US. March 2008. EU, and developing countries.
Bergstrom, J.C., Stoll, J.R., Randall, A., 1989. Information effects in contingent markets. Am. J. Agric. Econ. 71 (3), 685–691.
Bergstrom, J.C., Stoll, J.R., Randall, A., 1990. The impact of information on environmental commodity valuation decisions. Am. J. Agric. Econ. 72 (3), 614–621.
Bi, X., House, L., Gao, Z., 2016. Impacts of nutrition information on choices of fresh seafood among parents. Marine Resour. Econ. 31 (3), 355–372.
Blomquist, G.C., Whitehead, J.C., 1998. Resource quality information and validity of willingness to pay in contingent valuation. Resour. Energy Econ. 20 (2), 179–196.
Boncinelli, F., Piracci, G., Casini, L., 2021. Understanding the role of information and taste heterogeneity in consumer preferences for functional beef: the case of the omega-3 enriched burger. Meat Sci., 108614
Boyle, K.J., 1989. Commodity specification and the framing of contingent-valuation questions. Land. Econ. 65 (1), 57–63.
Brenner, M., Buchholz, C., Heemken, O., Buck, B.H., Köhler, A., 2012. Health and growth performance of the blue mussel (Mytilus edulis L.) from two hanging cultivation sites in the German Bight: a nearshore—Offshore comparison. Aquaculture International 20, 751–778.
Cao, L., Caldeira, K., Jain, A.K., 2007. Effects of carbon dioxide and climate change on ocean acidification and carbonate mineral saturation. Geophys. Res. Lett. 34 (5).
Capstick, S.B., Pidgeon, N.F., Corner, A.J., Spence, E.M., Pearson, P.N., 2016. Public understanding in Great Britain of ocean acidification. Nat. Clim. Chang. 6 (8), 763–767.
Caputo, V., 2020. Does information on food safety affect consumers' acceptance of new food technologies? The case of irradiated beef in South Korea under a new labelling system and across different information regimes. Australian Journal of Agricultural and Resource Economics 64 (4), 1003–1033.
Cardoso, C., Lourenço, H., Costa, S., Gonçalves, S., Nunes, M.L., 2013. Survey into the seafood consumption preferences and patterns in the Portuguese population. Gender and regional variability. Appetite 64, 20–31.
Carlsson, F., Frykblom, P., Liljenstolpe, C., 2003. Valuing wetland attributes: an application of choice experiments. Ecological Economics 47 (1), 95–103.
Chalak, A., Abiad, M., 2012. How effective is information provision in shaping food safety related purchasing decisions? Evidence from a choice experiment in Lebanon. Food Qual. Prefer. 26 (1), 81–92.
Champ, P.A., Boyle, K.J., Brown, T.C., 2003. A Primer on Nonmarket Valuation. Kluwer Academic Publishers.
Chen, W.Y., Cho, F.H.T, 2019. Environmental information disclosure and societal preferences for urban river restoration: latent class modelling of a discrete-choice experiment. J. Clean. Prod. 231, 1294–1306.
Chiabai, A., Quiroga, S., Martinez-Juarez, P., Higgins, S., Taylor, T., 2018. The nexus between climate change, ecosystem services and human health: towards a conceptual framework. Science of the Total Environment 635, 1191–1204.
Chung, D.H., Han, D.B., Nayga Jr, R.M., Lee, S.H, 2024. Does more information mean better choices? A study on calorie display and consumer behavior in restaurants. Food Qual. Prefer. 113, 105044.
Cooley, S.R., Doney, S.C., 2009. Anticipating ocean acidification's economic consequences for commercial fisheries. Environmental Research Letters 4 (2), 024007.
Curtin, P., Papworth, S., 2018. Increased information and marketing to specific individuals could shift conservation support to less popular species. Mar. Policy. 88, 101–107.
Czajkowski, M., Hanley, N., LaRiviere, J., 2016. Controlling for the effects of information in a public goods discrete choice model. Environmental and resource economics 63 (3), 523–544.
Daczkowska-Kozon, E.G., Pan, B.S., 2016. Environmental Effects On Seafood availability, safety, and Quality. CRC Press.
Ekstrom, J.A., Suatoni, L., Cooley, S.R., Pendleton, L.H., Waldbusser, G.G., Cinner, J.E., Ritter, J., Langdon, C., Van Hooidonk, R., Gledhill, D., 2015. Vulnerability and adaptation of US shellfisheries to ocean acidification. Nat. Clim. Chang. 5 (3), 207–214.
Emberger-Klein, A., Menrad, K., 2018. The effect of information provision on supermarket consumers' use of and preferences for carbon labels in Germany. J. Clean. Prod. 172, 253–263.
Eppink, F.V., Hanley, N., Tucker, S., 2019. How best to present complex ecosystem information in stated preference studies? Ecological Economics 158, 20–25.
Fifer, S., Rose, J., Greaves, S., 2014. Hypothetical bias in Stated Choice Experiments: is it a problem? And if so, how do we deal with it? Transportation Research Part A: Policy and Practice 61, 164–177. https://doi.org/10.1016/j.tra.2013.12.010.
Gazeau, F., Parker, L.M., Comeau, S., Gattuso, J.-P., O'Connor, W.A., Martin, S., Pörtner, H.-O., Ross, P.M., 2013. Impacts of ocean acidification on marine shelled molluscs. Mar. Biol. 160 (8), 2207–2245.
Gilbert, P., & Varadhan, R. (2016). *numDeriv: accurate Numerical Derivatives*. In https://cran.r-project.org/web/packages/numDeriv/index.html.
Gracia, A., Loureiro, M.L., Nayga Jr, R.M., 2009. Consumers' valuation of nutritional information: a choice experiment study. Food Qual. Prefer. 20 (7), 463–471.
Greenhill, B., Dolšak, N., Prakash, A., 2018. Exploring the Adaptation-mitigation Relationship: does Information on the Costs of Adapting to Climate Change Influence Support for Mitigation? Environ. Commun. 12 (7), 911–927.
Hasselström, L., Håkansson, C., 2014. Detailed vs. fuzzy information in non-market valuation studies: the role of familiarity. Journal of environmental planning and management 57 (1), 123–143.
Hoegh-Guldberg, O., Mumby, P.J., Hooten, A.J., Steneck, R.S., Greenfield, P., Gomez, E., Harvell, C.D., Sale, P.F., Edwards, A.J., Caldeira, K., 2007. Coral reefs under rapid climate change and ocean acidification. Science (1979) 318 (5857), 1737–1742.
Holmes, T.P., Adamowicz, W.L., Carlsson, F., 2017. Choice experiments. A Primer On Nonmarket Valuation. Springer, pp. 133–186.
Hu, W., Adamowicz, W.L., Veeman, M.M., 2009. Consumers' preferences for GM food and voluntary information access: a simultaneous choice analysis. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 57 (2), 241–267.
Johnston, R.J., Boyle, K.J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T.A., Hanemann, W.M., Hanley, N., Ryan, M., Scarpa, R., 2017. Contemporary guidance for stated preference studies. J. Assoc. Environ. Resour. Econ. 4 (2), 319–405.
Jones, B.A., Ripberger, J., Jenkins-Smith, H., Silva, C., 2017. Estimating willingness to pay for greenhouse gas emission reductions provided by hydropower using the contingent valuation method. Energy Policy 111, 362–370.
Kitano, S., Yamamoto, N., 2020. The role of consumer knowledge, experience, and heterogeneity in fish consumption: policy lessons from Japan. Journal of Retailing and Consumer Services 56, 102151.
Kroeker, K.J., Kordas, R.L., Crim, R., Hendriks, I.E., Ramajo, L., Singh, G.S., Duarte, C.M., Gattuso, J.P., 2013. Impacts of ocean acidification on marine organisms: quantifying sensitivities and interaction with warming. Glob. Chang. Biol. 19 (6), 1884–1896.
Kulesz, M.M., Lundh, T., De Koning, D.-J., Lagerkvist, C.-J., 2019. Dissuasive effect, information provision, and consumer reactions to the term 'Biotechnology': the case of reproductive interventions in farmed fish. PLoS. One 14 (9).
Li, Q., McCluskey, J.J., Wahl, T.I., 2004. Effects of information on consumers' willingness to pay for GM-corn-fed beef. J. Agric. Food Ind. Organ. 2 (2).

Louviere, J.J., Street, D., Burgess, L., Wasi, N., Islam, T., Marley, A.A., 2008. Modeling the choices of individual decision-makers by combining efficient choice experiment designs with extra preference information. J. Choice Model. 1 (1), 128–164.
Mackenzie, C.L., Ormondroyd, G.A., Curling, S.F., Ball, R.J., Whiteley, N.M., Malham, S. K., 2014. Ocean warming, more than acidification, reduces shell strength in a commercial shellfish species during food limitation. PLoS. One 9 (1), e86764.
Mann, M.E., Rahmstorf, S., Kornhuber, K., Steinman, B.A., Miller, S.K., Coumou, D., 2017. Influence of anthropogenic climate change on planetary wave resonance and extreme weather events. Sci. Rep. 7, 45242.
Mathews, K.E., Freeman, M.L., Desvousges, W.H., 2006. How and how much? Valuing Environmental Amenities Using Stated Choice Studies. Springer, pp. 111–133.
McFadden, J.R., Huffman, W.E., 2017. Consumer valuation of information about food safety achieved using biotechnology: evidence from new potato products. Food Policy. 69, 82–96.
Meenakshi, J., Banerji, A., Manyong, V., Tomlins, K., Mittal, N., Hamukwala, P., 2012. Using a discrete choice experiment to elicit the demand for a nutritious food: willingness-to-pay for orange maize in rural Zambia. J. Health Econ. 31 (1), 62–71.
Munro, A., Hanley, N.D., 2001. Information, uncertainty, and Contingent valuation. *Valuing Environmental Preferences: Theory and Practice of the Contingent Valuation Method in the US, EU, and Developing Countries*. Oxford University Press, Oxford, pp. 258–274.
Narita, D., Rehdanz, K., 2017. Economic impact of ocean acidification on shellfish production in Europe. J. Environ. Plann. Manage. 60 (3), 500–518.
Needham, K., Czajkowski, M., Hanley, N., LaRiviere, J., 2018. What is the causal impact of information and knowledge in stated preference studies? Resour. Energy Econ. 54, 69–89.
Olsen, S.O., 2003. Understanding the relationship between age and seafood consumption: the mediating role of attitude, health involvement and convenience. Food Qual. Prefer. 14 (3), 199–209.
Øvrum, A., Alfnes, F., Almli, V.L., Rickertsen, K., 2012. Health information and diet choices: results from a cheese experiment. Food Policy. 37 (5), 520–529.
Petit, O., Lunardo, R., Rickard, B., 2020. Small is beautiful: the role of anticipated food waste in consumers' avoidance of large packages. J. Bus. Res. 113, 326–336.
Ponce, R.D., Vasquez-Lavín, F., San Martin, V.A., Hernández, J.I., Vargas, C.A., Gonzalez, P.S., Gelcich, S., 2019. Ocean acidification, consumers' preferences, and market adaptation strategies in the mussel aquaculture industry. Ecological Economics 158, 42–50.
R Core Team. (2022). *R: a language and environment for statistical computing. R Foundation for Statistical Computing.* In https://www.R-project.org/.
Reuveny, R., 2007. Climate change-induced migration and violent conflict. Polit. Geogr. 26 (6), 656–673.
San Martin, V.A., Gelcich, S., Lavín, F.V., Oliva, R.D.P., Hernández, J.I., Lagos, N.A., Birchenough, S.N., Vargas, C.A., 2019. Linking social preferences and ocean acidification impacts in mussel aquaculture. Sci. Rep. 9 (1), 1–9.
Schläpfer, F., Roschewitz, A., Hanley, N., 2004. Validation of stated preferences for public goods: a comparison of contingent valuation survey response and voting behaviour. Ecol. Econ. 51 (1–2), 1–16.
Shr, Y.-H.J., Ready, R., Orland, B., Echols, S., 2019. How do visual representations influence survey responses? Evidence from a choice experiment on landscape attributes of green infrastructure. Ecol. Econ. 156, 375–386.
Solomon, S., Plattner, G.-K., Knutti, R., Friedlingstein, P., 2009. Irreversible climate change due to carbon dioxide emissions. Proc. Natl. Acad. Sci. 106 (6), 1704–1709.
Street, D.J., Burgess, L., 2007. The Construction of Optimal Stated Choice experiments: Theory and Methods, Vol. 647. John Wiley & Sons.
Sveinsdóttir, K., Martinsdóttir, E., Green-Petersen, D., Hyldig, G., Schelvis, R., Delahunty, C., 2009. Sensory characteristics of different cod products related to consumer preferences and attitudes. Food Qual. Prefer. 20 (2), 120–132.
Swait, J., Louviere, J., 1993. The role of the scale parameter in the estimation and comparison of multinomial logit models. Journal of marketing research 30 (3), 305–314.
Thomsen, J., Casties, I., Pansch, C., Körtzinger, A., Melzner, F., 2013. Food availability outweighs ocean acidification effects in juvenile M ytilus edulis: laboratory and field experiments. Glob. Chang. Biol. 19 (4), 1017–1027.
Tienhaara, A., Ahtiainen, H., Pouta, E., Czajkowski, M., 2021. Information use and its effects on the valuation of agricultural genetic resources. Land. Econ. 090319-090127R090311.
Train, K.E., 2009. Discrete Choice Methods With Simulation. Cambridge university press.
Trondsen, T., Braaten, T., Lund, E., Eggen, A., 2004. Consumption of seafood—The influence of overweight and health beliefs. Food Qual. Prefer. 15 (4), 361–374.
Urban, M.C., 2015. Accelerating extinction risk from climate change. Science (1979) 348 (6234), 571–573.
Vargas, C.A., Lagos, N.A., Lardies, M.A., Duarte, C., Manríquez, P.H., Aguilera, V.M., Broitman, B., Widdicombe, S., Dupont, S., 2017. Species-specific responses to ocean acidification should account for local adaptation and adaptive plasticity. Nat. Ecol. Evol. 1 (4), 1–7.
Vásquez, F., Gelcich, S., Lerdón, X.P., Bustos, F.M., 2016. The role of information in changing tourists behavioral preferences at the Humboldt penguin reserve in northern Chile. Ocean. Coast. Manage 125, 63–69.
Wang, X., Curtis, K.R., Moeltner, K., 2011. In: *Modeling the impact of new information on consumer preferences for specialty meat products* 55th Conference of the Australian Agricultural and Resource Economics Society. Melbourne, Australia.
Willer, D.F., Aldridge, D.C., 2020. Sustainable bivalve farming can deliver food security in the tropics. Nat. Food 1 (7), 384–388.