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When Risk Information Changes the Trip: Evidence from a Randomized Panel Combining Discrete Choice and Travel Cost Methods

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Abstract: Coastal bathing delivers large welfare benefits but exposes recreationists to low-probability, high-salience microbial risks that are likely to become more frequent under climate change. Because these risks are largely invisible, behaviour and welfare depend on beliefs and the effectiveness of risk communication. We provide causal evidence on how pathogen-risk information affects preferences and recreation demand using a three-wave panel survey of users of the Gulf of Gdańsk and the Vistula Lagoon (Poland). A stratified national sample identified 3,312 active coastal users in Wave 1 (spring 2024); 2,588 respondents returned in Wave 2 (summer 2024), where they were randomly assigned to receive either minimal information or increasingly detailed pathogen-risk scripts, and then completed a repeated beach-site discrete choice experiment. Approximately one year later (spring 2025), 1,507 users completed a policy-referendum discrete choice experiment on programs combining water-quality improvements, monitoring frequency, and household costs, alongside a repeated travel-cost module capturing multi-day trips and beach outings. Information treatments significantly increased objective and self-assessed knowledge and selectively raised willingness to travel/pay for risk-relevant attributes – especially frequent water-quality monitoring and water-quality improvements – while leaving unrelated attributes largely unchanged. Travel-cost models indicate that information affects trip-taking behaviour, yet the marginal travel-cost sensitivity remains stable, consistent with a demand shift rather than a change in the “price” slope. The results imply that welfare estimates are information-dependent and that credible risk communication can function as a scalable, low-cost complement to traditional coastal health-risk management.

Keywords: Bathing water quality, Pathogens, Microbial contamination, Risk communication, Information treatments, Discrete choice experiment (DCE), Travel cost method (TCM), Recreation demand, Welfare measurement, Consumer surplus, Climate adaptation, Coastal health risks, Baltic Sea, Poland

JEL codes: C93, C35, Q26, Q51, Q53, D91, I18

1. Introduction

Coastal recreation generates substantial use value and well-being benefits ([Czajkowski et al., 2024](#)), yet it also entails exposure to low-probability but highly salient health risks from microbial contamination (e.g., *E. coli*, enterococci, *Vibrio* spp., cyanobacteria) ([Löptien & Dietze, 2022](#); [Michalska et al., 2021](#); [Riedinger et al., 2024](#)). These risks are particularly challenging for policy because they are largely invisible to users at the time of decision-making: beachgoers typically observe weather, crowding, and amenities, but not microbiological contamination. As a result, behaviour and welfare depend not only on underlying hazard levels, but also on what individuals believe about the risk and how they interpret water-quality signals. In this setting, risk communication is not merely an “add-on” to monitoring – it is a policy lever that can shift demand, change the value people place on monitoring and mitigation, and potentially reduce exposure by influencing site choice and trip-taking.

Climate change strengthens the relevance of this mechanism ([Reusch et al., 2018](#)). Rising water temperatures and more frequent extreme rainfall episodes are expected to increase the prevalence and persistence of coastal pathogens, raising the likelihood of contamination events and bathing site closures ([Semenza, 2020](#)). The traditional response relies on a combination of (i) physical safety measures (designated bathing areas, lifeguards) and (ii) information systems (monitoring frequency, disclosure, warnings and signage). However, the welfare benefits of these measures may be substantially mismeasured if preferences are information-dependent – i.e., if people value monitoring and risk reduction differently once risks become salient and better understood.

We study these questions in one of Poland’s most important maritime recreation regions: the Gulf of Gdańsk and the Vistula Lagoon. The area is heavily visited and features a combination of open-coast and semi-enclosed waters with limited exchange, making it susceptible to pollution accumulation and microbiological contamination risks. It is also a setting where public information is available but can be fragmented, unevenly understood, and not always behaviourally effective – exactly the conditions under which an information intervention can matter for exposure and welfare.

This paper examines whether and how pathogen-risk information changes (i) preferences for bathing site attributes and (ii) coastal recreation demand and welfare. We do so by combining stated-preference and revealed-preference evidence within a panel and randomized experimental design. Specifically, we exploit a three-wave panel survey of coastal users in

which respondents were randomly assigned to information treatments of varying depth and format concerning the presence of bathing-water pathogens, exposure pathways, symptoms, vulnerable groups, and prevention guidance.

Our contribution is threefold. First, we provide causal evidence on information-driven preference updating using a two-wave panel discrete choice experiment (DCE) on beach-site choice, estimated within a framework that nets out time-invariant heterogeneity and generic panel conditioning. Second, we evaluate whether information has longer-run implications for policy support by analysing a subsequent “advisory referendum” DCE eliciting willingness to pay for programs that combine mitigation (reduced infection risk via improved water quality) and adaptation (more frequent monitoring and disclosure). Third, we complement these stated-preference results with a panel travel cost (TC) module that captures multi-day trips and beach outings, allowing us to assess whether the information shock is associated with shifts in trip-taking behaviour and whether the marginal travel-cost relationship remains stable over time.

The evidence indicates that the information treatments successfully increased both objective and self-assessed knowledge in the short run, confirming that respondents processed and learned from the scripts. In the beach-choice DCE, information selectively increases valuations for risk-relevant attributes – especially frequent water-quality monitoring and disclosure – while leaving unrelated safety and amenity attributes largely unchanged. This pattern is consistent with a risk-salience mechanism rather than a generic increase in attentiveness. In the policy-referendum DCE, prior exposure to pathogen information is associated with stronger preferences for water-quality improvements and, depending on the information format, higher support for monitoring frequency. Finally, the travel-cost analysis suggests that additional information affects trip-taking behaviour, while the relationship between travel cost and trips is stable within individuals – consistent with a demand shift induced by perceived risk rather than a change in “price” sensitivity.

These findings imply that welfare measures used in benefit–cost analysis are information-dependent: estimates derived under limited awareness may understate the benefits of monitoring and risk-reduction policies. More broadly, they position risk communication as a scalable and comparatively low-cost complement to conventional mitigation and adaptation measures in coastal water management.

2. Background and conceptual framework

Bathing-water quality is a salient environmental-health issue because microbial contamination can generate acute symptoms (e.g., gastrointestinal illness) and, for vulnerable users, potentially severe outcomes ([Ali et al., 2025](#); [Leddin & Macrae, 2020](#)). In the Polish Baltic context, the relevant hazards discussed in the study materials include *Escherichia coli*, intestinal enterococci, *Vibrio* spp., and cyanobacteria (blue-green algae) ([Sharma et al., 2003](#); [Theron & Cloete, 2002](#)). In contrast to many conventional beach attributes (e.g., amenities, weather, crowding), these risks are largely not directly observable at the time of recreation. Consequently, behaviour and welfare depend on beliefs and information processing, not only on the underlying hazard level.

The case study area – Gdańsk Bay and the Vistula Lagoon – provides a policy-relevant setting with intensive tourism and periodic beach closures tied to microbiological indicators and blooms. The official statistics note substantial closures in the 2023 season (e.g., 146 closures linked to cyanobacteria blooms and 41 and 34 closures linked to exceedances of *E. coli* and enterococci thresholds, respectively). The same sources emphasize that pathogen occurrence and closures are expected to become more pressing under climate change.

A crucial institutional detail for the information mechanism is how monitoring operates and how it is communicated. Respondents were informed that bathing waters in Poland are tested prior to the opening of the swimming season and then “upon necessity,” and that monitoring occurs roughly once every two weeks on average. This implies that (i) the frequency and visibility of monitoring can vary and (ii) users may not have a stable or accurate mental model of either monitoring intensity or what monitoring results imply for personal risk.

In this policy domain, managers typically deploy two broad classes of interventions: physical safety measures (e.g., designated bathing areas and lifeguards) and information systems (monitoring, disclosure, on-site boards, and warnings). These levers are conceptually distinct. Physical safety targets hazards such as drowning risk and acute incidents, whereas information systems target *exposure decisions* to microbial hazards by enabling avoidance, substitution, and precautionary behaviour (e.g., choosing monitored sites, adjusting timing, limiting contact).

This distinction matters for benefit–cost analysis because an information intervention can increase welfare even without changing objective hazard levels – by enabling better matching

between users' risk preferences/vulnerability and the recreation environment. The study framing therefore treats risk communication as a potentially scalable, comparatively low-cost “soft” adaptation tool – especially relevant where budgets constrain continuous high-frequency testing or large infrastructure expansions.

Evidence on information provision in stated-preference (SP) and field contexts is mixed. The literature notes that additional context can improve understanding without necessarily shifting mean willingness to pay (WTP), while more targeted “risk salience” treatments sometimes move valuations for attributes directly tied to the information content ([Bateman et al., 2023](#); [Czajkowski et al., 2016](#); [Hoehn et al., 2010](#); [Schneider & Zawadzki, 2025](#)). This motivates a central empirical expectation in the current study: information should not uniformly shift all tastes, but should primarily affect valuations for attributes that are *logically linked to pathogen risk* – notably water-quality monitoring and disclosure.

The information treatments were designed to create controlled variation in salience and framing. In the second wave, respondents were randomly assigned to receive varying degrees of information on pathogens, exposure pathways, health outcomes, and preventive measures, and then completed the same beach-choice DCE as in the first survey. Within the “more detailed information” group, the format was randomized further: combined information on multiple pathogens versus more detailed pathogen-specific information presented separately. The descriptions also included information explicitly referencing symptoms and emphasising that severe cases may require hospitalization and can be fatal in rare cases – features that plausibly amplify salience, especially for vulnerable individuals.

The underlying behavioural mechanism can be summarized as learning-driven preference updating: new, credible information about microbial risks changes beliefs about bathing-water safety and the value of monitoring and disclosure, which then changes trade-offs in beach choice and policy support. This explicitly links the setting to multiple learning channels – habit formation in recreation choices, learning from past positive/negative experiences, cognitive learning (attention, perception, memory, active search), and social learning through family/friends/media.

The experimental design implies that information is not a neutral “context” provided to respondents, but an integral part of the policy environment. In coastal bathing, exposure decisions are made under uncertainty, with imperfect and heterogeneous priors about what

pathogens are, how infection occurs, and what monitoring results mean for personal risk. In such settings, communication changes the decision problem by changing beliefs. This has direct consequences for welfare measurement. If people only partially understand microbial risks, baseline welfare estimates will reflect those priors and may understate the value of monitoring and disclosure. By contrast, when risk information is clearer and more salient, individuals may attach higher value to monitoring frequency and transparent reporting, implying that the welfare benefit of information systems is partly created through learning itself, not only through any underlying change in objective water quality. Moreover, information is likely to operate unevenly across the population: those with greater vulnerability or perceived susceptibility have stronger incentives to attend to risk signals and may update more strongly. This creates a distributional dimension to risk communication policy that benefit–cost analysis rarely captures – information can disproportionately benefit groups for whom exposure reductions have the largest health value.

These mechanisms yield a set of testable hypotheses consistent with the implemented treatments and panel structure:

- **H1 (Learning and salience).** Relative to the control group, respondents exposed to pathogen-risk information report higher subjective knowledge and demonstrate higher objective knowledge immediately after the intervention. The increase is expected to be graded by informational intensity, with the largest gains under the most detailed scripts.
- **H2 (Selective preference updating).** Information changes preferences primarily for attributes that directly mitigate pathogen exposure or help interpret pathogen-related risk – most notably the frequency and transparency of water-quality monitoring. Attributes not logically tied to pathogen exposure (e.g., general safety cues such as lifeguards or designation, and weather boards) should exhibit comparatively small or null treatment effects.
- **H3 (Policy valuation).** In the policy-referendum choice setting, prior exposure to pathogen-risk information increases willingness to pay for programs that reduce infection risk and improves support for more frequent monitoring and reporting. Any differences between combined-pathogen and pathogen-specific formats reveal whether granularity and diagnosticity of information matter for valuation.
- **H4 (Behavioural demand response).** In revealed-preference recreation demand, information exposure is associated with changes in trip-taking and/or site selection

consistent with avoidance or substitution under heightened perceived risk. The dominant empirical signature is a shift in the demand level (trip frequency and/or destination patterns) rather than a change in marginal travel-cost sensitivity, reflecting updated beliefs about baseline risk rather than altered responsiveness to the generalized “price” of travel.

In combination, these hypotheses formalize a central proposition: preferences relevant for coastal water management are not fixed primitives but are partly produced by the informational environment created by policy. Monitoring frequency, disclosure systems, and communication campaigns therefore affect welfare through two channels – by enabling exposure reduction and by reshaping the value people place on risk-relevant attributes once risks are understood. This perspective motivates the empirical strategy adopted in the remainder of the paper, which treats the randomized information scripts as an exogenous shock and traces its consequences across stated beach choices, policy valuations, and revealed recreation demand.

3. Data and experimental design

3.1. Study setting and target population

The empirical setting is coastal recreation in northern Poland, focusing on trips to the Gulf of Gdańsk and the Vistula Lagoon – an area that constitutes one of the country’s most important tourism destinations and experiences strong seasonal peaks in bathing-water use. The study targets *active users* of this recreation system: individuals who have visited either the Gulf of Gdańsk or the Vistula Lagoon for leisure or recreation within the previous 36 months.

3.2. Panel recruitment, screening, and retention across waves

The panel was recruited through a large baseline survey administered between May and August 2024 to a nationally representative sample (stratified by key demographics). A total of 12,254 respondents were invited to the baseline survey (S1). Eligibility for the panel component required meeting three screening criteria: (i) consent to participate in follow-up waves, (ii) having visited the sea or a lagoon in Poland for recreation/leisure within the past 36 months, and (iii) having visited specifically the Gulf of Gdańsk or the Vistula Lagoon within that period.

Applying these criteria yielded 3,312 qualified respondents (“active users”) included in the study. The second wave (S2) was fielded in July–August 2024 and produced 2,588 completed interviews, corresponding to a 78.14% retention rate relative to S1. The third

wave (S3) was conducted approximately one year later (July–September 2025) and yielded 1,593 completed interviews; retention relative to S1 and S2 was 48.10% and 61.55%, respectively. Because all S1 respondents were re-invited to S3, the design also allowed temporary attriters to return: 225 respondents skipped S2 but participated in S3. Table 1 summarizes the screening criteria and sample composition.

Table 1. Screening criteria - qualified “active users,”

Total number of invited respondents (total)	12,254		Number of respondents qualified for the study (included)	3,312
Variable	Number of respondents (total)	% (total)	Number of respondents (included)	% (included)
Sex/Gender				
Female	6,410	52.31%	1,830	55.25%
Male	5,805	47.37%	1,474	44.51%
Other	30	0.24%	7	0.21%
Refusal to answer	9	0.07%	1	0.03%
Age group				
18-24 years old	1,336	10.90%	357	10.78%
25-44 years old	4,809	39.24%	1,651	49.85%
45-64 years old	4,136	33.75%	995	30.04%
65+ years old	1,973	16.10%	309	9.33%
Education level				
Elementary, lower secondary, or basic vocational	1,377	11.24%	200	6.04%
Upper secondary (general and vocational) or post-secondary	6,952	56.73%	1,426	43.06%
Higher education (Bachelor's, Engineer's, Master's, Doctoral)	3,925	32.03%	1,686	50.91%
Screening question no. 1: Consent to participate in future survey waves				
Fulfilled	11,523	94.04%	3,312	100.00%
Visited the sea or a lagoon in Poland for recreation or leisure in the last 36 months				
Fulfilled	6,205	50.64%	3,312	100.00%
Visited the Gulf of Gdańsk or the Vistula Lagoon for recreational or leisure purposes within the last 36 months				
Fulfilled	3,312	27.03%	3,312	100.00%

3.3. Survey development, implementation, and ethics

Survey development was preceded by extensive background work on water quality conditions, closures, regulations, monitoring systems, and public information tools, supported by a literature review to align the interventions with best practices in water risk communication. Instrument development involved collaboration with local agencies and community groups to ensure local relevance and interpretability of informational content. The questionnaire was pretested using a verbal protocol to assess clarity, completeness, and respondent comprehension.

Fieldwork was implemented by a professional research firm selected through a transparent public procurement procedure, with documented consultation involving the university's legal/administrative services. The study underwent ethical review and received approval from the Ethical Committee, and survey implementation followed established quality and ethical guidelines, including the ICC/ESOMAR code. Data collection was conducted using CAWI (Computer-Assisted Web Interviewing).

3.4. Structure and sequencing of core modules (SP and RP integration)

The design integrates (i) a *revealed-preference* recreation-demand component (travel-cost module) and (ii) *stated-preference* discrete choice experiments, with randomized information treatments layered into the panel to identify causal impacts of risk communication on knowledge and preferences over time.

A critical sequencing feature is that baseline behavioral measures, opinions, motivations, and related constructs were collected *before* respondents were exposed to pathogen-risk information, to minimize priming and to preserve an interpretable pre-treatment benchmark. This sequencing supports clean comparisons across waves (and across randomized treatments) when estimating information-driven changes in knowledge, preferences, and welfare measures.

3.5. Information treatments (randomized risk communication)

The main information intervention was implemented in S2 as a randomized module on bathing-water pathogens and health risks. Approximately one-third of S2 respondents were assigned to a benchmark condition receiving minimal pathogen information (T0), aligned with baseline framing used earlier in the study. The remaining respondents received more detailed information addressing vulnerable groups, infection pathways, and possible outcomes, explicitly noting that while symptoms typically resolve within days, severe cases may require hospitalization and can (rarely) be fatal.

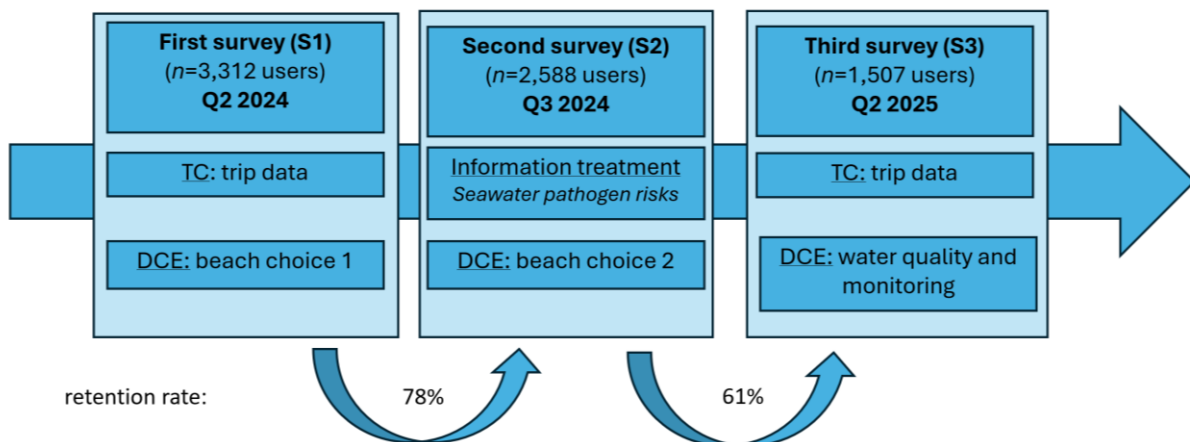
Within the detailed-information treatment, respondents were further randomized into two formats: (T1) combined information for four pathogens presented jointly, and (T2) more granular pathogen-specific information presented on separate screens. Across both formats, the scripts included pathogen characteristics, occurrence in Poland, and associated infection risks and health outcomes. All treated respondents then received prevention and risk-reduction

guidance (e.g., monitoring official information, hygiene/safety practices, food/water safety, and broader awareness).

After the information module, all respondents – including the benchmark group – completed repeated measures of perceived knowledge, beliefs, attitudes, and opinions, enabling within-respondent and between-group comparisons. S2 also introduced an objective knowledge quiz (13 true–false items) administered to all respondents.

S3 was designed to test longer-run persistence by revisiting knowledge, attitudes, behavior, and preferences one year after baseline, and it included a repeated travel-cost module to support longitudinal analysis of behavioral adaptation. In S3, a common baseline information script was provided to all respondents prior to the policy-referendum DCE to define the valuation good and standardize comprehension of the policy context. Figure 1 depicts the overall panel structure and sequencing of modules. Figure 1 summarizes the randomized information treatments and their key content elements.

Figure 1. Information treatment and study’s content elements



Notes: Information treatments were administered in S2. S3 includes a common baseline information script for valuation standardization. The key identification relies on within-person pre/post comparisons and between-treatment differences.

3.6. Discrete Choice Experiment 1 (DCE1): beach-choice (S1 and S2)

DCE1 elicits preferences over attributes of bathing sites, anchored in respondents’ own “usual” bathing trip to ensure realism and reduce hypothetical abstraction. Each choice task presents a status quo alternative alongside one or two experimentally varied alternatives. Respondents completed 12 choice tasks.

The attribute set captures both amenity and risk-management features: (i) whether the site is designated and whether lifeguards are present, (ii) whether a board provides weather monitoring and information (temperature, wind, sea state), (iii) the availability and frequency of water quality monitoring/information, and (iv) travel distance. Monitoring frequency varies from none/low frequency at baseline to more intensive schedules, including once per week, once every two days, and daily monitoring. Distance is implemented via a pivot design relative to the respondent's status quo distance (−50%, −25%, 0%, +25%, +50%, +100%), supporting individual-specific trade-offs between risk-related attributes and travel burden.

The efficient Bayesian experimental design with priors updated twice during data collection is employed, enabling precise estimation of substitution patterns and marginal values for monitoring improvements and other site characteristics. In S2, the DCE1 was repeated after the randomized information module, so that differences in choices can be attributed to information exposure rather than a change in the DCE1 instrument. Table 2 lists attributes and levels used in the beach-choice DCE1. Figure 2 shows an example choice task as presented to respondents.

Table 2. Beach-choice discrete choice experiment (DCE1): attributes and levels

Attributes	Levels
Designated bathing site	<ul style="list-style-type: none"> • No • Yes – designated • Yes – lifeguarded
Information on temperature, wind strength, and the state of the sea	<ul style="list-style-type: none"> • No • Yes
Information on water quality	<ul style="list-style-type: none"> • None • Once every 2 weeks • Once every 1 week • Once every 2 days • Every day
Distance	<ul style="list-style-type: none"> • -50% • -25% • 0% • +25% • +50% • +100%

Notes: Distance implemented as a pivot around each respondent's reported 'usual' site to improve realism and identify trade-offs. DCE1 was administered in S1 (baseline) and repeated in S2 after the information module. Attribute wording mirrored official/institutional framing used in local monitoring communication.

Figure 2. Example beach-choice choice task (DCE1) with status quo and two alternatives

Which of these locations (bathing sites) would you go to for recreation or outdoor water recreation?

	Location A	Location B	Location C
Designated bathing site	No	Yes	Yes - lifeguarded
Information on temperature, wind strength, and the state of the sea	No	Yes	No
Information on water quality	Yes – once every 2 weeks	Yes - once every 1 week	Yes - once every 2 days
Distance	5 km	6.25 km	7.5 km
Your choice:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Notes: Distance is pivoted around the respondent's reported usual site; other attributes vary per experimental design. Respondents were instructed to assume identical weather/crowding aside from the listed attributes.

3.7. Revealed-preference recreation demand: travel-cost module (S1 and S3)

The travel-cost module in S1 captures detailed recreational behavior for both multi-day trips and single-day outings to the study areas, with rich trip descriptors (routes, transport modes, accommodation, length of stay, activities). The module supports a two-tier demand framework reflecting how coastal recreation occurs in practice – combining tourism-type trips with individual beach outings – and provides a behavioral benchmark of respondents' exposure and engagement with coastal waters.

Descriptive benchmarks from S1 indicate an average of 1.39 multi-day trips over the preceding 12 months (3.20 over three years), with a mean duration of around 5.6 nights, a mean travel distance of 407 km, and a mean travel time of approximately 5 hours and 20 minutes; car travel dominated (69%), followed by trains (23%). Respondents also reported an average group size of 4.8 persons (including ~1.3 children) and an average of 14 coastal-water visits over the prior 36 months. The same travel-cost module was repeated in S3 to enable longitudinal analysis of whether information interventions and evolving risk perceptions translate into measurable changes in recreation demand and destination patterns.

3.8. Discrete Choice Experiment 2 (DCE2): policy-referendum program for bathing-water safety (S3)

S3 replaces the beach-choice DCE1 with a policy-oriented valuation task framed as an advisory referendum designed to strengthen consequentiality and improve incentive compatibility (Carson & Groves, 2007; Vossler et al., 2012; Vossler & Holladay, 2018). The policy-referendum DCE2 elicits willingness to pay for a national programme combining monitoring and risk-reduction measures for bathing-water safety, with alternatives defined by: (i) infection risk after bathing (expressed as infections per 1,000 bathers), (ii) frequency of water quality monitoring, and (iii) annual household cost (additional tax).

The risk attribute is explicitly quantified and interpreted for respondents (e.g., 20 per 1,000 as 2%, 10 per 1,000 as 1%, 5 per 1,000 as 0.5%, 2 per 1,000 as 0.2%), allowing valuation to be directly expressed in terms of avoided infections. Monitoring frequency ranges from monthly (status quo) to daily, with intermediate levels (twice per month, weekly, twice per week). The annual cost attribute spans a wide range (10–500 PLN), enabling estimation of WTP distributions and policy support under realistic budget envelopes.

A key design consideration is external validity. Notably, the policy-referendum DCE2 is administered to returning panelists classified as users and exposed to multiple design variations, implying that estimates should be interpreted as internally valid for the user panel rather than mechanically generalizable to population-level support. To strengthen external validity, the study implemented a replication wave (S4) with a fresh sample (September–October 2025; $n = 1,111$), closely mirroring S3 with minor adjustments for first-time respondents; these S4 data are documented for transparency and intended future analysis. Table 3 reports the policy-referendum attributes and levels. Figure 3 provides an example of a referendum choice task.

Table 3. Policy-referendum discrete choice experiment (DCE2): program attributes and levels

Attributes	Levels
<p>Water quality (risk of infection after bathing, number of infections per 1,000 people)</p>	<ul style="list-style-type: none"> • 20 per 1,000 – for every 1,000 swims, approximately 20 people will become ill (2%) • 10 per 1,000 – for every 1,000 swims, approximately 10 people will become ill (1%) • 5 per 1,000 – for every 1,000 swims, approximately 5 people will become ill (0.5%) • 2 per 1,000 – for every 1,000 swims, approximately 2 people will become ill (0.2%)
<p>Frequency of water monitoring</p>	<ul style="list-style-type: none"> • 1 time per month • 2 times per month (once every 2 weeks)

Attributes	Levels
	<ul style="list-style-type: none"> • 1 time per week • 2 times per week • daily
Annual cost for your household	<ul style="list-style-type: none"> • 10 PLN • 20 PLN • 50 PLN • 100 PLN • 200 PLN • 500 PLN

Notes: Risk levels were presented both as cases per 1,000 and as percentages to standardize comprehension. All respondents received a common baseline informational script prior to DCE2 to define the valuation good. DCE2 was administered in S3; a fresh-sample replication (S4) was fielded to support external-validity checks.

Figure 3. Example policy-referendum choice task (DCE2): infection risk, monitoring frequency, and annual tax

Which program would you vote for?			
If you think that none of the programs presented are worth the price, select the “status quo” option.			
	Option A	Option B	Status quo (no new program)
Water quality (risk of infection after bathing, number of infections per 1,000 people)	2 per 1,000	10 per 1,000	20 per 1,000
Frequency of water monitoring	daily	2 times per month	1 time per month
Annual cost for your household	50 PLN	100 PLN	0 PLN
Your choice:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Notes: Risk is presented as infections per 1,000 bathers, with percentage equivalents shown to aid interpretation. The status quo corresponds to no new program and zero additional cost.

4. Econometric strategy and welfare measures

This section sets out the identification strategy and the econometric models used to quantify (i) information-induced preference updating in the repeated beach-choice DCE (DCE1) and (ii) persistence of information effects in the later policy-referendum DCE (DCE2), and then links both to welfare measures.

4.1 Identification: randomized information as an exogenous “belief shock”

The core identification lever is the randomized assignment to pathogen-risk information in S2, combined with the panel structure of S1-S2 stated choices. In S2, respondents were allocated either to a benchmark group receiving minimal pathogen information (T0) or to more detailed scripts, with the detailed group further split between a “combined-pathogens” format (T1) and a “pathogen-specific/separate” format (T2). The S2 survey then replicated the S1 beach-choice DCE1, which enables within-person comparisons of preference parameters before and after the information intervention, while netting out time-invariant heterogeneity.

Formally, we treat the information script as an exogenous shock to the respondent’s beliefs and risk salience. In the repeated DCE1 setting, this motivates a difference-in-differences interpretation: the preference change from S1 to S2 among treated respondents (T1/T2) is compared to the contemporaneous preference change among the benchmark group (T0), who experience the same panel timing and instrument but without additional information. The key empirical objects are therefore *treatment-by-post* shifts in the marginal utilities of risk-relevant attributes (especially water-quality monitoring), rather than uniform shifts across all attributes.

In the S3 policy-referendum DCE (DCE2), all respondents receive a common baseline description defining the valuation good, but they differ in whether – and how – they were exposed to the more detailed information scripts one year earlier. The S3 analysis, therefore, exploits cross-group differences (T1/T2 vs T0) in policy preferences, interpreted as persistence (or longer-run imprinting) of information exposure on valuations. In the analysis, these longer-run differences are implemented via interactions of the random-parameter means with indicators for earlier information format.

4.2 Discrete choice models (DCE1 and DCE2)

Random utility and mixed logit

Choices are modelled within a Random Utility Model framework ([McFadden, 1973](#)). For respondent n , alternative j , and a choice task t , the utility can be expressed as:

$$U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt},$$

where x_{njt} is the vector of attribute levels (dummy-coded, with resources coded as continuous where applicable) and ε_{njt} is an i.i.d. extreme-value error term. Preference heterogeneity is captured by allowing β_n to vary across individuals (mixed logit / random-parameters logit), and

we allow for correlated random coefficients to flexibly represent substitution patterns and unobserved taste covariation ([Hensher & Greene, 2003](#); [Mariel & Meyerhoff, 2018](#)).

We assume Normal distributions for non-resource attributes and a Log-Normal distribution for the resource coefficient – distance in DCE1 and cost in DCE2 – so that the resource coefficient is constrained to be negative for all individuals.

For interpretability, we report estimates in (i) *willingness-to-pay* (WTP) space for DCE2 and (ii) *willingness-to-travel* (WTT) space for DCE1, where the marginal utilities of non-resource attributes are scaled by the individual-specific marginal utility of the resource.

At the same time, treatment-effect estimation in a fully interacted WTP/WTT space can be numerically unstable when random coefficients are correlated and when interaction terms are introduced on multiple parameters. To that end, we therefore estimate the main-effects model in WTP/WTT space and estimate treatment-induced preference shifts using a preference-space specification with interactions entered as covariates of the random-parameter means. This approach is designed to isolate systematic treatment shifts in tastes while retaining a robust mixed-logit structure.

For the repeated beach-choice DCE (S1 and S2), information affects preferences through interactions that capture post-treatment deviations from baseline. Let $Post_{nt}$ indicate S2 choice tasks and let $T1_n$ and $T2_n$ indicate assignment to combined or separate detailed scripts. The mean of a given random parameter k is modelled as:

$$\overline{\beta_{k,n}} = \overline{\beta_{k,0}} + \gamma_{k,Post}Post_{nt} + \gamma_{k,T1}(T1_n \times Post_{nt}) + \gamma_{k,T2}(T2_n \times Post_{nt}),$$

so that $\gamma_{k,T1}$ and $\gamma_{k,T2}$ identify causal shifts in the valuation of attribute k attributable to the information exposure, relative to the benchmark group's generic S2 shift. This parameterization aligns with our implementation, where treatment effects are read from interaction terms (“interactions of means”) in preference space.

The policy-referendum DCE (S3) elicits WTP for programs that combine (i) mitigation via lower infection risk, (ii) adaptation via monitoring frequency, and (iii) an annual household tax. The design and attribute definitions are explicitly policy-oriented and framed as an advisory referendum.

To test whether earlier information exposure has persistent effects, we again specify treatment-format indicators (from S2) as covariates, shifting the means of random parameters

in S3. These interactions are used to compare how joint versus pathogen-specific formats differentially shift preferences for risk reductions and monitoring intensity.

In all choice models, standard errors are computed with respondent-level clustering to account for repeated tasks per individual, and simulation-based integration is used to evaluate the mixed-logit likelihood ([Czajkowski & Budziński, 2019](#); [Hole, 2007](#)).

4.3. Recreation-demand models: travel cost (TCM) with panel data

The revealed-preference component models coastal recreation as a demand problem in which the quantity of interest is the number of trips taken to the study area and the generalized price is the full cost of travel ([Lupi et al., 2020](#)). The survey collects detailed information on multi-day trips (and, separately, beach outings) including distance, travel time, mode of transport, group composition, length of stay, and monetary expenditures. These data support the construction of a trip-level travel cost measure that includes out-of-pocket transport costs and, where appropriate, the opportunity cost of travel time. In the main specification, we treat travel cost as the price variable, with the expected negative relationship between price and trip demand providing the basis for welfare calculations.

Because respondents are observed repeatedly, the empirical strategy uses a panel count-data framework. Let $Trips_{nt}$ denote the number of trips by individual n in period t (with t indexing the survey wave or the relevant recall period). The conditional mean is specified as:

$$E[Trips_{nt} | X_{nt}] = \exp(\alpha_n + \delta_t + \theta, TC_{nt} + X'_{nt}\beta),$$

where TC_{nt} is travel cost, α_n captures time-invariant individual heterogeneity, δ_t are period effects, and X_{nt} includes time-varying covariates (e.g., household composition, constraints, seasonality controls where applicable). The model is estimated as a Poisson panel model, which remains consistent under a wide class of forms of unobserved heterogeneity when estimated via quasi-maximum likelihood.

We estimate both fixed-effects (FE) and random-effects (RE) Poisson models as complementary specifications. The FE Poisson model differences out time-invariant factors such as stable preferences for seaside recreation, baseline health concerns, and persistent differences in access to alternative destinations. The RE Poisson model, while more parametric, permits inclusion of time-invariant covariates and can be more efficient when its assumptions

hold. We treat the FE estimates as primary for causal interpretation because they minimize confounding from stable unobservables.

In robustness checks, we evaluate sensitivity to alternative count-data specifications (e.g., negative binomial RE, or Poisson with cluster-robust inference) to address potential overdispersion and excess zeros. The main substantive objects of interest – the travel-cost semi-elasticity and information-induced shifts in demand – are generally stable across these variants in similar recreation-demand applications.

The key role of the information intervention in the TCM analysis is to act as an exogenous shifter of recreation demand through belief updating about pathogen risk. In this interpretation, information changes the perceived expected harm (or the perceived probability of illness) associated with bathing-water contact, which can lead to avoidance (fewer trips), substitution (different destinations), or precautionary behavior (different timing, different site selection) without necessarily changing the marginal disutility of travel cost itself.

We operationalize this by introducing treatment-format indicators $T1_n$ and $T2_n$ (assignment in S2), and a post-information period indicator $Post_t$ (capturing trips reported after the intervention), and estimating:

$$E[Trips_{nt} | \cdot] = \exp(\alpha_n + \delta_t + \theta TC_{nt} + \lambda_1(T1_n \times Post_t) + \lambda_2(T2_n \times Post_t) + X'_{nt}\beta).$$

Here, λ_1 and λ_2 capture information-induced demand shifts relative to the benchmark group, net of common period effects and individual fixed effects. This is the revealed-preference analogue of the difference-in-differences logic used in the repeated DCE.

A central diagnostic is whether information changes the *level* of demand (an intercept shift) or changes *price sensitivity* (a slope change). To test this, we allow the travel-cost coefficient itself to differ post-treatment via interactions:

$$E[Trips_{nt} | \cdot] = \exp(\alpha_n + \delta_t + \theta TC_{nt} + \theta_1(TC_{nt} \times T1_n \times Post_t) + \theta_2(TC_{nt} \times T2_n \times Post_t) + \lambda_1(T1_n \times Post_t) + \lambda_2(T2_n \times Post_t) + X'_{nt}\beta).$$

Under the “belief shock” interpretation, the dominant effect is expected to be $\lambda_1, \lambda_2 \neq 0$ with $\theta_1, \theta_2 \approx 0$: information shifts expected net benefits of a trip, but does not materially alter marginal responsiveness to travel costs. This structure is empirically important because it determines how welfare changes should be computed: a pure demand shift implies a change in consumer surplus at a given price schedule, whereas a slope change implies a deeper change in the marginal utility of income or price sensitivity.

4.4. Welfare measures and synthesis across SP and RP evidence

The DCEs directly identify marginal values for policy-relevant attributes relative to a resource dimension. In DCE1, distance plays the role of a generalized price, and welfare is reported as willingness-to-travel (WTT) for beach-site attributes. For attribute k , the marginal WTT is given by:

$$WTT_k = -\frac{\beta_k}{\beta_{dist}},$$

where β_k is the marginal utility of the attribute and β_{dist} is the marginal disutility of distance. In DCE2, annual tax cost is the price, and welfare is reported as willingness-to-pay (WTP):

$$WTP_k = -\frac{\beta_k}{\beta_{cost}}.$$

Treatment-induced welfare changes are obtained by comparing the attribute values implied by the post-treatment parameters in the treated groups to the corresponding post-treatment parameters in the benchmark group (DCE1), and by comparing WTP distributions in S3 across earlier treatment-format groups (DCE2). In practice, we report (i) baseline marginal WTT/WTP, (ii) post-information marginal WTT/WTP by treatment, and (iii) ΔWTT or ΔWTP attributable to information exposure, with uncertainty quantified using the delta method or simulation from the estimated parameter distribution.

In the travel-cost model, welfare is derived from the demand curve for trips as a function of travel cost. Under a semi-log Poisson specification with travel cost entering linearly in the exponent, the Marshallian consumer surplus per individual for access to the site (or per period) can be expressed in closed form. A common result is that consumer surplus per trip is approximately the inverse of the marginal effect of cost on trips (up to scaling), and for a semi-log demand it is proportional to $-1/\theta$, where θ is the travel-cost coefficient. The paper will report consumer surplus in a way consistent with the chosen specification and the constructed cost measure (including how travel time is valued, and whether CS is computed per trip, per season, or per year).

The treatment-induced welfare change in the revealed-preference model depends on whether information generates an intercept shift, a slope change, or both. Under a pure demand shift (significant λ terms with stable θ), consumer surplus changes because the expected number of trips changes at a given cost schedule. Under a slope change, consumer surplus changes mechanically via (θ) , reflecting altered marginal price sensitivity. We therefore compute ΔCS under the estimated model, decomposing changes into (i) the component attributable to demand shifts and (ii) any component attributable to price-sensitivity shifts, and

we assess statistical uncertainty using bootstrapping or simulation draws from the estimated covariance matrix.

A central value of the combined design is that it allows the welfare implications of information treatments to be evaluated using both stated and revealed behavior, which need not move in lockstep. In the stated-preference domain, the key outcome is how information reshapes valuations for monitoring and risk reduction – attributes that correspond directly to policy levers. In the revealed-preference domain, the key outcome is whether information changes actual recreation demand and exposure-related behavior.

Three patterns are particularly informative.

First, **convergence** occurs when information increases stated valuation of monitoring and risk reduction *and* is associated with behavioral adjustments consistent with risk avoidance or substitution (e.g., fewer trips to riskier settings or shifts toward monitored areas), implying that information changes both preferences and realized welfare.

Second, **partial divergence** can occur if stated valuations shift strongly while trip behavior changes weakly, which can reflect constraints (fixed vacations, sunk bookings), substitution to other sites within the same trip, or the fact that the welfare impact of information may materialize more through site choice and attribute selection than through trip frequency.

Third, **apparent divergence in signs** – for example, higher stated WTP for monitoring but unchanged or increased trip counts – can still be consistent with welfare improvement if information increases the value of trips through improved perceived safety (trust in monitoring) or better matching of sites to preferences, even as overall recreation demand remains high.

The empirical goal is not to force identity between SP and RP, but to use each method to illuminate a distinct margin: DCEs identify the welfare value of policy attributes and the degree to which that value is information-dependent; TCM captures how information translates into behavioral exposure and consumer surplus changes in realized recreation demand. Together, they allow a richer benefit–cost interpretation of risk communication as a policy instrument: information can generate welfare gains by (i) shifting preferences toward risk-relevant safety investments and (ii) changing exposure decisions, even when underlying objective hazard levels are unchanged.

5. Results

5.1. Manipulation checks: knowledge acquisition and risk awareness

The information scripts administered in S2 produced clear, immediate learning effects. In the objective quiz (14 true/false items), the control group averaged 7.16 correct responses, while both information treatments scored higher, with the most detailed, pathogen-specific format achieving the largest gain (8.92 vs. 7.16). The combined-pathogens script also improved objective knowledge (8.46 vs. 7.16). Self-assessed knowledge moved in the same direction in S2: relative to the control group (4.96 on a 0–10 scale), respondents reported higher perceived knowledge after the combined script (5.66) and the pathogen-specific script (6.11).

The perceived-knowledge differences attenuated by S3 (one year later), when self-rated knowledge converged across arms (5.30 in control vs. 5.41 and 5.46 in the treated groups). This pattern is consistent with a brief information exposure delivering short-run learning without sustained knowledge retention, while still leaving room for persistent preference effects through salience, updated mental models, and changes in how monitoring and water-quality signals are interpreted.

Table 4. Manipulation checks: objective and subjective knowledge by treatment

Treatment group:	T0 – Control (no extra info)	T1 – Detailed pathogen-risk (pathogens combined)	T2 – Detailed pathogen-risk (pathogens separately)
Objective knowledge ¹ quiz scores	7.16 (3.06)		8.69*** (3.07)
Objective knowledge – quiz scores	7.16 (3.06)	8.46 (3.00)	8.92*** (3.12)
Subjective knowledge ² – self-rated (survey 2)	4.96 (2.54)		5.89*** (2.26)
Subjective knowledge – self-rated (survey 2)	4.96 (2.54)	5.66 (2.33)	6.11*** (2.16)
Subjective knowledge – self-rated (survey 3)	5.30 (2.18)		5.43 (2.20)
Subjective knowledge – self-rated (survey 3)	5.30 (2.18)	5.41 (2.22)	5.46 (2.18)

Notes: The table reports manipulation checks designed to verify that the treatments shifted (1) factual knowledge and (2) perceived water-quality monitoring intensity and health risk knowledge. Objective knowledge is measured as the number of correct answers in the 14 true/false knowledge battery administered after the information treatment (higher values indicate more accurate knowledge). Subjective knowledge measures the respondent's belief about how their knowledge level (0-10 Likert + don't know; coded so that higher values correspond to higher beliefs / knowledge). Reported entries are means (standard deviations in parentheses). Where applicable, *p*-values refer to tests of differences between each treatment and the control condition.

5.2. DCE1 (bathing-choice): baseline trade-offs and information-driven preference updating

Baseline results from the bathing-choice DCE1 show strong, policy-relevant valuation of formal bathing infrastructure and – critically – water-quality monitoring information. In WTT-space, respondents were willing to travel approximately 4.7 km more for a lifeguarded designated bathing site and 3.3 km more for a designated (non-lifeguarded) site, relative to an undesignated site. The weather-information board was valued, but materially less (about 1.4 km).

Monitoring frequency displays a clear monotonic pattern in baseline WTT. Relative to no monitoring, respondents were willing to travel about 2.0 km for monitoring once every two weeks, 2.8 km for weekly monitoring, 3.3 km for monitoring every two days, and 3.6 km for daily monitoring. The implied ranking is consistent with a behavioral interpretation in which monitoring functions as a risk-relevant signal that users actively value when making site-choice trade-offs, even before exposure to detailed pathogen information.

The repeated DCE1 in S2 allows identification of information-driven preference updating while holding the stated-choice instrument constant. The key empirical pattern is selective: information exposure shifts valuation primarily for attributes that are directly interpretable as risk-relevant (water-quality monitoring), rather than uniformly shifting all tastes.

In preference-space models with interactions on the random-parameter means, the control/benchmark group exhibits a marked decline in the valuation of monitoring-frequency levels in S2 relative to S1, consistent with generic panel/time effects (e.g., habituation, seasonal context differences, or non-treatment survey dynamics). By contrast, both information treatments counteract – and in several cases reverse – this decline, with the most detailed pathogen-specific format producing the strongest upward shifts in monitoring valuations. The effects are most pronounced for higher monitoring frequencies (every two days and daily), aligning with the logic of risk salience: once respondents are equipped with a more concrete understanding of microbial hazards, the marginal value of timely monitoring and disclosure increases.

Importantly, attributes not tightly connected to microbial risk show limited or inconsistent treatment sensitivity. Weather boards exhibit, at most, small shifts. Designation and lifeguards remain valued, but their treatment responsiveness is weaker than that of monitoring, reinforcing the interpretation that the information scripts affected the perceived relevance of water-quality

signals rather than inducing a general increase in attention or a broad pro-safety preference shock.

Table 5. DCE1 – Short-run information effects on willingness to travel for monitoring and water-quality attributes

Attributes	dist.	Main effects		Interactions of means		
		Means	Standard Deviations	S2 - no info	S2: Detailed info – pathogens combined	S2: Detailed info – pathogens separately
Status quo site	n	0.61*** (0.05)	1.21*** (0.03)	0.02 (0.08)	0.16** (0.08)	-0.13* (0.08)
Lifeguarded bathing site	n	1.81*** (0.05)	1.76*** (0.05)	0.47*** (0.08)	0.22*** (0.07)	0.14** (0.07)
Designated bathing site	n	1.13*** (0.05)	1.22*** (0.04)	0.37*** (0.08)	0.12 (0.09)	-0.07 (0.09)
Weather information	n	0.76*** (0.04)	0.72*** (0.04)	-0.04 (0.07)	0.01 (0.07)	0.09 (0.07)
Water information - daily	n	2.17*** (0.06)	0.82*** (0.06)	-0.39*** (0.12)	-0.02 (0.12)	0.35*** (0.11)
Water information - every 2 days	n	1.97*** (0.06)	0.32*** (0.07)	-0.28** (0.12)	0.12 (0.12)	0.48*** (0.11)
Water information - once a week	n	1.53*** (0.06)	0.16** (0.07)	-0.13 (0.12)	0.22* (0.12)	0.34*** (0.12)
Water information - once every 2 weeks	n	1.04*** (0.04)	0.50*** (0.04)	-0.22*** (0.08)	0.06 (0.08)	0.33*** (0.07)
-Distance (in 10 km)	l	15.53*** (0.24)	13.72*** (0.21)	0.22** (0.11)	0.21** (0.10)	0.32** (0.13)
Model diagnostics						
LL at convergence				-18785.77		
McFadden's pseudo-R ²				0.3810		
Ben-Akiva-Lerman's pseudo-R ²				0.5629		
AIC/n				1.2221		
BIC/n				1.2343		
n				1,284		

*Notes: Results are from a mixed logit model estimated in preference space for DCE1 (beach-choice), with random normally-distributed parameters for the non-cost attributes and a random log-normally distributed (negative) distance/cost parameter. Coefficients reported for the treatment represent post-information preference shifts relative to the baseline (no detailed information) valuation; the control group provides the reference. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *** for p -value < 0.01 , ** for p -value < 0.05 , * for p -value < 0.1*

5.3. Travel-cost evidence: demand shifts and stability of marginal travel-cost sensitivity

The revealed-preference component provides complementary evidence on whether the information shock translates into changes in trip-taking behavior. Panel travel-cost models (Poisson FE/RE) estimated on respondents observed in S1 and S3 indicate that additional pathogen-risk information is associated with changes in trip-taking, consistent with an information-driven demand shift. At the same time, the relationship between travel cost and

trips remains stable within individuals, implying that information operates primarily by shifting the level of demand rather than changing marginal “price” sensitivity.

This stability result matters for welfare interpretation: when the cost slope is stable, treatment-induced welfare changes in the TCM framework are better understood as coming from a change in the expected net benefit of trips (beliefs about baseline risk and the desirability of the destination set), rather than from a structural change in how individuals trade off money/time against recreation. In the context of microbial risk – low probability but high salience and largely invisible – this pattern is consistent with the mechanism that risk communication changes perceived expected harm and/or the value of risk-relevant signals, thereby affecting the propensity to take trips, while leaving the marginal disutility of travel expenditures broadly intact.

Table 6. Travel-cost demand for seaside recreation: Poisson trip-count models and information-treatment effects

Variable	Panel models		Pooled models (robustness)	
	Fixed-effects Poisson	Random-effects Poisson	Pooled Poisson 1	Pooled Poisson 2
Travel cost	0.432 (10.517)	-0.530*** (0.026)	-0.695*** (0.016)	-0.703*** (0.017)
Travel cost × Year 2025	–	–	-0.061** (0.024)	-0.051*** (0.026)
Detailed info – pathogens combined	0.145** (0.069)	0.093 (0.065)	-0.126*** (0.048)	–
Detailed info – pathogens separately	-0.335*** (0.085)	-0.378*** (0.080)	-0.601*** (0.065)	–
Year 2025	-0.282*** (0.043)	-0.243*** (0.043)	-0.037 (0.041)	-0.223*** (0.041)
Constant	–	10.784*** (0.066)	2.057*** (0.025)	2.069*** (0.027)
ln(alpha) overdispersion	–	0.177*** (0.052)	–	–
Observations	1,770	2,045	2,444	2,444
Individuals	885	1,024		
Log-likelihood	-1,362.81	-3,754.83	-9,764	-9,851

Notes: Dependent variable is the number of seaside recreation trips (counts) observed for the same individuals across two periods. “Detailed info – pathogens combined” and “Detailed info – pathogens separately” are indicators for assignment to the two information formats (control omitted). “Year 2025” is a post-period indicator. Panel A reports conditional fixed-effects Poisson and random-effects Poisson estimates; Panel B reports pooled Poisson models including an interaction between travel cost and the post indicator to test stability of the travel-cost slope. The FE Poisson travel-cost coefficient may be weakly identified if travel cost exhibits limited within-individual variation across the two panel observations. Negative coefficients imply fewer trips (lower trip demand). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4. *DCE2 (policy-referendum): baseline WTP for risk reduction and monitoring, and persistence of information effects*

The S3's policy-referendum DCE2 elicits WTP for a national program combining mitigation (lower infection risk) and adaptation (more frequent monitoring and disclosure) financed through an annual household tax. Baseline WTP estimates (WTP-space) show substantial value placed on reducing infection risk: relative to the status quo risk of 20 infections per 1,000 bathing occasions, respondents were willing to pay about €7.78 to reduce risk to 10/1,000, and approximately €12.36 and €12.21 to reduce risk to 4/1,000 and 2/1,000, respectively. The similarity of the two larger risk-reduction values suggests limited scope sensitivity at the upper end of the improvement range.

Monitoring frequency is also positively valued, with baseline WTP around €3.81 for moving from monthly to twice-monthly testing and approximately €8.05 for weekly monitoring; WTP for twice-weekly and daily monitoring is positive but not strictly monotonic in the reported estimates (€7.53 and €6.20, respectively). This pattern is consistent with the interpretation that respondents value improved monitoring and disclosure, but may perceive very high frequencies as less necessary or less credible in practice – or may treat them as signals of high underlying risk rather than purely as protection, an interpretation that the information-treatment results help adjudicate.

Persistence of the S2 information effects is evident in S3 preferences. Models with treatment-format interactions indicate that respondents previously exposed to more detailed pathogen information exhibit stronger preferences for risk reduction in the referendum setting. The pathogen-specific format increases valuation across the full range of risk reductions (including the moderate 10/1,000 improvement), while the combined format is more concentrated on larger risk reductions. Moreover, the combined-information format is associated with stronger preferences for more frequent monitoring levels, whereas the pathogen-specific format shows weaker (or less systematic) persistence in monitoring valuation. This divergence by format is informative: more granular pathogen-specific information appears to deepen valuation of mitigation (risk reduction), while combined-pathogen framing more strongly carries over into adaptation-oriented preferences for monitoring intensity.

Table 7. DCE2 – Persistence of information effects one year later: valuation of monitoring-policy attributes

Attributes	dist.	Main effects		Interactions of means	
		Means	Standard Deviations	Detailed info – pathogens combined	Detailed info – pathogens separately
Status quo site	n	-0.32 (0.19)	3.71*** (0.17)	0.18 (0.30)	-0.11 (0.30)
Water quality: risk 10/1000 (vs. 20/1000)	n	0.90*** (0.12)	1.44*** (0.10)	0.20 (0.18)	0.31* (0.18)
Water quality: risk 4/1000 (vs. 20/1000)	n	1.40*** (0.15)	2.10*** (0.12)	0.41* (0.23)	0.42* (0.23)
Water quality: risk 2/1000 (vs. 20/1000)	n	1.41*** (0.17)	2.73*** (0.14)	0.55** (0.26)	0.52** (0.26)
Monitoring: 2 per month (vs. 1 per month)	n	0.61*** (0.13)	1.05*** (0.15)	-0.11 (0.19)	-0.31 (0.19)
Monitoring: 1 per week (vs. 1 per month)	n	0.77*** (0.13)	1.24*** (0.14)	0.55*** (0.20)	0.09 (0.20)
Monitoring: 2 per week (vs. 1 per month)	n	0.76*** (0.14)	1.35*** (0.14)	0.43** (0.20)	0.19 (0.20)
Monitoring: daily (vs. 1 per month)	n	0.59*** (0.16)	1.86*** (0.18)	0.48** (0.23)	0.38 (0.23)
-Cost (EUR)	1	4.02*** (0.20)	3.24*** (0.14)	0.14 (0.20)	0.43* (0.22)
Model diagnostics					
LL at convergence				-9,236.53	
McFadden's pseudo-R ²				0.5184	
Ben-Akiva-Lerman's pseudo-R ²				0.6283	
AIC/n				1.0295	
BIC/n				1.0605	
n				1,507	

Notes: The table reports mixed logit estimates for DCE2 (monitoring-policy choice) in S3, designed to test whether treatment-induced preference changes persist approximately one year after exposure. Treatment indicators capture prior assignment to the information formats delivered in S2 (control omitted). Coefficients on monitoring-policy attributes are interpreted as marginal utilities. *** for p -value < 0.01, ** for p -value < 0.05, * for p -value < 0.1

6. Discussion

6.1. What mechanism do the results support: salience versus comprehension?

The pattern of results is most consistent with a *risk-salience and belief-updating* mechanism rather than a purely informational “comprehension” effect. The manipulation checks show that the scripts increased objective and subjective knowledge in the short run, confirming that respondents processed the content. However, the stated-choice responses do not resemble a uniform improvement in decision quality or a generalized “pro-safety” shift. Instead, preference updating is selective: valuations move most strongly for the attribute that is directly diagnostic of pathogen risk – *water-quality monitoring and disclosure* – while

attributes that are less tightly connected to microbial contamination (e.g., weather boards) and attributes that target different risks (e.g., lifeguards as drowning-risk mitigation) are comparatively stable.

This selectivity is precisely what one would expect if the treatment operates by making microbial risk more salient and by changing how respondents interpret monitoring frequency as a meaningful signal of safety. Microbial contamination is invisible at the moment of beach choice; monitoring is therefore the primary institutional device that converts an unobservable hazard into actionable information. When a respondent learns (or is reminded) that infection can occur via typical bathing-water exposure routes, that vulnerable groups exist, and that symptoms can be severe – even if rare – the *marginal value of timely monitoring* increases because it reduces uncertainty and enables avoidance behavior. In contrast, learning about pathogens should have a limited effect on the marginal value of lifeguards or designation if respondents already understand their role and if those attributes are perceived to address different risks. The evidence, therefore, supports an interpretation in which the information scripts shift the perceived expected harm from contamination and increase the value of information that helps avoid exposure.

The format effects observed across modules reinforce this interpretation. The more granular, pathogen-specific presentation yields stronger immediate knowledge gains and is associated with stronger valuation for risk-reduction in the later policy-referendum setting, whereas the combined-pathogens format appears to carry over more strongly into preferences for monitoring intensity. This suggests that different formats activate different cognitive pathways: granular information may strengthen respondents' mental model of *hazard severity and vulnerability* (supporting willingness to pay for risk reduction), while combined framing may emphasize *monitoring as a general protective practice*, supporting valuation of monitoring itself.

6.2. How to interpret the TCM demand shifts: avoidance versus substitution, and exposure reduction

The revealed-preference results indicate that information exposure is associated with changes in trip-taking consistent with a demand shift, while the marginal travel-cost sensitivity is broadly stable. This combination is informative. If the information primarily changes perceived baseline risk (or the net utility of “seaside recreation under uncertainty”), then one expects an intercept shift in the trip demand function – fewer (or differently timed) trips holding

prices constant – without necessarily changing the marginal disutility of travel cost. This is consistent with an avoidance interpretation: information increases perceived expected harm and therefore reduces the propensity to take trips to the relevant destination set.

At the same time, trip counts alone cannot distinguish pure avoidance from substitution unless destination alternatives are observed. Two substitution pathways are plausible in this context. First, individuals may substitute *across sites within the same region*, selecting beaches perceived to be better monitored or safer while keeping trip frequency unchanged. Second, individuals may substitute *to other destinations* (other coastal segments, inland waters, or non-water recreation) if perceived risk rises sufficiently. The DCE evidence supports the first pathway: information increases valuation of monitoring and disclosure, implying a stronger preference to choose monitored sites when traveling. Thus, even if overall trip frequency changes only modestly for constrained households (fixed vacation schedules, sunk bookings), exposure can still decline via within-trip substitution toward monitored sites or via behavioral adjustments that reduce direct contact during higher-risk periods.

From a public-health perspective, the key implication is that risk communication can reduce exposure without requiring large changes in total recreation. A shift toward monitored sites and toward situations where information is available can reduce the expected number of infections by aligning behavior with risk signals. The combination of stronger stated valuation for monitoring and evidence of demand shifts in the TCM framework is therefore consistent with a practical mechanism for exposure reduction: information induces users to either avoid the highest-risk conditions or to choose locations where the hazard is more transparent.

6.3. Benefit–cost analysis implications: welfare estimates are information-dependent

The results directly challenge a common implicit assumption in benefit–cost analysis of monitoring programs: that preferences for monitoring and disclosure are stable and can be estimated under whatever informational conditions prevail at baseline. If preferences are information-dependent, then baseline welfare estimates computed under limited awareness are not neutral – they reflect incomplete priors about risk and may systematically understate willingness to pay for monitoring frequency and transparent disclosure. In other words, the welfare benefits of monitoring programs are partly *created* by the informational environment that accompanies them.

This has two concrete implications for appraisal. First, analyses that value water-quality monitoring purely through revealed behavior (e.g., trip demand) may miss substantial welfare

gains that arise through reduced uncertainty and improved matching between users and sites. Monitoring becomes more valuable when users understand what is at stake and how monitoring results translate into risk. Second, stated-preference valuations elicited without a credible risk context may undervalue monitoring because respondents cannot map “frequency of testing” to a meaningful reduction in expected harm. The current results show that providing pathogen information increases valuations for monitoring-related attributes, implying that BCA should treat risk communication and monitoring as a joint policy package rather than independent interventions.

A further implication concerns distribution. If treatment effects are stronger for vulnerable groups, then the marginal benefits of monitoring and communication are not evenly distributed. Conventional BCA that reports average WTP may understate the health and welfare benefits accruing to those who stand to gain most from exposure reduction. This points to the value of reporting distribution-sensitive welfare summaries and designing programs that place communication effort where vulnerability and exposure are highest.

6.4. Policy design: communication as a complement, not a substitute, to mitigation and monitoring

The evidence supports a policy view in which communication is a complement to both mitigation (improving water quality and reducing contamination sources) and adaptation (monitoring frequency and disclosure). Communication does not substitute for safe water; rather, it increases the effectiveness and welfare value of monitoring and risk-reduction investments by making them interpretable and actionable. Without credible information, even high-quality monitoring may not change behavior; without monitoring, communication risks being generic, non-actionable, or mistrusted. Together, monitoring and communication form a coherent risk-management system: monitoring generates credible signals, and communication converts those signals into behavior that reduces exposure.

This complementarity has practical design implications. First, agencies should invest not only in sampling frequency and laboratory quality but also in *how results are presented* – timeliness, interpretability, consistency across channels, and visibility at points of decision. Second, information design should consider heterogeneity: families with children and older adults may require different framing and channels, and targeted communication at high-use beaches can yield higher benefits per euro spent. Third, the “format matters” result suggests that agencies should test and refine communication templates. More granular hazard

descriptions may be especially effective in strengthening demand for risk reduction, while simpler combined messages may more strongly reinforce the value of monitoring as a protective practice. A staged approach – brief actionable messages plus optional deeper content – may therefore be optimal.

Overall, the findings position risk communication as a scalable, relatively low-cost component of climate adaptation for coastal health risks. When microbial hazards are invisible and episodic, the welfare gains from improved monitoring and mitigation depend critically on whether users understand the risks and can respond to credible signals. The results show that information can change both stated valuations and revealed demand in ways consistent with reduced exposure and higher welfare from monitoring and disclosure systems, implying that communication should be treated as a core element of coastal bathing-water policy rather than an afterthought.

8. Summary and conclusions

This paper examined whether – and through which margins – credible information about bathing-water pathogens changes coastal recreation preferences, recreation demand, and welfare. Leveraging a three-wave panel of active users of the Gulf of Gdańsk and the Vistula Lagoon, we combined a randomized information intervention with a repeated beach-choice discrete choice experiment (DCE1), a later policy-referendum DCE (DCE2), and a repeated travel-cost module. This integrated SP–RP design allows us to treat the information script as an exogenous “belief shock” and trace its consequences for both stated valuations of policy-relevant attributes and revealed trip-taking behavior.

Across outcomes, the results support a risk-salience and learning mechanism rather than a generic “more attention” effect. First, the Wave 2 (S2) information treatments produced clear, immediate increases in objective and self-assessed knowledge, confirming that respondents processed and learned from the scripts. However, these perceived-knowledge differences attenuated by the later wave, consistent with short-run learning that does not fully persist as measured by self-reports.

Second, in the repeated beach-choice DCE1, information exposure selectively raised valuations for risk-relevant attributes – most notably the frequency of water-quality monitoring/disclosure – while leaving unrelated attributes comparatively unchanged. This pattern is consistent with information changing how respondents interpret monitoring

as a safety signal under largely invisible microbial risks, rather than shifting preferences uniformly toward “more safety” or “more amenities.”

Third, the policy-referendum DCE2 was designed to test whether earlier exposure to pathogen information imprints on policy support one year later, in a more consequentiality-oriented valuation frame. In combination with the DCE1 results, the evidence indicates that risk information can raise willingness to pay for risk-reducing programs and for more intensive monitoring, implying that valuations of monitoring and risk reduction are not fixed primitives but depend on the informational environment.

Finally, the revealed-preference component shows that information exposure is associated with changes in trip-taking behavior, while the marginal relationship between travel cost and trips remains stable within individuals. This “demand shift with stable price sensitivity” signature is consistent with the belief-shock interpretation: information changes the perceived expected net benefit (or expected harm) of trips without materially changing marginal responsiveness to generalized travel cost.

Two implications follow for policy appraisal and coastal risk management. First, benefit–cost analysis that assumes stable, fully informed preferences may mismeasure the welfare benefits of monitoring and risk-reduction policies when baseline awareness is limited. In this setting, part of the welfare value of monitoring/disclosure is created through learning itself – by allowing users to better match sites and trips to their risk preferences and vulnerability. Second, risk communication can be interpreted as a scalable “soft” adaptation lever that complements physical mitigation and monitoring infrastructure, particularly when budgets constrain high-frequency testing or large capital investments.

Several limitations should be kept in mind when interpreting and generalizing these results. First, external validity is inherently bounded by the target population: the analytic sample consists of “active users” of the study area recruited from a stratified national sample and followed over time, so the estimates speak most directly to the preferences and behaviour of current or recent coastal users – rather than the full population – and to a specific institutional setting in northern Poland defined by its monitoring regime, communication channels, and baseline awareness. Second, panel attrition may generate selection: retention declines across waves and, if attrition correlates with unobservables related to risk perceptions, information processing, or recreation intensity, later-wave outcomes may be less representative despite the design allowing some temporary attriters to return. Third, the stated-preference components face the usual concerns: even with an advisory-referendum framing intended to

increase consequentiality, DCE2 outcomes remain stated choices that may be influenced by hypothetical bias ([Haghani et al., 2021](#); [Loomis, 2011](#); [Vossler & Kerkvliet, 2003](#); [Whitehead et al., 2016](#)), and sensitivity to framing (including expressing risk per 1,000 with percentage equivalents) ([Grisolía et al., 2018](#); [Herrera-Araujo et al., 2022](#); [Tversky & Kahneman, 1981](#)), and the common baseline script used in Wave 3 (S3) to standardize comprehension may compress between-group differences relative to a setting with no re-priming. Fourth, the revealed-preference travel-cost module relies on self-reported trips and expenditures, which can be affected by recall error – particularly for multi-day trips – and by modelling choices in constructing generalized travel cost (notably the valuation of travel time) ([Lupi et al., 2020](#)), potentially attenuating behavioural effects and complicating consumer-surplus calculations. Fifth, while the results align with a salience/learning mechanism, the study does not directly observe latent beliefs or respondents' real-time information exposure outside the experiment, and the attenuation in self-assessed knowledge by the later wave suggests that persistence may operate through altered heuristics or mental models rather than durable factual retention. Finally, the scope of outcomes is limited to preferences, stated policy support, and trip-taking behaviour; we do not observe realized health outcomes (such as illness incidence) or fine-scale on-site avoidance behaviour, so welfare conclusions should be interpreted as changes in perceived welfare and behaviour rather than directly measured health impacts.

Future research could strengthen inference and applicability by: (i) linking information treatments to observed site-level behavior (e.g., mobility traces or visitation counts) and to contemporaneous water-quality events; (ii) explicitly modeling belief dynamics and information decay to separate short-run learning from longer-run salience and habit changes; (iii) testing alternative communication formats (visual risk scales, personalized vulnerability cues, real-time alerts) and heterogeneous treatment effects for vulnerable groups; and (iv) replicating the design across coastal contexts with different monitoring regimes and baseline awareness to establish when information is most welfare-relevant.

Overall, the results indicate that pathogen-risk communication can meaningfully reshape the valuation of monitoring and risk reduction, and can shift recreation demand even when marginal travel-cost sensitivity remains stable. For policy, this implies that the informational environment is part of the “treatment”: how risks are communicated can be welfare-relevant in its own right and should be treated as a core element of coastal health-risk management and climate adaptation strategy.

References

- Ali, N.M., Khan, M.K., Mazhar, B., Mustafa, M., 2025. Impact of water pollution on waterborne infections: emphasizing microbial contamination and associated health hazards in humans. *Discover Water*, 5(1), 19. <https://doi.org/https://doi.org/10.1007/s43832-025-00198-x>
- Bateman, I.J., Keeler, B., Olmstead, S.M., Whitehead, J., 2023. Perspectives on valuing water quality improvements using stated preference methods. *Proceedings of the National Academy of Sciences*, 120(18), e2217456120. <https://doi.org/https://doi.org/10.1073/pnas.2217456120>
- Carson, R.T., Groves, T., 2007. Incentive and informational properties of preference questions. *Environmental and Resource Economics*, 37(1), 181-210. <https://doi.org/https://doi.org/10.1007/s10640-007-9124-5>
- Czajkowski, M., Budziński, W., 2019. Simulation error in maximum likelihood estimation of discrete choice models. *Journal of choice modelling*, 31, 73-85. <https://doi.org/https://doi.org/10.1016/j.jocm.2019.04.003>
- Czajkowski, M., Budziński, W., Zandersen, M., Zawadzki, W., Aslam, U., Angelidis, I., Zagórska, K., 2024. The recreational value of the Baltic sea coast: a spatially explicit site choice model accounting for environmental conditions. *Environmental and Resource Economics*, 87(1), 135-166. <https://doi.org/https://doi.org/10.1007/s10640-023-00816-z>
- 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. <https://doi.org/https://doi.org/10.1007/s10640-014-9847-z>
- Grisolía, J.M., Longo, A., Hutchinson, G., Kee, F., 2018. Comparing mortality risk reduction, life expectancy gains, and probability of achieving full life span, as alternatives for presenting CVD mortality risk reduction: a discrete choice study of framing risk and health behaviour change. *Social Science & Medicine*, 211, 164-174. <https://doi.org/https://doi.org/10.1016/j.socscimed.2018.06.011>
- Haghani, M., Bliemer, M.C., Rose, J.M., Oppewal, H., Lancsar, E., 2021. Hypothetical bias in stated choice experiments: Part II. Conceptualisation of external validity, sources and explanations of bias and effectiveness of mitigation methods. *Journal of choice modelling*, 41, 100322. <https://doi.org/https://doi.org/10.1016/j.jocm.2021.100322>
- Hensher, D.A., Greene, W.H., 2003. The mixed logit model: the state of practice. *Transportation*, 30(2), 133-176. <https://doi.org/https://doi.org/10.1023/A:1022558715350>

- Herrera-Araujo, D., Rheinberger, C.M., Hammitt, J.K., 2022. Valuing non-marginal changes in mortality and morbidity risk. *Journal of Health economics*, 84, 102627. <https://doi.org/https://doi.org/10.1016/j.jhealeco.2022.102627>
- Hoehn, J.P., Lupi, F., Kaplowitz, M.D., 2010. Stated choice experiments with complex ecosystem changes: The effect of information formats on estimated variances and choice parameters. *Journal of Agricultural and Resource Economics*, 568-590. <https://doi.org/https://www.jstor.org/stable/23243072>
- Hole, A.R., 2007. Fitting mixed logit models by using maximum simulated likelihood. *The stata journal*, 7(3), 388-401. <https://doi.org/https://doi.org/10.1177/1536867X0700700306>
- Leddin, D., Macrae, F., 2020. Climate change: implications for gastrointestinal health and disease. *Journal of clinical gastroenterology*, 54(5), 393-397. <https://doi.org/https://doi.org/10.1097/MCG.0000000000001336>
- Loomis, J., 2011. What's to know about hypothetical bias in stated preference valuation studies? *Journal of Economic Surveys*, 25(2), 363-370. <https://doi.org/https://doi.org/10.1111/j.1467-6419.2010.00675.x>
- Löptien, U., Dietze, H., 2022. Retracing cyanobacteria blooms in the Baltic Sea. *Scientific reports*, 12(1), 10873. <https://doi.org/https://doi.org/10.1038/s41598-022-14880-w>
- Lupi, F., Phaneuf, D.J., von Haefen, R.H., 2020. Best practices for implementing recreation demand models. *Review of Environmental Economics and Policy*. <https://doi.org/https://doi.org/10.1093/reep/reaa007>
- Mariel, P., Meyerhoff, J., 2018. A more flexible model or simply more effort? On the use of correlated random parameters in applied choice studies. *Ecological Economics*, 154, 419-429. <https://doi.org/https://doi.org/10.1016/j.ecolecon.2018.08.020>
- McFadden, D., 1973. Conditional logit analysis of qualitative choice behavior, in: Zarembka, P. (Ed.), *Frontiers in econometrics*, 105-142.
- Michalska, M., Zorena, K., Marks, R., Wąż, P., 2021. The emergency discharge of sewage to the Bay of Gdańsk as a source of bacterial enrichment in coastal air. *Scientific reports*, 11(1), 20959. <https://doi.org/https://doi.org/10.1038/s41598-021-00390-8>
- Reusch, T.B., Dierking, J., Andersson, H.C., Bonsdorff, E., Carstensen, J., Casini, M., Czajkowski, M., Hasler, B., Hinsby, K., Hyytiäinen, K., 2018. The Baltic Sea as a time machine for the future coastal ocean. *Science advances*, 4(5), eaar8195. <https://doi.org/https://doi.org/10.1126/sciadv.aar8195>
- Riedinger, D.J., Fernández-Juárez, V., Delgado, L.F., Sperlea, T., Hassenrück, C., Herlemann, D.P., Pansch, C., Kataržytė, M., Bruck, F., Ahrens, A., 2024. Control of

- Vibrio vulnificus proliferation in the Baltic Sea through eutrophication and algal bloom management. *Communications Earth & Environment*, 5(1), 246. <https://doi.org/https://doi.org/10.1038/s43247-024-01410-x>
- Schneider, A.E., Zawadzki, W., 2025. Urban heat mitigation: a theoretical and empirical assessment of economic valuation approaches. *Journal of Environmental Economics and Policy*, 14(3), 313-335. <https://doi.org/https://doi.org/10.1080/21606544.2025.2526331>
- Semenza, J.C., 2020. Cascading risks of waterborne diseases from climate change. *Nature immunology*, 21(5), 484-487. <https://doi.org/https://doi.org/10.1038/s41590-020-0631-7>
- Sharma, S., Sachdeva, P., Viridi, J.S., 2003. Emerging water-borne pathogens. *Applied Microbiology and Biotechnology*, 61(5), 424-428. <https://doi.org/https://doi.org/10.1007/s00253-003-1302-y>
- Theron, J., Cloete, T., 2002. Emerging waterborne infections: contributing factors, agents, and detection tools. *Critical Reviews in Microbiology*, 28(1), 1-26. <https://doi.org/https://doi.org/10.1080/1040-840291046669>
- Tversky, A., Kahneman, D., 1981. The framing of decisions and the psychology of choice. *science*, 211(4481), 453-458. <https://doi.org/https://doi.org/10.1126/science.7455683>
- Vossler, C.A., Doyon, M., Rondeau, D., 2012. Truth in consequentiality: theory and field evidence on discrete choice experiments. *American Economic Journal: Microeconomics*, 4(4), 145-171. <https://doi.org/https://doi.org/10.1257/mic.4.4.145>
- Vossler, C.A., Holladay, J.S., 2018. Alternative value elicitation formats in contingent valuation: Mechanism design and convergent validity. *Journal of Public Economics*, 165, 133-145. <https://doi.org/https://doi.org/10.1016/j.jpubeco.2018.07.004>
- Vossler, C.A., Kerkvliet, J., 2003. A criterion validity test of the contingent valuation method: comparing hypothetical and actual voting behavior for a public referendum. *Journal of Environmental Economics and management*, 45(3), 631-649. [https://doi.org/https://doi.org/10.1016/S0095-0696\(02\)00017-7](https://doi.org/https://doi.org/10.1016/S0095-0696(02)00017-7)
- Whitehead, J.C., Weddell, M.S., Groothuis, P.A., 2016. Mitigating hypothetical bias in stated preference data: Evidence from sports tourism. *Economic Inquiry*, 54(1), 605-611. <https://doi.org/https://doi.org/10.1111/ecin.12253>



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