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Do numerical probabilities promote informed stated preference responses under inherent uncertainty? Insight from a coastal adaptation choice experiment

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Abstract: Inherent outcome uncertainty within stated preference surveys is invariant across valuation scenarios. It has received relatively little attention in the environmental stated preference literature. Specifically, it is unknown whether percentage probabilities—a ubiquitous means of communicating uncertainty in questionnaires—are an effective risk communication tool. This article systematically evaluates two treatments in a discrete choice experiment survey related to coastal climate change adaptation in Connecticut, USA: one provides only raw frequencies as a risk communication tool, while the other provides implied numerical probabilities in addition to the same raw frequencies. Results from a mixed logit model and from a latent class model that controls for sociodemographic influences show that the use of percentage probabilities to communicate inherent uncertainty has no additional effect on average welfare estimates or the choice behavior of respondents. Our findings suggest that percentage probabilities may not be an impactful way to communicate inherent uncertainty in environmental stated preference questionnaires.

Keywords: flood adaptation; inherent uncertainty; discrete choice experiment; stated preference; mixed logit; risk communication; WTP-space

JEL codes: D61, D83, H41, Q51, Q5

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1. Introduction

Outcome uncertainty (OU) within stated preference welfare analysis refers to uncertainty concerning whether effects communicated in scenarios would actually occur, were the scenario implemented as indicated in the questionnaire. OU can be related to numerous factors, including uncertainty in scientific models and predictions related to the efficacy of policy interventions and underlying or inherent uncertainty in ecological systems.[1] Most stated preference surveys provide no formal communication of OU, often with the unstated assumptions that scenario outcomes are certain, that presented attribute levels reflect expected values, and/or that utilities depend only on attributes' final states (Roberts, Boyer, and Lusk 2008; Wielgus et al. 2009; Glenk and Colombo 2013; Lundhede et al. 2015).[2] Concerns that these assumptions can have important implications for the interpretation and validity of model results have sparked a growing body of stated preference studies that address OU in scenario designs and preference modeling (e.g., Zhai, Fukuzono, and Ikeda 2007; Roberts, Boyer, and Lusk 2008; Wielgus et al. 2009; Rolfe and Windle 2010, 2015; Ivanova, Rolfe, and Tucker 2010; Glenk and Colombo 2011, 2013; Wibbenmeyer et al. 2013; Veronesi et al. 2014; Reynaud and Nguyen 2016; Torres, Bujosa, and Riera 2017; Torres, Faccioli, and Font 2017; Meldrum et al. 2020).

The majority of environmental stated preference studies that account for OU do so either by embedding exogenously varying numerical percentage probabilities in choice scenarios as standalone attributes (e.g., Zhai, Fukuzono, and Ikeda 2007; Roberts, Boyer, and Lusk 2008; Rolfe and Windle 2010, 2015; Ivanova, Rolfe, and Tucker 2010; Glenk and Colombo 2011, 2013; Wibbenmeyer et al. 2013; Veronesi et al. 2014; Reynaud and Nguyen 2016; Torres, Faccioli, and Font 2017; Glatt, Brouwer, and Logar 2019; Meldrum et al. 2020) or using such probabilities as

[1] Although stated preference literature describes this situation as "outcome uncertainty," most cases can be simplified to the narrower case of outcome risk, in which the probabilities of alternative outcomes are known. In formal terms, true uncertainty refers to a case in which both outcomes and their probabilities are unknown.

[2] An additional form of uncertainty may arise due to varying degrees of perceived policy and payment consequentiality, in which respondents perceive a less-than-certain probability that their survey responses will influence actual policies that are considered or the probability of payment that will be required (Herriges et al. 2010).

scenario framing variables.[3] To investigate the effect of this numerical risk information on welfare estimates, many of these studies evaluate the statistical significance of estimated parameters on included numerical probability attributes. In such cases, internal scope variation in the presented risk information enables respondents to see clearly that some scenarios and/or outcomes are associated with higher (or lower) percentage probabilities. The relevance of these probabilities for welfare estimation is then established using statistical tests that quantify the impact of this internal variation on responses or preference.

Other split-sample studies compare the results of one survey that includes exogenously varying numerical probabilities to those of an identical survey that entirely omits this numerical risk information (e.g., Roberts, Boyer, and Lusk 2008). These studies incorporate external variation in whether risk information is provided (in different split samples)—with outcome uncertainty being communicated to only part of the sample. When uncertainty is communicated, however, its importance to choices is still implied directly via the direct inclusion of internal probability variation within each choice task.

Ubiquitous approaches such as these are not directly applicable to cases of *inherent outcome uncertainty* (Torres, Faccioli, and Font 2017), which may be defined as uncertainty that does not vary across valuation scenarios. This type of uncertainty is generally (though not necessarily) related to underlying or inherent uncertainty in ecological systems that cannot be altered through short-term human interventions. For example, the effect of coastal flood defenses may depend on a probability of severe storms that is effectively fixed in the study area, and hence does not vary across DCE scenarios (Makriyannis, Johnston, and Whelchel 2018). In general, there

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[3] The current article focuses on the prospective use of numerical probabilities in discrete choice scenarios (DCEs), but other stated preference studies use descriptive (non-numerical) risk indicators. This is done despite concerns regarding the subjective interpretation of verbal risk indicators and hence the reliability of estimates (e.g., Patt and Schrag 2003; Hanley, Kriström and Shogren 2009; Shaw and Baker 2010; Akter and Bennet 2012). Lundhede et al. (2015), for example, use qualitative risk descriptors (e.g., "very certain" and "rather certain") in a DCE generating implicit prices for bird conservation policies under climate change. Phillips (2011) investigates beach visitors' preferences for coastal management options where the relative risk of flood damage to public and private property is a primary attribute that takes on the values "Low (1 in 20 years)", "Medium (1 in 10 years)" and "High (1 in 3 years)". Shaw and Baker (2010) estimate Hurricane Katrina evacuees' willingness to pay to avoid hurricane risks and also use "low", "medium" and "high" to characterize the risk. Rolfe and Windle (2009) value the benefits of controlling fire ants and embed verbal risk descriptors in choice option labels indicating "high" and "low" certainty of success.

is limited understanding of how respondents understand and process this type of scenario-invariant uncertainty within environmental DCEs. Although a few studies have considered the effect of communicating inherent uncertainty on environmental stated preferences (e.g., Wielgus et al. 2009; Torres, Faccioli, and Font 2017; Faccioli, Kuhfuss, and Czajkowski 2018; Makriyannis, Johnston, and Whelchel 2018), many important issues associated with this type of uncertainty remain unexplored in the stated preference literature.

Among these issues is the effect of different risk communication formats on choice behavior and resulting welfare estimates. The assumption underlying the common use of percentage probabilities to communicate uncertainty in environmental stated preference studies is that when stating preferences, respondents understand, interpret and use this information as dictated by neoclassical theories of choice (e.g., an expected utility framework), and that the resulting choices reveal their 'true' preferences for risky or uncertain outcomes. However, widespread evidence from economics and other disciplines suggests that individuals may not interpret or use numerical percentage probabilities as assumed by researchers (e.g., Slovic 1987; Black, Nease, and Tosteson 1995; Yamagishi 1997; Lipkus, Samsa, and Rimer 2001; Edwards, Elwyn, and Mulley 2002; Patt and Schrag 2003; Gilboa, Postlewaite, and Schmeidler 2008; Baker et al. 2009; Cameron, DeShazo, and Johnson 2011). This may be particularly true if presented probabilities disagree with respondents' prior perceptions, leading to scenario adjustment or rejection (Cameron, DeShazo, and Johnson 2011).

Recognizing these concerns, recent stated preference guidelines (Johnston et al. 2017, p. 329) suggest that 'scenarios should communicate [risk] information in terms that are readily understood by respondents,' considering that the risk communication literature does not typically recommend the use of numerical percentage probabilities as the sole means of risk communication. Despite this guidance and common practices to the contrary in the environmental stated preference literature, there have been few external validity tests of different risk communication formats within these studies (e.g., Loomis and duVair 1993), and, to our knowledge, none addressing inherent uncertainty.

This lack of insight is not trivial. In the absence of external (e.g., split-sample) tests that seek to evaluate the effect of percentage probabilities on preference modelling, it is difficult to draw credible conclusions on whether these are an effective form of risk communication within stated preference studies. Internal scope tests in DCEs that evaluate effects of OU using numerical percentage probabilities can mask inaccurate understanding of probabilities by respondents—these tests only require that respondents perceive that 'more is better' with regard to probabilities of positive outcomes. Moreover, internal variation of this type is not present under *inherent* outcome uncertainty, placing greater cognitive burden on respondents as they consider uncertain effects on their anticipated welfare that do not vary across scenarios.

Evaluation of the effect of different risk communication formats on stated preference results thus requires external, split-sample analyses that compare response properties and welfare estimates under alternative approaches of communicating the same inherent uncertainty for *otherwise identical* stated preference DCE surveys. To avoid confounding effects associated with embedding varying probabilities as additional attributes in choice scenarios (e.g., whether observed differences in welfare estimates are due to increased choice task complexity or percentage probabilities *per se*), the current investigation specifies the same level of (fixed) inherent uncertainty across survey treatments with identical choice scenarios, but uses different approaches to communicate this uncertainty. The goal is a formal test of whether numerical probabilities used to communicate the same inherent (scenario invariant) uncertainty lead to different welfare estimates and/or response properties (e.g., symptoms of scenario rejection such as increased choice randomness).

Results are illustrated using an application of DCEs to coastal flood adaptation in Connecticut, USA, where the effect of adaptation measures depends on the (inherently) uncertain future occurrence of severe coastal storms. Data are gathered using two otherwise identical survey treatments. Both treatments present information on historical storm frequency in the study area, but one also presents the numerical percentage probabilities consistent with this historical frequency—following the common approach of presenting probabilities in percentage form.

Comparison of results across these treatments provides insight into the relative effect of percentage probabilities as a tool for communicating inherent uncertainty—and tests explicitly whether and how this additional form of risk communication form influences stated preferences. Two models on pooled data from the two treatments are estimated: a mixed logit model in willingness-to-pay (WTP) space and a latent class model in WTP space. Each model allows for systematic variation in WTP estimates associated with the survey treatments. Taken together, results suggest that the use of numerical percentage probabilities to communicate inherent uncertainty has no additional effect on welfare estimates. These results suggest that in at least some types of environmental stated preference questionnaires, the use of percentage probabilities to convey information on inherent uncertainty may not provide useful information to respondents, beyond information conveyed via raw past event frequencies. These findings highlight the need for further research in the domain of uncertainty communication in valuation surveys.

2. Inherent Uncertainty in Stated Preference Studies

As described by Torres, Faccioli, and Font (2017, p. 231), 'inherent uncertainty is the component of environmental uncertainty which derives from the stochastic nature of an ecosystem's behavior as a result of interactions between physical, chemical, ecological and human factors (Thom, Diefenderfer, and Hofseth 2004; Ascough et al. 2008).' From the perspective of stated preference welfare elicitation, this type of uncertainty (or risk) is not typically considered to be controllable via management or policy interventions, and hence cannot vary across stated preference scenarios (or at least across those scenarios that reflect realistic possibilities). Uncertainties associated with many environmental phenomena—such as those associated with climate change impacts—are understood to be an irreducible aspect of socio-ecological systems (Viscusi and Zeckhauser 2006; Langsdale 2008). Because these uncertainties cannot be significantly reduced by scientific research or influenced by management (at least during the time frame covered by valuation scenarios), they cannot be credibly presented as variable within stated preference questionnaires (Torres, Faccioli, and Font 2017).

Examples of inherent uncertainty are common within environmental management but are rarely made explicit within valuation. For instance, the effect of management options to sustain coastal marshes depends on uncertain sea-level rise (SLR), and this inherent SLR uncertainty does not vary as a function of local marsh management actions (Duran et al. 2019). The effect of coastal flood adaptation actions (such as building sea walls) may depend on the likelihood of future intense coastal storms, where this underlying probability is not affected by local adaptation actions (Makriyannis, Johnston, and Whelchel 2018). Torres, Faccioli, and Font (2017) consider another case, in which management effects on bird species depend on irreducible ecological uncertainty.

Only a few studies consider cases of inherent uncertainty, in which probabilities do not vary across scenarios within each questionnaire (e.g., Wielgus et al. 2009; Torres, Faccioli, and Font 2017; Faccioli, Kuhfuss, and Czajkowski 2018; Makriyannis, Johnston, and Whelchel 2018). Even fewer (e.g., Makriyannis, Johnston, and Whelchel 2018) consider cases of true inherent uncertainty, in which uncertainty does not vary over either scenarios or different questionnaires (treatments). In such cases, the presentation of probabilities (describing the inherent uncertainty) that vary across scenarios may strain the credibility of survey scenarios, leading to scenario rejection caused by presented probabilities that respondents deem to be irrelevant, unrealistic, or inconsistent with their priors (Starmer 2000; Gilboa, Sochen, and Zeevi 2002; Meyerhoff and Liebe 2009; Cameron, DeShazo, and Johnson 2011; Fifer et al. 2011).

Environmental stated preference studies that consider inherent uncertainty typically communicate it using numerical percentage probabilities. In some cases, this is supported by visual aids to help respondents understand the presented information (e.g., Torres, Faccioli, and Font 2017). External tests when inherent uncertainty varies across different survey treatments typically find that the inclusion of—and variation in—percentage probabilities influences welfare estimates in predictable ways (e.g., Wielgus et al. 2009; Torres, Faccioli, and Font 2017; Faccioli, Kuhfuss, and Czajkowski 2018). This follows similar findings for more general types of outcome uncertainty in stated preference valuation.

However, to the best of the authors' knowledge, no prior stated preference study dealing with inherent uncertainty compares responses or welfare estimates across survey instruments whose sole difference is the inclusion (or exclusion) of a set of fixed percentage probabilities; all prior studies proceed under the maintained assumption (perhaps informed by focus groups) that respondents will use this risk information to inform their choice.

3. Hypotheses and Empirical Application

To test explicitly whether and how numerical percentage probabilities affect welfare estimates, we rely on data from a stated preference DCE concerning coastal flood adaptation in the town of Old Saybrook, Connecticut, USA. The analysis focuses on the risk related to the protection of homes vulnerable to flooding during storms of different intensities (Category 2 and Category 3 on the Saffir-Simpson Hurricane Wind Scale),[4] where these storms have different inherent probabilities of occurrence. Within this context, the effect of adaptation measures depends on inherent storm

[4] This common scale distinguishes five categories of hurricane intensity. These range from Category 1 (least intense, with sustained winds of 74–95 mph) to Category 5 (most intense, with sustained winds of 157 mph or higher). From National Oceanic and Atmospheric Administration, http://www.nhc.noaa.gov/aboutsshws.php, accessed May 13, 2021.

probabilities that may be characterized in terms of either historical storm frequencies (a commonly reported metric in the media) or numerical probabilities of storm categories (common in the stated preference literature).

Two treatments (or versions) of the stated preference survey were developed.. The first treatment, S1, describes only the historical frequencies of Category 2 and 3 storms within the past 75 years, but does not present corresponding numerical probabilities.[5] The second treatment, S2, provides identical information on historical storm frequencies but then also presents corresponding numerical percentage probabilities, rounded to the nearest 5%. These are calculated from a long-term storm frequency data that implies a 55% and 20% chance that a Category 2 and Category 3 (or more intense) storm, respectively, will strike Old Saybrook at least once by the year 2025.

Although the presented 75-year storm frequencies (in S1 and S2) and numerical probabilities (in S2) are accurate and factually consistent, the two types of information are not trivially identical. This was purposeful and reflected the fact that numerical probabilities (typically derived from long-term probability distributions) and short-term observed frequencies provide different perspectives on the same underlying inherent uncertainty. For example, it was not possible for respondents to directly calculate the presented storm probabilities (in treatment S2) using *only* the presented 75-year storm frequency information. Additional information was required. As of 2014, the true long-period average annual probability of a Category 3+ hurricane striking Connecticut was estimated to be 2% (Klotzbach and Gray 2013). This corresponds to a 20% chance of at least one Category 3+ storm during the 11 years from 2014 to 2025, which was the percentage presented in treatment S2.[6] One cannot calculate this long-period average using data from only the 75-year period anchored on a known storm date (1938). Hence, although treatments S1 and S2 convey information on the same inherent uncertainty drawn from observed weather patterns, they do so from different perspectives (shorter-term frequencies versus longer-

[5] This 75-year period was chosen because it spanned the difference between the well-known hurricane of 1938 in New England and the year of survey implementation (2014), rounded down to the nearest 5 years. Storm frequencies have been often discussed in New England since 1938, due to the major hurricane that occurred that year.

[6] This may be calculated most easily as one minus the probability that no storm will occur in the region over 11 successive years. For a Category 3 storm this is $1 - 0.98^{11} = 0.20$. The remaining 20% probability reflects the chance that one or more storms will occur during this time.

term percentages).[7]

Other than these differences in risk communication that were presented on a single page of the survey, the two DCEs were identical. Attributes in both DCEs are identical and present the number of homes that would be flooded conditional on a Category 2 storm and the number of *additional* homes that would be flooded conditional on a Category 3 or more intense storm (henceforth referred to simply as 'Category 3 storm'), both forecast as of the year 2025. Other attributes characterize expected changes in coastal wetland and beach areas, the extent of sea walls along the coastline, household cost, and whether the plan emphasizes hardened or natural coastal defenses.

3.1 Econometric Models and Hypotheses Tests

Our econometric approach follows a traditional random utility framework (McFadden 1974; Hanemann 1984) in which household h chooses their preferred option among three coastal adaptation policy options ($p = \{A, B, N\}$), with two options involving changes in the policy (A and B) and a status quo option (N) assuming no adaptation action and zero household cost. Every household takes a decision three times—that is, in three separate choice tasks ($j = \{1, 2, 3\}$). Each option is described by a vector of variables $\boldsymbol{X}_{pjh}$ representing non-monetary characteristics (attributes) of the adaptation policy and variable C_{pjh} expressing the monetary attribute related to unavoidable household cost of the policy implementation.

To account for possible heterogeneity in households' preferences and WTP values for the considered policy attributes, we apply two standard approaches: a mixed (random parameters) logit model (McFadden and Train 2000; Hensher and Greene 2003) and a latent class model (Greene and Hensher 2003). While the former assumes that preference heterogeneity can be characterized by continuous distributions of preference or WTP parameters described by means

[7]Given this difference between historical frequencies and numerical probabilities, it is important to note that comparing the results of a survey treatment that includes only frequencies to those of a survey treatment that includes only probabilities, would not constitute necessarily a true *ceteris paribus* test of the effect of numerical probabilities: under such a test, it would be unclear whether any observed differences in welfare estimates are due to different perspectives on each of the risk communication formats or due to numerical probabilities *per se*. The S1 versus S2 test put forth in the current study avoids any potentially confounding effects: any observed differences between the two survey treatments can be attributed *only* to the numerical probabilities.

and standard deviations, the latter considers discrete distributions of the parameters to capture the heterogeneity. Thus, the latent class model can be viewed as somewhat less flexible than the mixed logit model, since it approximates underlying continuous distributions with discrete distributions. However, the latent class framework does not require one to make assumptions when selecting parametric distributions for coefficients to be estimated (Greene and Hensher 2003). The literature is inconclusive about which modelling approach is superior, and in practice the choice between these two approaches depends on the analyst's assumptions regarding the form of preference heterogeneity likely to be most prevalent within the data. Here, the application and comparison of the two approaches enables us to identify the model that better fits our data and captures unobserved heterogeneity.

To test the primary hypotheses of interest, each model includes dummy variable S_h that identifies possible effects related to the survey treatment received by a household (that is, whether the survey questionnaire provided numerical probabilities to communicate inherent uncertainty, as in the S2 treatment, or whether it did not, as in the S1 treatment). Given a lack of *a priori* knowledge on how risk information communication form might influence choice behavior, we allow for two alternative ways that this might occur. In the mixed logit model, the survey treatment variable is used to examine potential shifts in the mean parameter estimates. In the latent class model, the treatment variable enters the class membership probability function, along with four sociodemographic variables that serve as a robustness check. The subsections below discuss and contrast the two approaches.

3.1.1 Mixed (random parameters) logit model

To develop the mixed logit WTP-space specification, we represent the utility of household h from choosing policy scenario p in choice task j as

$$U_{pjh}(\cdot) = V_{pjh}(\boldsymbol{X}_{pjh}, C_{pjh}) + e_{pjh} = \boldsymbol{\beta}_h{}'\boldsymbol{X}_{pjh} - \alpha_h C_{pjh} + e_{pjh}, \quad (1)$$

where $V_{pjh}(\cdot)$ is a function representing an observable component of the utility and e_{pjh} is an unobservable, or stochastic, component of the utility typically modeled as an econometric error. When choosing between options *A, B,* and *N*, with the utility specified as in (1), the household is assumed to choose the option which offers the greatest expected utility. As shown in the right-hand side of (1), such models are typically defined using an additively separable, linear functional form for utility, where α_h is the marginal utility of income (derived as a negative of the marginal utility of cost attribute C_{pjh}) and $\boldsymbol{\beta}_h$ is a conforming vector of marginal utilities associated with non-monetary attributes $\boldsymbol{X}_{pjh}$. All marginal utility parameters are household-specific, as suggested by indexing over h, which allows for heterogeneous preferences among households—a characteristic distinguishing the mixed logit approach.[8]

The underlying model in (1) may be estimated in either preference space or WTP space (Train and Weeks 2005). Mixed logit models in WTP space circumvent challenges associated with deriving welfare measures (such as WTP) from their preference- or utility-space counterparts (Scarpa, Thiene, and Train 2008; Thiene and Scarpa 2009; Hensher and Greene 2011),[9] while obtaining welfare estimates is of major interest in most valuation studies. Thus, the analysis is based on a mixed logit model in WTP space. To derive the WTP-space model, we first divide all arguments in (1) by the logit scale parameter μ_h, to obtain

$$U_{pjh}(\cdot) = \boldsymbol{\gamma}_h{}'\boldsymbol{X}_{pjh} - \lambda_h C_{pjh} + \varepsilon_{pjh}, \qquad (2)$$

where $\boldsymbol{\gamma}_h = {}^{\boldsymbol{\beta}_h}/_{\mu_h}$ is a vector of preference-space coefficients on non-monetary policy attributes $\boldsymbol{X}_{ph}$, $-\lambda_h = -{}^{\alpha_h}/_{\mu_h}$ is a preference-space coefficient on the policy cost, and the resulting error term ε_{pjh} has an i.i.d. type I extreme value distribution with constant variance $var(\varepsilon_{pjh}) = {}^{\pi^2}/_6$ (Train and Weeks 2005; Scarpa, Thiene, and Train 2008).

The vector of marginal WTP estimates (implicit prices) for a change in non-monetary attributes may be calculated as a ratio of the coefficients on these non-monetary attributes and the cost coefficient, $\boldsymbol{\omega}_h = {}^{\boldsymbol{\gamma}_h}/_{\lambda_h} = {}^{\boldsymbol{\beta}_h}/_{\alpha_h}$. We hence rewrite (2) to obtain the WTP-space specification (Train and Weeks 2005),

$$U_{pjh}(\cdot) = \lambda_h[(\boldsymbol{\gamma}_h/\lambda_h)'\boldsymbol{X}_{pjh} - C_{pjh}] + \varepsilon_{pjh} = \lambda_h(\boldsymbol{\omega}'_h\boldsymbol{X}_{pjh} - C_{pjh}) + \varepsilon_{pjh}, \qquad (3)$$

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[8] Assuming, instead, that parameters do not differ across households implies homogenous preferences and leads to a multinomial logit specification.

[9] The challenges are related particularly to the randomly specified cost coefficient (Hensher and Greene 2003; Train and Weeks 2005; Thiene, and Train 2008; Thiene and Scarpa 2009; Daly, Hess, and Train 2012; cf. Cameron and James 1987), whose presence in the denominator of the analytical WTP expression may lead to behaviorally and statistically implausible WTP values, for instance, due to infinite WTP moments (Daly, Hess, and Train 2012). Cost coefficient distributions that lead to finite WTP moments can lead to additional analytical challenges, such as problems associated with the long tails of the lognormal distribution typically assumed for the cost coefficient (Hensher and Greene 2003).

which is behaviorally equivalent to the preference-space specification in (2). The elements of vector $\boldsymbol{\omega}_h$ are random coefficients representing direct estimates of marginal WTP, assumed to be normally distributed. To ensure a positive marginal utility of income, we follow standard practice and specify $\lambda_h = e^{v_h}$, where v_h is the underlying latent normal factor that defines the lognormally distributed cost coefficient (Scarpa, Thiene, and Train 2008; Thiene and Scarpa 2009).[10]

Based on this underlying model, we extend (3) to allow for systematic variation in $\boldsymbol{\omega}_h$ between the S1 and S2 treatments. Recall that for treatment S2, respondents are provided also with the numerical percentage probability of storms. For treatment S1, only historical frequencies are presented. To allow for the possible systematic variation in parameter estimates between the S1 and S2 samples—helping identify the effect of numerical probabilities as a means of communicating inherent storm risk—we specify the vector of WTP parameters in (3) as

$$\boldsymbol{\omega}_h = \boldsymbol{\omega}_h^* + \boldsymbol{\rho} S_h, \tag{4}$$

where $\boldsymbol{\omega}_h^*$ has a multivariate normal distribution with a set of means and a covariance matrix to be estimated; $\boldsymbol{\rho}$ is a vector of parameters to be estimated; and S_h is an indicator variable that takes a value of one if household h received the S1 survey (which omits numerical probabilities) and a value of zero if household h received the S2 survey (which provides numerical probabilities).

Using the same notation, we redefine the cost coefficient as

$$\lambda_h = e^{v_h + \tau S_h}, \tag{5}$$

with parameter τ to be estimated. Equation (5) enables marginal utility of income and scale to vary systematically depending on the survey treatment.

Within this model, the key hypotheses relate to the parameters $\boldsymbol{\rho}$ and τ, reflecting the influence of different communication formats of inherent uncertainty. Specifically, we focus on whether the provision of this information as a percentage probability ($S_h = 0$) leads to variations in either $\boldsymbol{\omega}_h$ (WTP estimates) or λ_h. The presence of a significant effect would suggest that the provision of information on percentage probabilities (in addition to storm frequencies) led to different welfare estimates, at least potentially reflecting better-informed choices by respondents.

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[10] In WTP-space models, the random cost parameter, denoted here as λ_h , captures variation in both marginal utility of income and scale (Thiene and Scarpa 2009).

3.1.2 Latent class multinomial logit model

To develop the latent class multinomial logit model in WTP space, the utility of household *h* from choosing policy scenario *p* in choice task *j* can be expressed in a similar way to the earlier representation for the mixed logit model in (3), that is, as

$$U_{pjh}^{c}(\cdot) = \lambda_c(\boldsymbol{\omega}_c'\boldsymbol{X}_{pjh} - C_{pjh}) + \varepsilon_{pjh}. \quad (6)$$

The notation in (6) is analogous to that introduced in the earlier subsection on the mixed logit model, with the only difference being the indexing of utility by class *c* (*c* = {1, 2, …, *C*}) to which a household belongs. In the latent class model, WTP parameters and the cost coefficient are class-specific. Naturally, and as in reality, we are not able to determine with certainty to which class a household belongs, but we can estimate the probability with which a household is a member of a given class.

As introduced earlier, we define the probability of belonging to class *c* as a function of the survey treatment received by a household and socio-demographic characteristics. Specifically, the class membership probability is explained by variable S_h, specified as above, socio-demographic characteristics stack in vector $\boldsymbol{SD}_h$. Thus, the probability of belonging to class *c*, π_c, can be represented as

$$\pi_c = \frac{\exp\left(\delta_c + \kappa_c S_h + \boldsymbol{\varphi}_c'\boldsymbol{SD}_h\right)}{\sum_{m=1}^{C}\exp\left(\delta_m + \kappa_m S_h + \boldsymbol{\varphi}_m'\boldsymbol{SD}_h\right)} \quad (7)$$

where δ_c, κ_c and $\boldsymbol{\varphi}_c$ are parameters to be estimated for *c* = {1, 2, …, *C* – 1}. For identification, the parameters for the last class (i.e., class *C*) are equal to zero, that is, $\delta_C = 0$, $\kappa_C = 0$ and $\boldsymbol{\varphi}_C = 0$. As a result, the parameters can be interpreted in relation to class *C*, which constitutes a reference category.

Within the latent class model, the key hypotheses relate to the parameters δ_c and κ_c which allow preferences to vary via the effect of S_h on the latent class membership. Here, we focus on whether the risk communication with a percentage probability ($S_h = 0$) leads to differences in the probability of falling into different classes—and what this implies about choice behavior and welfare estimates.

3.1.3 Model estimation

The mixed logit model is estimated using the simulated maximum likelihood method with 6,000 Sobol draws, with mean WTP and cost coefficients specified as correlated and random with normal distributions for WTP parameters and a lognormal distribution for the cost parameter. The latent class model is estimated via maximum likelihood with three classes (i.e., $c = \{1, 2, 3\}$). To ensure the models' convergence, all continuous variables are scaled prior to the estimation by dividing non-monetary attribute levels by 10 and policy cost by 100. Several other specifications were estimated to ensure robustness of results, all of which have generated results consistent with those shown in this paper. The selection of the models presented in the paper is guided by model fit based on the value of the log-likelihood function and information criteria, including Akaike information criterion (AIC) and Bayesian information criterion (BIC). The econometric analysis is conducted in Matlab.[11]

4. Survey and Empirical Application

We implement the above models using a DCE addressing preferences for climate change adaptation in Old Saybrook, Connecticut, USA. The DCE considered approaches that could be used to protect homes and natural systems such as beaches and coastal marshes from flooding and erosion. The survey instrument was developed over two years in a collaborative process involving economists and natural scientists; meetings with town planners, engineers and stakeholder groups; and 13 focus groups with community residents. Attention to development and testing helped ensure that survey language, graphics, and format were understood by respondents; that respondents and researchers shared interpretations of survey terminology and scenarios; and that scenarios (including attributes and levels) captured adaptation outcomes viewed as relevant and realistic.[12]

The structure of the DCE follows the theoretical model described above: Household h chooses among three adaptation options, including two multi-attribute adaptation options (A, B) and a status quo (N) that involves no new adaptation actions and zero household cost. DCE

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[11] We use a custom code developed in Matlab, which is available at https://github.com/czaj/DCE under CC BY 4.0 license.

[12] DCE scenarios and protection options were informed using data provided by the Center for Climate Systems Research at Columbia University, NASA's Goddard Institute for Space Studies, the National Oceanic and Atmospheric Administration (NOAA) Services Center, and The Nature Conservancy. Attributes were selected based on a conceptual model combining input from focus groups; natural scientists with expertise in sea-level rise, coastal vulnerability and adaptation; coastal flooding scenarios; and interviews with community officials.

attributes reflect outcomes expected by the mid-2020s. These include attributes characterizing (a) the share of homes vulnerable to flooding in a Category 2 storm; (b) the additional share of homes vulnerable to flooding *only* in a Category 3 or greater storm; (c) wetland acreage expected to be lost because of flooding or erosion; (d) natural beach and dune acreage expected to be lost because of flooding or erosion; (e) the share of the coastline length to be hard-armored with sea walls; and (f) the emphasis of the adaptation plan on hard structures or soft (natural) measures compared to current approaches. Finally, the DCE includes an attribute indicating annual household cost in unavoidable taxes and fees. Table 1 provides a description for each variable, as well as attribute summary statistics for the S1 and S2 samples.

Table 1. Model Variable Names and Descriptive Statistics (means and standard deviations include the status quo option of no adaptation action.)

Choice Attribute and Model Variable Name	**Definition**	**S1 Survey (Omitted Numerical Probabilities) Mean (Std. Dev.)**	**S2 Survey (Included Numerical Probabilities) Mean (Std. Dev.)**
status quo	Alternative specific constant associated with the status quo (i.e., a choice of neither Option A or Option B).	0.33 (0.47)	0.33 (0.47)
homes2	The percentage of Old Saybrook homes that are expected to flood in a Category 2 or higher storm in the mid-2020s. With no new action, 28% of homes (1,411 of the current 5,034 homes in Old Saybrook) will be in this higher risk category by the mid-2020s.	26.18 (3.90)	26.42 (3.88)
homes3	The percentage of Old Saybrook homes that are expected to flood ONLY in a Category 3 or higher storm in the mid-2020s. They are not expected to flood in a Category 2 storm. With no new action, 23% of homes (1,174 of the current 5,034 homes in Old Saybrook) will be in this moderate risk category by the mid-2020s.	21.97 (3.46)	21.77 (3.42)
wetlands	The percentage of Old Saybrook's coastal marshes expected to be lost by the mid-2020s due to flooding or erosion. With no new action, 5% of Old Saybrook's coastal marshes (25 of 497 acres that exist today) are expected to be lost.	5.05 (2.63)	5.06 (2.61)
beaches	The percentage of Old Saybrook's beaches and dunes expected to be lost by the mid-	9.53 (4.28)	9.40 (4.32)

	2020s due to flooding or erosion. With no new action, 10% of Old Saybrook's beaches and dunes (about 3 of 30 acres that exist today) are expected to be lost.		
seawalls	The percentage of Old Saybrook's coast shielded by hard defenses. With no new action, 24% of Old Saybrook's coastline (12 of 50 miles) will have hard defenses by the mid-2020s. This is the same level as today.	24.94 (6.29)	24.77 (6.39)
hard	Binary variable that takes on a value of 1 if the adaptation option emphasizes hard defenses or shoreline armoring and a value of 0 otherwise.	0.19 (0.39)	0.20 (0.40)
soft	Binary variable that takes on a value of 1 if the adaptation option emphasizes soft or natural defenses and a value of 0 otherwise.	0.16 (0.37)	0.16 (0.37)
cost	How much the option will cost the household per year in unavoidable taxes and fees. These funds were assumed to be legally guaranteed to be spent only on the coastal protection option that the household voted for.	62.46 (56.49)	62.45 (56.14)
p_h	The household's self-reported, perceived probability of a Category 3 storm, measured between 0 and 1.	0.39 (0.28)	--

Attribute baselines and levels were grounded in inundation and adaptation scenarios identified by digital inundation models (i.e., future storm and flooding scenarios) developed for the Coastal Resilience decision-support platform (www.coastalresilience.org), combined with expert consultations. Following the guidelines of Johnston et al. (2012) and Schultz et al. (2012) for biophysical indicators within DCEs, all non-cost continuous attributes presented each adaptation method and effect in relative (percentage) terms with regard to upper and lower reference conditions (i.e., best and worst possible in Old Saybrook), as defined in survey informational materials. Scenarios also show the cardinal basis for relative levels where applicable. Relative attribute levels represent losses approaching the upper reference condition (100% loss), starting from the lower reference condition (0% loss). For example, the attribute representing the number of homes expected to flood in a Category 2 storm (*homes2*) is presented both as a cardinal number and as a percentage relative to the total number of homes in Old Saybrook. Table 2 provides the attribute levels used in the survey.

Table 2. Attribute Levels in the DCE

Attribute / Variable	Attribute / Variable Levels
homes2	20%; 24%; 28%; 32%
homes3	16%; 19%; 23%; 27%
wetlands	2%; 5%; 10%
beaches	3%; 5%; 7%; 10%
seawalls	15%; 24%; 35%
hard	0;1
soft	0;1
cost	$0; $35; $65; $95; $125; $155

Grounded in these attribute levels, a fractional factorial experimental design was generated using a D-efficiency criterion (Sándor and Wedel 2001, 2002; Ferrini and Scarpa 2007; Scarpa and Rose 2008; Rose and Bliemer 2009) for main effects and selected two-way interactions, yielding 72 profiles blocked in 24 booklets. Each respondent was provided with three choice questions and was instructed to consider each choice question as independent and non-additive. An example of a choice task is presented in Figure 1.

Prior to presenting choice questions, the survey provided information describing tradeoffs associated with alternative approaches to coastal adaptation, projected inundation scenarios in the mid-2020s, and baseline (status quo) effects with no new adaptation actions. Information was conveyed via a combination of text, graphics including geographic information system (GIS) maps, and photographs. Detailed instructions were also provided, including reminders to consider budget constraints and statements highlighting the survey consequentiality (Carson and Groves 2007). The survey language and graphics were subject to extensive pretesting in 13 focus groups and multiple cognitive interviews (Johnston et al. 1995; Kaplowitz, Lupi, and Hoehn 2004), including the use of verbal protocols to gain insight into respondents' comprehension and decision processes (Schkade and Payne 1994).

Figure 1. Sample Choice Question

PROTECTION OPTION A and **PROTECTION OPTION B** are possible protection options for Old Saybrook. **NO NEW ACTION** shows what is expected to occur with no additional protection. All plans involve hard and soft defenses in different areas. Given a choice between the three, how would you vote?

Methods and Effects of Protection	Result in 2020s with NO NEW ACTION	Result in 2020s with PROTECTION OPTION A	Result in 2020s with PROTECTION OPTION B
	No Change in Existing Defenses	More Emphasis on SOFT Defenses	More Emphasis on SOFT Defenses
Homes Flooded in Category 2 Storm	**28%** 1,411 of 5,034 homes expected to flood in a Category 2 storm	**32%** 1,611 of 5,034 homes expected to flood in a Category 2 storm	**28%** 1,411 of 5,034 homes expected to flood in a Category 2 storm
Homes Flooded Only in Category 3+ Storm	**23%** 1,174 of 5,034 homes expected to flood only in a Category 3+ storm	**23%** 1,174 of 5,034 homes expected to flood only in a Category 3+ storm	**27%** 1,359 of 5,034 homes expected to flood only in a Category 3+ storm
Wetlands Lost	**5%** 25 of 497 wetland acres expected to be lost	**2%** 10 of 497 wetland acres expected to be lost	**2%** 10 of 497 wetland acres expected to be lost
Beaches and Dunes Lost	**10%** 3 of 30 beach acres expected to be lost	**16%** 5 of 30 beach acres expected to be lost	**16%** 5 of 30 beach acres expected to be lost
Seawalls and Coastal Armoring	**24%** 12 of 50 miles of coast armored	**24%** 12 of 50 miles of coast armored	**24%** 12 of 50 miles of coast armored
Cost to Your Household per Year	**$0** Increase in annual taxes or fees	**$125** Increase in annual taxes or fees	**$95** Increase in annual taxes or fees
HOW WOULD YOU VOTE? (CHOOSE ONLY ONE) I vote for	☐ I vote for NO NEW ACTION	☐ I vote for PROTECTION OPTION A	☐ I vote for PROTECTION OPTION B

As noted above, the two treatments of the survey differ only in the communication of inherent uncertainty. All other aspects are identical. The first survey treatment, S1, provided only the historical frequencies of Category 2 and 3 storm events (Figure 2). These were highlighted on a dedicated section of the survey that provided information on storm uncertainty and identified areas of the community that would be expected to flood under storms of different intensities, under the status quo (i.e., no new flood adaptation measures). The second survey treatment, S2, supplemented the same historical frequency information with the numerical percentage probabilities of each of these two storm events occurring at least once by 2025, calculated based on their long-term historical frequency as described above (Figure 3). These probabilities are linked to choice scenarios through the attributes *homes2* and *homes3* (see above), which indicate the share of homes expected to flood in a Category 2 storm, and the share of additional homes expected to flood in a Category 3 storm, respectively. To ensure that respondents understood relationships between storms of different intensities and home flooding, the survey included a simple graphic illustrating the risk-related differences between these two groups of homes. This figure also clarifies the definition of these two groups of homes, highlighting, for example, that they are independent and non-overlapping groups.

Only the two home flooding attributes (*homes2* and *homes3*) were explicitly linked to storm occurrences and probabilities in the questionnaire. Other choice attributes such as *wetlands* and *beaches* (as defined in Table 1) are more influenced by ongoing erosion and sea-level rise rather than by instances of acute flooding. While home flooding will only occur under storms of different intensities (if and when they occur), other attribute changes would occur regardless of storm occurrence. These differences were made clear in the questionnaire.

Each mail-back survey treatment was sent to 576 randomly selected Old Saybrook households via U.S. mail during May through July 2014 together with a postage-paid return envelope, with repeated mailings following Dillman et al. (2009) to increase response rates. The analysis is based on 146 returns from the 493 deliverable S1 surveys, for a response rate of 29.6%, and 123 returns from the 508 deliverable S2 surveys, for a 24.2% response rate.

Figure 2. S1 Survey Treatment: Historical Storm Frequency

WHAT IS THE RISK?

Scientists categorize hurricane intensity by wind speed. Hurricanes that rank higher are more intense and pose greater risks.

Category	Wind Speed	Hurricane Intensity
Category 1	74 - 95 miles per hour (mph)	Low
Category 2	96 - 110 mph	Moderate
Category 3	111 - 130 mph	High
Category 4	131 - 155 mph	Very High
Category 5	156 mph or higher	Extremely High

Over the last 75 years, Old Saybrook has been struck by a **Category 2 storm in 1960, 1985 and 1991**, and by a **Category 3 storm in 1938 and 1954**. There have been no Category 4 or Category 5 storms. Although Hurricane Sandy was a Category 2 storm off the New Jersey coast, it weakened to below hurricane intensity before it reached Connecticut.

Your support for different protection options may depend on what kind of storms you expect in the future.

Question 3.

Please indicate how likely **you** think it is that each of the following hurricane events will strike Old Saybrook at least once by the mid-2020s (your best guess). For example, a score of 0% would mean that you feel there is **no chance** and a score of 100% would mean that you are **absolutely certain**. Check only one box for each.

	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
a. **Category 2**	☐ 1.	☐ 2.	☐ 3.	☐ 4.	☐ 5.	☐ 6.	☐ 7.	☐ 8.	☐ 9.	☐ 10.	☐ 11.
b. **Category 3 or greater**	☐ 1.	☐ 2.	☐ 3.	☐ 4.	☐ 5.	☐ 6.	☐ 7.	☐ 8.	☐ 9.	☐ 10.	☐ 11.

Figure 3. S2 Survey Treatment: Historical Storm Frequency and Corresponding Numerical Probabilities

WHAT IS THE RISK?

Scientists categorize hurricane intensity by wind speed. Hurricanes that rank higher are more intense and pose greater risks.

Category	Wind Speed	Hurricane Intensity
Category 1	74 - 95 miles per hour (mph)	Low
Category 2	96 - 110 mph	Moderate
Category 3	111 - 130 mph	High
Category 4	131 - 155 mph	Very High
Category 5	156 mph or higher	Extremely High

Over the last 75 years, Old Saybrook has been struck by a **Category 2 storm in 1960, 1985 and 1991**, and by a **Category 3 storm in 1938 and 1954**. There have been no Category 4 or Category 5 storms. Although Hurricane Sandy was a Category 2 storm off the New Jersey coast, it weakened to below hurricane intensity before it reached Connecticut.

Based on past storm events, scientists estimate that there is approximately a **55% (or about one in two) chance that a Category 2 storm will strike Old Saybrook at least once by the mid-2020s** (0% would mean there is no chance and 100% would mean it is absolutely certain).

In contrast, scientists estimate that there is approximately a **20% (or one in five) chance that a Category 3 or higher storm will strike Old Saybrook at least once by the mid-2020s**.

5. Results

This section presents the results of the mixed logit and latent class models used to evaluate parallel (but not structurally identical) hypotheses regarding the potential effect of a risk communication format. As described above, these tests are underpinned by an assumption that is seemingly implicit in the environmental stated preference literature—that the presentation of risk information in the form of percentage probabilities will lead to more informed responses and welfare estimates, or at least to different responses than would be observed in the absence of this information.

It is not straightforward to determine which econometric approach—the mixed logit model or the latent class model—matches the data better (cf. Greene and Hensher 2003). Although the log-likelihood value is slightly better for the mixed logit model, a log-likelihood ratio test suggests that the difference is not statistically significant. While the mixed logit model slightly outperforms the latent class model in terms of McFadden's pseudo-R^2, the latent class model is related to lower values of the Akaike and Bayesian information criteria (AIC and BIC, respectively) implying a better fit of this model to the data. Moreover, regardless of which model provides the best overall fit, each may provide distinct insights into the effect of the survey treatments in question. Hence, we proceed with a discussion and comparison of results from both models.

5.1 Mixed (random parameters) logit model

Results of the mixed logit model are shown in Table 3. Mean WTP coefficient estimates have anticipated signs and match preferences revealed during focus groups. Because non-monetary continuous attributes (that is, *homes2*, *homes3*, *wetlands*, *beaches* and *seawalls*) are specified as resource losses, negative WTP values are expected. We also find the anticipated positive coefficient estimate on the sign-reversed policy cost. We, thus, conclude that the signs are in line with standard neoclassical assumptions. However, not all of the mean WTP estimates are statistically significant at conventional significance levels. The statistically significant mean WTP coefficients include those on *status quo*, *homes2*, *homes3*, *wetlands* and *hard*. All coefficients on WTP standard deviations are large and statistically significant at $p \leq 0.01$, providing evidence of preference heterogeneity. This is also anticipated based on focus groups.

Our primary hypothesis test here relates to the last column of Table 3, which presents shifts (from the mean WTP estimates for S1 sample) in the mean coefficient estimates for S2 sample, who were provided with numerical probabilities informing about inherent storm risk. None of these terms, included to identify the treatment effects, are statistically significant, suggesting no significant differences in WTP values between the S1 and S2 samples. This result implies that the values displayed in column 'Mean WTP' can be interpreted as average estimates for any of the two samples. This is a key finding—we do not observe any statistically significant differences in WTP estimates between respondents who were provided with numerical probabilities characterizing the inherent uncertainty of storm events and respondents who were not provided with these probabilities. In other words, results of the mixed logit model suggest that the use of numerical probabilities to communicate inherent uncertainty (compared to short-term frequencies) does not affect WTP values on average.

Table 3. Results of the WTP-Space Mixed Logit Model

Variable	Mean WTP (Std. Error)	Standard Deviation (Std. Error)	Mean WTP Shift for S2 Sample (Std. Error)
status quo	-4.83*** (1.24)	10.34*** (3.01)	0.04 (0.48)
homes2	-1.38** (0.63)	4.18*** (1.18)	0.35 (0.68)
homes3	-1.23* (0.64)	4.47*** (1.23)	-0.44 (0.73)
wetlands	-1.32* (0.74)	3.64*** (0.99)	-0.17 (0.88)
beaches	-0.24 (0.42)	3.07*** (0.83)	-0.95 (0.61)
seawalls	-0.59 (0.38)	1.17*** (0.33)	0.50 (0.39)
hard	-1.47** (0.66)	2.16*** (0.59)	0.66 (0.61)
soft	-0.56 (0.52)	3.00*** (0.87)	0.47 (0.56)
A negative of *cost*	0.46 (0.53)	1.99*** (0.43)	0.33 (0.47)
Model diagnostics			
Log-likelihood at convergence		-678.50	
Log-likelihood at constants only		-883.88	
McFadden's pseudo-R^2		0.2324	
AIC/*n*		1.8422	
BIC/*n*		2.2094	
Number of observations (*n*)		805	
Number of respondents		282	
Number of parameters		63	

Notes: * means p-value ≤ 0.10, ** p-value ≤ 0.05 and *** p-value ≤ 0.01. For the cost coefficient, the estimates of the underlying normal distribution are provided. As per equation (3), we use a negative of the cost.

Since the model is estimated in WTP space, the mean coefficient estimates can be interpreted as WTP values per year in U.S. dollars. To recall, all continuous non-monetary attributes are divided by 10 prior to estimation and the cost attribute is divided by 100 to ensure convergence.[13] As such, the corresponding coefficient estimates of the continuous non-monetary attributes are multiplied by 10 to provide unscaled marginal WTP estimates. The resulting values may be interpreted as WTP for a one-percent-point change in a given attribute. For example, the estimate of -1.38 on *homes2* suggests that each household is willing to pay, on average, about \$13.8 annually to protect an additional percent point of homes from flooding in a Category 2 storm. The result for *homes3* implies a WTP of \$12.3 per year to prevent the flooding of an additional percent point of homes in a Category 3 storm. Similarly, the coefficient estimate on *wetlands* indicates that the average household is willing to pay \$13.2 per year to avoid one percent point loss of marsh acres. Other estimates are interpreted similarly.[14]

In summary, estimates from the mixed logit model show no evidence that the format used to present uncertainty information (S1 versus S2) led to variations in responses or welfare estimates. One possible explanation is that respondents simply ignored the information on inherent uncertainty—whether presented as percentages or frequencies. However, it is also possible that this information influenced responses in ways that are not immediately evident from mixed logit estimates. For example, the large-magnitude WTP standard deviations within this model might be interpreted as evidence that a unimodal, continuous distribution of preferences—as imposed by the mixed logit model—may not be sufficient to fully capture preference and response heterogeneity. At least in part, this heterogeneity could potentially be due to whether a subject received the S1 or S2 treatment. To further explore this possibility, we continue with results from the latent class model below, which considers a different potential mechanism through which the survey treatment might influence choice behavior.

5.2 Latent class multinomial logit model

Results of the three-class latent class multinomial logit model are presented in Table 4. The three-class model was selected based on the results of preliminary models with alternative numbers of classes. The three classes identify largely distinct preferences for choice attributes. Within this model, we allow the survey treatment, gender, degree of education, and current employment and

[13] This is a common approach for models of this type and has no substantive impact on the model results other than to promote convergence.

[14] The statistically insignificant cost coefficient estimate cannot be interpreted as a statistically insignificant estimate on the marginal utility of income (i.e., implying that the cost is irrelevant to respondents), because the estimate refers to the underlying normal distribution (not the lognormal distribution used to model the cost).

year-round residence status to influence preference estimates through the class membership function.[15] We discuss each class in a descending order of estimated class probability. Parameters in the class membership function are estimated relative to those for Class 3, which are set fixed and equal to zero.

Class 2, which constitutes the largest share in the pooled sample (56% probability), reveals WTP values consistent with the expectations based on standard neoclassical assumptions and consistent with the coefficient means estimated in the mixed logit model. This class holds statistically significant preferences for all attributes except *soft* and *beaches.* A household belonging to Class 2, for example, is willing to pay annually, on average, \$5.40 and \$5.50 to protect an additional percent point of homes from flooding in Category 2 and 3 storms, respectively, and \$6.50 to avoid a one percent point loss of coastal marsh acres (*wetlands*), among multiple other statistically significant welfare estimates. In sum, this class shows behavior and WTP estimates that are consistent with subjects who hold positive value for coastal adaptation policies that protect wetland habitats and homes vulnerable to flooding in Category 2 and 3 storms. The S2 survey treatment has no statistically significant impact on membership in Class 1 relative to Class 3 (the default).

In Class 3, only the cost attribute is statistically significant, which suggests that no other adaptation attributes are relevant for households within this class. In other words, households in Class 3 do not hold significant value for any type of climate change adaptation action or the protection of homes and natural habitats – instead, their choices are driven primarily by the program cost. This reveals a relatively common pattern identified in latent class models, wherein one class is motivated primarily by cost and/or holds little value for environmental outcomes (e.g., Hidrue et al. 2011; Morey, Thacher, and Breffle 2006). This type of behavior is consistent with neoclassical assumptions for individuals with preferences of this type. This class constitutes about 29% of the sample.

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[15] Although the results of a preliminary (three-class) latent class model that omits the sociodemographic variables suggest that the survey treatment affects the class membership, the results presented here show that this effect disappears when we control for sociodemographic characteristics. A log-likelihood ratio test also supports the latent class model with sociodemographic variables.

Table 4. Results of the WTP-Space Latent Class Multinomial Logit Model

	Class 1	Class 2	Class 3
Variable	**Mean WTP (Std. Error)**	**Mean WTP (Std. Error)**	**Mean WTP (Std. Error)**
status quo	0.76 (0.49)	-2.51*** (0.53)	1.58 (1.23)
homes2	1.37*** (0.50)	-0.54** (0.21)	-0.53 (0.55)
homes3	0.94** (0.44)	-0.55** (0.23)	-0.46 (0.48)
wetlands	0.11 (0.32)	-0.65** (0.26)	-0.74 (0.74)
beaches	1.16*** (0.32)	-0.22 (0.15)	-0.16 (0.39)
seawalls	0.47 (0.33)	-0.31** (0.14)	0.23 (0.32)
hard	-0.37 (0.34)	-0.46** (0.22)	-0.08 (0.52)
soft	0.62** (0.28)	-0.10 (0.20)	0.68 (0.64)
cost (sign-reversed)	-5.42 (3.40)	1.13*** (0.29)	1.55* (0.83)
Class membership probability function			
constant	-0.61 (1.55)	1.50 (1.16)	0.00 (fixed)
S2 sample	0.60 (0.51)	0.01 (0.32)	0.00 (fixed)
female	0.63 (0.62)	1.21*** (0.34)	0.00 (fixed)
degree	-0.07 (0.50)	0.02 (0.34)	0.00 (fixed)
currently employed	0.33 (0.51)	-0.42 (0.33)	0.00 (fixed)
Year-round resident	-0.80 (1.51)	-1.10 (1.13)	0.00 (fixed)
Average class probabilities			
	14.75	56.11	29.14
Model diagnostics			
Log-likelihood at convergence		-640.22	
Log-likelihood at constants only		-830.57	
McFadden's pseudo-R^2		0.2292	
AIC/*n*		1.7945	
BIC/*n*		2.0330	
Number of observations (*n*)		757	
Number of respondents		264	
Number of parameters		39	

Notes: * means p-value ≤ 0.10, ** p-value ≤ 0.05 and *** p-value ≤ 0.01.

Class 1 is the smallest predicted latent class (almost 15% inclusion probability), and includes several WTP parameters with signs opposite to expectations based on standard neoclassical assumptions. For example, the results suggest that households in this class would be willing to pay positive amounts for losses in the attributes *homes2*, *homes3* and *beaches*. This class is also characterized by seemingly high randomness of choices, as implied by the (relatively) large point-estimate magnitude, unanticipated negative sign, and statistically insignificant coefficient on *cost*. Because the marginal utility of income and scale are confounded in the *cost* parameter within WTP-space models, variations in choice randomness (and hence scale) are revealed through this parameter. The cause of the apparent choice randomness and unexpected welfare estimates within Class 1 is unknown, but could potentially be due to factors such as confusion, choice uncertainty, scenario rejection or protesting, the use of unanticipated decision heuristics, or other factors (cf. Cameron, DeShazo, and Johnson 2011; Dekker et al. 2016). The statistically insignificant coefficient estimates on the sociodemographic variables and *S2 sample* again suggest that these have no effect on the probability of membership in Class 1.

In conclusion, neither the mixed logit nor the latent class model produce any evidence that the inclusion of numerical probabilities affect WTP estimates or choice behavior. Stated differently, the provision of numerical probabilities as a means of communicating inherent uncertainty does not seem to help respondents make more informed choices. Finally, to explore the possibility that the provision of numerical probabilities may have had an effect on some respondents' propensity to complete the survey (i.e., participate in the research project), we test for sociodemographic differences between the S1 and S2 survey treatments.

The results of these sociodemographic difference tests are shown in Table 5. This analysis is based on the sample of 282 respondents, each of which answered at least one choice task. The last column shows that the two survey treatments are statistically significantly different only in terms of respondents' age (p-value = 0.043) and current employment status (p-value = 0.080) (two variables likely to be correlated, i.e., older respondents are more likely to have retired). Specifically, the average respondent that took the S1 survey (which omitted numerical probabilities) is somewhat older and less likely to be currently employed, relative to the average respondent that took the S2 survey (which included numerical probabilities in addition to storm frequencies).

Table 5. Selected Sociodemographic Descriptive Statistics for S1 and S2 Survey Samples (n = 282)

Sociodemographic Variable	**S1 Sample "subjective" (without numerical probabilities)**	**S2 Sample "objective" (with numerical probabilities)**	***p*-value**
Discrete Sociodemographic Variable			
Female	45.7%	40.0%	0.342
Graduate Degree	31.1%	30.1%	0.859
4-year college degree	30.4%	29.3%	0.839
2-year college degree	10.8%	13.0%	0.577
Some college	16.9%	13.8%	0.487
Currently Employed	55.4%	65.9%	0.080
Year-Round Resident	96.7%	96.8%	0.941
Continuous Sociodemographic Variable			
Age	62.7	59.9	0.043
Annual Household Income (USD)	119,154	126,364	0.400
Years of Residency	21.9	22.5	0.800

Notes: p-values are for the null hypothesis of no difference between S1 and S2 samples with respect to the indicated sociodemographic variable. For the discrete sociodemographic variables, the table shows the shares of respondents within each sample, and chi-squared tests of equality of proportions are used to test for differences. For the continuous variables, mean values are reported, and the Wilcoxon signed-rank test is used to test for differences. As household income was measured on an eight-point scale representing different income categories, midpoints of the categories are used.

The reason for this apparent difference is unclear, as the sample frames for both survey treatments were identical. It is possible—though seemingly unlikely—that risk communication format could have caused a difference in the propensity to respond (to the survey) across different demographic groups.[16] This variation may also be due, however, to simple statistical chance (Type I error). Although we lack the data to explore this issue further in the present case, this intriguing finding highlights the potential relevance of future research into whether and how numerical probabilities used to communicate inherent uncertainty might influence some residents' propensity to participate in a questionnaire.

5.3 Summary and discussion

Overall, the models produce no evidence that numerical probabilities, used in addition to information on raw event frequencies over time, provided any advantage as a means of communicating inherent uncertainty in environmental stated preference surveys. The majority of surveyed respondents in both treatment samples appear to make trade-offs consistent with standard neoclassical economics assumptions, are willing to pay to avoid negative environmental effects related to storm risk, and derive positive marginal utility from income. The results of sociodemographic difference tests, however, provide some evidence that the use of numerical probabilities to communicate inherent outcome uncertainty might have influenced some respondents' propensity to take the survey. Hence, results do not appear to support the use of numerical percentage probabilities to communicate inherent uncertainty within environmental DCEs, in addition to other forms of risk communication[17]; i.e., we find no evidence that the provision of numerical percentage storm probabilities—in addition to historical storm frequency—helped respondents make more informed or 'better' choices.

One possible explanation for this "negative" result is that respondents receiving the S2 treatment may have overlooked the provided percentage probabilities when reading the

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[16] In the context of the current research, for example, it is conceivable that older, retired adults that disagreed with the shown probabilities of future storm events (S2 survey) were more reluctant to engage in this policy-relevant research study related to climate adaptation – lest this leads to higher taxes, unwelcome changes to property rights, friction between neighbors and friends, or other outcomes that increase financial and social uncertainty as they age.

[17] Note that the use of percentages to communicate probabilities is distinct from the use of percentages to communicate changes in non-probability attributes within DCEs. Whereas the risk-communication literature argues against the use of percentage probabilities to communicate risk (see citations above), the environmental DCE literature provides evidence directly supporting the use of percentages along with supporting cardinal numbers (as done here) to communicate non-probability attributes, such as the proportion of homes subject to flooding (Johnston et al. 2012; Schultz et al. 2012).

questionnaire. Although this is possible, evidence indicates that it is highly unlikely. For example, qualitative feedback from individual focus group participants suggests that residents paid close attention to survey text which provided information about the likelihood of future storm events—as this was among the central features of the questionnaire. This qualitative feedback during survey design and testing suggests that the likelihood that respondents simply ignored this added information was remote.

6. Conclusions

The environmental stated preference literature often reports WTP estimates derived using choice scenarios that present exogenously varying numerical probabilities. In such cases, the internal variation in probabilities within choice tasks may promote internal sensitivity to these objective probabilities, even if these probabilities are not fully understood or accepted by all respondents. External tests are rarely conducted to evaluate whether respondents behave in ways that are consistent with an accurate understanding of this information (or even attendance to this information), despite evidence that respondents may reject scenarios that are inconsistent with their prior beliefs. These concerns are magnified in cases of inherent uncertainty, in which internal variation in probabilities is not present.

Results of the present study suggest that further research is required to determine whether and how respondents react to information on inherent uncertainty within stated preference studies—and particularly when this information is presented using the ubiquitous percentage probability format. Although some past work has shown sensitivity to information of this type when combined with visual aids (Torres, Faccioli, and Font 2017), results of the present analysis provide no evidence that the provision of numerical probabilities alone enhances respondents' ability to make more informed and fully compensatory choices, when this information is provided to supplement other types of risk information (here, raw past storm frequencies). Rather, our model results are consistent with studies outside the stated preference literature suggesting that individuals may not use numerical probabilities as researchers expect (Slovic, 1987; Black, Nease, and Tosteson 1995; Yamagishi 1997; Lipkus, Samsa, and Rimer 2001; Edwards, Elwyn, and Mulley 2002; Patt and Schrag 2003; Gilboa, Postlewaite, and Schmeidler 2008).

We emphasize that the results presented here are specific to our case study of coastal adaptation in a community familiar with coastal hazards. As such, residents may have strong prior beliefs regarding associated risks. Similar findings may or may not apply to other contexts. Case studies addressing less risky and/or lower-stakes topics may find, for example, that the provision of objective numerical probabilities enables respondents to adjust their beliefs as opposed to adjusting or rejecting given scenarios. The on-going debate on how risk is understood depending on context warrants such concerns (Slovic, Fischhoff, and Lichtenstein 1985; Edwards, Elwyn, and Mulley 2002; Aven 2010). These and other caveats aside, the present results suggest that the use of numerical probabilities within choice scenarios may not necessarily be an effective way of communicating inherent uncertainty. Additional research in this area is needed. When interpreting inherent uncertainty in stated preference questionnaires, researchers should not take for granted that respondents will use percentage probabilities as expected.

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