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A discrete choice experiment to measure the impact of flood risk information on residential location choices

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Abstract

This article investigates residential choice in flood-prone areas with attractive natural amenities. In a discrete choice experiment involving 472 French homeowners, we analyse the effects of flood risk information disclosure. Respondents make trade-offs between house characteristics, amenities and location in flood-prone areas, with two information treatments about the consequences of flooding and protection measures. We also examine the influence of existing information tools. The econometric models reveal a general aversion to flood-prone areas and a negative effect of information about the consequences of flooding. Buyer-tenant information influences the decision to leave flood-prone areas, while zoning influences the decision to stay.

Keywords: choice experiment; flood risk-amenity trade-off; information treatment; mixed logit; attribute willingness to pay; residential choice

JEL Classification: Q54; Q51; C25

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1 Introduction

Extreme flood events pose a major risk to people, property, and economic and social activities (Glaus et al., 2020, Munich RE, 2020). Flooding accounts for 40% of all natural disasters worldwide and causes about half of all deaths resulting from natural disasters (Ohl and Tapsell, 2000). Between 1980 and 2019, floods caused economic losses of 1,092 billion US dollars globally (Munich RE, 2020). Furthermore, the issue of flood exposure is becoming increasingly pressing, due to urbanization in flood-prone areas and climate change (Alfieri et al., 2015, IPCC, 2014). In France, almost half of the municipalities (46%) and more than 17 million permanent residents are exposed to floods (MTES-CGDD, 2020). Annual economic damage exceeds one billion euros (MEDDE, 2012) and is expected to increase due to climate change. Reducing flood risks is hence a crucial policy issue (Beltrán et al., 2018). In particular, it is essential to understand why people persist in settling in flood-prone areas and how information policies can target those who are misinformed.

Two sides of the issue can be considered: public policies and individual decisions. At the individual level, households can reduce exposure to risks either by implementing individual adaptation measures (Champonnois and Erdlenbruch, 2021, Kunreuther, 2006, Richert et al., 2017), or by avoiding risk-prone areas (Creach et al., 2015). Avoidance is a particularly effective risk-reduction measure (Creach et al., 2015) if people are well informed. However, people may choose not to avoid risk for various reasons. For instance, they may be attracted by lower real estate prices in flood-prone areas compared to similar properties located outside these areas (Beltrán et al., 2018, Bin, 2004, Bin et al., 2008, Boustan et al., 2012, Glaus et al., 2020, Mauroux, 2015). Households' residential location choice may be influenced by the presence of natural and urban amenities, such as coastal areas, rivers, green spaces, and proximity to schools or hospitals. Additionally, their perception of flood risks may not align with their actual exposure (Beltrán et al., 2018, Bin et al., 2006, Turner and Landry, 2023). These three reasons may be combined. The literature has extensively shown the significance of natural amenities in this decision-making process (Bakkensen and Barrage, 2022, Cohen et al., 2019, Dieleman, 2001, Nilsson, 2014, Phaneuf et al., 2013, Schaeffer et al., 2016, Traoré, 2019, Tu et al., 2016, Waltert and Schläpfer, 2010). Cohen et al. (2019) showed the attractiveness of waterfronts. Schaeffer et al. (2016) found that natural amenities contribute to residential segregation, with heterogeneous effects depending on household size and socio-professional status.[1] A common methodological issue in this context

[1]The study focused on two metropolitan areas in France: Grenoble in the Alps, and Marseilles on the Mediter-

is the relationship between amenities and risks. Many areas with high natural amenity values are also susceptible to natural hazards. As a result, amenities may offset the impact of flood risk exposure, making it difficult to identify these risks in the property market, as underlined by Beltrán et al. (2018) and Bin (Bin, 2004, Bin et al., 2006, 2008). Another methodological issue is that the population's understanding and perception of risks may vary (Bakkensen and Barrage, 2022, Beltrán et al., 2018, Bubeck et al., 2012, Lee, 2022). Bakkensen and Barrage (2022) for example show that people living in at-risk areas tend to underestimate the risk and, as a result, overestimate the value of at-risk houses (as demonstrated in their study on coastal houses in the US). In this article, we argue that discrete choice experiments (DCE) can control for these caveats. DCE allows for the independent variation of risk and amenities characteristics in the experiment, while also accounting for individual heterogeneity.

On the other hand, many public policies aim to inform individuals about flood risk exposure. Several authors have evaluated the impacts of information disclosure policies on property prices, using hedonic pricing, difference-in-differences approaches and regression discontinuity. In general, they reveal a one-digit discount in real estate prices in flood-prone areas. Votsis and Perrels (2016) analysed the effect of flood-risk mapping on housing prices in Finland, using a difference-in-difference approach, and showed a significant decrease in prices following the disclosure of information. Bakkensen and Ma (2020) showed that there was a price discount of 6% in at-risk areas in Florida, using regression discontinuity. Dubos-Paillard et al. (2019) analysed the impact of the implementation of flood risk prevention plans on real estate transactions around Paris in France, using hedonic pricing.[2] They showed that the release of information about floods results in a 7% decrease in house prices (3% for apartments), and this effect remains for up to 2.5 years. Mauroux et al. (2015) focused on the impact of a seller's disclosure on housing prices in France, using hedonic pricing. The study found no significant price difference for houses, but revealed an average decrease of 6% in apartment prices. Finally, Lee (2022) analyzed the impact of a sellers' disclosure in the US, using a difference-in-discontinuity design at the boarder of flood-prone areas. The study showed that information disclosure reduces the population at risk, in addition to affecting prices. This literature is distinct from studies that assess the price decrease due to flood events, which are significant immediately after the occurrence of an event but then

ranean coast. They showed, for instance, that the Mediterranean coast is primarily sought after by retirees and executives.

[2]In France, there exist several types of regulatory information disclosure tools. The two main ones are flood risk prevention plans (*Plan de prévention du risque inondation*, PPRi) and buyer-tenant information (*Information Acquereur-locataire*, IAL). The PPRi is an official map drawn up by experts in hydrological modelling; the IAL is a form used by real estate experts before a property transaction.

disappear over time (Bin and Landry, 2013). The literature has also shown that the lack of information about flood risks, combined with lower prices, may exacerbate segregation. Specifically, low-income and ethnic minority groups tend to sort into flood-prone areas (Bakkensen and Ma, 2020, Lee, 2022). In this article, we distinguish the effects of information from other factors by implementing various information treatments. To measure individual preferences for location choices, we utilise the DCE method, which considers differences in information and knowledge. Additionally, DCE helps to avoid issues such as correlated omitted variables, endogeneity of explanatory variables, and multicollinearity.

Various authors have evaluated flood risk policies using a DCE. For instance, Zhai et al. (2007) assessed the attributes of public flood prevention measures in Japan, while Reynaud and Nguyen (2016) estimated the value of flood risk reductions in Vietnam. Botzen et al. (2009) evaluated the willingness-to-pay (WTP) of Dutch households for individual adaptation measures in exchange for reduced insurance premiums. Reynaud et al. (2018) assessed the WTP of Vietnamese households for different types of flood insurance. Rey-Valette and Rulleau (2017) estimated French households' preferences for various coastal retreat policies. The use of DCE studies allows for the decomposition of decision-making elements and the linking of decisions to individuals' characteristics, such as social status and risk perceptions. However, only very few studies address the issue of residential location choices. On the other hand, among the individual location choice models, no study uses DCE and only a few use stated preference methods. An interesting exception is the study conducted by Bakkensen and Barrage (2022). However, they focus on a simple contingent valuation choice set where only the distance to the sea changes. Bakkensen and Ma (2020), on the other hand, consider a location choice model with a more complete set of attributes, including housing characteristics, flood zone characteristics, and natural and urban amenities. This is similar to our setting. However, their residential sorting model is based on revealed preferences and hedonic data, whereas our DCE is based on a choice set that includes one observed actual residential choice and several stated choices from hypothetical alternative residential scenarios.

The main focus of this paper is to investigate how the disclosure of information regarding flood risks affects the trade-off between risk and amenity that households consider when choosing a residential location. The data on preferences were obtained from a face-to-face survey conducted in seven municipalities in southern France, with a final sample of 472 homeowners. Respondents' preferences were elicited through a pivotal DCE. Residential choice was modelled using a random utility model (RUM), specifically, a conditional logit and mixed logit models were used. Furthermore, our study allows for the separation of amenities and risks, as well as the detection of individual heterogeneity in choices. In terms of information policies, the originality of our work is to include both actual flood risk information and hypothetical measures based on the DCE design.

This paper is organised as follows. Section 2 describes the design of the DCE and the implemented information treatments. Section 3 presents the econometric models, including conditional and mixed logit models, based on the RUM, the econometric specifications used, and the approach to compute households' WTP. Section 4 provides a brief overview of the case-study area, outlines the survey method, and presents descriptive statistics of the data. Section 5 presents the econometric results for both the basic models based on the main attributes of location choices and the models with interactions that consider individual characteristics and municipality fixed effects. Additionally, the WTP for flood risk avoidance are computed. The final section summarises the main results, highlights policy implications, and concludes.

2 A discrete choice experiment for residential location

2.1 Choice of attributes and risk-amenity trade-off

Six important attributes were identified to understand residential location choices and the underlying trade-offs between risk and amenities, based on the objectives of our study. To achieve this, we relied on key findings from the literature (Beltrán et al., 2018, Bin et al., 2006, Dieleman, 2001, Schaeffer et al., 2016) as well as input from stakeholders and researchers during pre-tests (see section 4).

Next to the home price and the home size, we chose three criteria describing the localization with respect to its distance to the town center, the seaside and a natural site. We also took into account whether the home is in a flood-prone area or not. We decided to measure the distance to the amenities by the time people need to get to the site, which is information they can easily give. As natural site we used the site each respondents stated to visit most often (and asked for its name). Time needed could be indicated by car, by bike or walking.[3] In order to make the choice alternatives easy to understand, we limited the choice sets to situations in which the home prices and size increase, whereas the distance to the amenities decreases. Note that we

[3]We checked our results with different measures of distance but results did not change substantially.

decided not to integrate attributes such as 'being close to the work place' or 'being close to a school' since many of the inhabitants in the study area are already retired. However, we insisted that all other attributes of the proposed houses are supposed to be equal. Chosen attributes and levels are shown in Table 1.[4]

Table 1: Description of the attributes and their levels

Attributes	**Levels**
Time to get to the town center	current, -20%, -40%, -60%, -80%
Time to get to the sea	current, -20% -40% -60% -80%
Time to get to a natural site	current, -20% -40% -60% -80%
Flood risk exposure	outside the flood-prone area inside the flood-prone area
Home size	current, +10%, +20%, +30% +40%
Home price	current, +5%, +10%, +15%, +20%

We use a pivot experimental design in which respondents refer to their current situation to make choices. Respondents have to choose between three homes: their current home, the characteristics of which are known from the first part of the survey and two hypothetical homes which are built around this current situation. Such designs enhance people's familiarity with the choice set and, hence, the realism of the studied outcomes.

We constructed ten choice sets using the Ngene software,[5] that satisfied the orthogonality conditions, thus allowing an independent estimate of the influence of each design attribute on choice.[6] The smallest design that can be obtained with respect to our attributes and their levels is ten different scenarios divided into two blocks of five choice sets. Respondents were informed of both the percentage change in each attribute and its absolute level from the status quo. This information was computer calculated. Choice sets were shown to the respondents on a mini-computer (see section 4).

[4]Note that five of the six attributes in this study have five levels of variation each, while flood exposure is a binary attribute. This being the case, the attributes with five levels of variation are considered to be continuous variables.

[5]Ngene is distributed by ChoiceMetrics: www.choice-metrics.com

[6]Unlike orthogonal designs, efficient designs aim to produce data that generate parameter estimates that minimise standard errors. To do this, such designs require the specification of prior values for the parameters to be estimated. The methodological approach initially envisaged was based on the implementation of a pilot study, which opened up the possibility of an efficient design. However, the efficient design could not be used because the econometric results of the pilot survey did not converge. However, Walker et al. (2018) point out that the efficient designs are substantially less powerful under varying degrees of prior error, especially when the priors are derived from pilot studies or rely on previous studies or expert judgement and thus have few observations. This leads to misspecification of the priors.

2.2 Information treatments

In addition to different scenarios to elicit individuals' preferences in terms of home attributes, an important objective of our article is to test the effect of flood risk information on the residential location choices. To do so, we divided the sample of individuals to be surveyed into three different groups, to which individuals were assigned randomly, and defined as follows:

- Group 1 (G1) does not receive any additional information on flood risk.
- Group 2 (G2) receives additional information on the negative and unpleasant consequences of flood risk, at the beginning of the experiment.
- Group 3 (G3) also receives additional, but less negative information about flood risk, at the beginning of the experiment. Indeed, the risk is described as being mitigated via protection measures carried out by the government.

The full instructions for the different treatments are described in Appendix A. For both G2 and G3, the instructions indicated that flooding is an event that occurred three times over the past 50 years and during which the water reached 50 centimeters inside the home. This is an indirect and easily understandable way to represent the probabilistic nature of flood risks.

For G2, a text then describes the damage caused to the ground floor of the home. It is indicated that the furniture and personal belongings were damaged and that the household flooded had to clean the floor and the walls. A photo illustrates the treatment showing the ground floor of a just-flooded building (see Appendix A). In the case of upstairs accommodations, it is stated that the entrance hall of the building as well as the mailbox and the parking lot were flooded and devastated, and a different picture is shown (see Appendix A). In both cases, respondents are also told that insurance covered the material damage afterwards, as would be the case in the French context.

For G3, the text states that flood protection, namely the construction of dikes and an evacuation channel, has been implemented to reduce the risk of flooding. These structures protect against all floods smaller than or equal to the 100-year flood.[7] A photo illustrates one of the existing protection structures, a dike with a spillway.

[7] The 100-year flood is very commonly used as a reference flood fro infrastructure projects.

3 Models and econometric specifications

3.1 The random utility model

Our analysis is based on the consumer theory of Lancaster (1966) combined with an econometric random utility model (RUM) McFadden (1973, 2001, 1981).[8] The central assumption is that the household chooses the home that maximizes its utility when faced with several possible choices and that this choice depends on the characteristics of the homes (Adamowicz et al., 1998, Lee and Waddell, 2010, Schaeffer et al., 2016, Traoré, 2019, Tu et al., 2016). We believe that the RUM framework, based on a non-deterministic approach, is general enough to address the issue of choice under risk and uncertainty and violations of expected utility theory. However, de Palma et al. (2008) recommend caution when modelling decisions in situations of risk, uncertainty or ambiguity, and that including simple proxies instead could lead to bias or misspecification.[9]

In a given sample with N respondents, each respondent will be confronted with S choice sets and each choice set has J alternatives. The indirect utility for respondent n to choose alternative j in the choice set s is written as:

$$U_{njs} = V_{njs} + \varepsilon_{njs}, \quad n = 1, ..., N, \ j = 1, ..., J, \ s = 1, ..., S, \tag{1}$$

where V_{njs} is the deterministic part of the regression and ε_{njs} is a random error term i.i.d. such as a Gumbel law (or type I extreme value).[10] The deterministic part V_{njs} is a function of X_{njs}, a vector of observed attributes (including a price attribute) related to alternative j, and other observed factors such as individual characteristics Z_n:[11]

$$V_{njs} = V(X_{njs}, Z_n).$$

As in most studies using the DCE approach, logit models are most frequently used to estimate the random utility of individuals' alternatives when faced with multiple choices (Adamowicz et al., 1998, Louviere et al., 2000, Train, 2009).

[8] Although we often cite many of McFadden's references when referring to RUM, the work of Marschak (1960), Thurstone (1927) is considered to have pioneered the view of choice as a derivative of utility maximisation.

[9] See also Ben-Akiva et al. (2012), who develop a general framework that extends choice models by including an explicit representation of the decision-making process, with some elements such as attitudes, affect, and perceptions/beliefs, as well as the context, including social networks.

[10] The Gumbel density for each error term of utility is $g(\varepsilon_{njs}) = \exp(-\varepsilon_{njs})\exp[-\exp(-\varepsilon_{njs})]$ and the cumulative distribution is $G(\varepsilon_{njs}) = \exp[-\exp(-\varepsilon_{njs})]$, with a variance of $\frac{\pi^2}{6}$ if we normalize the scale of utility.

[11] In our empirical study, we added fixed effects specific to the municipalities where the household is located to account for unobserved heterogeneity related to the residential municipality.

Assuming the rationality of individuals, a respondent n is assumed to associate each alternative j with a random utility level U_{njs}, and to choose the option that maximizes the utility within a given choice set. Therefore, respondent n will choose alternative i in the choice set s if this random utility U_{nis} is greater than the random utility U_{njs}:

$$U_{nis} \geq U_{njs}, \qquad \forall j, i \in s, \ j \neq i.$$

Since only the choice preferred by the individual n is observed, we estimate the probability of the individual n choosing the alternative i for each choice set s based on random utility maximisation:

$$p_{ns}(i) = \Pr(\varepsilon_{njs} - \varepsilon_{nis} \leq V_{nis} - V_{njs}), \qquad \forall j, i \in s, \ j \neq i,$$

where the new error term $\epsilon_{nis} = \varepsilon_{njs} - \varepsilon_{nis}$ follows a logistic distribution, giving the choice probabilities: $p_{ns}(i) = \frac{\exp(\epsilon_{nis})}{\sum_{j=1}^{J} \exp(\epsilon_{njs})}$.

3.2 Econometric models

In our empirical analysis, we used two multinomial discrete choice models, i.e., the conditional logit and the mixed logit models. For the sake of simplicity, we first present these models by only including attribute variables that depend on alternatives and not individual variables. Thus, the parameters β are associated with the differences between the value of attributes for a given alternative and those of the attributes of the reference alternative called the status quo. In the next subsection, we will introduce individual variables and municipality-specific effects according to different specifications.

The conditional logit model

The (alternative-specific) conditional logit (CL) model is the most commonly used multinomial model to explain discrete choices (McFadden, 1973). Even though it has the advantages of computation ease, tractable interpretation of estimates in terms of substitution, and a good ability to represent preference differences in terms of observed attributes (Train, 2009), a first important drawback of the CL model is that it relies on the assumption of independence of irrelevant alternatives (IIA). Indeed, the errors are independently and identically distributed as a type I extreme-value distribution, which implies that the odds ratio between two alternatives does not change if another alternative is included or excluded. Hence, the CL model can yield inconsistent estimates and unrealistic substitution results between alternatives if this assumption is violated. For each choice set s, the probability of household n choosing alternative i can be written as:

$$p_{ns}(i) = \frac{\exp(X_{nis}\beta)}{\sum_{j=1}^{J}\exp(X_{njs}\beta)}. \tag{2}$$

Since we accounted for the panel structure of the data (i.e., individuals n choose among several different choice sets s), we used the clogit command of Stata MP 18.0, which fits a conditional fixed effects logit model.[12]

The second important drawback of the CL model (like other multinomial models) is that it does not allow for random parameters and thus account for unobserved heterogeneity. This is why we consider a more flexible multinomial logit, the mixed logit, which does not have the two main limits of the CL model.

The mixed logit model

In its most straightforward derivation, the mixed logit (MXL) model allows model parameters to vary randomly over individuals in the population. Thus, it accounts for individual heterogeneity. A MXL model can also be defined as an error component model that includes a random individual error term,[13] and that explicitly accounts for correlations in unobserved utilities over repeated choices made by each individual. That means it is assumed that the preferences vary across respondents but not across choices of the same respondent (Train, 2009). Therefore, the model is no longer constrained by the IIA property. Moreover, in order to be able to estimate individual marginal WTP, we chose to specify our MXL model with individual-specific parameters based on the assumption that they follow a random distribution with density $f(\beta)$ (Train, 2009).

In our case of repeated choices, conditional on β_n, the probability that a household n chooses the alternative i for the choice set s is written as (Revelt and Train, 1998):

$$p_{ns}(i|\beta_n) = \frac{\exp(X_{nis}\beta_n)}{\sum_{j=1}^{J}\exp(X_{njs}\beta_n)}. \tag{3}$$

In the case of repeated choices for each respondent, the logit probability refers to the probability that the individual n will make the sequence of S choices with J alternatives each. Therefore,

[12] An individual-specific effect α_n is introduced into the regression but not estimated. When the number of periods (or choice sets) is fixed, the estimates of parameters α_n and β are not consistent. A conditional probability exists that does not involve α_n and that makes it possible to consistently estimate β.

[13] A MXL model representing error components can also be used with random parameters.

the probability of the observed sequence of S choices conditional on β_n is given by:

$$p_n(i_{n1}, ..., i_{nS}|\beta_n) = \Pi_{s=1}^{S} p_n(i_{ns}|\beta_n),$$

where i_{ns} represents the alternative chosen by individual n in choice set s.[14] The unconditional probability is the conditional probability integrated over all the possible values of β_n according to the distribution of β_n:

$$L_n(\theta) = \int p_n(i_{n1}, ..., i_{nS}|\beta_n) f(\beta_n|\theta) d\beta_n.$$

β_n varies over individuals in the population with density function $f(\beta_n|\theta)$, where θ is a vector of the true parameters of the density (i.e., the mean and covariance parameters). We have chosen to follow the most common practice, which is to assume a normal distribution for the random parameters. However, in some cases other distributions can be used, for example a log-normal distribution, which is often the case for the price attribute. In this case, the sign of the marginal utility of the price attribute in question is, by construction, the same for everyone. However, in our study, we suppose for simplicity that the parameter associated with the price is constant.

While the CL model is estimated using a standard maximum likelihood procedure, the MXL model is estimated via simulated maximum likelihood estimation. As explained in Train (1999),'choice probabilities in mixed logit models take the form of a multidimensional integral over a mixing distribution... [which] has been approximated though simulation using random draws from the mixing distribution'. Following Hole (2007), our model is first fitted with 50 Halton draws to quickly identify the good specification, and then the number of Halton draws is 500 to reduce the simulation error in the estimated parameters in order to find the final model. We used the mixlogit package (Hole, 2007) with Stata MP 18.0.

3.3 Econometric specifications

We start with a basic econometric specification in which the indirect utility derived from location choice is a linear function of all attributes only. We separate the price attribute, P, and non-price attributes, x, to make the analysis of WTP clearer. We also introduce an alternative-specific constant (ASC_{SQ}) associated with the status quo (SQ_{nj}), which is equal to 1 when the current home is preferred to other alternatives, and to zero otherwise. We consider the most general case

[14]Note that the number of choice sets could be different between respondents and would be denoted as S_n.

with individual specific parameters. For each choice set s, the specification of the utility part V_{nj} becomes:

$$V_{nj} = ASC_{SQ}\, SQ_{nj} - \alpha_n\, P_{nj} + \beta_n'\, x_{nj}, \tag{4}$$

where α_n, the parameter associated with the price attribute, should be estimated with a negative sign.

Since the results of several studies confirm the importance of taking individual characteristics of the respondents into account in addition to the selected attributes (Reynaud and Nguyen, 2016, Reynaud et al., 2018, Schaeffer et al., 2016, Traoré, 2019, Tu et al., 2016), we introduce interaction terms between the SQ_{nj} constant and various respondent-specific characteristics Z_n, to account for individual heterogeneity. We also introduce interactions between the constant SQ_{nj} and the fixed effects dummy variables D_m, where m denotes the municipality in which the respondent n lives. This takes into account the heterogeneity of municipalities due to different contexts (economic, environmental, etc.):

$$V_{nj} = ASC_{SQ}\, SQ_{nj} - \alpha_n\, P_{nj} + \beta_n'\, x_{nj} + \gamma_{nSQ}'\, SQ_{nj} \times Z_n + \mu_{nSQ}'\, SQ_{nj} \times D_m. \tag{5}$$

Since the contribution of Ai and Norton (2003), applied econometricians using non-linear models such as probit and logit models pay more attention to the issue of interaction effects. Indeed, contrary to linear models, the partial effect of the interaction term does not allow to elicit the interaction effect. Ai and Norton (2003) show that this problem arises in many commonly used non-linear models, including logit, probit and tobit, but it is also the case of multinomial logit models. Let's consider the partial effects on the probability of choosing an alternative j when estimating a conditional logit (or mixed logit). From the widely used specification (5) with interaction terms between the constant SQ_{nj} and each specific variable, we can quickly see that the sign of the coefficient associated with the interaction term gives the sign of the interaction effect. As emphasised by Greene (2010) in the case of a probit model in which a dummy variable is interacted with a continuous variable, the interaction effect, i.e., the effect of a regime switch in the dummy variable on the partial effect of the continuous variable is quite simple. In the case of a conditional logit where individual variables cannot appear alone in the specification, it is even simpler. The effect of a regime switch in SQ on the probability p_{ns}, defined by equation (2), is:

$$\frac{\Delta p_{ns}}{\Delta SQ} = \frac{\exp(ASC_{SQ}\,SQ - \alpha_n\,P_{nj} + \beta_n'\,x_{nj} + \gamma_{nSQ}'\,SQ \times Z_n + \mu_{nSQ}'\,SQ \times D_m)}{\sum_{j=1}^{J}\exp(ASC_{SQ}\,SQ - \alpha_n\,P_{nj} + \beta_n'\,x_{nj} + \gamma_{nSQ}'\,SQ \times Z_n + \mu_{nSQ}'\,SQ \times D_m)}$$
$$- \frac{\exp(-\alpha_n\,P_{nj} + \beta_n'\,x_{nj})}{\sum_{j=1}^{J}\exp(-\alpha_n\,P_{nj} + \beta_n'\,x_{nj})},$$

and therefore the partial effect of Z_n on the partial effect of the SQ variable, i.e., the interaction effect, is:

$$\frac{\partial^{\Delta p_{ns}}/_{\Delta SQ}}{\partial Z_n} = \gamma_{nSQ}'\,SQ \times p_{ns}(1 - p_{ns}).$$

It is therefore clear that the sign of this partial effect is the same as that of γ_{nSQ}.

However, the partial effects on the expected utility of an alternative j (i.e. the parameters estimated for the attributes) are marginal utilities and are therefore fully interpretable and given by a linear model, and hence its estimated parameters.

3.4 Estimation of willingness-to-pay

Marginal WTP for a specific attribute expresses respondents' preferences for this attribute in monetary terms. On the basis of the RUM as expressed by Equation (1) and, for the sake of simplicity, on the basis of the simplest specification as defined by Equation (4), we can easily derive the WTP for attributes. When the parameter of the price is assumed to be fixed, marginal WTP is obtained through the ratio of the attribute x_k parameter (in expectation) to the price parameter (Hole, 2013):

$$E[WTP_{x_k}] = \frac{E[\beta_{nk}]}{\alpha_n}, \tag{6}$$

where β_{nk} are the random parameters of the non-monetary attributes x_k and α_n are the fixed parameters of the price attribute. The estimated WTP for the CL model is simply expressed as $\frac{\beta_k}{\alpha}$.

4 Survey and data

4.1 Study area

Areas in the south of France have numerous natural amenities such as the coastline, forests or rivers, but are also very exposed to flooding. In addition, they are subject to strong demographic pressure constraining buyers to important trade-offs among positive and negative amenities.

We have selected one municipality per department along the Mediterranean arc, as shown in

Figure 4 in appendix B: Aubagne in the Bouches-du-Rhône, Biot in the Alpes-Maritimes, Cuxac-d'Aude (and adjacent Ouveilhan) in the Aude, Lattes in the Hérault, Roquebrune-sur-Argens in the Var, Sommières in the Gard and Saint-Laurent de la Salenque in the Pyrénées Orientales department. All the municipalities selected for our study have at least a part of their territory in flood-prone areas.[15] Most of the selected municipalities have already experienced major floods, but at different dates. Some municipalities are affected by floods on a fairly regular basis, such as Sommières, and others are rarely affected by floods but are located in flood-prone areas, such as Aubagne. Lattes plays a special role because a large part of the municipality is protected by dykes. Some municipalities are rural (Cuxac-d'Aude, Saint-Laurent de la Salenque); others are close to an agglomeration (Aubagne is part of the Marseille agglomeration; Lattes is just next to Montpellier). Some municipalities have the attraction of being within the immediate proximity of the coast (the municipality of Roquebrune, for example, is on the coast); others are more inland (Sommières). Overall, our study area represent a diversity of situations along the Mediterranean arc.

4.2 Sampling, questionnaire and data collection

Our study is based on a survey consisting of (i) a questionnaire to collect information about the respondents' current residence and personal characteristics; and (ii) a DCE. Prior to the final survey, we met with several key stakeholders in the selected areas (mayors, agents in charge of urban development, flood risk managers, real estate agencies) to shape our survey according to the key-issues in our study areas. We then pretested different parts of the questionnaire with some stakeholders, researchers and households, triggering discussions on the most important elements of residential choice. A pilot survey was conducted in late October/early November 2019 on 60 randomly selected households, which allowed to adjust some formulations of the questionnaire and showed first consistent results for the DCE. The final survey was implemented via face-to-face interviews at respondents' homes. Using a GIS-based database of French homes, the 'BD parcellaire' of the IGN, we randomly selected the homes the interviewers had to visit, both in flood-prone-areas and outside flood-prone areas. We targeted an overall proportion of interviewees living in flood-prone areas of 53%.[16] The survey was advertised with posters in different public places and the mayors supported the survey with official letters to the interviewers.

[15] The entire surface area of St-Laurent de la Salanque is flood-prone.

[16] This percentage varied for each municipality, depending on the overall flood risk exposure. The interviewers were equipped with maps that color-coded the different homes to visit. They used mini-PCs to implement the questionnaire.

The final survey took place from November 14^{th} to December 14^{th}, 2019, and from January 13^{th} to 17^{th}, 2020, with 721 completed questionnaires. For the sake of this article, we decided to focus on homeowners only, disregarding renters, which lead us to consider 472 individuals. The questionnaire was divided into seven sections:

- The first section contained questions on the characteristics of the respondent's home: ownership, date of acquisition, size, purchase price, etc.
- The second section contained questions on the characteristics of the respondent's area of residence, in particular, the distance to the various urban and natural amenities. We also asked respondents about their modes of transportation to get to the different places and how long it takes to get there.
- The third section contained information about when the respondents chose their current home, where their home is located, and whether people think it is located in a flood-prone area.
- The fourth section was the DCE, as described in Section 2. An example of the choice set is given in Table A1 in appendix B.
- The fifth section dealt with the respondents' attitudes towards risk and time.
- The information requested in the sixth section concerned the respondent's experience with past flooding, e.g., whether he or she was possibly affected by past floods, and at what level of severity.
- Finally, the last section of the survey was used to retrieve socio-demographic characteristics of the respondents such as their age, gender, income, or the socio-professional category to which they belong.

4.3 Descriptive statistics

In the following, we based our analysis on the sub-sample of homeowners. In total, 472 homeowners answered all the sections of the questionnaires and DCE.[17] Descriptive statistics of residential and individual characteristics are presented in Table 2.

[17] We also have data from renters. Their reasoning for location choices is quite different from the reasoning of home-owners. We hence decided to focus on the sub-sample of homeowners for this analysis.

Table 2: Descriptive statistics

Variable name	N	Unit	Description	Mean	Min	Max
observed DCE attributes						
Time_to_town	472	min.	Time to the town center	9.928	0	60
Time_to_sea	472	min.	Time to the sea	22.648	0	75
Time_to_nature	472	min.	Time to a natural site	33.254	0	180
Flood_area	472		Stated living in a flood-prone area	0.396	0	1
Home_size	472	m2	Home size	109.036	20	290
Home_Price	472	1 000 €	Current home value	333.468	25	2 500
Individual characteristics						
HOUSEHOLD	466		# of people living in the house	2.25	1	7
AGE	472	year	Age of the respondent	62.76	18	100
RISKTAKER	472		Stated risk aversion (1=risk-averse, 11=risk-taking)	4.65	1	11
				Freq.		% (1 = yes)
Flood_expe	472		Past experience with floods	306		64.83
PPRI	472		Knows the flood risk prevention plan	310		65.68
IAL	472		Knows the buyer-tenant information	187		39.62
EDUC	472		Education level of the respondent			
			No formal qualification	10		2.12
			Primary School Certificate	63		13.35
			First and professional diplomas	118		25.00
			High school diploma	104		22.03
			Bachelor	110		23.31
			Master's degrees and PhD	67		14.19
NATIVE	472		Native of the Mediterranean arc	234		49.58

In our sample, the percentage of respondents who claimed to live in a flood-prone area is quite high, with a value of 39.6%, while 64.83% reported to have experienced at least one flood in their life.[18] Moreover, 65.68% of the respondents are aware of the existence of flood risk prevention plans (PPRi), but only 39.02% are aware of the system of information for buyers and tenants (IAL), whereas it has been compulsory since a law was passed in 2003.

Households take an average of 10 minutes to get to the town center, 23 minutes to get to the sea, and 33 minutes to get to a natural site. The average size of the home is 109 m^2, and there are approximately two people living in the home. The average price of the home is € 333,468. The level of education is a qualitative variable ordered according to the number of years and has been used in the econometric application as a continuous variable that takes six values ranging from 0 to 5. The percentage of respondents born in a town on the Mediterranean arc (natives) is 49.58%.

Finally, Table A2 in appendix B shows the distribution of individuals in the different groups according to information we gave them with respect to a control group with no information

[18] In the survey, we specify that experiencing a flood means 'having seen water accumulating in the streets of the municipality. The water can come from rain, river flooding or rising groundwater.'

(G1). Individuals in G2 received an additional information on the negative consequences of floods, whereas individuals in G3 received an information about flood mitigation by protection measures.

5 Econometric results

5.1 Status quo and choice of alternatives

Each household was asked to complete five choice sets. In each choice set, each respondent chooses between three alternative homes: the current home (or the status quo) and two hypothetical alternatives 1 and 2. In our DCE, respondents selected the status quo option (current home) in 58.18% of the cases, while alternatives 1 and 2 were chosen in 41.82% of the cases, see Table A3 in appendix B. According to Adamowicz et al. (1998) this high percentage of status quo answers is not unusual in DCE. Although rational choice explanations can be provided, the large number of respondents choosing the status quo option may have a variety of reasons (regret, avoidance, mistrust, minimum risk, etc.). This is the well-known status quo bias in decision-making. We address this problem by including an alternative specific constant (ASC_{SQ}) to capture unobservable influences beyond the attributes present in the choice sets in the RUM specification.

In the following, we present the estimation results obtained from two different models: first, the CL of McFadden (1973), which considers individual preferences as being homogeneous, followed by the MXL, as described by Train (2009), with individual heterogeneity.

5.2 Estimation results of the basic model

Table 3 presents the estimation results of a basic model (both the CL and MXL models) that uses only DCE attributes and that includes a constant specific to the status quo, as defined in Equation 4. In the MXL model, all attribute parameters are assumed to be random and normally distributed, excepted for the price attribute, which is assumed to be constant.

Table 3: CL and MXL estimation results with only DCE attributes

Variable	CL		MXL Mean		MXL SD	
Price	-0.003	***	-0.008	***		
	(0.001)		(0.002)			
ASC_{SQ}	1.050	***	2.148	***	8.163	***
	(0.071)		(0.461)		(0.788)	
Home_size	0.001		0.002		-0.002	
	(0.002)		(0.002)		(0.006)	
Time_to_town	-0.010		0.021	*	0.063	**
	(0.006)		(0.011)		(0.025)	
Time_to_sea	0.002		0.011	***	0.000	
	(0.003)		(0.004)		(0.007)	
Time_to_nature	-0.006	***	-0.009	***	-0.000	
	(0.002)		(0.003)		(0.004)	
Flood_prone	-0.112	**	-0.634	***	-0.443	**
	(0.054)		(0.089)		(0.180)	
Log-likelihood	-2279		-1445			
AIC	4571		2916			
LR $\chi^2(7)$ (P-value)	628.45 (0.000)					
LR $\chi^2(6)$ (P-value)			1667.49 (0.000)			

Obs.: 7,080 = 472 individuals x 3 alternatives x 5 choice sets.
Halton draws for the MXL = 500.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The value of the χ^2 statistics for the MXL is the result of a LR test for the joint significance of the standard deviations.
The sign of the estimated standard deviations is irrelevant: interpret them as being positive. (returned by Stata)

The estimation results indicate that both models globally fit well the data. The results of the two LR tests associated with each model confirm this result. Indeed, for the CL model, the null hypothesis that all the coefficients are equal to zero is largely rejected. For the MXL model, the null hypothesis that all the standard deviations are equal to zero is also largely rejected, validating the random parameter specification. We thus comment only estimation results from the MXL specification.

First, we can notice that one attribute (Home_size) has no significant impact on residential location choice. Second, the highly significant positive sign of the coefficient ASC_{SQ} shows strong preferences for the status quo (i.e., the current home). As mentioned above, there can be many reasons for this preference, such as aversion to moving or high transaction costs. However, the standard deviation of ASC_{SQ} is significantly different from zero and large (8.163) compared to the mean (2.148), meaning that some households are willing to move to another home. Third, the price attribute coefficient is also strongly significantly different from zero and negative, indicating that a higher price has a negative effect on respondent residential choice, as expected. Concerning the non-monetary attributes, the significantly negative coefficients of Time_to_nature and Flood_prone indicate that households have a preference for homes close to natural sites and an aversion to those in flood-prone areas, respectively. The attributes Time_to_sea and Time_to_town have significant effects with a positive sign. That indicates that households prefer being located far from the sea and from the city center. However, note that the standard deviation for Time_to_town is is significantly different from zero and large (0.063) compared to the mean (0.021) meaning a large heterogeneity for this attribute. Concerning the attribute Time_to_sea, we can speculate that households are not attracted by living close to the sea due to negative externalities of tourism (e.g., too many people, traffic), similar to the results reported by Schaeffer et al. (2016).

5.3 Treatment effects

Estimation results in Table 4 allow us to assess the treatment effects. Adding the variables interacting the flood risk exposure with the variables of information treatment shows contrasting effects. Individuals in the group without specific treatment (G1) significantly prefer a residential location outside the flood-prone zone, regardless the model. Adding negative information on flood risk (G2) has a negative effect in both the CL and MXL models. This effect is stronger than the G1 treatment effect, with an estimate of -1.414 (in G2) vs. -0.879 (for individuals in G1), in the MXL. However, the associated standard deviation is significantly different from zero, clearly showing heterogeneity in preferences among participants. Adding positive information on flood mitigation policies (G3) only has a significant positive effect in the CL model. All other results are similar to the model in Table 3.

Table 4: CL and MXL estimation results with treatment effects

	CL		MXL			
Variable			Mean		SD	
Price	-0.003	***	-0.009	***		
	(0.001)		(0.002)			
ASC_{SQ}	1.036	***	2.212	***	8.221	***
	(0.071)		(0.490)		(0.798)	
Home_size	0.001		0.001		0.005	
	(0.002)		(0.002)		(0.011)	
Time_to_town	-0.008		0.0247	**	0.064	**
	(0.006)		(0.011)		(0.029)	
Time_to_sea	0.002		0.011	***	-0.000	
	(0.003)		(0.004)		(0.007)	
Time_to_nature	-0.006	***	-0.009	***	-0.000	
	(0.002)		(0.003)		(0.005)	
Flood_prone × G1	-0.201	**	-0.879	***	0.089	
	(0.098)		(0.157)		(0.508)	
Flood_prone × G2	-0.400	***	-1.414	***	1.065	***
	(0.093)		(0.206)		(0.279)	
Flood_prone × G3	0.188	**	0.058		0.006	
	(0.083)		(0.121)		(0.147)	
Log likelihood	-2266		-1409			
AIC	4551		2852			
LR chi2(9) (P-value)	652.7 (0.000)					
LR chi2(8) (P-value)			1715 (0.000)			

Obs.: 7,080 = 472 individuals x 3 alternatives x 5 choice sets.
Halton draws for the MXL = 500.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.4 Effects of current information disclosure tools and flood experience

In Table 5, we add current information disclosure tools, as an interaction with the status-quo variable. We also test the impact of flood risk experience. First, having personal experience of past floods seems to confirm the status-quo effect with a significant and positive coefficient (with a value of 0.310) in the CL model. Personal experience does not change the choice of leaving or staying in the current home in the MXL but we find a significant standard deviation showing heterogeneity among individuals. Concerning knowledge about current information disclosure tools, results are mixed. We don't observe any significant effect of the knowledge of a flood risk prevention plans (PPRi) on the residential choice. However, there is a significant effect of buyer-tenant information, IAL: The probability to leave the current home is stronger with IAL knowledge, but with strong heterogeneous effects (with a highly significant standard deviation of 5.109). All other results are similar to the previous tables.

Table 5: CL and MXL estimation results with flood experience and current information disclosure tools

Variable	CL		MXL Mean		MXL SD	
Price	-0.003	***	-0.009	***		
	(0.001)		(0.002)			
ASC_{SQ}	1.141	***	2.514	***	6.021	***
	(0.107)		(0.747)		(0.686)	
Home_size	0.000		0.001		0.008	
	(0.002)		(0.002)		(0.007)	
Time_to_town	-0.004		0.024	**	0.061	*
	(0.006)		(0.011)		(0.031)	
Time_to_sea	0.003		0.011	***	-0.000	
	(0.003)		(0.004)		(0.007)	
Time_to_nature	-0.004	**	-0.008	***	0.001	
	(0.002)		(0.003)		(0.005)	
Flood_prone × G1	-0.243	**	-0.882	***	0.054	
	(0.101)		(0.156)		(0.484)	
Flood_prone × G2	-0.420	***	-1.453	***	1.107	***
	(0.094)		(0.213)		(0.283)	
Flood_prone × G3	0.212	**	0.065		0.000	
	(0.084)		(0.122)		(0.149)	
ASC_{SQ} × Flood_Exp	0.310	***	1.257		-1.787	**
	(0.092)		(0.991)		(0.706)	
ASC_{SQ} × PPRi	-0.055		0.389		5.430	***
	(0.101)		(1.075)		(1.085)	
ASC_{SQ} × IAL	-0.796	***	-3.777	***	-5.109	***
	(0.094)		(1.206)		(1.290)	
Log likelihood	-2219		-1394			
AIC	4462		2835			
LR chi2(12) (P-value)	747.6 (0.000)					
LR chi2(11) (P-value)			1649 (0.000)			

Obs.: 7,080 = 472 individuals x 3 alternatives x 5 choice sets.
Halton draws for the MXL = 500.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The sign of the estimated standard deviations is irrelevant: interpret them as being positive. (returned by Stata)

5.5 Accounting for individual variables and municipality fixed effects

In Table 6, we investigate the effect of different individual characteristics (column 1), which we combine with the status-quo variable, in a MXL model. Moreover, we add municipality fixed effects (column 2), using interaction terms between municipalities dummies and the SQ constant, as defined in specification (5). In this latter model, we omitted the SQ constant as we introduced all of the interactions with the municipalities to avoid the dummy trap.

In both models, we can observe that age increases the preference to stay in the current home (status quo), while higher education and being a risk taker decrease the preference for status quo. Controlling for possible unobserved heterogeneity through municipality-specific effects, we

Table 6: MXL estimation results with individual characteristics

	(1)				(2)			
Variable	Mean		SD		Mean		SD	
Price	-0.00853	***			-0.00856	***		
	(0.00177)				(0.00192)			
$ASC_{SQ} \times$ AGE	0.0992	***			0.0383	***		
	(0.0311)				(0.0129)			
$ASC_{SQ} \times$ EDUC	-1.199	***			-0.593	***		
	(0.303)				(0.156)			
$ASC_{SQ} \times$ RISKTAKER	-0.267	*			-0.174	**		
	(0.162)				(0.0822)			
$ASC_{SQ} \times$ NATIVE	0.208				0.885	**		
	(0.752)				(0.402)			
$ASC_{SQ} \times$ HOUSEHOLD	0.621				0.897	***		
	(0.392)				(0.231)			
time_to_town	0.0219	*	-0.0552		0.0251	*	-0.0704	**
	(0.0116)		(0.0337)		(0.0136)		(0.0297)	
time_to_sea	0.0114	***	6.45e-05		0.0104	**	-0.00557	
	(0.00417)		(0.00788)		(0.00469)		(0.0208)	
time_to_nature	-0.00814	***	-0.000240		-0.00715	**	0.00781	
	(0.00257)		(0.00449)		(0.00305)		(0.00669)	
home_size	0.00144		-0.00739		0.00103		-0.0186	***
	(0.00224)		(0.00808)		(0.00272)		(0.00480)	
Flood_prone $\times$ G1	-0.879	***	-0.0771		-0.835	***	0.708	**
	(0.156)		(0.497)		(0.186)		(0.300)	
Flood_prone $\times$ G2	-1.425	***	1.110	***	-1.619	***	1.898	***
	(0.212)		(0.283)		(0.289)		(0.333)	
Flood_prone $\times$ G3	0.0715		0.00546		0.0995		-0.00207	
	(0.122)		(0.146)		(0.126)		(0.162)	
$ASC_{SQ} \times$ Flood_Exp	0.109		3.050	***	1.095	*	-4.276	***
	(0.815)		(1.165)		(0.628)		(0.803)	
$ASC_{SQ} \times$ PPRi	2.018	**	7.232	***	1.234	*	-5.583	***
	(0.927)		(0.952)		(0.725)		(0.948)	
$ASC_{SQ} \times$ IAL	-3.146	***	4.786	***	-1.529	*	6.145	***
	(1.101)		(1.031)		(0.900)		(1.179)	
ASC_{SQ}	-1.003		4.340	***				
	(3.070)		(0.579)					
Municipality effect	No				Yes			
Log likelihood	-1355				-1368			
AIC	2800.09				2800.69			
LR chi2(11) (P-value)	1504 (0.000)							
LR chi2(10) (P-value)					1186 (0.000)			

Obs.: 6990 = 466 individuals x 3 alternatives x 5 choice sets. Halton draws for the MXL = 1000.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The sign of the estimated standard deviations is irrelevant: interpret them as being positive. (returned by Stata)

also find that being born in a town on the Mediterranean arc (NATIVE) and household size increase the preference for the status quo.

Furthermore, the previous observations regarding the impact of DCE attributes remain consistent. However, small differences can be observed compared to the estimates in Table 5. Although the effect of home size on preferences remains non-significant, heterogeneity is now observed among individuals with a highly significant standard deviation (with a value of -0.019 in the MXL with municipality effects). The non-significance of home size in the residence choice may appear unexpected. However, this can be explained by the age structure of the population in the municipalities included in our sample, which has a higher average age than the French population. Our econometric results confirm that younger people consider the size of the house as an important factor, while it is not a significant attribute for people over 65 (see Table A4 in Appendix C).[19]

Furthermore, although residing in a flood-prone area has a negative impact on individuals in the control group G1 (i.e., individuals having received any specific information), we now observe significant heterogeneity among individuals in this group, as evidenced by the presence of a significant standard deviation in column (2). Considering the impact of information disclosure tools, we can observe the following. The impact of IAL is still significantly negative in the MXL with individual characteristics, but less significant after introducing municipality fixed effects. In contrast, the coefficient of the interaction term between the status-quo dummy and PPRi and the status-quo dummy and the Flood_Exp variable are both positive (although significant at the 10% level in the model with fixed effects in column (2) and with a large and significant standard deviation). This indicates that individuals with past experience of flooding and knowledge of flood risk prevention plans are more likely to choose the status quo. There are several possible explanations for this phenomenon. Experiencing a flood may lead individuals to feel more capable of dealing with future floods. Similarly, knowledge of the existence of a PPRi may give people the impression that flood risk is being addressed by public policies. Alternatively, individuals may simply be trying to reduce cognitive dissonance by remaining in a flood-prone area despite the risks involved. To check these speculations, we divided the sample into two groups: those who had experienced flooding and those who had not. The estimation results are presented in Table A5 in Appendix C. The findings indicate that individuals who have previously experienced flooding and are aware of the existence of a PPRi are more likely to choose the status quo, while those who have not experienced flooding are indifferent.

[19]Estimation results also show that older individuals prefer to reside in close proximity to nature, whereas younger individuals prioritize the attributes time_to_city and time_to_sea when making their residential location choice (and prefer being farther away from the city centre and the sea).

5.6 Estimates of marginal willingness to pay

Marginal WTP in the basic model

In Table A6 in appendix D, we report the (mean) marginal WTPs obtained for the DCE attributes, from the most basic specification with only DCE attributes, as described by Eq. (6), and for both CL and MXL models, along with the 95% confidence intervals.[20]

Detailed results are described in the appendix D. Note here that in both models, the marginal WTP associated with the variable Flood-prone is significantly negative. Respondents are willing to pay € 37,756 and € 76,351 to avoid a flood-prone area in the CL model and the MXL model, respectively. The confidence interval is much smaller in the case of the MXL, whereas the one of CL has a lower bound at € 77,152. That seems to indicate that the value of WTP is closer to this amount.

Marginal WTP in MXL with individual variables

In this paragraph, we present WTP estimates based on the most complete model (as presented in Table 6), after estimating the MXL with individual characteristics and fixed effects, including the disclosure of information on flood risk exposure. Table 7 shows the households' marginal WTPs along with their confidence intervals.

Table 7: Marginal WTP (in thousands €) from the complete MXL specification

Variable	Marginal WTP		95% CI
Time_to_town	2.934 (1.787)		[-0.568 ; 6.435]
Time_to_sea	1.215 (0.615)	**	[0.009 ; 2.421]
Time_to_nature	-0.8368 (0.350)	**	[-1.524 ; -0.148]
Home_size	0.120 (0.319)		[-.5056 ; 0.7458]
Flood_prone G1	-97.587 (27.355)	***	[-151.202 ; -43.973]
Flood_prone G2	-189.153 (48.071)	***	[-283.371 ; -94.935]
Flood_prone G3	11.630 (15.625)		[-18.995 ; 42.255]

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.
95% CI are calculated using the delta method.

The results confirm people's strong willingness to avoid flood-prone areas. For those who had no

[20] We use the command nlcom of Stata 18.0 to compute WTP estimates, standard errors, significance levels, and confidence intervals for nonlinear combinations of parameter estimates.

additional information about the nature of the risk (group G1), we find that the WTP to avoid homes in flood-prone areas is of € 97,587. This reference value is slightly higher than that found in the basic MXL model (€ 76,351). We can relate this value to the average house price in the sample, which is of € 333,468. Hence, the marginal WTP to avoid flood-prone areas is 29% of the average reported house value.

We presented extreme scenarios to treatment groups G2 and G3: a negative scenario with a 6% chance of flooding every year and a positive protection scenario that suppresses flooding below the 100-year flood. This leads to extreme marginal WTPs. We do not believe that these values are meaningful in terms of policy implications. However, we maintain that group G2 has a significant WTP to avoid flood prone areas. In contrast, for individuals in group G3, the WTP to avoid flood-prone areas is not significantly different from zero. In other words, when given this reassuring information, respondents are indifferent as to whether they live in a flood-prone area or not.

For the other significant WTPs,[21] we found slightly lower values than in the basic MXL: we estimated a marginal WTP of € 1,215 for a one minute longer journey to the sea (compared to € 1,354 in the basic MXL). Extrapolated, this would correspond to a WTP of € 72,900 for being one hour further from the sea, a significant value, which might indicate the limits of extrapolation. However, the significant positive value of WTP shows that people do not primarily seek to be closer to the sea. Instead, we found that people are willing to pay € 837 to be one minute closer to nature (compared to € 1,083 in the baseline MXL). Again, assuming that we can extrapolate marginal values, this corresponds to a signifant WTP of € 50,220 for being one hour closer to nature. People thus show a significant willingness to be closer to nature, after avoiding being too close to the sea and avoiding being in flood-prone areas.

6 Policy implications and conclusion

In this article, we carried out a DCE to study the housing characteristics that determine the residential location choices of households in municipalities faced with flood risk. This study focused on the households' preferences for environmental attributes, especially the distances to natural sites and to the sea, and the flood risk exposure of the housing, in order to identify a possible

[21] We also have non-significant values: the positive WTP when the distance to the city centre increases is not significantly different from zero at the 10% level. There is a small positive value of WTP for an additional square metre of housing, but the confidence intervals and standard errors are too large to consider these values as significantly different from zero.

trade-off between the different environmental externalities. In addition, we attempted to assess the impact of risk information disclosure on household's residential choices in a number of ways: (i) by testing current regulatory mechanisms such as flood risk prevention plans (PPRi) or buyer-tenant information (IAL), and (ii) by testing whether groups with different visual information scenarios make different choices.

First of all, people seek to avoid flood-prone areas when choosing where to live. To do so, they are willing to pay on average € 98,038 with no additional specific information about consequences of flood. However, with a strong and visually negative information about the negative impact of flooding on their home, people's willingness to avoid flood-prone areas increases sharply. Furthermore, individuals seem to be very receptive to information about protective measures as their WTP for avoiding flood-prone areas in their residential choice is no longer significantly different from zero.

Second, the effect of the existing information system is mixed. Regulatory buyer-tenant information has a significant impact on individuals, increasing their propensity to leave flood-prone areas. On the contrary, the existence of a PPRi and its knowledge play the opposite role in decision making, with significant heterogeneity across individuals.

On the one hand, these results are encouraging, since they show that people are receptive to additional information about floods. On the other hand, they show that people tend to listen reassuring information as much as alarming information. Indeed, the protective measures do not eliminate the risk but people behave as if they were eliminating it.

Overall, our results confirm the interest in individually tailored information disclosure formats, such as IAL (buyer-tenant information). They also show the limits of administrative information such as a PPRi (flood risk prevention plan) and the interest in having more personal information about floods. Stories or photo exhibitions with local images of floods could be a means to achieve this goal.

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References

Adamowicz, W., Boxall, P., Williams, M., and Louviere, J. (1998). Stated Preference Approaches for Measuring Passive Use Values: Choice Experiments and Contingent Valuation. *American Journal of Agricultural Economics*, 80(1):64–75.

Ai, C. and Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, 80(1):123–129.

Alfieri, L., Burek, P., Feyen, L., and Forzieri, G. (2015). Global warming increases the frequency of river floods in europe. *Hydrology and Earth System Sciences*, 19:2247–2260.

Bakkensen, L. A. and Barrage, L. (2022). Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics. *Review of Financial Studies*, 35(8):3666–3709.

Bakkensen, L. A. and Ma, L. (2020). Sorting over flood risk and implications for policy reform. *Journal of Environmental Economics and Management*, 104:102362.

Beltrán, A., Maddison, D., and Elliott, R. J. (2018). Is Flood Risk Capitalised Into Property Values? *Ecological Economics*, 146:668–685.

Ben-Akiva, M., Palma, A., McFadden, D., Abou-Zeid, M., Chiappori, P.-A., Lapparent, M., Durlauf, S., Fosgerau, M., Fukuda, D., Hess, S., Manski, C., and Ar (2012). Process and context in choice models. *Marketing Letters*, 23(2):439–456.

Bin, O. (2004). A prediction comparison of housing sales prices by parametric versus semi-parametric regressions. *Journal of Housing Economics*, 13(1):68–84.

Bin, O., Crawford, T., Kruse, J. B., and Landry, C. E. (2006). Valuing Spatially Integrated Amenities and Risks in Coastal Housing Markets. The Center for Natural Hazards Research.

Bin, O., Kruse, J. B., and Landry, C. E. (2008). Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *Journal of Risk and Insurance*, 75(1):63–82.

Bin, O. and Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management*, 65(3):361–376.

Botzen, W. J., Aerts, J. C., and van den Bergh, J. C. (2009). Willingness of homeowners to mitigate climate risk through insurance. *Ecological Economics*, 68(8-9):2265–2277.

Boustan, L. P., Kahn, M. E., and Rhode, P. W. (2012). Moving to higher ground: Migration response to natural disasters in the early twentieth century. *American Economic Review*, 102(3):238–244.

Bubeck, P., Botzen, W. J. W., and Aerts, J. C. J. H. (2012). A review of risk perceptions and other factors that influence flood mitigation behavior. *Risk Analysis*, 32(9):1481–1495.

Champonnois, V. and Erdlenbruch, K. (2021). Willingness of households to reduce flood risk in southern France. *Journal of Flood Risk Management*, 14(2):16.

Cohen, J. P., Danko, J. J., and Yang, K. (2019). Proximity to a water supply reservoir and dams: Is there spatial heterogeneity in the effects on housing prices? *Journal of Housing Economics*, 43(April 2018):14–22.

Creach, A., Pardo, S., Guillotreau, P., and Mercier, D. (2015). The use of a micro-scale index to identify potential death risk areas due to coastal flood surges: lessons from Storm Xynthia on the French Atlantic coast. *Natural Hazards*, 77(3):1679–1710.

de Palma, A., Ben-Akiva, M., Brownstone, D., Holt, C., Magnac, T., McFadden, D., Moffatt, P., Picard, N., Train, K., Wakker, P., and Walker, J. (2008). Risk, uncertainty and discrete choice models. *Marketing Letters*, 19(3):269–285.

Dieleman, F. M. (2001). Modelling residential mobility; a review of recent trends in research. *Journal of Housing and the Built Environment*, 16(3-4):249–265.

Dubos-Paillard, E., Lavaine, E., and Millock, K. (2019). The effect of flood risk information on property values around Paris. In *European Conference on Risk Perception, Behaviour, Management and Response*, Cergy-Pontoise, France.

Glaus, A., Mosimann, M., Röthlisberger, V., and Ingold, K. (2020). How flood risks shape policies: flood exposure and risk perception in Swiss municipalities. *Reg Environ Change*, 20(4):120.

Greene, W. (2010). Testing hypotheses about interaction terms in nonlinear models. *Economics Letters*, 107(2):291–296.

Hole, A. R. (2007). Fitting mixed logit models by using maximum simulated likelihood. *Stata Journal*, 7(3):388–401.

Hole, A. R. (2013). Mixed logit modeling in Stata – an overview. United Kingdom Stata Users' Group Meetings, September 2013, https://www.stata.com/meeting/uk13/abstracts/materials/uk13_hole.pdf.

IPCC (2014). Annex ii: Glossary. In Barros, V. R., Field, C. B., Dokken, D. J., Mastrandrea, M. D., Mach, K. J., Bilir, T. E., Chatterjee, M., Ebi, K. L., Estrada, Y. O., Genova, R. C., Girma, B., Kissel, E. S., Levy, A. N., MacCracken, S., Mastrandrea, P. R., and White, L. L., editors, *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 1757–1776. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kunreuther, H. (2006). Disaster Mitigation and Insurance: Learning from Katrina. *The Annals of the American Academy of Political and Social Science*, 604(1):208–227.

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, 74:132–132.

Lee, B. H. and Waddell, P. (2010). Residential mobility and location choice: A nested logit model with sampling of alternatives. *Transportation*, 37(4):587–601.

Lee, S. (2022). Adapting to Natural Disasters through Better Information: Evidence from the Home Seller Disclosure Requirement. *SSRN Electronic Journal*, 21(17).

Louviere, J. J., Hensher, D. A., Swait, J. D., and Adamowicz, W. (2000). *Stated Choice Methods: Analysis and Applications.* Cambridge University Press.

Marschak, J. (1960). Binary choice constraints and random utility indicators. In Arrow, K., editor, *In Mathematical Methods in the Social Sciences*, pages 312–329. Stanford: Stanford University Press.

Mauroux, A. (2015). Exposition aux risques naturels et marchés immobiliers. *Revue d'économie financière*, 117(1):91–103.

Mauroux, A., Marcus, V., Ostapchuk, M., and Tarayoun, T. (2015). L'information préventive améliore-t-elle la perception des risques? Impact de l'information Acquéreur Locataire sur le prix du logement. Etudes et documents. Commissariat général au développement durable. n° 132, Collection "Études et documents" du SEEIDD du CGDD.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behaviour. In Zarembka, P., editor, *Frontiers in Econometrics*, pages 105–142. Academic Press New York, New York, NY, USA.

McFadden, D. (2001). Economic choices. *American Economic Review*, 91(3):351–378.

McFadden, D. L. (1981). Econometric models of probabilistic choice. In Manski, C. F. and McFadden, D. L., editors, *Structural Analysis of Discrete Data with Econometric Applications*, pages 198–272. MIT Press, Cambridge, MA, USA.

MEDDE (2012). Mieux savoir pour mieux agir : principaux enseignements de la première évaluation des risques d´inondation sur le territoire français 2011. Technical report, Ministère de l'écologie, du développement durable, et de l'énergie - French ministry in charge of the Environment.

MTES-CGDD (2020). Service de l'observation et des statistiques (SOES). https://ree.developpement-durable.gouv.fr/donnees-et-ressources.

Munich RE (2020). The natural disasters of 2018 in figures - Munich Re. https://www.munichre.com.

Nilsson, P. (2014). Natural amenities in urban space - A geographically weighted regression approach. *Landscape and Urban Planning*, 121:45–54.

Ohl, C. A. and Tapsell, S. (2000). Flooding and human health: the dangers posed are not always obvious. *BMJ Clinical Research*, 321(7270):1167–8.

Phaneuf, D. J., Taylor, L. O., and Braden, J. B. (2013). Combining revealed and stated preference data to estimate preferences for residential amenities: A GMM approach. *Land Economics*, 89(1):30–52.

Revelt, D. and Train, K. (1998). Mixed logit with repeated choices: households' choices of appliance efficiency level. *Review of economics and statistics*, 80(4):647–657.

Rey-Valette, H. and Rulleau, B. (2017). Evaluation des préférences des résidents pour le caractère concerté d'une politique : le cas de la relocalisation des biens face à la montée du niveau de la mer. *Canadian Journal of Regional Science*, 40(2):133–140.

Reynaud, A. and Nguyen, M.-H. (2016). Valuing Flood Risk Reductions. *Environmental Modeling & Assessment*, 21(5):603–617.

Reynaud, A., Nguyen, M.-H., and Aubert, C. (2018). Is there a demand for flood insurance in Vietnam? Results from a choice experiment. *Environ Econ Policy Stud*, 20(3):593–617.

Richert, C., Erdlenbruch, K., and Figuières, C. (2017). The determinants of households' flood mitigation decisions in France - on the possibility of feedback effects from past investments. *Ecological Economics*, 131:342–352.

Schaeffer, Y., Cremer-Schulte, D., Tartiu, C., and Tivadar, M. (2016). Natural amenity-driven segregation: Evidence from location choices in French metropolitan areas. *Ecological Economics*, 130:37–52.

Thurstone, L. L. (1927). A law of comparative judgement. *Psychological Review*, 34:278–286.

Train, B. K. (1999). Halton sequences for mixed logit.

Train, K. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press, New York, NY, USA, second edition edition.

Traoré, S. (2019). Residential location choice in a developing country: What matter? A choice experiment application in Burkina Faso. *Forest Policy and Economics*, 102(January):1–9.

Tu, G., Abildtrup, J., and Garcia, S. (2016). Preferences for urban green spaces and peri-urban forests: An analysis of stated residential choices. *Landscape and Urban Planning*, 148:120–131.

Turner, D. and Landry, C. E. (2023). Flood risk perceptions. *Land Economics*.

Votsis, A. and Perrels, A. (2016). Housing Prices and the Public Disclosure of Flood Risk: A Difference-in-Differences Analysis in Finland. *J Real Estate Finan Econ*, 53(4):450–471.

Walker, J., Wang, Y., Thorhauge, M., and Ben-Akiva, M. (2018). D-efficient or deficient? a robustness analysis of stated choice experimental designs. *Theory and Decision*, 84(2):215–238.

Waltert, F. and Schläpfer, F. (2010). Landscape amenities and local development: A review of migration, regional economic and hedonic pricing studies. *Ecological Economics*, 70(2):141–152.

Zhai, G., Fukuzono, T., and Ikeda, S. (2007). Multi-attribute evaluation of flood management in Japan: A choice experiment approach. *Water and Environment Journal*, 21(4):265–274.

Appendix

A DCE instructions for different treatments

In the following we translated the most important instructions used for the DCE (which was conducted in French). The DCE was implemented during face-to-face interviews. Interviewers used mini-PCs to generate the pivot designs and to be able to randomly attribute interviewed households to one of the three treatment groups.

A.1 General instructions

'We will provide you with fictional scenarios in which you are the main actor. Imagine that you are looking for an accommodation today. You will see a series of homes and we invite you to choose the one you prefer. These homes differ in six characteristics, as shown in this table. [A table with an example choice set is shown on a separate sheet and explained by the interviewer, by pointing to the corresponding columns.]

- The first column contains the characteristics of the homes considered.[22] The second column corresponds to your home: for example the time needed to get to the town center is [the time you are currently spending].
- The third column presents another type of home. For example, the time to go to the sea is reduced by 40 percent compared to your current situation (hence xx minutes) and the size of the accommodation is 20 percent larger (hence yy m^2). However, the home is located in a flood-prone area.
- The fourth column presents still another type of home. Here, the time to get to the town center is reduced by 40 percent (hence xx minutes). The price is 20 percent higher (hence yy euros), etc.

What is important is that all other features you could think of are the same for all three homes. For example, the time it takes you to get to work or the time to go to your children's school is the same for all.'

[22] The interviewer reads the characteristics and explains their meaning. He or she answers all the questions the respondents might have. Details of the instructions to the interviewers are available from the authors on request.

A.2 Group 1

'We will now present you with five different situations with choices to make. What home would you choose if you had to make your choice today?' [The five choice sets of the randomly selected block are presented in turn to the respondents.]

A.3 Group 2

'We will give you a little more information on flooding: in your case, when a home is said to be inside the flood-prone area, this means that it has been flooded three times in the last 50 years. During these floods, the water rose to 50 centimeters inside the home.'

- Home with a ground floor

  'The furniture and personal belongings on the ground floor were damaged as shown in this photo [the photo from Figure 1 is presented on a large-sized sheet] and the members of the flooded household had to clean the floor and walls. Insurance reimbursed the flooded household for the cash value of the furniture.'

Figure 1: Picture of a flooded ground floor of a home presented to Group 2.

- Home situated upstairs

  'The entrance hall of the building as well as the mailbox and the parking lot have been flooded and devastated, as shown in this photo [the photo from Figure 2 is presented on a large-sized sheet]. Members of the flooded households had to clean the floor and the walls. Insurance reimbursed the flooded household for the cash value of the furniture.'

Figure 2: Picture of a flooded building presented to Group 2.

'We will now present you with five different situations with choices to make. What home would you choose if you had to make your choice today?' [The five choice sets of the randomly selected block are presented in turn to the respondents.]

A.4 Group 3

'We will give you a little more information on flooding: in your case, when a home is said to be inside a flood-prone area, this means that it has been flooded three times in the last 50 years. During these floods, the water rose to 50 centimeters inside the house. Recently, the public authorities have carried out mitigation works (construction of dikes, an evacuation channel) to reduce the risk of flooding in your municipality, as shown in this photo [the photo from Figure 3 is presented on a large-sized sheet]. These constructions protect against all floods less than or equal to the 100-year flood, i.e., a flood that occurs an average of once in 100 years.'

Figure 3: Picture of a collective protection structure, a dike with a spillway, presented to Group 3.

'We will now present you with five different situations with choices to make. What home would you choose if you had to make your choice today?' [The five choice sets of the randomly selected block are presented in turn to the respondents.]

A.5 Debriefing

The DCE was followed up by different debriefing questions that are available upon request from the authors.

B Additional information about the DCE survey

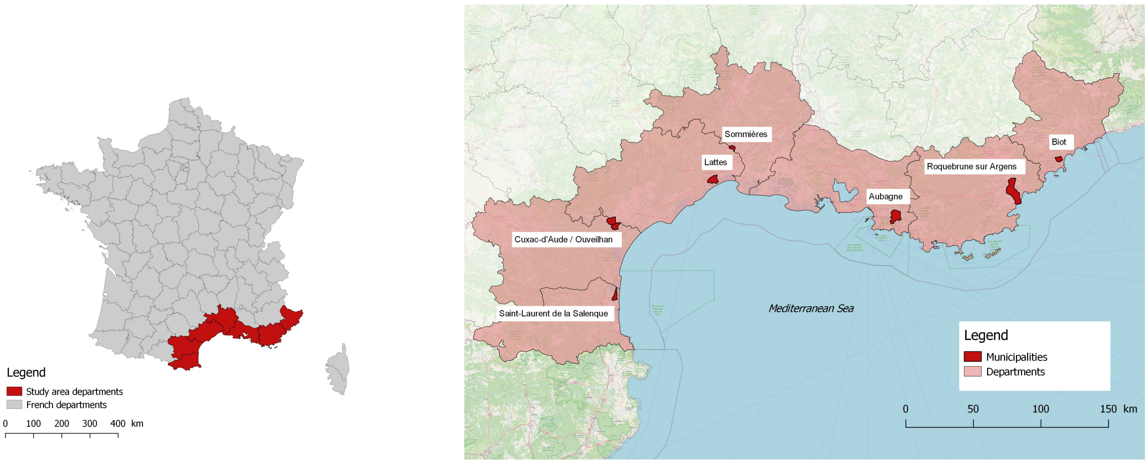

Figure 4: Study areas: departments (left) and selected municipalities (right)

Table A1: Example of a choice set

Attributes	**Current home**	**Alternative 1**	**Alternative 2**
Time to get to the town center	*Current* 20 minutes	*Current* 20 minutes	*Minus 60%* 8 minutes
Time to get to the sea	*Current* 30 minutes	*Minus 80%* 6 minutes	*Current* 30 minutes
Time to get to a natural site	*Current* 10 minutes	*Current* 10 minutes	*Minus 80%* 2 minutes
Flood risk exposure	outside flood-prone area	inside flood-prone area	outside flood-prone area
Home size	*Current* 80 m^2	*Current* 80 m^2	*Plus 40%* 112 m^2
Home price	*Current* € 200,000	*Current* € 200,000	*Plus 10%* € 220,000
Check your choice		**X**	

Table A2: Distribution of individuals according to flood information

	Description	Freq.	%
G1	No additional information	135	28.60
G2	Additional information about the negative consequences of flood	151	32.00
G3	Additional information about flood mitigation via protection measures	186	39.40

N=472

Table A3: Frequency of individual choices on the different choice sets in the DCE.

Choice	Freq.	%
Status quo (current home)	1 373	58.18
Alternative 1	464	19.66
Alternative 2	523	22.16

$N = 472$, $N \times S = 2,360$.

C Robustness checks

Table A4: MXL estimation results according to the age of respondents

	Age < 65		Age ≥ 65	
Variable	Mean	SD	Mean	SD
Price	-0.00567**		-0.0164***	
	(0.00248)		(0.00332)	
$ASC_{SQ} \times$ AGE	-0.0374		0.186**	
	(0.0312)		(0.0746)	
$ASC_{SQ} \times$ EDUC	-0.706***		-1.029***	
	(0.270)		(0.333)	
$ASC_{SQ} \times$ RISKTAKER	-0.259**		-0.0144	
	(0.129)		(0.145)	
$ASC_{SQ} \times$ NATIVE	0.659		1.187	
	(0.610)		(0.786)	
$ASC_{SQ} \times$ HOUSEHOLD	0.466		2.014***	
	(0.293)		(0.543)	
time_to_town	0.0331*	0.110***	0.0157	0.000406
	(0.0191)	(0.0304)	(0.0137)	(0.0194)
time_to_sea	0.0160**	-0.0202*	0.00642	7.51e-05
	(0.00711)	(0.0117)	(0.00696)	(0.0101)
time_to_nature	-0.00542	0.0134**	-0.0120**	-7.17e-05
	(0.00429)	(0.00670)	(0.00474)	(0.00880)
home_size	0.00611*	-0.0105	-0.00505	0.0195***
	(0.00342)	(0.00967)	(0.00402)	(0.00634)
Flood_prone × G1	-0.801***	-0.503	-0.930***	-0.645
	(0.223)	(0.516)	(0.312)	(0.496)
Flood_prone × G2	-1.442***	3.095***	-1.878***	-0.0331
	(0.490)	(0.597)	(0.263)	(0.365)
Flood_prone × G3	0.0937	0.0261	0.00669	0.0117
	(0.167)	(0.222)	(0.199)	(0.224)
$ASC_{SQ} \times$ Flood_Exp	0.507	4.281***	2.091*	5.939***
	(0.817)	(0.961)	(1.122)	(1.066)
$ASC_{SQ} \times$ PPRi	1.211	4.521***	2.327*	7.451***
	(0.955)	(0.819)	(1.236)	(1.162)
$ASC_{SQ} \times$ IAL	-2.103*	6.709***	1.586	7.759***
	(1.160)	(1.118)	(1.502)	(1.910)
Observations	3330		3660	
Log likelihood	-753.6		-567.4	
LR chi2(10) (P-value)	603.7 (0.000)		628.2 (0.000)	

Municipality effects included.
Halton draws for the MXL = 500.
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A5: MXL estimation results according to whether people experienced flooding or not

Variable	Flood_Exp = Yes Mean	Flood_Exp = Yes SD	Flood_Exp = No Mean	Flood_Exp = No SD
Price	-0.00925***		-0.00898***	
	(0.00262)		(0.00299)	
$ASC_{SQ} \times$ AGE	-0.00110		0.0367**	
	(0.0155)		(0.0171)	
$ASC_{SQ} \times$ EDUC	-0.704***		-0.729***	
	(0.158)		(0.200)	
$ASC_{SQ} \times$ RISKTAKER	-0.253**		-0.163*	
	(0.1000)		(0.0947)	
$ASC_{SQ} \times$ NATIVE	1.150***		0.658	
	(0.378)		(0.526)	
$ASC_{SQ} \times$ HOUSEHOLD	-0.683**		1.216***	
	(0.285)		(0.327)	
Time_to_town	0.0262	0.133***	0.0193	0.000690
	(0.0198)	(0.0306)	(0.0161)	(0.0321)
Time_to_sea	0.0107	0.0144	0.0153*	0.0206
	(0.00667)	(0.0128)	(0.00809)	(0.0139)
Time_to_nature	-0.00569	-0.000225	-0.0113*	-0.0214*
	(0.00359)	(0.00570)	(0.00628)	(0.0111)
home_size	0.00143	-0.00927	-0.00314	0.0347***
	(0.00332)	(0.00957)	(0.00564)	(0.00631)
Flood_prone $\times$ G1	-0.893***	-0.717*	-0.888***	-0.866**
	(0.245)	(0.373)	(0.319)	(0.404)
Flood_prone $\times$ G2	-2.044***	2.034***	-1.378***	1.974***
	(0.404)	(0.470)	(0.434)	(0.448)
Flood_prone $\times$ G3	-0.0321	-0.0289	0.229	0.00488
	(0.152)	(0.256)	(0.229)	(0.322)
$ASC_{SQ} \times$ PPRi	3.083***	6.724***	0.410	4.757***
	(0.889)	(1.383)	(0.776)	(1.248)
$ASC_{SQ} \times$ IAL	-0.582	13.02***	-0.788	3.535**
	(2.814)	(2.189)	(1.098)	(1.397)
Observations	4560		2430	
Log likelihood	-834.6		-520	
LR chi2(9) (P-value)	789.3 (0.000)		250.3 (0.000)	

Municipality effects included.
Halton draws for the MXL = 500.
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

D Marginal willingness to pay in the basic model

Table A6 reports the (mean) marginal WTPs from the most basic specification with only DCE attributes and for both CL and MXL models, along with the 95% confidence intervals. Standard errors and confidence intervals of the WTP estimates are obtained using the delta method.

Table A6: Marginal WTP (in thousands €) from the basic CL and MXL models

Variable	CL Marginal WTP		CL 95% CI	MXL Marginal WTP		MXL 95% CI
Home_size	0.375		[-0.728 ; 1.478]	0.230		[-0.271 ; 0.732]
	(0.563)			(0.256)		
Time_to_town	-3.267		[-7.931 ; 1.397]	2.499	*	[-0.378 ; 5.376]
	(2.380)			(1.468)		
Time_to_sea	0.737		[-1.606 ; 3.080]	1.354	**	[0.238 ; 2.471]
	(1,195)			(0.570)		
Time_to_nature	-1.858	**	[-3.473 ; -0.243]	-1.083	***	[-1.7041 ; -0.463]
	(0.824)			(0.3167)		
Flood_prone	-37.756	*	[-77.152 ; 1.639]	-76.645	***	[-104.545 ; -48.745]
	(20.100)			(14.235)		

Standard errors in parentheses and 95% confidence intervals in brackets derived using the delta method. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

As discussed in the text, respondents are willing to pay € 37,756 and € 76,351 to avoid a flood-prone area in the CL model and the MXL model, respectively. The following other results can be stated. The negative sign associated with the variable Time_to_nature indicates that the WTP decreases by € 1,858 and € 1,083 for a one-minute longer journey to a natural site for CL and MXL estimation, respectively. If we assume that these marginal values can be extrapolated, this amounts to € 111,480 and € 64,980 for a journey one hour longer, respectively. Otherwise said, the closer a residence is located to a natural site the higher the well-being of the household. For the attribute Time_to_sea, we have a significant estimate for the MXL. The marginal WTP is positive, meaning that households are willing to pay € 1,354 more for being one-minute further away from the sea, equivalent to € 81,240 for a one-hour distance to the sea. Concerning the variable Time_to_town, we found opposite signs of WTP according to the model estimation and a significantly positive marginal WTP only for the MXL model. We can conclude that the WTP is € 2,499 for a one-minute longer journey to the town, but only at the 10% level. Finally, even though the marginal WTP is positive for an extra square meter of housing, the confidence interval is too large for both models to consider this value as being significantly different from zero. This issue has been discussed above on the basis of our robustness checks.