

# Chapter 25 Do Information and Citizens Characteristics Affect Public Acceptability of Landslide Protection Measures? A Latent Class Approach

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**Abstract** The Italian Alps are increasingly vulnerable to landslides. Residents and visitors are exposed to serious socio-economic consequences from these natural events. Hence, risk mitigation is a major safety issue for local authorities. Publicly funded adaptation interventions are expensive to implement and cause the need to better understand acceptability of protection measures, and their economic efficiency. We investigate social demand for landslide protection in Boite Valley (North-Eastern Alps) by adopting a choice experiment survey approach. We specifically address the impact of information on preferences by eliciting them before and after providing respondents with visual simulations of possible catastrophic events. Choice data are used to estimate a Latent Class-Random Parameters model. This allows us to identify segments of the population with different preference profiles towards safety measures and their sensitivity to information treatments. Marginal willingness to pay (mWTP) values for protection measures are estimated and mapped to describe the spatial distribution of benefits from risk reduction. Overall, we found mWTP values to vary spatially and to be dependent on information and socio-economic characteristics.

# Introduction

Over the last few decades the number of landslides events in the Dolomites (Italy) has increased. Among other factors, this is a consequence of more frequent extreme rainfalls and increased availability of debris material (Bernard et al. 2019; Gregoretti

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et al. 2019). Hence, people living in such area are exposed to serious socio-economic consequences and there is high social demand for protection.

Due to the high hydrogeological risk level—which has been exacerbated by climate change—several landslides occurred in the Boite Valley (North-Eastern Alps, the study area) and caused deaths and damage to houses and other property. In 1814, a massive debris-flow destroyed two villages, killing 257 people. In 1925, a similar event caused 288 victims and 53 people went missing. In summer 2015 intense rainfalls over a short period triggered eight events, causing significant damage to public infrastructure and three victims among tourists. More recently one victim was caused in 2017 in Cortina and other landslides took place in 2018. Hence, risk mitigation is a major component of climate change adaptation and a safety issue for local authorities. Accounting for social preferences is crucial to inform fairly the ongoing public debate on this matter.

We report the results of an application of choice experiments (CE) in the Boite Valley aimed at estimating residents and tourists' willingness to pay (WTP) for different safety devices. Stated preference approaches have a broad record of use in the context of natural hazards, such as in floods (e.g. Brouwer and Schaafsma 2013; Ryffel et al. 2014; Arora et al. 2019), avalanches (e.g. Leiter and Pruckner 2009; Haegeli and Strong-Cvetich 2018), wildfires (e.g. Wibbenmeyer et al. 2013; Holmes et al. 2013) and landslides (Flügel et al. 2015; Thiene et al. 2017).

We also analyse the extent to which information (through simulations of possible events) affects respondents' stated preferences. Estimates of welfare measures have, in fact, been shown to be impacted by information provided to survey respondents (e.g. Aoki et al. 2019). Finally, we mapped average values of marginal WTP estimates at the individual level within each municipality. This approach roots on the increasing evidence that benefits from public goods are spatially heterogeneous (Campbell et al. 2008; De Valck et al. 2017; Sagebiel et al. 2017).

The remainder of this paper is organised in four sections. Section 2 describes data collection and Sect. 3 outlines the econometric approach adopted for the study. Section 4 reports the results. Finally, the conclusions are drawn in Sect. 5 along with the policy implications for landslide risk mitigation in the Boite Valley.

#### **Survey Design and Data Collection**

This section describes survey design and sampling procedure. More details can be found in Mattea et al. (2016).

The questionnaires used in the survey included seven sections: the first posed questions about subjective risk perception, attitudes toward risk activities and natural hazards, and personal experience with landslides. The second focused on recreational behaviour. The questionnaire was designed to include a CE in the third part and a "repeated" CE in the fifth. In-between (fourth section) two hydro-geological simulations of landslides were shown to respondents. The first simulation (Fig. 25.1) referred to three sites in the upper part of the valley and showed all debris-flow

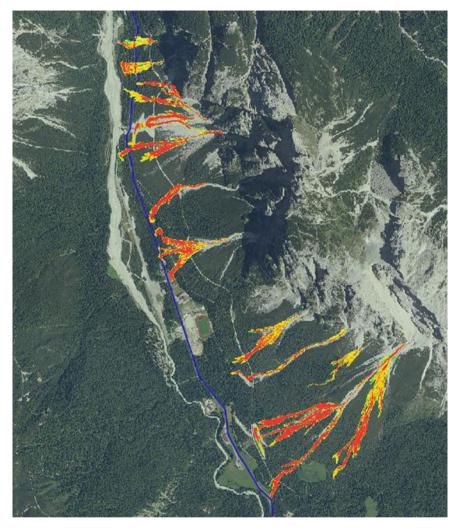


Fig. 25.1 Debris-flow simulation in the upper part of Boite Valley (Gregoretti 2014)

possible trajectories. The second simulation modelled debris-flow trajectories in a specific site with and without a channel (Fig. 25.3). The green lines show possible trajectories with a channel, while green and yellow lines are the trajectories without such safety device. The sixth section included follow-up questions, whereas the last one focused on socio-economic ones (Fig. 25.2).

The CE used five attributes to describe alternative scenarios (Table 25.1). Four attributes represented safety devices, namely diverging channel and retaining basin (passive devices) and video cameras and acoustic sensors (active devices). The fifth attribute is a hypothetical road toll to be paid by vehicles in transit across the valley.

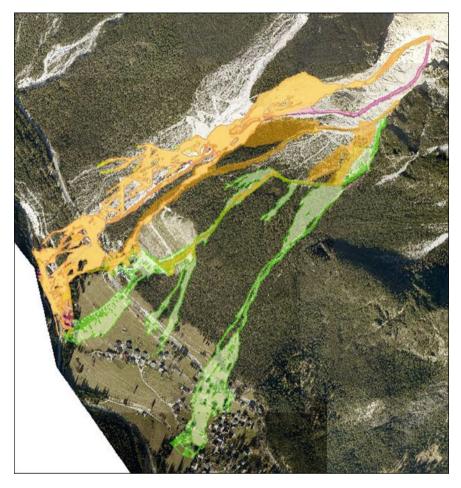


Fig. 25.2 Debris-flow simulation with (yellow area) and without (yellow and green areas) channel (Gregoretti 2014)

The toll was defined as a one-time payment valid for eight months to financially support the implementation of the mitigation programs. In the data all attribute levels are dummy-coded (presence of the safety device = 1, else = 0) with the exception of the monetary attribute that takes four numeric values. The experimental design used was an optimised orthogonal design (Ferrini and Scarpa 2007, Scarpa and Rose 2008) which generated 60 choice sets. The choice sets were blocked into 10 groups, so each respondent faced 6 scenarios.

Responses to the questionnaires were obtained during face-to-face interviews to a sample of 250 respondents, randomly sampled on-site among residents and visitors of the valley.

| Attribute        | Acronym | Description  | Levels  |
|------------------|---------|--|---|
| Channel          | CHAN    | Diverging channel is a man-made channel built<br>to redirect water. The water is carried off in a<br>different way that the sediment and rocks<br>mitigating the impact of the debris-flow   | 1 if present<br>0 otherwise                                       |
| Basin            | BAS     | Retaining basin is a dam where the solid and<br>liquid mass is collected prior to damage roads<br>and villages   | 1 if present<br>0 otherwise                                       |
| Video cameras    | VIDEO   | Video cameras monitor the debris-flow during<br>the night and, in case of emergency, they will<br>activate the alarm system and the traffic lights on<br>the road  | 1 if present<br>0 otherwise                                       |
| Acoustic sensors | SENS    | Acoustic sensors detect soil movement in slopes<br>prior to landslides. The sensors consist of pipes<br>inserted vertically in the flank of a debris-flow<br>slope. They provide with acoustic emissions<br>used to give early warnings of landslide<br>occurrence as well as activated the traffic lights | 1 if present<br>0 otherwise                                       |
| Road toll        | TOLL    | A road toll to pay for eight months (from April<br>to November of a specific year) daily for transit<br>in the valley by car for residents and tourists  | $ \begin{array}{c} \in 1 \\ \in 2 \\ \in 3 \\ \in 4 \end{array} $ |

**Table 25.1**CE attributes and levels

#### **Data Analysis**

We modelled choice data by means of a Latent Class—Random Parameters (LC-RPL model) (Bujosa et al. 2010), which assumes that respondents' preferences vary discretely across C classes and continuously within each class.

To specify class membership probability, we use a logit formulation for the class allocation model (Bhat 1997). The probability  $(\pi_{nc})$  that individual *n* belongs to segment *C* vector is given by

$$\pi_{nc} = \frac{\exp(\theta_c' Z_n)}{\sum_{c=1}^{c=C} \exp(\theta_c' Z_n)}$$
(25.1)

with  $Z_n$  being a vector of socioeconomic variables and  $\theta_c$  a vector of estimated coefficients.

Respondents' preferences  $\beta_{nc}$  vary continuously within each class with class specific hyper-parameters (e.g. mean  $\mu_c$  and st. dev.  $\sigma_c$ ). Such parameters can be derived by estimating the conditional probability of individual *n* choosing alternative *i* out of a set of alternatives *J*:

$$\pi_{nti|c} = \int \prod_{t=1}^{t=T} \frac{\exp(\beta'_{nc} \mathbf{x}_{ti})}{\sum_{j=1}^{j=J} \exp(\beta'_{nc} \mathbf{x}_{tj})} f(\beta_{nc}) d\beta_{nc}$$
(25.2)

where random parameters follow a separate distributional law (Train 1999; McFadden and Train 2000). Finally, the LC-RPL unconditional probability that individual n chooses the t sequences of i in their choice task sequence can be derived from Eqs. (25.1) to (25.2):

$$\pi_{nti} = \sum_{c=1}^{c=C} \pi_{nc} \pi_{nti|c}$$
(25.3)

To investigate the role of information on preferences we estimated a pooled utility function and included an interaction variable between each attribute and a dummy variable *I*, which is defined as equal to 1 for data collected after the exposure to information. Finally, we created maps illustrating the spatial distribution of individual-specific mWTP values for each safety device.

# Results

## LC-RPL Estimates

The LC-RPL model has been estimated by simulated maximum likelihood using Pythonbiogeme software (Bierlaire 2003). The choice probabilities are simulated in the sample log-likelihood with 500 pseudo-random draws of the modified Latin hypercube sampling (MLHS) type. All the attributes' coefficients are assumed to have a normal distribution, except for the cost attribute that is fixed. Additionally, the model includes an alternative specific constants (ASCs) for the baseline option.

To identify the optimal number of classes, we estimated alternative specifications and compared them by using information criteria (Table 25.2). Based on these criteria and on the number of significant parameters in each class, we selected the specification with two classes.

To obtain a better profiling of the two classes we included several sociodemographic characteristics in the class membership function (Table 25.3). Many showed a significant effect and the signs suggest that women with higher education and income and larger families are more likely to belong to class 1. Class membership probabilities averaged across all individuals are nearly 55% for class 1 and the remaining 45% for class 2.

| N = 250           |            |       |      |      |      |
|-------------------|------------|-------|------|------|------|
| Number of classes | Parameters | lnL   | AIC  | BIC  | AICc |
| 2                 | 43         | -2425 | 4936 | 5087 | 4894 |
| 3                 | 63         | -2378 | 4882 | 5103 | 4820 |

 Table 25.2
 Criteria for the selection of the number of classes

|                       | Class 1 (55%) |       |       | Class 2 (45%) |       |       |
|-----------------------|---------------|-------|-------|---------------|-------|-------|
| Parameters            | Value         | ltl   | mWTP  | Value         | ltl   | mWTP  |
| Mean parameters       |               |       |       |               |       |       |
| Basin                 | 4.21          | 8.88  | 2.26  | 1.37          | 4.45  | 0.82  |
| Channel               | 4.99          | 5.67  | 2.68  | 1.48          | 4.29  | 0.89  |
| Sensor                | 3.12          | 6.98  | 1.68  | 0.95          | 2.66  | 0.57  |
| Camera                | 3.48          | 8.81  | 1.87  | 0.71          | 2.30  | 0.43  |
| Toll                  | -1.86         | 7.91  |       | -1.67         | 14.69 |       |
| Status quo            | -2.31         | 6.66  | -1.24 | -1.01         | 4.41  | -0.60 |
| Interaction paramet   | ers           |       |       |               |       |       |
| Info $\times$ basin   | 0.33          | 0.43  | 0.18  | 0.21          | 0.83  | 0.13  |
| Info $\times$ channel | 0.66          | 2.08  | 0.35  | 0.28          | 2.11  | 0.17  |
| Info $\times$ sensor  | 0.38          | 0.32  | 0.20  | 0.12          | 0.01  | 0.07  |
| Info $\times$ video   | -0.06         | 0.34  | -0.03 | 0.15          | 1.61  | 0.09  |
| Info $\times$ toll    | 0.11          | 0.87  | 0.06  | 0.17          | 0.27  | 0.10  |
| Info × status quo     | -0.48         | 1.99  | -0.26 | -0.25         | 2.08  | -0.15 |
| Standard deviation    | parameters    |       |       |               |       |       |
| Basin                 | 1.28          | 10.98 |       | 1.15          | 3.75  |       |
| Channel               | 2.01          | 11.21 |       | 0.24          | 5.40  |       |
| Sensor                | 1.41          | 9.87  |       | 0.27          | 3.35  |       |
| Camera                | 1.25          | 6.89  |       | 0.44          | 4.77  |       |
| Class membership p    | arameters     |       |       |               |       |       |
| Constant              |               |       |       | 1.06          | 2.02  |       |
| Woman                 |               |       |       | -0.62         | 2.01  |       |
| Age                   |               |       |       | 1.12          | 0.81  |       |
| Income                |               |       |       | -0.42         | 2.01  |       |
| Degree                |               |       |       | -0.36         | 2.81  |       |
| Number of family m    | -0.41         | 2.36  |       |               |       |       |

Table 25.3LC-RPL Estimates

The estimates suggest a consistent preference for the improvement of the current scenario (negatives signs for status quo in both classes), as well as the existence of heterogeneity of preferences both among and within classes (significant standard deviation parameters). The coefficient of the cost attribute is negative and significant in both classes, as expected. In both classes the coefficients associated with safety devices are significant and positive, thus suggesting that citizens would generally benefit from the implementation of such measures.

The main difference among the two classes lies in the magnitude of WTP values. Specifically, such values are consistently higher in class 1 for all safety devices. This is consistent with the profile of the two classes emerged from the class membership function, and in particular with the higher income that members of class 1 are likely to have.

More in detail, the construction of a channel is associated with the highest WTP values in both classes ( $\in 2.68$  and  $\in 0.89$ , respectively). The basin is the second preferred protection device in both cases ( $\in 2.26$  and  $\in 0.82$ ). In class 1 respondents slightly preferred video camera ( $\in 1.87$ ) to acoustic sensor ( $\in 1.68$ ), while in class 2 was the opposite ( $\in 0.57$  vs.  $\in 0.43$ ). It is also interesting to notice that members of class 1 are more averse to the status quo than those belonging to class 2, which seems to confirm that the former are willing to pay more to improve current safety programs.

Moving to the analysis of the information effect, it is interesting to notice that the interaction terms between treatment and safety devices are all insignificant, with the exception of the one for channel. Specifically, the positive sign in both classes suggests that the information treatment led to an increase in the perceived benefit from this safety device (and consequently in the WTP for its implementation). This result is consistent with the simulations being focused specifically on such device and seems to suggest that the provision of information only affects the interested attribute.

## Mapping Results and Policy Implications

This section reports the mapping of the estimated individual-specific mWTP for each attribute and class within sampled municipalities. Individual class membership probabilities were computed, and each person was assigned to the class he/she has the highest probability to belong to.

Figure 25.3 reports the maps for channel and basin and Fig. 25.4 for sensor and camera. We considered only the municipalities in the Belluno province, given the low number of respondents from other provinces. The municipalities delimitated by the black line are those in the Boite Valley. By looking at the maps, a common pattern seems to emerge across all devices and classes: higher WTP values are in most cases retrieved in municipalities inside the valley boundaries or in its proximity. As expected, inhabitants of such municipalities are those more exposed to damages caused by catastrophic events in the valley. Hence, it is plausible that they may be generally willing to pay more to prevent (or at least limit) such damages, compared to individuals living at further distance.

## Conclusions

We presented results of a choice experiment evaluating alternative protection policies in the context of landslide risk reduction. Results show evidence of preference heterogeneity for safety devices, by reflecting estimates of marginal WTP values which are well-differentiated across different segments of the population. We also

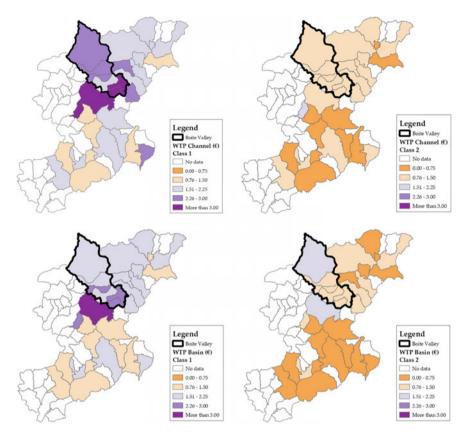


Fig. 25.3 Geographical distribution of mWTP values for channel and basin

find evidence of a treatment effect associated with the provision of visual information. While not clear-cut, the mapping of the estimated values seems to suggest that people living in the Boite Valley or in its proximity are generally willing to pay more for all devices than those living elsewhere.

With regards to policy implications, the estimates suggest that policymakers should focus on the implementation of plans which include the construction of passive devices, as residents and visitors of the valley are willing to contribute more to their realization. The analysis of information effect suggests that investment in information campaigns and educational activities could be a useful tool to increase financial support to public safety measures by the population. Specifically, it seems advisable to focus such activities on measures that policymakers are already planning to adopt, in order to increase their public acceptance. As a closing remark, it should be noted that our results do not account for the costs of implementing different safety devices. Future research should address this limitation and integrate our results with a cost-benefit analysis in order to inform more efficiently the public debate on protection plans.

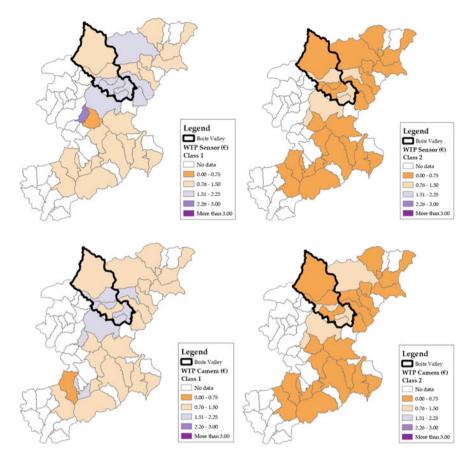


Fig. 25.4 Geographical distribution of mWTP values for acoustic sensor and video camera

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