Three Essays on Stated Choice Experiments for Nonmarket Valuation of Landslide Protection

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Abstract

This thesis consists of three essays that improve the general understanding of the public demand for safety programmes in the context of natural hazards. With the growing importance of this topic around the world, this study provides a practical and methodological contribution to the literature on Environmental Economics and Policy, especially local policy.

In particular, this research examines people's preferences and their willingness-to-pay for landslide mitigation programmes. The primary aim is to assess how the residents of and visitors to a mountain valley in the Alps value and trade off the multiple attributes of protection programmes for landslide risk reduction by applying Discrete Choice Modelling methodology. To address the current needs of local decision-makers, the investigation of the determinants of preference heterogeneity is the central theme of the research. The study is based on a panel choice dataset created from a Discrete Choice Experiment, based on full ranking, administered in person by the author to 250 respondents in the Boite Valley, Italy.

The first essay examines the stability of preferences, investigating to what extent additional information has an impact on estimated values. Specifically, it studies whether respondents adjust their preferences based on scientific information provided on one specific attribute. A mixed logit model in willingness-to-pay space is implemented to account for preference heterogeneity. The findings suggest that respondents perceive the existing protection measures as insufficient. The provision of information affects only the attribute subject to additional information and the consideration of the current status of protection. Preferences for the other attributes remained stable. Preliminary evidence of spatial heterogeneity is also detected.

The second essay addresses the issue of the stability of parameter estimates obtained through simulation using choice models with latent variables. Specifically, it analyses the stability of the coefficients to the number of simulation draws and the increasing number of latent variables. Three Random Parameter logit models with respectively one, two and three latent variables are fitted with six sets of increased numbers of draws. The landslide risk perceptions of respondents are modelled as latent sources of heterogeneity in the consideration

of the riskiest scenario. Overall, the results show very stable estimates for the attributes' coefficients but not for the latent variables. Thus, increasing the complexity by adding more latent factors into the model implies the necessity of additional draws in the simulation process to ensure empirical identification. The results also show how preferences are strongly related to the underlying perceptions of own mortality risk due to landslides and risk severity.

The third essay explores multiple sources of preference heterogeneity, accounting for its spatial determinants. It emerges that the inclusion of more observables allows for a better segmentation of the policy based on respondents' and municipalities' characteristics. The findings show the importance of distinct spatial effects, such as geographical characteristics, spatial error components for road tracts and site-specific choice-sets, with relevant insights into the priority of intervention. In addition, residual unobserved heterogeneity is analysed at a higher hierarchical scale using spatial models at the municipality level.

Overall, the empirical results of this thesis provide important policy implications for local decision-makers in charge of public safety, given the relevant information on the distributional effects of protection across different groups of beneficiaries.

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Chapter 1

Introduction

1.1 Overview of the problem

Landslides are among the most important natural hazards in mountain areas, causing thousands of fatalities and massive damage every year, worldwide. Like most other natural hazards, landslides are characterised by low probabilities of occurrence and high impacts. Given the complex nature of the phenomena, accurate predictions of occurrence are not possible.

Such natural disasters can cause widespread damage to people, property and the environment. The World Bank Report (Dilley et al., 2005) stated that globally the land area prone to landslides is approximately 3.7 million square kilometres. Almost 5% of the world's population (i.e. 300 million people) lives in landslide hazard areas. Unfortunately, we can expect this number to grow in coming years due to population growth and the intensification of extreme weather events. With regard to historical data, Petley (2012) reported the occurrence of 2,620 landslides around the globe from 2004 to 2010, with a death toll of 32,322 victims. Of the 8,733 fatalities in 2016 resulting from natural disasters, 361 were attributed to landslides (Guha-Sapir, Hoyois, Wallemacq, & Below, 2016). Asia has seen the majority of human losses, specifically in the Himalayan Mountains and China (Petley, 2012). Europe is the second worst continent in the world for fatalities and the worst for landslide-related economic losses. According to Klose (2015), Munich Re's dataset of natural disasters ("NatCatSERVICE") reported a global economic loss for landslide damage to buildings and infrastructure of approximately $US20 billion per year, averaged over the period 1980-2013. This amount is almost 17% of the annual global losses for natural disasters, which totalled $US121 billion (Klose, 2015).

Along with this worrisome data, researchers have noticed that landslide occurrence is increasing over time (e.g. Gobiet et al., 2014; Haque et al., 2016). Human factors, such as deforestation and inappropriate land use, contribute substantially to its intensification. Deforestation and infrastructure construction impact heavily on the soil's ability to retain water, reducing natural protection against landslides. This is especially true in some developing countries that have been greatly affected (e.g. China, India, Ethiopia and Uganda). However, the main triggers of landslides are extreme weather events due to climate change, especially high precipitation over a relatively short period of time. EEA (2017) reports a significant increase in the frequency of extreme weather events such as rainstorms in recent years, which is consistent with the increased number of landslide events.

In Europe, a significant upward trend in landslide events has also been reported by Haque et al. (2016). Over the twenty-year period from 1995-2014, they reported a total of 476 fatal landslides causing 1370 deaths. This means that, on average, 69 people are victims of landslides each year. Because of the difficulty in obtaining accurate data on causes of mortality, it is plausible that the number of landslide-related fatalities officially reported is underestimated. In comparison to death tolls from other natural hazards (such as earthquakes and floods), the victims of landslides are relatively low, probably because of the local scale of the calamities. However, a lower bound on the true economic loss in Europe is estimated at about €4.7 billion per year (Haque et al., 2016), when based only on the payout by private insurance companies. Given country-specific morphology, Italy, Turkey, Switzerland and Norway are among those most affected. It has been calculated that around 1.3-3.7 million Europeans live in highly susceptible areas (17,000-84,000 km^2), while between 8,000 and 20,000 kilometres of transport network are exposed to landslide hazards (Jaedicke et al., 2014).

Italy is the European country most susceptible to hydrogeological disasters, with approximately 75% of the total landslide areas (Van Den Eeckhaut, Hervás, & Montanarella, 2013). A national classification of landslides was conducted in the Project “IFFI” (“Inventario dei Fenomeni Franosi in Italia”). It accounts for 614,799 landslides over an area of 22,000 square kilometres, i.e. approximately the 7.5% of the land surface of Italy (ISPRA, 2016). Between 1990 and late 1999, 263 deaths were reported, with an average of 26 people killed each year (Guzzetti, 2000). Salvati, Bianchi, Rossi and Guzzetti (2010) reported a total of 3,139 landslide events in the forty-year period from 1968 to 2008. From an economic perspective, the total landslide losses per year amount to $US3.9 billion (Klose, 2015). Globally, Italy is the country with the largest economic impact from landslides, in relation to its gross domestic product (0.2% of the national GDP) (Trezzini, Giannella, & Guida, 2013; Klose, 2015).

Italians mostly rely on the provision of public protection programmes as the most efficient way to mitigate the impact of landslide events. The adoption of private protection measures is very limited due to the high costs and the magnitude of the threat. Unlike other European countries, insurance mechanisms against natural hazards are not compulsory in Italy. Covers for landslide hazard are not (yet) available for private citizens, and the few exceptions are very costly.

Therefore, local authorities and decision-makers have to invest a significant amount of public money in safety measures since mitigation devices are expensive. The cost of installation of a passive device that provides physical protection is roughly €1-2 million, while early warning devices could cost under €1 million (C. Gregoretti, personal communication, December 2017). The lifespan of the devices is difficult to predict since it depends on many factors, such as landslide damage and technological obsolescence. It may be assumed that 50 years could be a reasonable lifetime for a passive device, but this is reduced for active devices (approximately 10-20 years). Many existing protection measures from the 19th or early 20th centuries now need to be replaced (FOEN, 2016). Maintenance costs for existing protection measures are another item of public expenditure that varies considerably with device type and hazard location.

Given the high number of locations under landslide threat, the estimated public expenditure for protection would be significantly high. Therefore, it is often the case that public funds for landslide risk mitigation are allocated only after major landslide events. In 2014, the Italian government enacted a decree for the institution of a national project, called “ItaliaSicura”, to accelerate the realisation of mitigation programmes against natural hazards. Despite the legislative effort, the lack of public money implies that protection funds are partial and not immediately available.

In addition to the well-known direct impacts, landslides create indirect social, economic and environmental effects on human well-being that are difficult to quantify. Damaging landslides can considerably impact population development in mountain areas. For example, public concern over indirect economic losses is still rising in the mountain valleys of the Alps, especially with regard to road closures. Such secondary effects of landslides are frequently underestimated, given that road interruptions can significantly compromise the quality of life of people living in mountain regions. Given the living conditions and the harsh geography, a “landslide domino-effect” may result. This can contribute to the process of social and economic marginalisation of mountain regions. The phenomenon of progressive mountain depopulation, due to opportunities of wealth enhancement in urban areas, has been well known for decades (Toniolo, 1937) and afflicts more and more Alpine areas. If protection and road access are not guaranteed, the future of the mountain population can be further compromised, and more people will be forced to move, leading to further geographical and economic deterioration of these areas.

So, policies for landslide mitigation are of fundamental importance not just for increasing public safety but also for contributing to the maintenance of the natural and historical heritage of mountain areas.

1.2 Background

1.2.1 Theoretical background

For an optimal allocation of resources from the social welfare perspective, one must consider not only the deployment costs of mitigation programmes but also the public demand for protection against landslides. Government and local authorities in charge of protection of their citizens have to calibrate the funding for landslide mitigation programmes to the public demand for safety. In practical terms, this takes the form of an on-going debate between local authorities in charge of securing protection and the population of affected residents. This is particularly important in those locations where the current level of protection does not meet the desired safety levels.

For an adequate level of expenditure to be reached (i.e. the social costs) government authorities need to evaluate the benefits that can be obtained with alternative programmes for landslide mitigation. When economic efficiency is a goal of policymaking, a formal Cost-Benefit Analysis (CBA) is required to compare policy outcomes. While market prices can provide an evaluation of the cost of protection measures, the quantification of the social benefits (protection of human health, environmental quality, etc.) in monetary terms poses some challenges due to their nonmarket nature. However, they cannot be inferred from the market given that safety of settlements and roads have clear public good characteristics. Here, public safety is considered as a public non-tangible commodity (Spiegel, 2002). Following Samuelson (1954), public safety has the characteristics of being non-excludable and non-rivalrous (in consumption). Protection from natural hazards is provided to every citizen in the form of a common amount by the local authorities and the government. So, all citizens as a group are affected equally with a share in consumption, but each of them can value safety in different ways (Varian, 2006). Nevertheless, the social benefits provided by a protection programme can be calculated as the area under the marginal value function of a landslide management policy. This, in turn, is obtained from the vertical sum of all the marginal value functions of the beneficiaries. As a characteristic of public goods, the sum of the marginal rates of substitution must equal the marginal social cost at the optimal amount of good (Samuelson & Nordhaus, 2005).

Mitigation policies are designed to reduce the impacts of landslides and, therefore, to prevent direct and indirect damage to people, properties, and the environment. The tangible benefits of policy actions aim to reduce the number of fatalities and injuries, and the damage to houses, buildings, and public infrastructures. Furthermore, landslide protection programmes generate a wide range of intangible benefits and associated values that are not directly represented by market prices. Those benefits involve nonmarket goods and services such as the prevention of negative physical and mental consequences of landslide disasters, social disruptions, visual amenity, safety, and related environmental issues (ecosystem degradation) (Gibson et al., 2016). Hence, much attention has been given to assessing the monetary values of those material and immaterial benefits so as to account for all the policy benefits in a CBA.

As a consequence, in the last fifty years, nonmarket valuation techniques have been largely used in environmental economics (Pearce, 2002). Essentially, the nonmarket valuation techniques that can be used in the context of landslide mitigation policies are grouped into two categories: revealed preference (RP) and stated preference (SP) methods.

The first group (RP methods) considers the real behaviour of people and their expenditure to determine indirectly the value that people place on a good or service (Bateman et al., 2002). Within this group, the Hedonic Pricing method relies on choices made by people in real markets. It studies the link between the characteristics of the environmental goods or services provided and the price of marketed goods. However, this technique is not applicable to the study areas given that it has the disadvantage of not reflecting the total economic value of landslide protection programmes. In fact, the housing market in mountain areas has never been stable and well-functioning, given that supply and demand rarely matched. Another applicable RP method is the Defensive Behaviour method, which estimates the value of avoiding landslide consequences by studying how much people invest in actions aimed at preventing landslide-related outcomes. However, this technique is not ideal for the present study, due to the fact that the safety of the population is mainly a collective concern, and individual actions are therefore uncommon.

The second group (SP methods) elicits the value of the good or service by asking people directly about their willingness-to-pay (WTP) for a given improvement in the good or service or their willingness-to-accept (WTA) compensation for a reduction of the good or service (Bateman et al., 2002). These methods rely on hypothetical scenarios, among which the respondents are asked to choose.

The first method in this group is the Contingent Valuation Method (CVM), which enables the researcher to evaluate the amount of money that people are willing to pay for enjoying benefits derived by a policy aiming at providing a certain amount of public good or service. It pursues that by asking respondents to indicate their WTP for the specific policy comparing it to the *status quo*. The second method is the Discrete Choice Experiment (DCE), which provides respondents with a set of alternative policy scenarios to evaluate and choose from. Each alternative is described by several characteristics, known as attributes, and the quantitative or qualitative levels that these take (Bennett & Blamey, 2001). Respondents make trade-offs among the attributes, revealing the extent to which they are willing to pay for an improvement in the specific commodity. Hence, choices are used to infer the marginal value placed on each attribute. Usually, people are presented with a series of choice sets, each containing two or more alternatives from which respondents choose the preferred one (Louviere & Woodworth, 1983; Hanley, Wright, & Adamowicz, 1998a). Other elicitation formats exist, such as full or partial ranking of alternatives, or their rating according to some rating scale, or the simplest paired comparison.

Both the two groups of nonmarket valuation techniques (RP and SP methods) are relevant for decision-makers since they can provide estimates of the welfare impacts of specific changes in landslide policy. In addition to being able to capture both use and non-use values, SP methods offer more flexibility than RP methods primarily because of their capacity to estimate values for situations beyond those that are currently observable. The SP methods fit well with the purpose of covering a more extensive range of attributes when revealed data do not encompass all the proposed changes in attributes' levels. Nevertheless, they are vulnerable to a number of biases. The National Oceanic and Atmospheric Administration (NOAA) Blue Ribbon Panel provided a set of guidelines for avoiding the most common biases of CVM, pointing out the need of future investigations into embedding bias and "yea-saying" bias (Arrow et al., 1993). The embedding bias implies that people fail to properly value the scenario provided because they confuse the specific good/service with a more general concept; "yea-saying" bias implies that people overestimate their WTPs because they feel good about the good/service itself even though the declared amount does not reflect the real value to them. In their recent publication, Johnston et al. (2017) offer a more comprehensive set of guidelines for SP studies that includes the two decades of research since the NOAA panel.

The DCE method provides more information about people's trade-offs among alternatives' attributes in comparison with CVM. Also, it allows the valuing of single attribute and situation changes. Knowing the marginal value of changing certain attributes of an environmental good, instead of only the total value of environmental change, is more useful for policymakers especially for a benefits transfer perspective (Hanley et al., 1998b). Moreover, DCE reduces the strategic behaviours of respondents and some of the potential bias of CVM (e.g. "yea-saying") (Bateman et al., 2002; Birol, Karousaki, & Koundouri, 2006). On the other hand, DCE may raise some issues of complexity. It can require a considerable effort from the respondent in making trade-offs among many attributes and alternatives in repeated choice sets (Hanley, Mourato & Wright, 2001; DeShazo & Fermo, 2002), and from the researcher in designing appropriate scenarios using realistic attributes.

1.2.1.1 Literature on public preferences for natural hazard mitigation

Natural hazards have been studied extensively in Europe and in other countries around the world, mainly with a focus on the prevention of human and economic losses. However, public preferences in the context of natural hazards mitigation have been investigated in a limited number of empirical studies using both RP and

SP approaches. Gibson et al. (2016) offer a review of the existing literature. With regard to SP studies, CVM and DCE studies were applied in the context of inland water-related hazards, such as floods and landslides, with some differences. Those natural threats present distinctive features due to different spatial scale and dynamics of hazards. Floods are perhaps the most common natural hazard globally that can affect vast areas and a large portion of the population. Landslides, instead, are point events in space, hard to predict and with a potentially higher destructive power compared to floods. Also, the majority of landslides fatalities occurred inside, while flood fatalities tend to happen frequently outside. Therefore, the vulnerability of the population to floods and landslides varies among and within countries based on the specific study context.

Few studies employed nonmarket valuation techniques, especially SP techniques, to estimate the value of landslide risk reductions programmes. Among them, Ahlheim et al. (2009) carried out a CV study to investigate householders' WTP for supporting the implementation of protection measures against landslides in Northern Vietnam. Again in a DCE, Mori et al. (2006) conducted a study on the economic evaluation of landslide mitigation in the community for three pilot development projects in Armenia. Rheinberger (2011) investigated how much society is willing to pay for reducing the mortality risk on Swiss alpine roads due to avalanches and rock falls. Once again, in Norway, Flügel, Rizzi, Veisten, Elvik and Ortúzar (2015) investigated the WTP of car drivers for different landslide protection programmes using DCE. Vlaeminck et al. (2016) conducted an investigation in Uganda on resettlement strategy to mitigate landslide risk using the same approach. In a DCE, Thiene, Shaw and Scarpa (2016) investigated the public perceptions of risk for landslides and related events in Italy.

With regard to floods, Brouwer and Bateman (2005) analysed the economic value that society puts on flood control measures in wetland conservation in the Netherlands using the CVM. A similar study on flood control for wetland protection was conducted by Ragkos, Psychoudakis, Christofi and Theodoridis (2006) in Greece. Birol, Koundouri, & Kountouris (2008) carried out a DCE survey in Poland with the purpose of investigating flood risk reduction policy. Zhai, Sato, Fukuzono, Ikeda and Yoshida (2006) and Zhai, Fukuzono and Ikeda (2007) studied public preferences for flood control measures for risk reduction in Japan using CVM and DCE approaches. Again in a CV study, Brouwer, Akter, Brander and Haque (2009) pointed out the strong relationship between annual flood damage and household income with the estimates of WTP for flood risk reduction in Bangladesh. Reynaud and Nguyen (2013) implemented a DCE to explore households' WTP for flood risk reduction interventions in Vietnam. Brouwer and Schaafsma (2013) investigated householder behaviour under different flood risk scenarios. The economic value of risk reduction was derived by analysing WTP estimates for insurance policies in the Netherlands. Another DCE study was conducted in the Netherlands by Dekker, Hess, Brouwer and Hofkes (2016) on decision uncertainty for flood risk reduction. Recently, Johnston and Abdulrahman (2017) elicited preferences for policy actions to protect the coastal areas of Connecticut, USA, against flooding and erosion.

However, none of those previous studies looked at public preferences for engineering solutions for natural hazards' mitigation, despite the general lack of effective protection systems in many countries worldwide. This opens up the opportunity for contribution, especially given the limited literature on the topic of nonmarket valuation of landslide protection.

1.2.2 Methodological background

To provide an adequate background for readers, I present a review of the development of choice behaviour modelling.

The theoretical foundations of choice modelling were provided by Thurstone (1927) and Luce (1959) in their pioneering works. Later, choice modelling methods for the analysis of discrete choices were developed by McFadden (1974). In that research, he proposed a modification of the logistic regression model for multinomial discrete choices, originally called the Conditional Logit model. The model relates the choices made by people to the attributes of the alternatives in the choice set. This was originally contrasted with the Multinomial Logit (MNL) model, which related choice probabilities to the characteristics of the decision-maker. In later practice, the MNL model has been extended to include mixtures of both. Under the random utility maximisation (RUM) paradigm, the probability of choosing a specific alternative is the probability that the utility associated with that alternative is higher than those of any other available alternative. Hence, people are assumed to choose the alternative that maximises their utility (welfare) from the options presented.

The MNL model is commonly used as a base model for choice modelling analysis due to its convenience in estimation. Despite this advantage, the model is often an unrealistic representation of the empirical data given the presence of some restrictive assumptions. Firstly, the error terms are independently and identically distributed (IID) Type I Extreme values (EV1) (McFadden, 2001), implying uncorrelated unobservable factors over different alternatives. Secondly, the logit specification assumes that choice probabilities must satisfy the independence from irrelevant alternatives (IIA) property (Luce, 1959). It states that the probability of choosing one alternative over another does not depend on other alternatives. Lastly, the key behavioural restriction of the MNL model is the assumption of preference homogeneity across individuals.

A rich set of choice models was developed in an attempt to relax or partially relax the limitations of the MNL model. The Nested Logit model is one of the early extensions of the MNL model (Williams, 1977; McFadden, 1978; Ortúzar, 2001) where the set of alternatives is divided into subsets called nests. In this way, the IIA property holds within each nest but not between different nests (Koppelman & Sethi, 2000). Generalisations of the NL models exist, and fall into the Generalised Extreme Value models family. However, while GEV models relax some of the limitations of the MNL model, the assumption of homogeneity across respondents still holds (Train, 2009).

A flexible family of models is the mixed logit (MXL) models, initially developed in the 1980s but which underwent rapid growth later, in the middle of the 1990s, due to advances in simulation methods (Revelt & Train, 1998; Hensher & Greene, 2003). This group of models allows the unobservable factors to follow any distribution; hence they potentially approximate any choice model under certain conditions (McFadden & Train, 2000). In comparison to the standard choice specification, the MXL models do not exhibit an IIA property and can identify heterogeneity in preferences since parameter estimates are allowed to vary across the population. Their choice probabilities are the integrals of logit probabilities over a density of parameters (Train, 2009). The MXL family of models comprises two specifications that are identical from a mathematical viewpoint but differ in the interpretation of the outputs: the Random Parameter Logit (RPL) and the Error Component (EC) logit models. The RPL model allows preferences to be heterogeneous across individuals and with a continuous distribution (typically assumed to be normal or lognormal) over the population.

The EC model accommodates correlation across the utilities of different alternatives (i.e. flexible substitution patterns) through the use of shared error components. Scarpa, Ferrini and Willis (2005) suggested the use of this model in choice experiments when respondents are likely to consider the *status quo* option differently from the other alternatives.

Different approaches have been developed over the years to estimate the distribution of marginal willingness-to-pay (mWTP). The classical approach, also called *model in preference space*, requires first specifying the coefficients' distributions and then deriving the distribution of WTP. Then, the WTP estimate for a specific attribute is given by the ratio of the attribute coefficient to an estimate of the marginal utility of money (cost coefficient). Given that the cost coefficient enters the denominator, the choice of its distribution is important when deriving WTP values. To overcome the issue of a denominator close to zero (resulting in large WTP), a solution is to specify a fixed cost coefficient. The fixed cost restriction avoids complications associated with estimating the WTP as a ratio of two distributions and facilitates estimation. However, this assumption may not always be realistic and may lead to heterogeneity bias (i.e. fail to account for heterogeneity in the cost coefficient). Daly, Hess and Train (2012) pointed out alternative paths to assure WTP distributions with finite moments (e.g. models in WTP space, latent class models, and appropriate distributions for the random cost coefficient). Among those, an alternative approach is offered by *models in WTP space* (Train & Weeks, 2005). First, the analyst specifies the distribution of WTP and then derives the distribution of the coefficients. In comparison to preference space, the parameters in WTP space directly denote the mWTPs of the individuals (implicit prices) rather than the estimated coefficients of the utility function (marginal utilities). Among the advantages, this approach seems to produce more realistic WTP values and provides more freedom in the specification of the distribution of WTP (Scarpa, Thiene, & Train, 2008).

Another option for investigating preference heterogeneity is the Latent Class (LC) model, popular in marketing and psychology. The model identifies latent groups of respondents with homogeneous preferences within each group and heterogeneous preferences across groups rather than across individuals (Train, 2009). The outputs generated from the model are class-specific parameter estimates and membership probabilities for each class (Hensher & Greene, 2003). The model specification provides powerful insight into the segmentation of individuals with different preferences and is particularly useful for policy decisions (Scarpa & Thiene, 2005).

Choice models with mixtures of modelling approaches have also been proposed in the literature. Latent Class-Random Parameter Logit (LC-RPL) models combine discrete and continuous description of preferences, accommodating heterogeneity in tastes across respondents by using separate classes with different values for the taste coefficients (Bujosa, Riera, & Hicks, 2010).

Other discrete choice models have been proposed in recent decades (Ben-Akiva et al., 1999; Ben-Akiva et al., 2002). Among them, the Hybrid Choice models, also called Integrated Choice and Latent Variable (ICLV) models, represent an increasingly popular extension of choice models with latent variables in the utility function. Behavioural researchers have stressed the importance of accounting for the cognitive process underlying choice formation. Therefore, perceptions, attitudes and beliefs are more frequently included in the model specification as latent psychological factors to explain underlying determinants of choices. However, given that latent variables cannot be directly observed, they are identified through attitudinal indicators and treated as explanatory variables in the utility function. The model structure integrates different specifications into a single one that is simultaneously estimated.

As indicated by the literature, the most commonly used choice models are mainly extensions of logit models. Another group of models is the probit models (Thurstone, 1927), which are less in use in the choice modelling field. The probit specification assumes that unobservable factors follow a normal distribution, allowing for correlations over alternatives and choices (Daganzo, 2014). Despite the flexibility of the probit, the normal distribution may be not appropriate in specific circumstances, especially with regard to the monetary coefficient. Given that the integral of the choice probability does not have a closed form, optimisation problems are another concern in the adoption of this specification, especially in the frequentist approach. In applications, probit models can incur identification problems that are difficult to detect (Dow & Endersby, 2004).

An alternative way to estimate discrete choice modelling is by the use of the Bayesian approach (Allenby & Lenk, 1994; Allenby & Rossi, 2003). Given the data and a statistical model, Bayesian inference assigns "prior distributions" to the unknown parameters of the model, which are combined with the likelihood function derived from the statistical model according to Bayes' theorem (Train, 2009). Bayesian estimation procedures can be faster than their classical counterpart and can overcome the difficulties associated with the maximisation of the simulated likelihood function since they do not require its maximisation (Train, 2009). The fact that the Bayesian approach can provide individual-specific WTP estimates is particularly appealing as an alternative to the standard approach that derives the mean conditional estimates for each respondent. Despite the clear advantages, applications are still uncommon since practitioners are not yet familiar with these techniques.

In choice data analysis, various forms of heterogeneity have been largely considered with regard to preferences, choice strategies and model structures. Heterogeneity in preferences among respondents (e.g. McFadden & Train, 2000) can be captured by RPL models, LC models or mixtures of those. In the former case, the taste variation is among individuals while in the latter case preferences are allowed to vary between different latent groups. Another type of heterogeneity can be found in the error variance when the error variance is not constant across individuals and their choices. Then, there is a risk of confounding heterogeneity in preferences with heterogeneity in error variance, leading to incorrect utility estimates (Louviere & Eagle, 2006; Hess & Rose, 2012). To remove the possible confusion between these two types of heterogeneity, models such as Heteroscedastic Conditional Logit models (Hensher, Louviere, & Swait, 1999), Generalised-MNL models (Fiebig, Keane, Louviere, & Wasi, 2010; Greene & Hensher, 2010), Scale-Adjusted Latent Class models (Magidson & Vermunt, 2007) and LC-RPL models with specific scale-class values (Thiene, Scarpa, Longo, & Hutchinson, 2017) have received attention. However, problems with the interpretation of their results are still present, because scale variations (Swait & Louviere, 1993) may exist among respondents, alternatives, choice sets, survey instruments (e.g. RP and SP dataset), and survey processes (e.g. the effects of fatigue and learning effects). Therefore, a scale parameter is introduced into the model for scaling utility to reflect the variance of the unobserved utility. The scale factor is inversely related to the error variance (Train, 2009).

A significant part of choice modelling research has recently been dedicated to the study of respondents' decision processes other than the classical RUM rule. The actual behavioural process or decision rule used in making a choice may, in fact, vary between respondents. Some models assume that the decision rule is intrinsically probabilistic, while others consider that the individual's decision rule is deterministic (Ben-Akiva & Bierlaire, 1999). In complex or uncertain choice situations, individuals frequently use heuristic rules to reduce the complexity of the decision task. From a psychological point of view, different decision processes can exist or coexist. Respondents may rank the attributes and choose the favourite alternative accordingly (Lexicographic decision process; Tversky, 1969); they may focus on a few selected attributes to accept or eliminate alternatives from the choice set until they are left with the best (Elimination By Aspects decision process; Tversky, 1972); or they may even use a mixture of decision rules (Hess, Stathopoulos, & Daly, 2012). Choice models with other paradigms such as Random Regret Minimization have been applied in recent studies (Chorus, 2010; Boeri, Longo, Doherty, & Hynes, 2012; Thiene, Boeri, & Chorus, 2012). This operates on the assumption that people choose the alternative that provides them with minimum regret instead of maximum utility. More recently, mixtures of behavioural choice models have been put forward to allow for decision rule heterogeneity (Chorus, 2014; Boeri, Scarpa, & Chorus, 2014).

Related topics that have attracted the attention of researchers are *(i)* attribute non-attendance (i.e. ignoring some attributes) (Hensher, Rose, & Greene, 2005; Scarpa, Thiene, & Hensher, 2010), *(ii)* the increasing selection of the *status quo* option (i.e. *status quo* bias) (Scarpa et al. , 2005; Marsh, Mkwara, & Scarpa, 2011), *(iii)* ordering effects due to fatigue or learning (Carlsson, Mørkbak, & Olsen, 2012; Czajkowski, Giergiczny, & Greene, 2014), and *iv)* choice set formation and antecedent volition (Swait & Marley, 2013; Swait & Adamowicz, 2014).

1.3 Study context

Given the significance of the landslide problem in the Alps, an Italian mountain valley, called the Boite Valley, was selected as a case study. This mountain valley is located in the Dolomites (Eastern Italian Alps), an area frequently affected by destructive landslide events (Sterlacchini, Frigerio, Giacomelli, & Brambilla, 2007; Salvati et al., 2010). Just recently, in August 2017, a massive landslide killed people and essentially destroyed a hamlet. Similarly, in 2015, three tourists died trapped in their cars, while road interruptions isolated a settlement for days. Two other people died in 2009 due to an error in protection system planning.

Many other events have occurred over time, with significant damage and fatalities at times.

The geological composition of the mountains around the valley makes them particularly susceptible to erosion processes and consequently subject to landslides. In this alpine environment, the most common type of landslide is better known as a debris flow. These are particularly dangerous because of their high speed (5-20m/s) and destructive impact. These natural hazards are generated when three trigger factors coexist: *(i)* availability of materials such as rocks and trees; *(ii)* strong declivity; and *(iii)* heavy rainstorms that generate a significant quantity of water (Gregoretti, 2000). The solid-liquid mixtures of water, mud, sediment and woody debris can reach settlements and roads very rapidly, without providing much escape time for people living in the area or in transit on the roads. The speed and the volume of materials transported by these landslides at the valley floor are remarkable. It was estimated that the landslide of 2016 in the municipality of San Vito deposited about 100,000 cubic metres of rocks and debris.

A large part of the valley is vulnerable to landslide hazards. More than 350 potential or active landslides have been identified as potential hazards to settlements and roads (Bossi, Deganutti, Pasuto, & Tecca, 2011). This number is extremely high considering the 35 kilometre length of the valley, with a total population of 11,707 inhabitants occupying the foothills of the mountains (Istat, 2017). The situation gets even worse considering the high level of danger of the detected landslides and the short return period of 1-3 years for some of them (Gregoretti & Dalla Fontana, 2008).

As mentioned earlier, concerns for the future of this mountain population are rising. Residents rely heavily on the road network to move and work. Therefore, road interruptions represent an issue for the mobility of locals as well as visitors. The strong repercussions of landslide occurrences are of interest in the tourism economy. The frequent landslide events of recent years could encourage visitors to choose other locations for recreation, resulting in a significant monetary loss for the entire mountain economy. Tourism has been the primary economic sector in this area since the Winter Olympics in 1956 and inclusion in the UNESCO World Heritage List in 2009. A total of 336,610 arrivals were registered in the year 2016 (Regione Veneto - U.O. Sistema Statistico Regionale, 2017).

Given the critical situation, the implementation of mitigation policies for landslides is currently being discussed by local decision-makers in the Boite Valley. However, the high costs of mitigation measures and inadequate public budgets have caused serious delays in securing desirable levels of public safety. Additionally, a suitable agreement on actions to be taken has not been reached (yet) and the negotiation process continues between decision-makers and the local population.

The cost of the installation and maintenance of protection devices is very high; in the order of millions of Euros per year. A rough estimate of the total cost of landslide protection for the entire Boite Valley is at least €60 million, of which €20 million is for one specific location (Cancia). To give an idea of the costs involved, a diverging channel to deviate the debris could cost between €100,000 and €600,000, while a basin for collecting landslide materials costs even more (€1-2 million). With regard to the early warning systems, such as video cameras and sensors, the installation cost could be around €900,000 in a high-risk area. The maintenance costs are also significant, amounting to €80,000/year. In contrast, the cost of smaller systems drops to €100,000, and the related maintenance costs also fall (€7,000/year).

Even more expensive are the restoration costs after a landslide event, which amount to millions of Euros per event. For the recent landslide of 2017, a preliminary valuation of the damage to the hamlet of Alverà was estimated at about €17.5 million, subdivided into 12 million for public property, 2.5 million for private property and 3 million for productive land. In another event that caused repeated road interruptions near Acquabona during 2016, the public funds provided were €6.5 million during the emergency phase.

The Belluno Province is in charge of the hydrogeological protection of the Boite Valley, in accordance with the law (L.R. 8 August 2014, n. 25) for administrative decentralisation with regard to soil defence. The Province receives around €15 million every year from concessions for the management of integrated water services that are supposed to be used for reducing hydrogeological instability. Following landslide disasters, all the governing bodies at different hierarchical levels (Province, Region and central Government) provide economic support to the affected regions.

1.3.1 The survey instrument

A DCE method was adopted here as an appropriate tool for nonmarket valuation in the context of landslide hazard mitigation. This nonmarket valuation method was chosen over other methods for its previously mentioned advantages.

For the purpose of this research, I used the DCE with the ranking elicitation format, also called Contingent Ranking Experiment. This format provides a full ranking of alternatives that is equivalent to a sequence of discrete choices but with more information on the underlying preferences. The specific approach adopted was the Best-Worst (B-W) ranking technique, which means that respondents sequentially choose the best and then the worst scenario among a set of alternatives and then the second best and the second worst options and so on (e.g. Louviere et al., 2008; Scarpa, Notaro, Louviere & Raffaelli, 2011).

Although ranking acquires more preference information on a limited set of observations, the computational time for the complex models can become very demanding. Therefore, this research also used the recoded ranking data in the DCE format that considers only the first rank as the option chosen. Despite some criticisms raised by Boyle, Holmes, Teisl, and Roe (2001) regarding the different cognitive process, Caparros, Oviedo and Campos (2008) found that welfare estimates derived from first choice elicitation approach are not significantly different from those obtained from first rankings, after accounting for differences in scale and experimental design. Specifically, the first paper used the full dataset accommodating pre- and post-treatment with only the first rank (3,000 observations). Instead, the second paper used the pre-treatment choices with only the first rank (1,500 observations). Like the second, the third paper used the pre-treatment choices but with the full ranking dataset (9,000 observations).

1.3.1.1 What attributes matter in protection?

The attribute selection was conducted with the help of scientists who provided a list of devices that can potentially reduce the occurrence and impacts of landslides. Some devices were excluded due to people’s unfamiliarity with those protection measures. The final selection of attributes was made based on two categories of protection systems: traditional or more innovative technological devices.

The traditional devices are passive systems that guarantee mechanical protection, reducing the impact of a landslide. Those are the diverging channel (a channel built to carry off the water in a different direction from sediments and rocks) and the retaining basin (a dam that collects the debris).

Among the more innovative technological devices, night-vision video cameras (which detect soil movement) and acoustic sensors (which capture soil vibrations) were selected. These are active measures of protection that warn residents or travellers subject to the risk of imminent landslide hazard. In case of a landslide event, these active devices can activate alarms and traffic lights on the roads to stop the traffic flow.

A monetary attribute was included in the form of a provisional road toll to be paid for supporting the construction/installation of the protection systems. The length of the toll period was eight months (from April to November of a specific year). This length was determined based on the seasonality of landslide events. Other payment vehicles were initially considered, such as a tax. However, the toll was judged the best payment mechanism since it affects residents and visitors based on their travels in the valley. In this way, it was possible to investigate the preferences of residents and visitors using the same questionnaire. The inclusion of visitors in this research was important, given that they would also benefit from the implementation of protection programmes. It is true that some beneficiaries, who do not travel by car, are excluded from making payment. However, these are a minority because the car is the transport mode used in the majority of trips in mountain areas.

1.3.1.2 Pretesting

I conducted a qualitative and a quantitative pretesting. One-on-one interviews were carried out among locals with different landslide knowledge levels to ensure appropriate comprehension of the survey questions and to select a restricted number of attributes easily understood by lay people. Then, I tested an initial version of the questionnaire, including the DCE, with a pilot sample of 30 respondents, residents and visitors to the Boite Valley. The pilot survey provided insight into whether respondents understood the *status quo* and the attributes presented in the scenarios, including the payment vehicle. It allowed me to refine the language of the questionnaire and address any issues before starting the data collection.

1.4 Motivations

The motivations for this research project were two-fold. From a practical point of view, the SP literature is missing studies aimed at investigating public opinion on decisions related to protection from landslide hazard. Additionally, local authorities and decision-makers need information regarding the social acceptability of proposed mitigation measures and beneficiaries' willingness-to-pay to support the realisation of the policy actions. In the Boite Valley, the public sector (Belluno Province, Veneto Region and Government) spends an enormous amount of money, at least €12 million per year, to ensure the safety of settlements and road networks from landslides. However, such spending programmes are mainly focused on assessing the efficiency of protection measures with regard to the cost component. In other words, attention is primarily focused on aspects of the provision of services (i.e. people safety and the maintenance of environmental services), while ignoring the characteristics of demand (i.e. the preferences of the beneficiaries of such services). Given that protection programmes are mostly funded with public money, the acquisition of information regarding beneficiaries' profiles is of fundamental importance for an efficient allocation of public resources.

From a methodological viewpoint, the study contributes by responding to open research questions in the SP literature. Three main research gaps were detected with regard to the specific method in use, focused on the central idea of addressing preference heterogeneity and its determinants. Accounting for preference heterogeneity in public policy for landslide mitigation is important for outlining the characteristics of the social demand for safety against landslides.

This is relevant especially in the presence of different categories of beneficiaries with different characteristics. In fact, the social acceptability of the implementation of new policy actions may vary based on *(i)* the type of respondents (residents or visitors) and their geographical context; *(ii)* people's risk perception; *(iii)* the value attributed to the environment and the loss of benefits and services provided by environmental goods; *(iv)* individual financial ability to support the realization of the mitigation policies; and *(v)* personal knowledge of the issue and the level of information provided on the topic.

A concern is that econometric models that ignore sources/determinants of preference heterogeneity may introduce bias in parameters and WTP estimates and, as a consequence, wrongly evaluate different effects of policy actions. This can generate negative repercussions, affecting public consensus around decisions taken by local authorities. This is particularly true in mountain areas, where wrong decisions can compromise the future development and quality of life of the population.

A lack of internal and external validity is a major concern for SP studies, especially those aiming at informing policy. Despite the widespread use of this method, debate is still ongoing about some validity aspects (Bateman et al., 2002; Bishop, 2003; McFadden & Train, 2017). Along with hypothetical bias, which may arise when stated preferences differ from the actual behaviour of the respondents (Hausman, 2012), other criticisms have been offered. In a recent work, McFadden and Train (2017) pointed out the unreliability of CVM in the context of environmental policy. They stressed CVM's inadequate response to scope; i.e. whether the estimates account for the scope of the environmental good or just for the concept of improvement. With regard to DCE, Lancsar and Swait (2014) claimed that external validity is an under-researched topic when dealing with policy recommendations. In assessing internal validity, the statistical significance of results and their economic significance should be taken more seriously into account (Rakotonarivo, Schaafsma, & Hockley, 2016).

A better understanding of preference heterogeneity and its determinants is essential for providing policymakers with credible results. An important assumption behind this research is that by accounting for preference heterogeneity and related preference dynamics, the validity and consistency of the WTP estimates for landslide mitigation programmes may be improved. A series of research questions result from the need to conduct explorative research into preference heterogeneity and its sources.

1.5 Research questions

I present my work in the form of three papers in choice modelling, each of which is presented in line with an identified research gap in the SP literature.

The papers focus respectively on:

1) an investigation of preference heterogeneity for mitigation devices and the effect of visual science-based information on preference stability;
2) a study of the stability of parameter estimates in a simulation-based estimation procedure in the presence of an increasing number of latent variables revealing underlying risk perceptions (as possible drivers of preference heterogeneity);
3) an exploration of individual and spatial sources of preference heterogeneity through the use of geographical determinants, spatial error components and site-specific chioice sets.

In more detail, the specific sets of research questions (RQ) addressed by each paper are as follows:

RQ1. Research questions addressed in Paper 1:

a) Do people perceive the current level of protection from landslide hazard as inadequate?

b) Does the provision of scientifically based information for an attribute have an impact on people's preferences?

c) Are the distributions of the willingness-to-pay estimates and the effect of information provision spatially heterogeneous?

Given recent landslide events, I question whether the current level of protection is perceived as sufficient by the people living in or visiting the Boite Valley. Preference heterogeneity for different mitigation measures is also investigated as well as spatial heterogeneity. The next research question looks at the effect of visual information, in the form of simulations of potential landslide events, on preference stability.

RQ2. Research questions addressed in Paper 2:

d) How stable are the simulated parameter estimates from Integrated Choice and Latent Variable models when the number of latent variables is increased?

e) Is heterogeneity in preference across respondents driven by underlying psychological factors such as perceptions of landslide risk?

f) If so, may strong risk perceptions related to landslides have a positive impact on the aversion to status quo conditions (i.e. the riskiest option)?

The first research question is motivated by concerns over the stability of the parameter estimates to the number of draws in the simulation-based estimation procedure for choice models with latent variables. A concurrent hypothesis is that latent risk perceptions can be drivers of preference heterogeneity in the context of natural disasters, such as landslides. Additionally, I investigate whether strong risk perceptions may result in an aversion to the current level and/or type of protection.

RQ3. Research questions addressed in Paper 3:

g) *Do spatial determinants contribute to explaining the patterns of preference heterogeneity for landslide protection?*
h) *Do spatial choice models at the municipality level offer a useful tool for understanding the spatial dimensions of preference heterogeneity?*

Given the local nature of landslide protection benefits, I explore individual and spatial sources of taste variations for landslide policy actions. A related research question assesses the importance of spatial determinants and dimensions of preference heterogeneity. Specifically, I question whether spatial choice models, at the municipality level, may provide an alternative approach for policy decisions taken at the municipality scale.

1.6 Outline of the thesis

To address the research questions in a structured way, the thesis consists of five chapters. The central body of this work consists of three peer-reviewed papers that, at the time of thesis submission, have either been submitted to a journal (Chapters 3 and 4) or published in a scientific journal (Chapter 2).

- Paper 1 (Chapter 2) - *“Valuing landslide risk reduction programs in the Italian Alps: The effect of visual information on preference stability”*

  This paper traces the impact of the provision of visual science-based information on WTP estimates for protection devices against landslides (directionality effect). The information is provided in the form of landslide event simulations with and without a specific protection measure. The specification search suggests a Mixed Logit model with random utility in the WTP space inclusive of interaction effects as the best model. This provides relevant indications on the directionality effect of information that only affects the mWTP of the specific protection measure and not those of the other attributes. Geographical representations of averaged mWTP estimates for each sampled municipality are also obtained to denote the spatial heterogeneity of the geographical distribution of WTP estimates. This paper is policy-orientated since it offers policy recommendations for local decision-makers on the implementation of best mitigation strategies, along with insight into spatial heterogeneity. The paper has been published, after peer review, in *Land Use Policy* (Mattea, Franceschinis, Scarpa, & Thiene, 2016).

- Paper 2 (Chapter 3) – "*Exploring the stability of parameter estimates to the number of draws in choice models with latent variables*"

  Given the relevance of psychological factors that may influence the choice process, the second paper considers underlying risk perceptions as latent drivers of preference heterogeneity. An integrated choice and latent variable framework is used to control for the stability of the simulated parameter estimates when more complexity, in the form of latent variables, is added into the model specification. One to three latent variables related to landslide risk perceptions are included. Estimates are evaluated across six sets of progressively higher numbers of draws in the simulation of the sample log-likelihood. The estimate precision is assessed progressively at each step. Results show that increasing the complexity of the model specification requires a higher number of draws to secure that the model is empirically identified. This paper makes a methodological contribution to the debate on the questionable value of this model specification for deriving policy implications. The paper has been submitted to a peer-reviewed journal.

- Paper 3 (Chapter 4) – "*Exploring spatial sources of preference heterogeneity for landslide protection*"

  In this paper, I investigate multiple sources of preference heterogeneity including spatial determinants. It was possible to combine observables in terms of conventional individual socio-economic characteristics as well as geographical information relating to road segments and municipality of residence. The findings show the importance of distinct spatial effects, such as geographical characteristics, spatial error components for road tracts and site-specific choice-sets. It reveals richness in the structure of preferences, with relevant insights into the priority of intervention in different landslide sites. The importance of accounting for spatial heterogeneity is stated, given that taste variations are present at both individual and municipality levels. This paper is policy and methodologically-orientated, given that it provides relevant insights into the preference structure and the spatial dimensions of heterogeneity together with a contribution to spatial choice models. The paper has been submitted to a peer-reviewed journal. It has been reviewed and revised and is awaiting a further decision from the editorial office of *Land Economics*.

Overall, this thesis is expected to make methodological and policy contributions to the literature on nonmarket valuation of natural hazard mitigation in the field of environmental economics.

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Chapter 2

Valuing landslide risk reduction programs in the Italian Alps: The effect of visual information on preference stability

Abstract

Climate change has increased the frequency and intensity of weather-related natural hazards everywhere. In particular, mountain areas with dense human settlements, such as the Italian Alps, stand to suffer the costliest consequences from landslides. Options for risk management policies are currently being debated among residents and decision-makers. Preference analysis of residents for risk reduction programs is hence needed to inform the policy debate. We use discrete choice experiments to investigate the social demand for landslide protection projects. Given the importance of information in public good valuation via surveys, we explore the effect of specific visual information on the stability of preference estimates. In our survey, we elicit preferences before and after providing respondents with scientific-based information, based on visual simulations of possible events. This enables us to measure information effects. Choice data are used to estimate a Mixed Logit (MXL) model in WTP space to obtain robust estimates of marginal willingness-to-pay (mWTP) values and control for the effect of information. Mapping posterior individual specific mWTP estimates provide additional policy implications. Overall, we found the mWTP estimates to be dependent on information.

Keywords:

Landslides; information effect; MXL model in WTP space; geographical representation; discrete choice experiments.

2.1 Introduction

Climate change has increased the frequency of geo-hydrogeological calamities, over both time and space. Worldwide a growing number of people are affected by such natural phenomena. This study specifically addresses landslides in the Italian Alps, an area where landslides are an increasingly common major natural hazard. They are complex events for which current data records provide no precise estimations of risk; scientists are hence unable to provide accurate predictions of the probability of occurrence. In the engineering literature, there have been several proposals of technical solutions aimed to reduce the impacts of landslide events (Berti, Genevois, Simoni & Tecca, 1999; Gregoretti & Dalla Fontana, 2008; D'Agostino, Cesca & Marchi, 2010). Most solutions consist of specific safety devices to mitigate the risk in pre-existing landslides' trajectories. However, few studies address individuals' preferences for the proposed solutions.

Landslides have been studied extensively in Europe, especially in Italy, Norway, Switzerland and the UK, mainly with a focus on their economic impact. From the analysis of previous literature on this topic, it emerges that few studies employed nonmarket valuation techniques, and especially stated preference techniques, to estimate the value of landslide risk reductions programs (Ahlheim et al., 2008; Mori et al., 2006; Flügel, Rizzi, Veisten, Elvik & Ortúzar, 2015; Thiene, Shaw & Scarpa, 2016; Vlaeminck et al., 2016). However, there is still limited work carried out in the investigation of the social acceptability of risk mitigation programs, and on their specific demand.

This study reports the results of a Discrete Choice Experiment (hereafter DCE) for the evaluation of landslide protection devices. This approach is well suited for such analysis as it allows researchers to elicit individuals' preferences for alternative policy measures. The present investigation contributes to the small literature on people's preferences for landslide mitigation programs. Specifically, we estimate the implied willingness-to-pay (WTP) of the local population of visitors and residents of the Boite Valley (Belluno, Italy) inferring it from a sample. The WTP estimates concern different engineering solutions designed to increase safety from potential landslides. To develop preferences over the alternative solutions, the population during the debate should be exposed to scientific-based information such as hydro-geological simulations of possible events. So, we also test whether the provision of visual information affects the stability of our estimates of respondents' preferences. In particular, we focus on detecting whether information about a safety device increases individuals' WTP for that specific device. This is particularly relevant from a policy perspective, as it may help policymakers to evaluate whether it is appropriate to allocate resources in promoting information campaigns. This analysis is grounded on previous literature that showed that WTP estimates are impacted by the type of information provided to respondents (Munro & Hanley, 2002; Chanel, Cleary & Luchini, 2006; MacMillan, Hanley & Lienhoop, 2006; Oppewal, Morrison, Wang & Waller, 2010). Furthermore, uninformed respondents may underestimate benefits of protection projects for the community. Finally, to explore the validity of our results, we map the mean values of marginal WTP estimates at the individual level within each municipality. To our knowledge, the analysis of how the sample estimates of marginal WTP are distributed over space has not been previously employed to evaluate alternative risk management policies.

The remainder of this paper is organized into four sections. Section 2.2 presents the case study by giving the reader an overview of the landslide hazard, the policy context of the study and presenting the hypotheses to be tested. Section 2.3 describes the survey design and the modelling approach used for the data analysis and the hypotheses' tests. In section 2.4 we discuss the results, including the geographical representations of the respondent-specific marginal WTP estimates. Finally, our conclusions are reported in section 2.5 along with the policy implications for landslide risk mitigation in the Boite Valley.

2.2 The case study

2.2.1 The case study and policy debate

In the steep mountain areas of the Dolomites (North-East of Italy), there is substantial evidence of recent and past landslide occurrences. The high vulnerability of this area to landslides, especially debris flows, is likely to be exacerbated by future climate change. The local population are exposed to the risk of serious socio-economic consequences from these natural events. Historical records show that they often resulted in fatalities, homelessness, damaged buildings and interrupted road traffic (Sterlacchini, Frigerio, Giacomelli &

Brambilla, 2007; Salvati, Bianchi, Rossi & Guzzetti, 2010). These occurrences harshly affect the main local industry, which is based on tourism.

Due to high hydrogeological risk levels, several landslides occurred in the Boite Valley – the specific location of our study – and caused deaths and damage to houses and other property. In 1814, a massive landslide destroyed two villages, killing 257 people. The biggest events happened in 1925, causing 288 victims and 53 people went missing. In the last decade, this area suffered a series of devastating landslides. Recently, in summer 2015, intense rainfall over a short period of time triggered eight events, causing significant damage to public infrastructure and three victims among visitors. Geologists believe that there are approximately 350 potential and active landslides that can be highly dangerous for the population living in the valley (Guidoboni & Valensise, 2014).

Local authorities are still debating with the community what possible landslide risk mitigating options to undertake. A large-scale evaluation of both public support and acceptability for alternative risk-reducing programs is underway. This is because: *(i)* realisation costs are high and many roads and municipalities are at risk; *(ii)* protection devices could have major environmental impacts; and *(iii)* major changes of the municipalities' planning are expected.

2.2.2 Hypotheses

This paper specifically investigates the following three hypotheses:

H1: People perceive the current level of protection from landslide hazard as inadequate.

Because of recent landslide events, it is clear that risk mitigation is still a major safety issue for local authorities in the Boite Valley. However, interventions to mitigate the risk are expensive to implement. A unanimous decision about the measures to be adopted in the valley has not yet been reached. Therefore, there is a need for better understanding public acceptability of landslide risk management for an efficient use of public funds. For this reason, it seems useful to acquire additional information on preferences of residents and visitors, given that they would be the main beneficiaries, but also they would be the main financial contributors. The inclusion of social preferences in the public debate allows policymakers to take into account the economic dimension (expressed in terms of WTP), in addition to the other dimensions that feed into such debate. Specifically, preferences regard the use of a range of mitigation devices to increase protection. No previous studies have investigated respondents' preferences among a variety of safety devices against natural hazards.

H2: The provision of specific scientific-based information will shift the WTP for the specific attribute for which the information was provided as well as for the other attributes.

Many stated preference researchers had investigated the impact of various types of graphical and non-graphical information on stated preference values, starting from the seminal work of Bergstrom, Stoll and Randall (1989). Findings from previous studies in the context of environmental goods showed controversial results. The majority of the studies found that provision of information about a good leads to changes in WTP estimates. Among them, Munro and Hanley (2002) showed that an individual's WTP increased if positive information about the good was provided. The information effect was also investigated by O'Brien and Teisl (2004) regarding environmental certification and labelling. Their results suggest that additional information considerably altered estimates of mWTP for specific attributes. Instead, the results of a study conducted by Oppewal et al. (2010) suggest that providing explanatory information about an unfamiliar attribute not only results in parameter shifts for the particular attribute but also affects the estimates of the remaining attributes and the scale unit of the utility function. The study conducted by Czajkowski and Hanley (2012) suggested that respondents were more deterministic in their choices when provided with additional information. In a contingent valuation study, Chanel et al. (2006) showed that scientific information could have a positive impact on the respondents' WTP, but not so for public opinion. Other studies focused on the effect of information provision for goods that differ in term of familiarity. Among them, MacMillan et al. (2006) found that half of the respondents changed their WTP over successive rounds of information provision, especially for the less familiar good.

In our case, people might value more those protection measures offering the highest level of safety, such as passive devices, than those offering a lower safety level, such as active devices.

H3: There is spatial heterogeneity in the distribution of the WTP estimates and in the effect of information provision.

Residents in the Boite Valley can, in fact, benefit more for the implementation of landslide mitigation programs than visitors. Therefore, there could be evidence of a distance decay effect. Respondents' familiarity with the problem and exposure to it can lead to different impacts of additional information across the region.

It is an empirically well-founded expectation that welfare changes display spatial heterogeneity, and that this heterogeneity can be policy relevant. An expanding literature of stated preference studies addresses the relevance of spatial factors for the estimation of WTP. Particularly relevant for this study is the contingent valuation study conducted by Johnston, Swallow and Bauer (2002), which found a significant impact of spatial attributes on WTP estimates in surveys providing cartographic details. Spatial distributions of WTP estimates from DCE surveys have been investigated in several studies, starting from the seminal works by Campbell, Scarpa and Hutchinson (2008) and Campbell, Hutchinson and Scarpa (2009) in which WTP estimates for rural landscape features were mapped across the Irish landscape. They revealed that WTP is positively spatially autocorrelated in relation to non-site specific landscape improvements. Similarly, the spatial heterogeneity in WTP for environmental attributes was also investigated by Abildtrup, Garcia, Olsen and Stenger (2013), Broch, Strange, Jacobsen and Wilson (2013) and Termansen, Zandersen and McClean (2008). Yao et al. (2014) used data on forest distance from respondent's homes found evidence of a significant distance-decay effect, which means that respondents tend to have a higher WTP if living closer to the environmental good evaluated. Furthermore, Czajkowski, Budzinski, Campbell, Giergiczny and Hanley (2017) found that respondents' WTP was higher the closer was their place of residence to the nearest forest, and the scarcer forests were in the surrounding area. They also found that respondents from different regions had different WTP for each attribute. Among others, limitations of the traditional distance-decay method were pointed out by Meyerhoff (2013) that showed the existence of local clusters with similar WTP for wind power generation. Following this line of thought, Johnston and Ramachandra (2014) used local indicator of spatial association to explore hot spots in stated preference welfare estimates.

2.3 Survey design and data

2.3.1 Discrete choice experiment attributes

We developed a five attributes DCE, described in Table 2.1. Four attributes represent devices to protect against landslides: two passive devices (diverging channel and retaining basin) and two active ones (video cameras and acoustic sensors). We identified the four technical attributes following the advice of geologists and engineers with the purpose of making the scenarios as realistic as possible. The fifth attribute is a hypothetical road toll to transit in the valley for a one-time period of approximately eight months to financially support the implementation of the mitigation programs. All attribute levels are dummy-coded (presence of the safety device = 1, else = 0) except the monetary attribute that takes four numeric values.

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

Table 2.1 – Attributes and levels of the DCE.

2.3.2 Experimental design and questionnaire development

The generic DCE used an optimised orthogonal experimental design (Ferrini & Scarpa, 2007; Scarpa & Rose, 2008; Rose & Bliemer, 2009; Bliemer & Rose, 2010; Bliemer & Rose, 2011). The unlabelled choice sets design was carried out using the software Ngene (ChoiceMetrics, 2012). A full factorial experimental design for four 2-level attributes and one 4-level attribute provided $2^4 \times 4 = 64$ combinations of alternatives. A full factorial design permits to identify both the main effect of each attribute and the effect of the interactions between them. However, as the focus of the study was on the main effect of each attribute, a fraction of the full factorial design was adopted. The fractional design consisted of 60 choice sets that were blocked into 10 groups of six each. Each respondent could reply to six choice sets from one of the 10 blocks to which s/he was randomly assigned. The issue of ordering effect was addressed by randomising the choice sets order for half of the sample (Day et al., 2012). Each choice set comprised seven alternatives among which to choose the preferred option (Figure 2.1). Among them, the seventh alternative represented the *status quo* (S.Q.) option, i.e. the hypothesis of maintaining the current situation without any additional costs and no safety improvement.

Site 1 - CANCIA

Alternatives	A	B	C	D	E	F	Status quo
Channel	-	-	-	channel	channel	channel	-
Basin	-	basin	basin	Basin	-	-	insuff. basin
Video cameras	video	-	video	-	-	video	-
Acoustic sensors	-	-	sensors	-	sensors	sensors	-
Road toll	€3	€4	€1	€1	€3	€3	€0
Your choice							

Figure 2.1 – An example of a choice set for a specific site.

Six locations were selected on the valley, each of them with a high landslide risk. Each choice set presented to respondents explicitly referred to one of these six sites. Therefore, a different *status quo* option was included for each site. The choice sets have been considered as independent and not additive choices. In some locations, respondents were informed of the existence of insufficient or under-dimensioned safety devices when these were unable to provide reasonable protection against landslides. Unsafe protection devices were treated as absent in the data analysis, because inactive for protection. To facilitate space awareness, we gave respondents maps of the valley with marked locations of each site. Table 2.2 reports the actual situation of safety devices in each location.

Sites	Passive devices		Active devices	
	Channel	Basin	Video cameras	Sensors
1. Cancia	absent	insufficient	absent	absent
2. Chiapuzza	insufficient	insufficient	absent	absent
3. Acquabona	absent	present	absent	absent
4. Fiames Km 106	present	absent	absent	absent
5. Fiames Km 108	absent	absent	absent	absent
6. Fiames Km 109	present	insufficient	absent	absent

Table 2.2 – *Status quo* in each site.

The survey consisted of seven sections: the first included warm-up questions followed by questions about attitudes toward risk and knowledge about landslide hazard. The second section asked questions on recreational behaviour. The questionnaire was designed to include a DCE in the third part and a "repeated" DCE in the fifth. A fourth section provided respondents with the information treatment, which consisted of visual representations of hydro-geological simulations of landslides, the effect of which was at the core of our investigation. Debriefing questions were asked in the sixth section investigating preference over payment vehicles and the feeling of urgency of such protective policy measures. The final section of the questionnaire consisted of demographic questions.

The two DCEs before and after the information treatment were identical. Specifically, the additional information was provided in the form of two hydro-geological simulations of possible landslides. The first simulation (Figure 2.2) referred to three sites in the upper part of the valley and showed all the possible trajectories of the landslides. The second simulation modelled landslide trajectories in a specific site with and without a safety device, the channel. This simulation is reported in Figure 2.3. The yellow and green areas describe all possible landslide trajectories without the channel. Alternatively, after building the channel, the yellow areas do not constitute possible landslide trajectories.

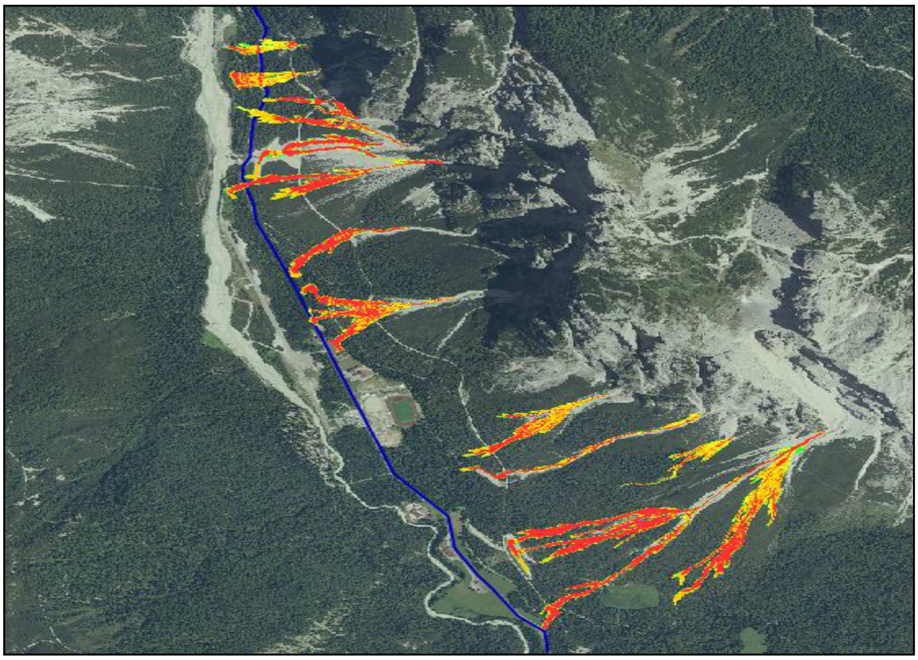

Figure 2.2 – First simulation: possible landslide events in the upper part of the Boite Valley (C. Gregoretti, personal communication, July 2014).

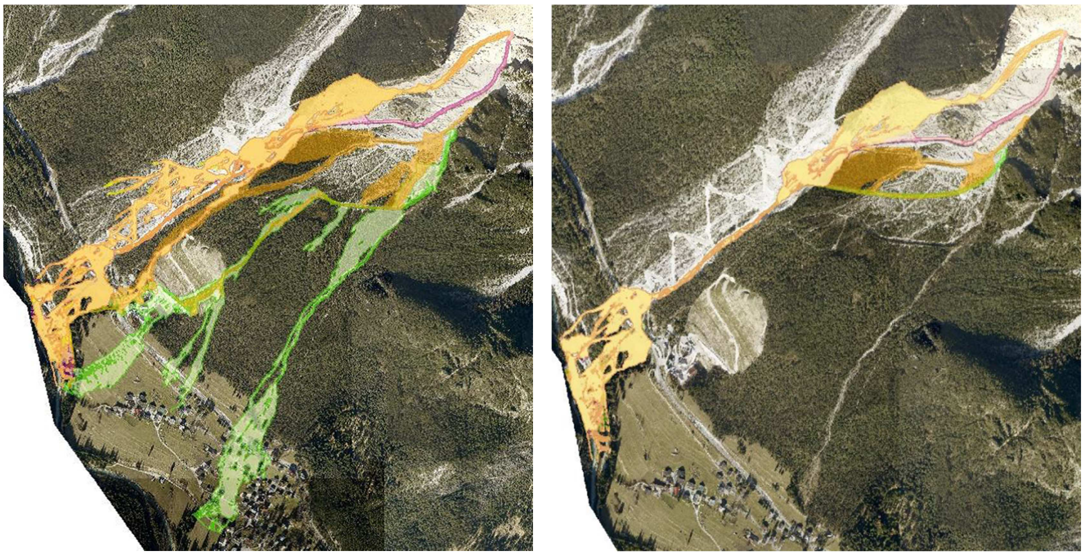

Figure 2.3 – Second simulation: a possible landslide with (only yellow area) and without channel (yellow and green areas) in site 2 – Chiapuzza (C. Gregoretti, personal communication, July 2014).

2.3.3 Sampling procedure

Given the specificity of the study, scientists' advice was used for identifying the most important safety devices for landslide protection in the specific locations. Then, interviews were carried out among locals with different knowledge levels to select a restricted number of attributes easily understood by lay people. An initial version of the questionnaire was tested on a sample pilot of 30 respondents, residents and visitors to the Boite Valley. The pilot proceeded smoothly, which led to minor changes in the survey instrument.

After the necessary amendments, the full-scale data collection was carried out in September-October 2014 by in-person surveys. 250 respondents were randomly sampled on-site among the residents and the visitors of the valley. The two identical repetitions of the DCE per respondent produced a total of 3,000 choice observations.

Regarding socio-economic characteristics, the sample consisted of 133 men (53.2%) and 117 women (46.8%). The respondents were all aged between 18 and 92 years. The average age was 47.7 years, respectively 49.5 for men and 45.8 for women. Almost half of the sample was resident in the valley (43.2%, 108 respondents out of 250) and the other half was composed of different types of visitors (56.8%, 142 respondents). However, almost 90% of the respondents are residents in the Belluno province. The local scale of the investigation appears to be necessary because residents and people that live in the nearby valleys are the main beneficiaries of the policy implementation. A summary of the socio-demographic and economic characteristics of the sample is presented in Table 2.3. More information regarding the geographical distribution of the sample is provided in section 2.4.2.

Variable	Description	Frequency	%
Age	Less than 30 years	29	11.6
	30-39 years	46	18.4
	40-49 years	64	25.6
	50-59 years	55	22.0
	60 or more	56	22.4
Gender	Male	133	53.2
	Female	117	46.8
Family members	Single	45	18.0
	Couple	68	27.2
	Three members	68	27.2
	Four members	56	22.4
	More than four members	13	5.2
Minor family members	No minor members	191	76.4
	One minor member	39	15.6
	Two minor members	17	6.8
	Three minor members	1	0.4
	More than three minor members	2	0.8

Continued on next page

Table 2.3 – continued from previous page

Variable	Description	Frequency	%
Education	Primary school	8	3.2
	Intermediate school	61	24.4
	High school	118	47.2
	Bachelor degree	15	6.0
	Master degree	43	17.2
	Post-graduate degree	5	2.0
Job position	Self-employed	42	16.8
	Employee	114	45.6
	Professional	18	7.2
	Businessman	12	4.8
	Student	11	4.4
	Housewife/retired/unemployed	53	21.2
Family net income	Less than €15,000	69	27.6
	€15,000-€30,000	102	40.8
	€30,000-€45,000	55	22.0
	€45,000-€60,000	16	6.4
	More than €60,000	8	3.2
Respondent type	Residents	108	43.2
	Second-house owner	12	4.8
	Daily visitor	92	36.8
	Overnight visitor	3	1.2
	Other (work, study, transit)	35	14.0

Table 2.3 – Socio-economic characteristics of the sample (N=250).

2.3.4 Econometric model

In our DCE respondents are presented with two series of six choice sets, each containing various landslide protection scenarios, for a panel of 12 choice sets. Although respondents were asked to rank the scenarios from best to worst using a reiterated best-worst approach, in the analysis reported here we only use data on the most favourite alternative. Each choice in the sequence is modelled as a function of the attributes using Random Utility Theory (or RUT, see for example Luce, 1959; McFadden, 1974; Train, 2003).

Several RUT models have been proposed in the literature, and most recently focus has been placed on those able to relax the independence of irrelevant alternative assumption, such as Mixed Logit models (Train, 1998; Revelt & Train, 1998). In this paper, we adopt a Mixed Logit specification in

WTP space (Train & Weeks, 2005; Scarpa, Thiene & Train, 2008). The utility function for choice occasion t is specified as:

$$U_{nit} = \lambda_n^*(\omega_n' X_{nit} - p_{it}) + \epsilon_{nit} \quad \text{(Eq. 2.1)}$$

where X_{nit} is a vector of non-monetary attributes, p_{it} is the cost attribute and ω_n is a conformable vector of marginal WTPs for each non-monetary attribute and respondent n. λ_n^* is defined as $\lambda_n \delta_n$, where λ_n is the scale of the i.i.d. Gumbel error $\varepsilon_{nit.}$ and δ_n is the realization of the cost coefficient for respondent n.

To test the first hypothesis (*H1*) that visitors and residents perceive the current level of protection from landslide hazard as inadequate, we included in our model the alternative specific constant (ASC) for the *status quo* alternative. A negative sign of the ASC would support our hypothesis.

To further investigate variations in estimated parameters across individuals, a covariance structure was estimated to account for correlation across the elements of the vector ω_n :

$$\wedge = \begin{bmatrix} \sigma_{b,b} & & & \\ \sigma_{c,b} & \sigma_{c,c} & & \\ \sigma_{s,b} & \sigma_{s,c} & \sigma_{s,s} & \\ \sigma_{v,b} & \sigma_{v,c} & \sigma_{v,s} & \sigma_{v,v} \end{bmatrix} \quad \text{(Eq. 2.2)}$$

where σ are standard deviations of random parameters, b denotes basin, c denotes channel, s denotes sensor and v denotes video camera.

One of our main hypotheses was that a protection device would be valued more after respondents received detailed information about it (hypothesis *H2*). To test such hypothesis, we estimated a utility function on the pooled choice data (pooling before and after information provision) and include one interaction variable between each attribute and a dummy variable I for the information effect. The generic linear utility function for the alternative i in the pooled data can be expressed as:

$$V_i = \omega_n' X_i + \Delta_n'(X_i \times I) \quad \text{(Eq. 2.3)}$$

where X_i is the vector of attributes. A statistically significant element Δ_n will support the hypothesis of an information treatment effect on value.

To test the hypothesis of spatial heterogeneity of benefits associated with safety measures (*H3*), we represented the geographical distribution of mWTP across the region. We first simulated mWTP$_n$ population distributions by generating 10,000 pseudo-random draws from the unconditional distribution of the estimated parameters and calculating individual-specific estimates for each draw (Train, 1998; von Haefen, 2003; Scarpa & Thiene, 2005). We then sorted the values by municipality and computed the respective means. Finally, we mapped mean values with ArcGIS to obtain the geographic distribution of estimates in each municipality.

2.4 Results and discussion

2.4.1 Model estimation

The Mixed Logit (MXL) model in WTP space has been estimated by simulated maximum likelihood using Biogeme 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 (Hess, Train & Polak, 2006). All the attributes' coefficients, as well as the alternative specific constant (ASC) for the *status quo* option, are assumed to have a normal distribution. The specification includes interaction terms between each attribute and the perception of information, coded as a dummy variable (0 = before receiving the information, 1=after receiving the information).

For comparison, a Multinomial Logit (MNL) model and the counterpart Mixed Logit model in preference space have also been estimated. The information criteria for the three models are presented in Table 2.4. All information criteria are concordant to indicate that the specification in WTP space outperforms the others in terms of goodness-of-fit, suggesting that this model is better suited to explain the observed dependent variable and to capture the heterogeneity of respondents' tastes.

N = 250	MNL	MXL in preference space	MXL in WTP space
lnL	-3041	-2459	-2403
AIC	6106	4870	4758
BIC	6148	5051	4939
AICc	6107	4850	4738

Table 2.4 – Models comparison.

The estimated parameters of the MXL model in WTP space are shown in Table 2.5. The estimated mean/median value for the coefficient alternative specific constant for the *status quo* is negative (-1.98±1.9), which suggests that respondents generally consider the current level of protection differently from the proposed alternatives. The construction of a channel is associated with the highest mean WTP value (€2.12±0.92) followed by the construction of a basin (€1.83±0.7). Respondents seem therefore to prefer passive devices. However, the construction of active devices is perceived as beneficial as well, as both devices of this kind are associated with positive WTP values, with sensors slightly preferred to video cameras (€1.26±0.42 and €1.19±0.57). Both the negative perception of *status quo* and the positive WTP values for implementation of new devices support our first hypothesis. The mWTP values, ranging from €1.19 to €2.12 per day per attribute, seem to be reasonable given that the payment vehicle is in the form of a provisional road toll for a maximum of 244 days.

We investigated the effect of the information provided by simulation scenarios by means of interaction terms between each attribute and post-treatment indicator variable. The coefficients of the interaction terms with the attributes are all insignificant, except the interaction term for the attribute channel. This suggests that the information treatment led to a change of the perceived benefit from improvement only for this attribute. This result is consistent with the fact that one of the landslide simulations provided was focused on a possible building of a channel in one of the areas under study. It supports our hypothesis of an information effect on the perceived safety measure of those alternatives singled out for information provision. Specifically, the positive sign of the significant interaction coefficient suggests that after the information provision, respondents valued the benefit derived from the channel 42 cents more. We did not find evidence, instead, of information effect for devices for which additional information was not provided. Therefore, hypothesis *H2* is partially rejected. Finally, it is interesting to note that the interaction term between the ASC for the *status quo* and the dummy variable for the information treatment is also significant (*p*-value 0.03), which suggests that after receiving information respondents changed their perception of current protection measure. In particular, the negative sign of the coefficient associated with the interaction term (-0.15) suggests that respondents value even less the current scenario.

	Value	Std. Err.	*p*-value
Mean parameters			
μ BAS	1.83	0.36	<0.001
μ CHAN	2.12	0.47	<0.001
μ SENS	1.26	0.21	<0.001
μ VIDEO	1.19	0.29	<0.001
μ ASC_SQ	-1.98	0.97	<0.001
μ ln(λ)	-2.05	1.12	<0.001
Interaction parameters			
Info × BAS	0.13	0.16	0.24
Info × CHAN	0.42	0.20	<0.001
Info × SENS	0.34	0.31	0.19
Info × VIDEO	0.08	0.14	0.56
Info × TOLL	0.04	0.24	0.81
Info × ASC_SQ	-0.15	0.09	0.03
Standard deviation parameters			
σ BAS	1.21	0.35	<0.001
σ CHAN	1.36	0.38	<0.001
σ SENS	0.99	0.41	<0.001
σ VIDEO	1.01	0.58	<0.001
σ ASC_SQ	0.87	0.63	<0.001
σ ln(λ)	1.81	0.95	<0.001
Log-likelihood	-2402.88		

Table 2.5 – Estimates of the MXL model in WTP space.

Table 2.6 reports the estimated correlation terms among random coefficients associated with non-monetary attributes. Most of the correlation terms (four out of six) are statistically significant, and all of them are positive. This suggests that tastes for different devices do not vary independently but are positively correlated across different individuals. We note that the highest degree of correlation is found to be between protection devices of the same class, in particular between channel and basin (0.68).

	BAS	CHAN	SENS	VIDEO
BAS	1.00			
CHAN	**0.68**	1.00		
	(0.18)			
SENS	0.12	**0.08**	1.00	
	(0.13)	(0.02)		
VIDEO	**0.02**	0.06	**0.29**	1.00
	(0.01)	(0.09)	(0.11)	

Note: Bolded values are statistically significant at 95%. Standard errors are reported in brackets

Table 2.6 – Correlation among the random coefficients of non-monetary attributes.

2.4.2 Geographical representations

This section explores the geographical distribution of benefits that would derive from policy measures aimed at increasing landslide protection in the Boite Valley. The sample covered 31 out of 67 villages on a 3,678 km² surface of Belluno province (209,430 inhabitants). From the total 250 respondents, almost 90% (89.6%; 224 out of 250) were resident in the province. The other 26 came from other parts of Italy, but mostly within the same administrative region (Veneto Region). Due to the low number of respondents from other provinces, we considered only the municipalities in the Belluno province. Moreover, people living in or close to the valley are more likely to be affected by the implementation of future mitigation projects.

The average WTP value for each municipality was computed by averaging the respondent-specific estimates across residents in each municipality. We used ArcGIS 10.3 (ESRI, 2010) to create the maps.

Figure 2.4 illustrates the average WTP for the construction of a channel, before and after information provision. We focus on this attribute as it was the only one affected by the information treatment. The map on the left illustrates the geographical distribution of mean WTP before receiving the information treatment, whereas the one on the right shows the values after such treatment.

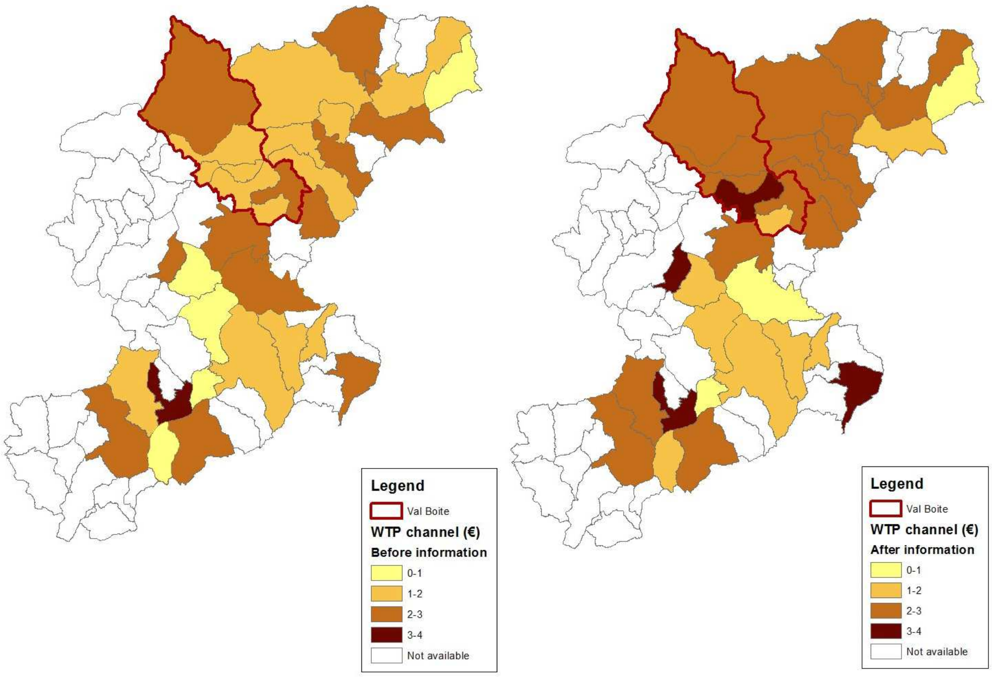

Figure 2.4 – Mean WTP for the attribute “channel” (before on the left, after on the right).

The maps provide some evidence of spatial heterogeneity of the estimates, as values change in different areas of the region, thus supporting our third hypothesis. However, there does not seem to be a strong evidence of a distance-decay effect on the estimates, as high WTP values were retrieved also in municipalities located far from the Boite Valley. However, most of the municipalities that show a high marginal WTP value are located in mountain areas and in the province where there is a real risk of landslide. We notice a general increase in the post-information mean value of WTP in almost all municipalities, which is consistent with population estimates. Before information provision in most of the municipalities the average WTP values are between €1 and €2, followed by values between €2 and €3. Only one municipality exhibits WTP values higher than €3. After information provision, instead, most of the municipalities have values within €2 and €3. Additionally, there is also an increase in the number of municipalities with WTP values higher than €3. Information seems to affect residents of Boite Valley and those living in municipalities on the East border. An increase in the perceived value after information provision is also detected in some municipalities in the southern part of the province, which is far from the valley. Individuals living in this area are likely to have lesser knowledge of the landslide problem of the Boite Valley, which may explain the strong effect of the information treatment among them.

2.5 Conclusions

In this study, we presented the results of a data analysis from a DCE designed to evaluate alternative protection actions in the context of landslide risk reduction. The study provides salient indications regarding both the effect of additional information and geographical distribution of WTP estimates. Our study was motived by three hypotheses: *(i)* current safety measures are perceived as inadequate; *(ii)* information provision affects individuals' mWTP for safety measures; *(iii)* there exists spatial heterogeneity of both mWTP and information provision effect.

In support of our first hypothesis, we found that surveyed residents and visitors perceive negatively the *status quo* and have positive WTP valuations for the proposed improvements of the existing protection systems. In particular, passive devices (channel and basin) are preferred to active ones (video camera and sensors).

In partial support of our second hypothesis, we found strong evidence of a positive treatment effect linked to the provision of visual information regarding a specific policy action. Differently from other studies, the information does not have additional effects (positive or negative) on the attributes about which no additional information was provided. However, a change in the perception of the *status quo* was also detected since respondents appear to value current safety measures less after receiving information.

As far as it concerns our third hypothesis, the mapping of the geographical distribution of WTP estimates provides some evidence of spatial heterogeneity of WTP values, although there are no immediately distinguishable spatial patterns. This suggests that the benefits associated with the construction of a channel are perceived differently by people living in different areas. The comparison of the geographical distribution of values before and after information shows which municipalities benefit most from increased awareness. Interestingly, the information effect appears to be substantial in some areas located far from the Boite Valley, in which respondents are more likely to be least familiar with the landslide issue.

With regard to policy implications, the estimated mean values of marginal WTPs offer insight on the relative importance of each protection device n each municipality. Having information about individual preferences of residents is important to public decision-makers to avoid controversies. The results of this study suggest that policymaker should focus on the implementation of plans which include the construction of passive devices, as residents and visitors of the Boite Valley are willing to contribute more to their realisation. In particular, it seems appropriate to promote the construction of channels as this device is associated with the highest WTP values, even before information provision. With regard to the effect of information, it appears that better-informed respondents make choices consistent with higher willingness-to-pay which are specific to the policy measure for which the information is provided.

This unsurprising result suggests that investment in education may be appropriate to increase people's inclination to contribute to the implementation of specific actions. In particular, it may be useful to focus such campaigns on civil engineering measures that policymakers plan to adopt. The analysis of the geographical distribution of the benefits may have important repercussions on the scheme to be adopted to apportion protection costs locally. Specifically, accounting for the spatial heterogeneity of individuals' preferences might induce a broader acceptance of public intervention and support (i.e. cost-sharing) over a larger geographical area. Despite these interesting conclusions, these estimates should be used with caution. These results should be integrated with a cost-benefit analysis for an efficient decision-making tool in risk management policy.

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Chapter 3

Exploring the stability of parameter estimates to the number of draws in choice models with latent variables

Abstract

The paper explores the stability of parameter estimates in simulation-based estimation for models integrating latent variables in choice analysis. The purpose of the study is to assess the consistency of simulation results while increasing the number of latent variables and gradually increasing the number of simulation draws. Specifically, we consider three Random Parameter Logit models with Latent Variables, which incorporate respectively one, two and three latent constructs. Since the optimum number of draws required to obtain a stable set of estimates is not pre-determined, we use six sets of progressively larger draws to assess estimates' sensitivity, always using the same set of starting values. We use data from a survey on landslide mitigation preferences, taking into account psychological and unobservable sources of heterogeneity in people's preferences for alternative risk prevention policies. Overall, the results suggest that an unusually large number of draws was needed to check for empirical identification, much larger than what is conventionally adopted in most of the published literature. Different degrees of instability are observed when more latent variables are incorporated. Although it is difficult to generalise, using a conventional number of draws appears to fail to detect heterogeneity in the sample with regard to key latent variables. Since little systematic attention has been paid to the consequences of unstable results when deriving policy implications, the conclusions report some general recommendations for practitioners when adopting this analytical framework.

Keywords:

Parameter stability; empirical identification; estimation by simulation; draws; Integrated Choice and Latent Variable model; risk perceptions.

3.1 Introduction

In the field of choice modelling, the issue of stability of parameters' estimates has not gained enough attention when estimation is carried out by simulation methods. To date, studies discussing this important issue are still limited (e.g. Walker, 2001; Hensher & Greene, 2003; Walker, Ben-Akiva, & Bolduc, 2007; Chiou & Walker, 2007). They mostly focus on Mixed Logit models, highlighting the need to verify the stability of the estimates with a "sufficiently large" number of draws. Experience suggests that the required number of draws for obtaining a stable set of parameter estimates increases with model complexity (Hensher & Greene, 2003). Also, the size and quality of the dataset play a key role. Since there is no objective criterion regarding the precise number of draws to use, the routine is to estimate the model over an incremental range of draws. Although it is not an exhaustive criterion, relatively stable estimates among consecutive draws could be considered an indicator of satisfactory stability being reached.

Assessing the consistency of the simulation results with an increased number of draws has gained renewed importance with the advent of more complex models, such as the Integrated Choice and Latent Variable (ICLV) models. These models provide a flexible framework for modelling choice data in the presence of latent constructs related to human behaviour not directly observed by the analyst. ICLV models were first proposed by McFadden (1986) and further developed over the last two decades (Ben-Akiva et al., 1999; Ben-Akiva et al., 2002; Bolduc, Ben-Akiva, Walker, & Michaud, 2005). Rapid improvements in estimation software have contributed to a significant increase in the number of studies that have adopted this model framework, which is used mainly in the transportation field. However, some applications have also appeared in the field of environmental studies in recent years, starting with the contributions of Alvarez-Daziano and Bolduc (2009) and Hess and Beharry-Borg (2012).

This family of models offers a framework to enrich the understanding of preference heterogeneity, providing insights into different potential sources of taste heterogeneity. Moreover, they provide a high explanatory power for the models' results (Bolduc et al., 2005), allowing for the identification of relationships between observable and latent variables. Improvement in model fit (Ashok, Dillon, & Yuan, 2002; Raveau, Álvarez-Daziano, Yáñez, Bolduc, & Ortúzar, 2010) and correction for omitted variables bias and measurement error are other advantages being claimed by the proponents. Accounting for latent constructs in the estimation process may lead to a richer understanding of the respondents' choice behaviour. In practical terms, this means more reliable findings for the decision-makers (Ben-Akiva et al., 1999) and a tool to support policy decisions applying complex behavioural theories.

Despite the previously mentioned benefits, these models have also been criticised as having weak points. High estimation effort and complex interpretation of the model outputs are criticisms raised recently by econometricians. Following this line of thought, Chorus and Kroesen (2014) expressed concerns regarding the value of the framework with regard to the derivation of policy implications. They stated that these models could not support travel demand policies aimed at changing travel behaviour through changes in latent variables because of *(i)* the non-trivial endogeneity of the latent variable; and *(ii)* the cross-sectional nature of the latent variable. The issue of over-parameterised choice models with latent variables may arise because of the large number of parameters involved for each single latent variable (Rungie, Coote, & Louviere, 2012). Vij and Walker (2014) concentrated on the problem of theoretical and empirical identification of the model, pointing that the number of draws also plays a major role in masking identification issues. Again, Vij and Walker (2016) compared an ICLV model with a reduced form choice model without latent variables, assessing the gains of the former specification. They found that in some cases the simplest model could fit the data at least as well as the ICLV model. The inclusion of this group of models in the routine suite of models used in environmental science was discussed by Mariel and Meyerhoff (2016).

This paper investigates the stability of the simulated parameter estimates for a different number of latent variables and an increased number of draws, under the ICLV framework. The purpose is to test for empirical identification. Specifically, we fit three latent variable-random parameter logit (LV-RPL) models using six sets of draws (100, 1000, 2000, 5000, 8000 and 10,000). Then, we compare the results from the same model specification to verify the precision of the parameter estimates over the draws, as suggested by Hensher and Greene (2003). However, the range of draws adopted in the previously-mentioned paper was limited to 2,000. Here we significantly extend the number of draws to 10,000.

The application is a nonmarket valuation study in the context of environmental risk, where respondents were asked to choose among protection programmes against landslide damage. The case study and the model specifications allow us to investigate potential unobservable preference heterogeneity that is modelled in two different ways, using random parameters and latent variables. We assume that people's choices are not only dependent on the attributes of the Discrete Choice Experiment (DCE) but also on some psychological factors that influence the choice process. Therefore, we suppose that the heterogeneity in preference across respondents is driven by underlying perceptions of mortality risk, risk severity, and landslide fear. Since perceptions are not directly measurable, they are considered latent constructs that can be inferred from survey questions, which work as psychometric indicators. These latent factors are considered to be a function of the socio-demographic characteristics of the respondents, and they are assumed to play a role in people's answers to the survey questions.

In the context of risk behaviour, socio-psychological approaches have been successfully applied in studies of risk behaviour to explore the processes that lead to the perception of risk and the factors that promote risk-reducing reactions. Among them, the Protection Motivation Theory (PMT), initially proposed by Rogers (1975), offers a valid approach for understanding the landslide protective behaviour of respondents and consequently their choices, along with the costs of the proposed measures and their social benefits. The inclusion of PMT constructs, through the use of latent variables, may add a further dimension to the interpretation of people's choices in the context of health and environmental threats.

The rest of the paper is structured as follows. The next section illustrates the theoretical framework adopted. Section 3.3 presents the case study and describes the survey questions and the DCE, with a subparagraph on the specific model structure. Section 3.4 then reports the results of the three LV-RPL models. A comparison of model results is discussed, together with the stability of the estimates (to the number of draws) within each model. The last section, section 3.5, presents a set of conclusions on the consistency of the results as related to the number of draws when estimation by simulation method is used. We conclude with a discussion of the "good practices" behind the adoption of this framework when the results are used for policy decisions.

3.2 Theoretical framework

A number of approaches have been used to integrate latent constructs into an ICLV framework (Ben-Akiva et al., 1999). In the present paper, the incorporation of latent variables is done by treating the observed indicators, i.e. responses to survey questions that aim to capture the latent factors, as endogenous. In contrast, other studies have directly incorporated the indicators as explanatory variables in the utility function (i.e. Morey, 1981; Harris & Keane, 1998). As pointed out by Ben-Akiva et al. (1999), Ben-Akiva et al. (2002) and Bolduc et al. (2005), this specification may suffer from measurement error and endogeneity bias, since responses to survey questions are indicators and not direct measures of perceptions. Especially when the question requires categorical responses, the measurement scale appears to be arbitrary. Thus, incorporating the latent constructs through the use of indicators rather than directly as explanatory variables is an additional justification that supports the choice of this framework.

The following sections describe the ICLV model, decomposing it into its components: the latent variable model and the choice model.

3.2.1 The latent variable model

The approach used to specify the latent variables relates the demographic characteristics of respondents to latent constructs and makes use of indicators to reflect the latter. In econometric terms, the latent variable model is composed of two parts: a structural component and a measurement component.

For respondent n and alternative i, the structural equation explains the latent variable (η) using respondents' characteristics (S). We define it below as:

$$\eta_{iln} = \sum_{q} \gamma_{iql} S_{iqn} + \omega_{iln} \qquad \text{(Eq. 3.1)}$$

where l denotes the specific latent variable, q is the specific socio-economic characteristic of the respondents and γ refers to the vector of unknown parameters that represent the effect of the explanatory variables on the latent constructs. The random disturbance term ω captures remaining variation in the latent constructs, which cannot co-vary with observables.

The measurement equations connect the latent variable to the indicator through a vector of unknown parameters λ_{il}, defining how the latent psychological aspects explain the responses to survey questions. Where the indicators are categorical variables, as here, the measurement equation is modelled like an ordered logit model as done by Daly, Hess, Patruni, Potoglou, and Rohr (2012):

$$I_{idn} = \left\{ \begin{array}{lll} 1 & if & -\infty < \eta_{iln} \leq \tau_{d1} \\ 2 & if & \tau_{d1} < \eta_{iln} \leq \tau_{d2} \\ 3 & if & \tau_{d2} < \eta_{iln} \leq \tau_{d3} \\ 4 & if & \tau_{d3} < \eta_{iln} \leq \tau_{d4} \\ & & \dots\dots\dots\dots\dots \\ m & if & \tau_{d(m-1)} < \eta_{iln} \leq +\infty \end{array} \right\} \qquad \text{(Eq. 3.2)}$$

where I_{idn} represents a vector of indicators for the latent variables, *d* denotes the *d*th indicator among all *D* indicators, τ_d is a vector of estimated threshold parameters. In this case, *m-1* thresholds parameters are identified. The respondent selects a specific category that follows between two thresholds.

Therefore, the likelihood of observing a specific reply to the indicator *I* is as follows:

$$\begin{aligned} Pr(I_d|\eta_l, \lambda_d) = \; & I_{(I_d=1)} \left[\frac{1}{1+\exp(\lambda_d\eta_l - \tau_{d1})}\right] \\ & + I_{(I_d=2)} \left[\frac{1}{1+\exp(\lambda_d\eta_l - \tau_{d2})} - \frac{1}{1+\exp(\lambda_d\eta_l - \tau_{d1})}\right] \\ & + I_{(I_d=3)} \left[\frac{1}{1+\exp(\lambda_d\eta_l - \tau_{d3})} - \frac{1}{1+\exp(\lambda_d\eta_l - \tau_{d2})}\right] \\ & + I_{(I_d=4)} \left[\frac{1}{1+\exp(\lambda_d\eta_l - \tau_{d4})} - \frac{1}{1+\exp(\lambda_d\eta_l - \tau_{d3})}\right] \\ & + \ldots + I_{(I_d=M)} \left[1 - \frac{1}{1+\exp\left(\lambda_d\eta_l - \tau_{d(m-1)}\right)}\right] \end{aligned} \qquad \text{(Eq. 3.3)}$$

3.2.2 The choice model

According to the Random Utility Theory (McFadden, 1974), it is assumed that respondents are rational decision-makers who maximise their perceived utility U_{in} over all the available alternatives. The utility of choosing alternative *i* among a set of *J* alternatives, denoted by *j=1,…,J*, for respondent *n* is a function of the *K* attributes of the alternative i. The utility function (Equation 3.4) is composed of a deterministic part V_{in} and an unobserved stochastic term ε_{in}, assumed to follow an i.i.d. Type 1 Extreme Value distribution:

$$U_{in} = V_{in} + \varepsilon_{in} \qquad \text{(Eq. 3.4)}$$

The term V_{in} in the utility function is modelled as a linear function of the vector of the explanatory variables X_{ikn} and associated parameters β_k, which measure the marginal utility associated with each attribute. When latent variables are incorporated, they may be modelled in different ways. We consider the case in which the latent variables η_{iln}, together with the related parameters θ_l, are added to the utility function. Therefore, the utility function can be rewritten in the form given in Equation 3.5:

$$U_{in} = \sum_l \theta_l \eta_{iln} + \sum_k \beta_k X_{ikn} + \varepsilon_{in} \qquad \text{(Eq. 3.5)}$$

The choice y_{in} of the individual n according to the available alternatives in the choice set C_n is defined as:

$$y_{in} = \begin{cases} 1, if\ U_{in} > U_{jn} \\ 0, otherwise \end{cases} \quad \forall j \in C_n, i \neq j \qquad \text{(Eq. 3.6)}$$

Thus, the conditional probability of respondent n choosing alternative i out of J alternatives can be defined as a logit:

$$Pr(y_{in}|X_{ikn}, \eta_{iln}, \beta_k, \theta_l) = \frac{\exp(\theta_l' \eta_{iln} + \beta_k' X_{ikn})}{\sum_{j=1}^{J} \exp(\theta_l' \eta_{jln} + \beta_k' X_{jkn})} \qquad \text{(Eq. 3.7)}$$

Over the T choice sets, the probability of the sequence of independent choices y_{in}^t by respondent n is a product of logits:

$$Pr(y_{in}^t|X_{ikn}, \eta_{iln}, \beta_k, \theta_l) = \prod_{t=1}^{T} \frac{\exp(\theta_l' \eta_{iln} + \beta_k' X_{ikn})}{\sum_{j=1}^{J} \exp(\theta_l' \eta_{jln} + \beta_k' X_{jkn})} \qquad \text{(Eq. 3.8)}$$

3.2.3 Maximum simulated likelihood estimation

In order to fit the model to the empirical choices in the sample, the software simultaneously estimates the distributional features of random utility parameters and the coefficients of the latent variables by maximising the joint likelihood of the observed responses to the survey questions and the sequence of choices in the DCE. The log-likelihood (LL) function is given by Equation 3.9:

$$LL\,(y_{in}, I_d) = \sum_{n=1}^{N} \log \int_{\omega} \left[Pr(y_{in}|X_{ikn}, \eta_{iln}, \beta_k, \theta_l) \prod_{d=1}^{D} Pr(I_d|\eta_l, \lambda_d) \right] g(\omega) d\omega \quad \text{(Eq. 3.9)}$$

where $Pr(y_{in}|X_{ikn}, \eta_{iln}, \beta_k, \theta_l)$ denotes the probability of the choice model (defined in Eq. 3.7), and $Pr(I_d|\eta_l, \lambda_d)$ denotes the probability of the latent variable model (defined in Eq. 3.3). The two models are linked by $g(\omega)$, which is the density of the distribution of ω over the population. Since ω is unobserved due to its latent nature, the error terms of the structural equation are integrated out over their distributions.

When the integral in the Equation 3.9 for the LL function does not have a closed form, an approximation is obtained by using simulation methods. After taking R draws of $\omega^{(r)}$ from the population density $g(\omega)$, the $Pr(I_d|\eta_l, \lambda_d)$ is calculated for each draw. Consecutively, the simulated probability for the latent variable model is given by the average of $Pr(I_d|\eta_l, \lambda_d)$ over R draws (Equation 3.10).

$$\widehat{Pr}(I_d|\eta_l, \lambda_d) = \frac{1}{R} \sum_{r=1}^{R} Pr(I_d|\eta_l, \lambda_d) \quad \text{(Eq. 3.10)}$$

Therefore, the simulated log-likelihood (SLL) function includes the simulated probability for the latent model as presented in Equation 3.11:

$$SLL\,(y_{in}, I_d) = \sum_{n=1}^{N} \log \left[\int_{\beta} \int_{\omega} \left[Pr(y_{in}|X_{ikn}, \eta_{iln}, \beta_k, \theta_l) \prod_{d=1}^{D} \widehat{Pr}(I_d|\eta_l, \lambda_d) \right] g(\omega) f(\beta) d\omega d\beta \right]$$

(Eq. 3.11)

In the case of random heterogeneity in the attributes' coefficients β_k, a layer of integration has to be added to the equation in addition to the integration over the unobservable components of the latent variables ω.

3.3 Application to landslide hazard

3.3.1 Case study

With the purpose of exploring the role of psychological factors in people's decision processes, we investigated the impact of risk perceptions on people's preferences. The specific application was a DCE study regarding the preferences of people for mitigation programmes for landslide events.

We administered a structured questionnaire to a sample of respondents in a mountain valley of the Italian Alps. The first part of the questionnaire asked respondents' risk perception questions. Then, respondents took part in the DCE. Data was gathered from 250 individuals using face-to-face interviews, obtaining a total of 1,500 observations. We report the summary of the demographic information from the sample in Appendix 3.7 (Table 3.7).

To collect information about the latent constructs, a set of questions elicited information on the perception of the respondents for natural hazards' risk with a specific focus on landslides. The survey questions were developed based on the area of investigation and designed to match the cognitive process of the respondents, as proposed by the protection motivation theory (PMT). This psychological theory is well established in the context of health and environmental risk (e.g. Floyd et al., 2000; Grothmann & Reusswig, 2006). The two components of the PMT are the threat appraisal process and the coping appraisal process (Rogers, 1975). The first element aims to interpret the mental processes of people in assessing threats; the second one presents the components that are relevant to evaluate the coping alternatives (Floyd, Prentice-Dunn, & Rogers, 2000). The threat appraisal is composed of three parts: *(i)* perceived threat vulnerability, which establishes the respondent's exposure to the threat; *(ii)* perceived threat severity, which indicates the size of the threat; and *(iii)* fear, which denotes the degree of fear experienced by the respondent. We exclusively address the threat appraisal of the PMT, as we suppose it may have an impact on choice behaviour in the context of safety programmes. To be consistent with the

PMT, we selected three questions as indicators for three different latent variables. These questions were assumed to be the most representative of the unstated choice behaviour.

Specifically, the first question asked respondents their perception of their own mortality risk with regard to landslides. We used a direct risk elicitation technique (e.g. Viscusi, 1990), asking the respondents to state the probability that the given outcome (i.e. being a victim of a landslide) would occur during the next year. Respondents indicated their annual chance of dying using a marking on a continuous risk ladder from 0 to 100%. The inclusion of a visual linear scale was adopted to reduce the otherwise excessively frequent 50-50 replies, which are much more common when using an open-ended format (Fischhoff & Bruine de Bruin, 1999). This elicitation technique is commonly used to investigate subjective probabilities in DCE studies. Specifically, this scale of concern was adopted by Thiene, Shaw, and Scarpa (2016) in their earliest work on landslide risk perceptions. We were aware of the possible bias in eliciting perceptions in the form of numerical probabilities since direct elicitation methods are more challenging for respondents to process (Zimmer, 1983). However, in their recent work, Bruine de Bruin and Fischhoff (2017) reported that the use of probabilistic questions is preferable to verbal quantifiers. They pointed out that verbal quantifiers are vague, leading to responses that are not comparable with observed probabilities. Alternative elicitation approaches, such as lotteries (Bartczak, Chilton, & Meyerhoff, 2015), were also discarded so that we could take advantage of existing data on scientific measures of the statistical probability of dying due to landslides.

The other two questions were rating responses. They asked respondents to state their perceptions of the degree of risk, using a five-point Likert response format (from 1="very low" to 5="very high"). Specifically, the second question concerned the perception of risk severity at the local scale for different natural disasters: landslide, avalanche, earthquake and flood. The correlation coefficients for natural hazards are reported in Appendix 3.7 (Table 3.8). Finally, the third question aimed to work as an indicator of the degree of fear of landslides. On a 1 ("very low") to 5 ("very high") scale, respondents had to rate their fear of landslide occurrence. Table 3.1 provides the descriptive statistics for the survey questions used as psychometric indicators in our models.

Questions	Mean	St.dv.
1. On a scale from 0% (=cannot happen) to 100% (=definitely will happen), what do you believe is the chance that you might be killed by a landslide in the coming year?	11.35	16.53
2. On a scale from 1 (=very low) to 5 (=very high), what do think is the severity of risk for the following natural events?		
a. Landslide	4.34	0.88
b. Avalanche	3.06	1.32
c. Earthquake	2.80	1.34
d. Flood	3.01	1.32
3. On a scale from 1 (=very low) to 5 (=very high), what is your fear of a landslide event?	3.46	1.28

Table 3.1 – Descriptive statistics of the survey questions.

The DCE elicits the willingness-to-pay (WTP) of the respondents to support the implementation of public mitigation programmes for landslides, aimed at protecting people's health and avoiding damage to property. Each hypothetical scenario was described by four protection devices and a monetary attribute. The four protection devices are all engineering solutions that reduce the impact of future landslide events, such as basins ("*BAS*"), channels ("*CHAN*"), sensors ("*SENS*"), and video cameras ("*VIDEO*"). There are two levels for these attributes: the device is either present or absent. The monetary attribute ("*TOLL*") was expressed in the form of a provisional road toll for travel in the mountain valley (from €1 to €4 daily) (Appendix 3.7 – Table 3.9).

The experimental design adopted was an optimised orthogonal design (Ferrini & Scarpa, 2007; Scarpa & Rose, 2008; Rose & Bliemer, 2007) and was generated using the software Ngene (ChoiceMetrics, 2012). The final fractional design involved 60 choice sets that were blocked into 10 groups. Each respondent was randomly assigned to one of the blocks and selected the preferred alternative in six choice sets. Each choice set contained six unlabelled alternatives and a *status quo* option. The respondent ranked the alternatives using a reiterated best-worst approach. For the purpose of this study, we only used the first best.

3.3.2 Estimation

We fitted a set of LV-RPL models that account for multiple sources of preference heterogeneity in two ways: *(i)* by including latent variables as a function of socio-economic characteristics of the respondents (the latent variable model), and *(ii)* by considering continuous taste variation among respondents (the random parameter choice model). Furthermore, we allowed the marginal effect of the latent variable/s to vary among individuals, as done by Yañez, Raveau and Ortúzar (2010). In our models, all the random parameters (ω, β) were assumed to be normally distributed. Note that the same models with fixed latent variable/s were fitted but not included since they provided lower performances than the models with random latent variable/s. Three different model specifications were considered; each of them was estimated with six sets of draw sizes (R=100, 1000, 2000, 5000, 8000 and 10,000). The model structures differed with regard to the number of latent variables, from the simplest, with only one latent variable, to the most complex model with three.

In the following section, we describe the most complex model specification adopted, the LV-RPL with three random latent variables. All the other specifications can be considered as reduced forms of this model. The three latent variables incorporated into the model are: own mortality risk due to landslide ("MOR_{in}"), severity of natural hazards ("SEV_{in}"), and fear of landslide ("FEA_{in}"). Six ordinal indicators captured the effects of these latent variables.

The structural equations for the three latent variables are given in Equations 3.12, 3.13 and 3.14:

$$MOR_{in} = \gamma_{fem_{MOR}} Female_{in} + \omega_{MOR,in} \qquad \text{(Eq. 3.12)}$$

$$SEV_{in} = \gamma_{fem_{SEV}} Female_{in} + \omega_{SEV,in} \qquad \text{(Eq. 3.13)}$$

$$FEA_{in} = \gamma_{fem_{FEA}} Female_{in} + \omega_{FEA,in} \qquad \text{(Eq. 3.14)}$$

where γ_{fem} represents the effect of the explanatory variable "*Female*" on the latent construct and "*Female*" indicates the gender. The error terms of the structural equations, denoted by ω, are i.i.d. standard normally distributed.

Gender was the only explanatory variable included in the structural equation for all latent variables. No other socio-economic variables seemed to be good predictors of the latent variables under investigation. The fact that this family of models often suffer from weak structural equations is in line with our findings. As noticed by Vij and Walker (2016), the observable explanatory variables are sometimes poor predictors of the latent variables. Therefore, the inclusion of measurement indicators leads to statistically significant improvements in fit, in comparison to the reduced model without latent variables.

The measurement equations use the indicators as dependent variables to represent the latent variables. Table 3.2 describes the latent variables and their ordinal indicators.

Variables	Description of the variables	Description of the indicators
MOR	η_{MOR}= own mortality risk	d_1= mortality risk for landslide
SEV	η_{SEV}= severity of natural disasters	d_2= severity of landslide
		d_3= severity of avalanche
		d_4= severity of earthquake
		d_5= severity of flood
FEA	η_{FEA}= fear of landslide	d_6= fear of landslide

Table 3.2 – Description of the latent variables and their indicators.

The first latent variable "MOR_{in}" has one ordinal indicator (d_1). The original variable measures the perception of own mortality risk in conjunction with landslide using a percentage scale from 0 to 100%. However, we discretised this variable, taking advantage of the fact that we had an objective measure of risk (<0.1% annually). So, the transformed variable becomes an ordinary variable that takes the value 1 if the perception matches or approximates the scientific measure (0-5%), 2 if the perception is double (6-10%), 3 if it is three times higher (11-15%), 4 if it is four times higher (16-20%) and 5 if it is more than four times higher than the real measure of risk (>20%). We were aware of the fact that the objective measure of risk is not necessarily the same for every respondent. However, since the objective measure was a very small number that approximated zero we assumed a tolerance level of 5% could be representative of the entire sample. This transformation offers an easier interpretation of the results as well as the possibility of smoothing unrealistic replies due to overestimation of low probability risks such as landslide mortality estimates.

The second latent variable "SEV_{in}" has four ordinal indicators (d_2, d_3, d_4, d_5) that measure the perceived severity of the consequences of natural disasters. Landslides, avalanches, earthquakes and floods are the main natural hazards affecting the area of the study.

The third latent variable "FEA_{in}" has one ordinal indicator (d_6) that refers to the self-reported fear of landslides.

The utility functions for the *status quo* and non-*status quo* options are reported below (Eq. 3.15a and 3.15b):

$$U_{SQ,n} = ASC_{SQ} + \theta_{MOR,n}MOR_{in} + \theta_{SEV,n}SEV_{in} + \theta_{FEA,n}FEA_{in} + \beta_{CHAN,n}CHAN_{in} + \beta_{BAS,n}BAS_{in} + \beta_{SENS,n}SENS_{in} + \beta_{VIDEO,n}VIDEO_{in} + \beta_{TOLL}TOLL_{in} + \varepsilon_{in} \quad \text{(Eq. 3.15a)}$$

$$U_{\neq SQ,n} = \beta_{CHAN,n}CHAN_{in} + \beta_{BAS,n}BAS_{in} + \beta_{SENS,n}SENS_{in} + \beta_{VIDEO,n}VIDEO_{in} + \beta_{TOLL}TOLL_{in} + \varepsilon_{in} \quad \text{(Eq. 3.15b)}$$

where $U_{SQ,n}$ is the utility function of the *status quo* option, which is the riskiest option, and $U_{\neq SQ,n}$ is the utility function of the proposed mitigation scenarios. The latent variables were entered only in the utility function of the current scenario since we aimed to investigate the marginal effects of the latent factors on the utility of the riskiest choice. ASC_{SQ} is an alternative specific constant that is present only in the *status quo* alternative. All the attributes' coefficients were assumed to have a normal distribution, except for the fixed cost attribute (β_{TOL}), This is because we assumed that the marginal utility of income is constant and equal for all individuals given that cost is a small fraction of individual incomes. The subscript *n* indicates that the marginal effects could vary across respondents.

All the models' coefficients were estimated by simulated maximum likelihood using PythonBiogeme software (Bierlaire, 2016). The choice probabilities were simulated using Monte Carlo integration. Halton draws were taken from the distribution of the random variables of integration (Halton, 1960). We also considered alternative types of draws, but the Halton draws were chosen because they provide better coverage over the domain of the mixing distribution than random draws (Train, 2000; Bhat, 2001). The choice of this specific set of draws was made with the purpose of covering the interval between 100 and 10,000 draws. As far as we know, recent publications in the literature of choice modelling have adopted up to 10,000 draws, with a minimum of 100. As pointed out in previous studies on this topic (e.g. Ben-Akiva & Bolduc, 1996; Walker, 2001; Choi & Walker, 2007), a low number of draws (i.e. under 1,000) can provide estimates that are apparently identified, but they could be unidentified by either the model or the data. Therefore, verifying the stability of the parameter estimates for an increased number of draws (i.e. empirical identification) is paramount to every econometric analysis.

As done by Hole and Yoo (2017) in their recent study, we tried various sets of starting points to avoid convergence at an inferior optimum and to increase the chances of reaching the global maximum. However, repeatedly obtaining the same results using different starting points is not proof of having found the global maxima. To compare the estimates, we kept the starting points constant among the set of draws. The estimation time reported for each model refers to the time required for the computation of simulated estimates carried out on an Asus Intel Core i7 1.90GHz 2.40GHz PC with an Ubuntu 14.04 operating system.

3.4 Results and discussion

In the following section, we provide a comparison between a random parameter logit (RPL) model and the three variants of the LV-RPL model with random latent variable/s. Then, we present the results with regard to the stability of the parameters to an increased number of draws. For completeness, we report the results of the RPL model (Appendix 3.7 – Table 3.10) that was used as a benchmark for testing the empirical identification as we added more latent constructs into the model. See Appendix 3.7 for the complete table (Table 3.11) with the results of the eighteen LV-RPL models that were fitted.

3.4.1 Comparison of models' results

Table 3.3 shows the comparison of the models at 10,000 draws. We report the derived standard errors of the parameters in squared brackets. We consider the parameters as statistically significant at the 5% level. The performance of different models is not taken into account as the focus is on the empirical identification of the models.

In the RPL model, the coefficients for the attributes are all significant, with the expected sign and magnitude. Among the safety devices, the channel is the attribute with the highest estimates, followed by the basin, video cameras, and sensors. The estimated standard deviations of every random coefficient are highly significant, indicating that there is a high heterogeneity of preference, as the coefficients do vary in the population. The constant term of the *status quo* option captures the effect of the unobservable factors in the utility of the *status quo* option relative to the alternatives with a higher degree of safety. Here the ASC_{SQ}

has a very small magnitude and is insignificant, meaning that the respondents did not consider the riskiest option differently to the other alternative scenarios. However, the LV-RPL models tell a different story. In all the LV-RPL models, the fact that the constant ASC_{SQ} is negative and significant means that respondents in the sample did consider the actual scenario differently from the proposed alternatives. They preferred to avoid the actual situation (i.e. the riskiest option) in favour of new mitigation programmes. Since additional information can be derived from the latent variable component, in the following sections we describe the results from the three LV-RPL models in detail.

The first LV-RPL model has one latent variable "MOR_{in}", i.e. own mortality risk due to a landslide. Its coefficient has a negative sign as expected, adding a large negative value of the latent variable (-4.25) to the already negative ASC_{SQ} (-1.35). The respondents with a high risk perception, exceeding the objective measure of risk, were those willing to pay most for improving the current protection systems. The standard deviation of the latent variable σ_{MOR} is 4.57, which is large in comparison to the estimated parameter "MOR_{in}", showing that there was a significant psychological heterogeneity among the respondents with regard to the latent construct. Additionally, there is a positive association between the latent variable and the indicator $I_{id_1 n}$ since the coefficient λ_{MOR_risk} in the measurement equation is positive and significant (1.18). The estimates for the threshold parameters ($\tau_{MOR\_risk1}, \tau_{MOR\_risk2}, \tau_{MOR\_risk3}, \tau_{MOR\_risk4}$) are in the expected order. The coefficient of the socio-economic variable *Female* ($\gamma_{Female,MOR}$) in the structural equation is significant and positive, demonstrating that female respondents had a higher own mortality risk perception than males. Conversely, males had a weaker desire for new interventions against landslides.

In the second LV-RPL model, in which a new latent variable is added, the latent factor "SEV_{in}" provides information on the perception of the severity of four natural hazards, in terms of their consequences in the investigated areas. The coefficients of both latent variables are negative and large in magnitude (-3.72 and -1.58, respectively). An extreme aversion toward the level of protection in place is also shown by the negative ASC_{SQ} (-1.60). In contrast to the previous model, here the coefficient λ_{MOR_risk} in the measurement equation is insignificant. However, the four coefficients for each natural hazard ($\lambda_{SEV\_land}, \lambda_{SEV\_aval}, \lambda_{SEV\_eart}, \lambda_{SEV\_flood}$) have all a positive and significant impact on the latent variable "SEV_{in}". The two coefficients of the socio-economic variable *Female* ($\gamma_{Female,MOR}$ and $\gamma_{Female,SEV}$) are both positive and significant. Females had a higher mortality risk perception as well as a higher perception of the severity of natural events.

The third LV-RPL model with three latent variables is the most complex, adding a third source of psychological heterogeneity. The latent variable "FEA_{in}" indicates the degree of fear of landslides. In contrast with what we were expecting, the coefficient of this latent variable was the only one to be insignificant. Basically, the fear of landslide did not act as a latent driver for the rejection of the riskiest scenario as the other latent variables did. This is perhaps because the own mortality risk and the severity of consequences evoke unpleasant emotional feelings. Instead, fear of a natural event is an abstract concept that does not necessarily bring to mind a tragic situation. The coefficients of the first two latent variables are negative and different in magnitude (-4.15 and -1.65, respectively). It appears that the latent variable "MOR_{in}" outweighs the other latent variables. The negative sign confirms the previous tendency of disapproval of the baseline scenario, supported initially by a negative ASC_{SQ} (-1.46). Heterogeneity of taste and psychological heterogeneity were both present in the sample, and with large magnitudes. Nevertheless, only the standard deviation of the latent variable "MOR_{in}" is significant. Since the coefficient of the third latent variable is insignificant, we observe no major differences in comparison to the previous model with two latent variables. We note that there is no impact of the indicator λ_{FEA} on the associated latent variable and the difference between men and women for this latent variable is insignificant.

Variables	Coefficient estimates			
	RPL	LV-RPL		
		1LV	2LV	3LV
Mean parameters				
β_{CHAN}	2.96***	3.12***	3.10***	3.12***
	[0.203]	[0.183]	[0.196]	[0.202]
β_{BAS}	2.70***	2.66***	2.66***	2.67***
	[0.200]	[0.185]	[0.196]	[0.201]
β_{VIDEO}	2.26***	2.04***	2.05***	2.05***
	[0.204]	[0.156]	[0.165]	[0.168]
β_{SENS}	1.88***	1.82***	1.82***	1.83***
	[0.190]	[0.138]	[0.145]	[0.148]
β_{TOLL}	-1.53***	-1.49***	-1.49***	-1.50***
	[0.051]	[0.056]	[0.059]	[0.060]
ASC_{SQ}	-0.07	-1.35**	-1.60**	-1.46**
	[0.168]	[0.507]	[0.593]	[0.639]
θ_{MOR}	-	-4.25***	-3.72***	-4.15***
	-	[0.844]	[0.817]	[0.911]
θ_{SEV}	-	-	-1.58**	-1.65**
	-	-	[0.683]	[0.707]
θ_{FEA}	-	-	-	0.70
	-	-	-	[1.070]
St.dv. parameters				
σ_{CHAN}	1.89***	1.62***	1.63***	1.63***
	[0.225]	[0.215]	[0.224]	[0.229]
σ_{BAS}	2.08***	1.85***	1.84***	1.85***
	[0.215]	[0.221]	[0.226]	[0.229]
σ_{VIDEO}	1.92***	1.16***	1.15***	1.15***
	[0.194]	[0.184]	[0.194]	[0.203]
σ_{SENS}	1.48***	0.73***	0.73***	0.74***
	[0.180]	[0.192]	[0.195]	[0.201]
σ_{MOR}	-	4.57***	3.77***	3.95***
	-	[0.827]	[0.905]	[0.833]
σ_{SEV}	-	-	1.54*	0.99
	-	-	[0.905]	[1.230]
σ_{FEA}	-	-	-	0.30
	-	-	-	[1.790]
Model fit				
LL	-1522.57	-1691.89	-3090.80	-3471.49
AIC	3065.28	3420.24	6265.96	7044.36
BIC	3118.26	3515.42	6481.44	7301.33
cAIC	3065.29	3420.27	6266.02	7044.43
est. time	01h42'57"	10h45'52"	21h26'05"	24h13'41"

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]

Table 3.3a – Models' results at 10,000 draws.

Variables	Coefficient estimates			
	RPL	LV-RPL		
		1LV	2LV	3LV
Structural equations				
$\gamma_{Female,MOR}$	-	0.84***	0.75**	0.90**
	-	[0.272]	[0.299]	[0.425]
$\gamma_{Female,SEV}$	-	-	0.49**	0.47**
	-	-	[0.176]	[0.194]
$\gamma_{Female,FEA}$	-	-	-	0.76
	-	-	-	[0.860]
Measurement equations				
λ_{MOR_risk}	-	1.18**	0.94*	0.90*
	-	[0.600]	[0.495]	[0.527]
τ_{MOR_risk1}	-	1.04**	0.85***	0.92***
	-	[0.374]	[0.301]	[0.314]
τ_{MOR_risk2}	-	1.88***	1.62***	1.69***
	-	[0.514]	[0.396]	[0.402]
τ_{MOR_risk3}	-	2.17***	1.89***	1.95***
	-	[0.555]	[0.421]	[0.427]
τ_{MOR_risk4}	-	2.49***	2.19***	2.25***
	-	[0.599]	[0.454]	[0.457]
λ_{SEV_land}	-	-	0.74***	0.74***
	-	-	[0.225]	[0.228]
τ_{SEV_land1}	-	-	-4.52***	-4.52***
	-	-	[0.645]	[0.671]
τ_{SEV_land2}	-	-	-3.26***	-3.27***
	-	-	[0.376]	[0.409]
τ_{SEV_land3}	-	-	-1.67***	-1.67***
	-	-	[0.220]	[0.234]
τ_{SEV_land4}	-	-	-0.07	-0.08
	-	-	[0.174]	[0.191]
λ_{SEV_aval}	-	-	1.15***	1.15***
	-	-	[0.221]	[0.224]
τ_{SEV_aval1}	-	-	-1.91***	-1.91***
	-	-	[0.256]	[0.264]
τ_{SEV_aval2}	-	-	-0.58**	-0.59**
	-	-	[0.216]	[0.224]
τ_{SEV_aval3}	-	-	0.87***	0.87***
	-	-	[0.225]	[0.235]
τ_{SEV_aval4}	-	-	2.08***	2.08***
	-	-	[0.293]	[0.300]
λ_{SEV_eart}	-	-	1.31***	1.30***
	-	-	[0.228]	[0.232]
τ_{SEV_eart1}	-	-	-1.65***	-1.65***
	-	-	[0.259]	[0.270]
τ_{SEV_eart2}	-	-	0.17	0.16
	-	-	[0.224]	[0.231]
τ_{SEV_eart3}	-	-	1.28***	1.27***
	-	-	[0.248]	[0.257]
τ_{SEV_eart4}	-	-	2.48***	2.47***
	-	-	[0.330]	[0.337]
λ_{SEV_flood}	-	-	1.97***	2.00***
	-	-	[0.496]	[0.504]
τ_{SEV_flood1}	-	-	-2.17***	-2.20***
	-	-	[0.435]	[0.450]

Continued on next page

Table 3.3b – continued from previous page

Variables	Coefficient estimates			
	RPL	LV-RPL		
		1LV	2LV	3LV
τ_{SEV_flood2}	-	-	-0.65**	-0.66**
	-	-	[0.306]	[0.322]
τ_{SEV_flood3}	-	-	1.10***	1.10***
	-	-	[0.336]	[0.353]
τ_{SEV_flood4}	-	-	2.83***	2.84***
	-	-	[0.531]	[0.554]
λ_{FEA_land}	-	-	-	1.09
	-	-	-	[1.670]
τ_{FEA_land1}	-	-	-	-2.52**
	-	-	-	[1.160]
τ_{FEA_land2}	-	-	-	-1.01*
	-	-	-	[0.564]
τ_{FEA_land3}	-	-	-	0.27
	-	-	-	[0.276]
τ_{FEA_land4}	-	-	-	1.59*
	-	-	-	[0.834]

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]

Table 3.3b – Models' results at 10,000 draws.

3.4.2 Stability of the results

In this section, we focus on testing the stability of the estimates when the number of draws is increased in each of the six steps (R=100, 1000, 2000, 5000, 8000 and 10,000). The stability of the parameter estimates is explored mainly for the latent variable/s, mostly because the other estimates appear to be already stable at a low number of draws. We make a distinction between models with consistent conclusions across draw sizes and those with conclusions subject to change across draw sizes.

There is no consensus definition of stability to the number of draws in the literature. Hence, we adopted a rule of thumb and arbitrarily defined an estimated parameter as "stable" when the results lay within one standard error of each other over consecutive runs with an increased number of draws (Walker, 2001; Vij & Walker, 2014). Specifically, the subjective criterion adopted by Walker (2001) distinguishes between "very stable" estimates (within one standard error), "fairly stable" estimates (within two standard errors) and unstable estimates (larger than two standard errors). In the following tables, the fairly stable and unstable estimates are shown in bold, with the unstable parameters highlighted with a square.

3.4.2.1 LV-RPL model with one random latent variable

Table 3.4 reports the results of the LV-RPL model with one latent variable. All the estimated parameters are stable when the number of draws increases from 100 to 1,000, 2,000 and then 5,000. However, some instability in the latent variable model is shown when the model is fitted with 8,000 draws. In contrast, the attributes' parameters are all stable through increased numbers of draws, as is the constant term ASC_{SQ}. The coefficient (θ_{MOR}) of the latent construct "MOR_{in}" is negative and significant for the six sets of draws. However, its magnitude varies from -5.38 to -4.25 from the first to the last step. The standard deviation of the latent variable (σ_{MOR}) becomes significant just by using a large number of draws (e.g. 8,000) and is the only parameter presenting strong instability using a low number of draws. A minor instability is present in the structural equation and in the measurement equation. Looking at the stability with 10,000 draws, the last parameter estimates are all within one standard error of the model fitted with 8,000 draws. Therefore, we may consider the final estimates at 10,000 draws as stable. Furthermore, we observe a slight increase in almost all standard errors as the draws increase in number. Similar results were reported by Train (2000) and Bhat (2001) with regard to the simulation variance and simulation error in mixed logit models. However, it seems that the standard errors become steady when the parameter estimates can be identified.

The precision of the model fitted with a large number of draws leads to consistent conclusions that identify the heterogeneity of a latent variable not previously detected using a conventional number of draws (such as those in Hensher & Greene, 2003). The changes in the magnitude of the latent variable coefficient do not have a substantial impact on policy decisions. This is because its magnitude is high to overcome the estimates' fluctuations using different numbers of draws.

	LV-RPL with one latent variable					
	100	1,000	2,000	5,000	8,000	10,000
Mean parameters						
β_{CHAN}	2.90***	3.02***	3.09***	3.08***	3.13***	3.12***
	[0.148]	[0.169]	[0.178]	[0.178]	[0.184]	[0.183]
β_{BAS}	2.48***	2.55***	2.61***	2.59***	2.68***	2.66***
	[0.156]	[0.175]	[0.177]	[0.182]	[0.186]	[0.185]
β_{VIDEO}	1.92***	1.98***	2.01***	2.02***	2.07***	2.04***
	[0.132]	[0.146]	[0.147]	[0.151]	[0.157]	[0.156]
β_{SENS}	1.73***	1.78***	1.80***	1.80***	1.83***	1.82***
	[0.131]	[0.132]	[0.135]	[0.134]	[0.144]	[0.138]
β_{TOLL}	-1.44***	-1.46***	-1.48***	-1.49***	-1.50***	-1.49***
	[0.053]	[0.055]	[0.056]	[0.056]	[0.056]	[0.056]
ASC_{SQ}	-1.98***	-2.17**	-1.77**	-1.88**	-1.37**	-1.35**
	[0.594]	[0.775]	[0.719]	[0.779]	[0.513]	[0.507]
θ_{MOR}	-5.38***	-5.24***	-5.22***	-5.40***	**-4.06*** **	-4.25***
	[0.492]	[0.574]	[0.560]	[0.623]	**[0.815]**	[0.844]
St.dv. parameters						
σ_{CHAN}	1.40***	1.53***	1.59***	1.58***	1.63***	1.62***
	[0.181]	[0.208]	[0.211]	[0.210]	[0.216]	[0.215]
σ_{BAS}	1.73***	1.81***	1.82***	1.83***	1.86***	1.85***
	[0.186]	[0.210]	[0.220]	[0.214]	[0.225]	[0.221]
σ_{VIDEO}	1.06***	1.08***	1.09***	1.13***	1.19***	1.16***
	[0.163]	[0.184]	[0.181]	[0.187]	[0.183]	[0.184]
σ_{SENS}	0.63***	0.62***	0.69***	0.67***	0.81***	0.73***
	[0.192]	[0.204]	[0.192]	[0.200]	[0.182]	[0.192]
σ_{MOR}	<0.001	<0.001	<0.001	<0.001	**4.41*** **	4.57***
	[a]	[a]	[<0.001]	[a]	**[0.723]**	[0.827]
Model fit						
LL	-1712.98	-1699.11	-1699.19	-1696.71	-1691.48	-1691.89
AIC	3462.42	3434.68	3434.84	3429.88	3419.42	3420.24
BIC	3557.60	3529.86	3530.02	3525.06	3514.60	3515.42
cAIC	3462.45	3434.71	3434.87	3429.91	3419.45	3420.27
est. time	00h05'17"	01h16'12"	02h12'00"	04h51'02"	08h44'15"	10h45'52"
draws	100	1,000	2,000	5,000	8,000	10,000

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]. [a]=1.8e+308.

Table 3.4a – Results of the model LV-RPL with one latent variable.

	LV-RPL with one latent variable					
	100	1,000	2,000	5,000	8,000	10,000
Structural equation						
$\gamma_{Female,MOR}$	0.48***	0.42**	0.56***	0.49**	**0.80*** **	0.84***
	[0.122]	[0.164]	[0.185]	[0.188]	**[0.259]**	[0.272]
Measurement equation						
λ_{MOR_risk}	0.58***	0.60***	0.62***	0.62***	1.22*	1.18**
	[0.191]	[0.200]	[0.206]	[0.209]	[0.626]	[0.600]
τ_{MOR_risk1}	0.60***	0.58***	0.63***	0.63***	**1.04** **	1.04**
	[0.157]	[0.157]	[0.165]	[0.164]	**[0.373]**	[0.374]
τ_{MOR_risk2}	1.30***	1.28***	1.34***	1.33***	**1.89*** **	1.88***
	[0.183]	[0.181]	[0.191]	[0.191]	**[0.519]**	[0.514]
τ_{MOR_risk3}	1.54***	1.52***	1.58***	1.57***	**2.18*** **	2.17***
	[0.196]	[0.196]	[0.205]	[0.205]	**[0.563]**	[0.555]
τ_{MOR_risk4}	1.81***	1.79***	1.86***	1.85***	**2.50*** **	2.49***
	[0.204]	[0.204]	[0.214]	[0.214]	**[0.610]**	[0.599]

Table 3.4b – Results of the model LV-RPL with one latent variable.

3.4.2.2 LV-RPL model with two random latent variables

The estimates of the LV-RPL model with two random latent variables are shown in Table 3.5. The results with 10,000 and 8,000 draws seem to be "very stable"; however, instability was detected in earlier steps. The estimates at 1,000 draws appear to be fairly stable, not just for the latent variables but also for the attributes' coefficients. The results at 2,000 draws seem to be stable, but then some instability is noted in the latent variable model with 5,000 draws. Similarly, the coefficients of the structural and the measurement equations show instability only when using 5,000 draws for the first latent variable. Even if the coefficients of the latent variable are quite stable in this model structure, the fact that there is an apparent stability in the model that is not confirmed in subsequent steps using higher draws is a significant finding. This suggests that the definition of stability of parameter estimates should be expanded to include the concept of stability within sequential steps of draws.

A different degree of instability is present in the standard deviations of the latent variables (σ_{MOR} and σ_{SEV}), which are within two standard errors of the estimates of the previous model up to 5,000 draws. These two results are considered as special cases because they were not appropriately calculated with 100 and 2,000 draws. This implies that the heterogeneity connected with the latent components may be hidden if a conventional number of draws is used. As stated in the discussion of the previous model, here the standard errors also seem to be slightly higher at each step, but then they appear to be stabilised when the coefficients are identified. Also, the model with two latent variables is empirically identified at a very large number of draws, such as 8,000.

Consistent conclusions can be drawn about the weight of each latent factor. The coefficient of the latent variable representing mortality risk decreases in magnitude as draw sizes increase. On the other hand, the perception of the severity of consequences increases. In practical terms, using a conventional number of draws could have led to underestimating the latent importance that people place on the seriousness of the consequences of landslide events.

	LV-RPL with two latent variables					
	100	1,000	2,000	5,000	8,000	10,000
Mean parameters						
β_{CHAN}	2.86***	3.02***	3.09***	3.09***	3.15***	3.10***
	[0.146]	[0.177]	[0.187]	[0.191]	[0.196]	[0.196]
β_{BAS}	2.40***	2.55***	2.60***	2.62***	2.63***	2.66***
	[0.150]	[0.189]	[0.191]	[0.196]	[0.196]	[0.196]
β_{VIDEO}	1.81***	**2.00*** **	2.00***	2.03***	2.05***	2.05***
	[0.126]	**[0.157]**	[0.158]	[0.166]	[0.166]	[0.165]
β_{SENS}	1.66***	1.80***	1.79***	1.81***	1.82***	1.82***
	[0.134]	[0.147]	[0.138]	[0.141]	[0.148]	[0.145]
β_{TOLL}	-1.39***	**-1.47*** **	-1.48***	-1.49***	-1.50***	-1.49***
	[0.053]	**[0.057]**	[0.058]	[0.057]	[0.058]	[0.059]
ASC_{SQ}	-2.38***	**-1.22* **	-1.75**	-1.68**	-1.62**	-1.60**
	[0.661]	**[0.632]**	[0.784]	[0.633]	[0.609]	[0.593]
θ_{MOR}	-5.54***	-5.04***	-5.43***	**-3.90*** **	-4.23***	-3.72***
	[0.532]	[0.657]	[0.624]	**[0.864]**	[0.899]	[0.817]
θ_{SEV}	-0.33**	**-0.81** **	-0.85*	-1.47**	-1.32**	-1.58**
	[0.206]	**[0.349]**	[0.479]	[0.626]	[0.542]	[0.683]
St.dv. parameters						
σ_{CHAN}	1.22***	**1.54*** **	1.61***	1.59***	1.63***	1.63***
	[0.172]	**[0.208]**	[0.219]	[0.221]	[0.229]	[0.224]
σ_{BAS}	1.63***	1.81***	1.84***	1.82***	1.88***	1.84***
	[0.177]	[0.211]	[0.228]	[0.214]	[0.230]	[0.226]
σ_{VIDEO}	0.90***	**1.10*** **	1.10***	1.16***	1.13***	1.15***
	[0.175]	**[0.191]**	[0.190]	[0.195]	[0.193]	[0.194]
σ_{SENS}	0.53***	**0.76*** **	0.63***	0.68***	0.76***	0.73***
	[0.189]	**[0.191]**	[0.199]	[0.195]	[0.189]	[0.195]
σ_{MOR}	<0.001	**2.22** **	**<0.001**	**3.90*** **	3.84***	3.77***
	[<0.001]	**[0.885]**	**[a]**	**[0.864]**	[1.050]	[0.905]
σ_{SEV}	<0.001	0.08	<0.001	**1.44** **	0.85	1.54*
	[<0.001]	[0.782]	[<0.001]	**[0.611]**	[1.040]	[0.905]
Model fit						
LL	-3131.61	-3099.33	-3100.82	-3090.49	-3090.69	-3090.80
AIC	6347.58	6283.02	6286.00	6265.34	6265.74	6265.96
BIC	6563.06	6498.50	6501.48	6480.82	6481.22	6481.44
cAIC	6347.64	6283.08	6286.06	6265.40	6265.80	6266.02
est. time	00h15'30"	03h26'45"	06h26'46"	16h09'55"	19h45'34"	21h26'05"
draws	100	1,000	2,000	5,000	8,000	10,000

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]. [a]=1.8e+308.

Table 3.5a – Results of the model LV-RPL with two latent variables.

	LV-RPL with two latent variables					
	100	1,000	2,000	5,000	8,000	10,000
Structural equations						
$\gamma_{Female,MOR}$	0.28***	**0.60*** **	0.48**	**0.80** **	0.63**	0.75**
	[0.113]	**[0.197]**	[0.204]	**[0.293]**	[0.271]	[0.299]
$\gamma_{Female,SEV}$	0.50***	0.49**	0.51***	0.47**	0.44**	0.49**
	[0.149]	[0.180]	[0.167]	[0.176]	[0.174]	[0.176]
Measurement equations						
λ_{MOR_risk}	0.54***	0.51**	0.52**	**1.11* **	0.89*	0.94*
	[0.193]	[0.223]	[0.218]	**[0.575]**	[0.462]	[0.495]
τ_{MOR_risk1}	0.56***	0.61***	0.59***	**0.98*** **	0.79***	0.85***
	[0.164]	[0.185]	[0.175]	**[0.339]**	[0.276]	[0.301]

Continued on next page

	LV-RPL with two latent variables					
	100	1,000	2,000	5,000	8,000	10,000
τ_{MOR_risk2}	1.25***	1.30***	1.28***	**1.80*** **	1.55***	1.62***
	[0.188]	[0.213]	[0.200]	**[0.465]**	[0.360]	[0.396]
τ_{MOR_risk3}	1.49***	1.53***	1.51***	**2.08*** **	1.81***	1.89***
	[0.200]	[0.225]	[0.210]	**[0.502]**	[0.393]	[0.421]
τ_{MOR_risk4}	1.76***	1.80***	1.78***	**2.39*** **	2.10***	2.19***
	[0.211]	[0.236]	[0.219]	**[0.546]**	[0.423]	[0.454]
λ_{SEV_land}	0.68***	0.70***	0.72***	0.72***	0.73***	0.74***
	[0.237]	[0.223]	[0.233]	[0.221]	[0.222]	[0.225]
τ_{SEV_land1}	-4.50***	-4.48***	-4.49***	-4.50***	-4.52***	-4.52***
	[0.633]	[0.644]	[0.641]	[0.654]	[0.644]	[0.645]
τ_{SEV_land2}	-3.25***	-3.23***	-3.24***	-3.25***	-3.27***	-3.26***
	[0.379]	[0.372]	[0.370]	[0.373]	[0.374]	[0.376]
τ_{SEV_land3}	-1.67***	-1.65***	-1.65***	-1.67***	-1.68***	-1.67***
	[0.210]	[0.218]	[0.215]	[0.217]	[0.219]	[0.220]
τ_{SEV_land4}	-0.10	-0.07	-0.07	-0.09	-0.10	-0.07
	[0.159]	[0.170]	[0.169]	[0.169]	[0.171]	[0.174]
λ_{SEV_aval}	1.07***	1.24***	1.16***	1.13***	1.18***	1.15***
	[0.222]	[0.238]	[0.231]	[0.218]	[0.228]	[0.221]
τ_{SEV_aval1}	-1.91***	-1.93***	-1.89***	-1.91***	-1.95***	-1.91***
	[0.236]	[0.272]	[0.254]	[0.252]	[0.262]	[0.256]
τ_{SEV_aval2}	-0.60***	-0.57**	-0.57**	-0.60**	-0.62***	-0.58**
	[0.192]	[0.229]	[0.211]	[0.214]	[0.219]	[0.216]
τ_{SEV_aval3}	0.83***	0.93***	0.88***	0.84***	0.84***	0.87***
	[0.199]	[0.238]	[0.222]	[0.223]	[0.228]	[0.225]
τ_{SEV_aval4}	2.01***	2.18***	2.08***	2.04***	2.07***	2.08***
	[0.268]	[0.311]	[0.294]	[0.287]	[0.295]	[0.293]
λ_{SEV_eart}	1.24***	1.34***	1.32***	1.28***	1.31***	1.31***
	[0.239]	[0.243]	[0.236]	[0.223]	[0.229]	[0.228]
τ_{SEV_eart1}	-1.67***	-1.64***	-1.63***	-1.65***	-1.68***	-1.65***
	[0.234]	[0.263]	[0.252]	[0.251]	[0.258]	[0.259]
τ_{SEV_eart2}	0.14	0.20**	0.18	0.14	0.13	0.17
	[0.201]	[0.231]	[0.218]	[0.218]	[0.222]	[0.224]
τ_{SEV_eart3}	1.24***	1.32***	1.28***	1.24***	1.24***	1.28***
	[0.231]	[0.260]	[0.246]	[0.244]	[0.248]	[0.248]
τ_{SEV_eart4}	2.41***	2.55***	2.48***	2.43***	2.45***	2.48***
	[0.327]	[0.346]	[0.333]	[0.325]	[0.329]	[0.330]
λ_{SEV_flood}	1.56***	1.69***	2.02***	2.14***	1.97***	1.97***
	[0.329]	[0.389]	[0.498]	[0.564]	[0.481]	[0.496]
τ_{SEV_flood1}	-2.02***	-2.01***	-2.16***	-2.29***	-2.22***	-2.17***
	[0.298]	[0.366]	[0.426]	[0.489]	[0.434]	[0.435]
τ_{SEV_flood2}	-0.66**	-0.60**	-0.64**	-0.70**	-0.70**	-0.65**
	[0.230]	[0.274]	[0.301]	[0.332]	[0.309]	[0.306]
τ_{SEV_flood3}	0.91***	1.01***	1.12***	1.14***	1.04***	1.10***
	[0.246]	[0.294]	[0.338]	[0.359]	[0.329]	[0.336]
τ_{SEV_flood4}	2.44***	2.62***	2.87***	2.95***	2.77***	2.83***
	[0.374]	[0.440]	[0.539]	[0.577]	[0.512]	[0.531]

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]. [a]=1.8e+308.

Table 3.5b – Results of the model LV-RPL with two latent variables.

3.4.2.3 LV-RPL model with three random latent variables

Table 3.6 summarises the results obtained from the LV-RPL model with three random latent variables. Some instability is present in the estimates with 1,000 draws, not just for the latent variables but also for the attributes' coefficients. Instability in only the latent variables' coefficients is detected using an intermediate number of draws, such as 1,000, 2,000 and 8,000 draws. The estimated value of the first latent variable θ_{MOR}, own mortality risk, appears to be quite accurate even though it fluctuates between -5.37 and -3.27. However, its stability becomes questionable using 8,000 draws, uncovering a minor instability. There is a different tendency for the second latent variable's coefficient, θ_{SEV}, which varies from -0.92 to -2.06, showing stable estimates after 5,000 draws. This is reinforced by the fact that the severity of landslides' consequences is the only latent factor to have stable structural and measurement equations through the set of draws. The third latent variable indicating fear of landslides is insignificant in all runs. The mortality risk variable has a significant mean as well as a significant standard deviation almost for all the draws, with 2,000 draws representing the only exception. Here, the standard deviation drops from 4.01 to 1.59, becoming insignificant. The psychological heterogeneity with regard to mortality risk cannot be entirely confirmed. Instead, the latent variable "SEV_{in}" shows a reduction in the significance of its standard deviation, which varies considerably between successive steps. As previously stated, the variable "FEA_{in}" is insignificant in mean, and it shows a reduction in the significance of the standard deviation through the draws, leading to an insignificant parameter.

The model fitted with 10,000 draws seems to provide more stable estimates than the previous ones. However, not all the parameters can be identified, as shown by the standard deviation of the second latent variable. Overall, this model follows the trend of showing higher standard errors when more draws are used. As noticed in the previous model, some standard errors seem to settle using a very large number of draws.

We conclude that this model is not identified at 10,000 draws because one coefficient (of the latent variable) is not stable. Consistent conclusions cannot be derived at this stage. As initially pointed out, the more latent variables are included in the model structure, the more draws are needed for the simulation procedure to discover if a coefficient can be identified. However, the increased computation cost for a Monte Carlo simulation procedure has to be considered before using a number of draws larger than 10,000. This result is in line with previous studies that pointed out the difficulty to estimate several latent variables and having them all significant.

	LV-RPL with three latent variables					
	100	1,000	2,000	5,000	8,000	10,000
Mean parameters						
β_{CHAN}	2.88***	3.03***	3.10***	3.10***	3.14***	3.12***
	[0.153]	[0.188]	[0.196]	[0.193]	[0.205]	[0.202]
β_{BAS}	2.33***	**2.58*****	2.61***	2.65***	2.65***	2.67***
	[0.144]	**[0.201]**	[0.199]	[0.201]	[0.200]	[0.201]
β_{VIDEO}	1.83***	1.99***	2.01***	2.04***	2.04***	2.05***
	[0.133]	[0.156]	[0.162]	[0.165]	[0.166]	[0.168]
β_{SENS}	1.69***	1.80***	1.81***	1.80***	1.82***	1.83***
	[0.139]	[0.143]	[0.148]	[0.148]	[0.151]	[0.148]
β_{TOLL}	-1.39***	**-1.48*****	-1.49***	-1.49***	-1.50***	-1.50***
	[0.055]	**[0.059]**	[0.061]	[0.058]	[0.059]	[0.060]
ASC_{SQ}	-1.29**	-1.72**	-2.49**	-2.05***	-2.08***	-1.46**
	[0.593]	[0.698]	[0.894]	[0.725]	[0.675]	[0.639]
θ_{MOR}	-4.88***	-5.37***	-4.66***	-4.14***	**-3.27*****	-4.15***
	[0.520]	[0.896]	[0.853]	[0.887]	**[0.830]**	[0.911]
θ_{SEV}	-1.64***	**-0.92****	**-2.06*****	-1.99**	-1.67**	-1.65**
	[0.209]	**[0.361]**	**[0.641]**	[0.718]	[0.625]	[0.707]
θ_{FEA}	-0.58	**1.12**	1.72	1.00	**0.24**	0.70
	[0.424]	**[0.718]**	[1.060]	[0.759]	**[0.725]**	[1.070]
St.dv. parameters						
σ_{CHAN}	1.26***	**1.57*****	1.64***	1.60***	1.63***	1.63***
	[0.182]	**[0.188]**	[0.231]	[0.224]	[0.230]	[0.229]
σ_{BAS}	1.53***	**1.86*****	1.86***	1.82***	1.86***	1.85***
	[0.176]	**[0.218]**	[0.233]	[0.218]	[0.228]	[0.229]
σ_{VIDEO}	0.98***	1.08***	1.10***	1.14***	1.12***	1.15***
	[0.177]	[0.185]	[0.197]	[0.197]	[0.197]	[0.203]
σ_{SENS}	0.55***	0.66***	0.66***	0.69***	0.75***	0.74***
	[0.196]	[0.206]	[0.201]	[0.190]	[0.200]	[0.201]
σ_{MOR}	<0.001	**4.01*****	**1.59**	**4.14*****	4.11***	3.95***
	[a]	**[0.923]**	**[1.210]**	**[0.887]**	[0.806]	[0.833]
σ_{SEV}	1.26***	**0.04**	**1.79***	1.40**	**2.27****	**0.99**
	[0.300]	**[0.934]**	**[0.952]**	[0.565]	**[0.767]**	**[1.230]**
σ_{FEA}	1.06**	**<0.001**	**1.31**	0.97*	0.97	0.30
	[0.423]	**[a]**	**[0.800]**	[1.450]	[1.290]	[1.790]
Model fit						
LL	-3512.04	-3476.67	-3475.13	-3470.68	-3470.13	-3471.49
AIC	7125.46	7054.72	7051.64	7042.74	7041.64	7044.36
BIC	7382.43	7311.69	7308.61	7299.71	7298.61	7301.33
cAIC	7125.53	7054.79	7051.71	7042.81	7041.71	7044.43
est. time	00h43'01"	04h44'07"	08h35'37"	11h39'57"	19h46'18"	24h13'41"
draws	100	1,000	2,000	5,000	8,000	10,000

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]. [a]=1.8e+308.

Table 3.6a – Results of the model LV-RPL with three latent variables.

	LV-RPL with three latent variables					
	100	1,000	2,000	5,000	8,000	10,000
Structural equations						
$\gamma_{Female,MOR}$	0.41**	**1.11*** **	1.01*	**0.72** **	0.61**	0.90**
	[0.181]	**[0.253]**	[0.528]	**[0.272]**	[0.252]	[0.425]
$\gamma_{Female,SEV}$	0.68***	0.50**	0.50**	0.47**	0.47**	0.47**
	[0.154]	[0.187]	[0.188]	[0.185]	[0.185]	[0.194]
$\gamma_{Female,FEA}$	0.69	2.30	1.81	**0.54**	0.63	0.76
	[0.484]	[1.680]	[1.26]	**[0.343]**	[0.587]	[0.860]
Measurement equations						
λ_{MOR_risk}	0.43**	0.66**	0.63**	1.22*	1.40	0.90*
	[0.204]	[0.279]	[0.291]	[0.725]	[0.899]	[0.527]
τ_{MOR_risk1}	0.57***	**0.84*** **	0.77***	0.98**	1.02**	0.92***
	[0.179]	**[0.260]**	[0.253]	[0.392]	[0.461]	[0.314]
τ_{MOR_risk2}	1.24***	**1.56*** **	1.49***	1.83***	1.92**	1.69***
	[0.201]	**[0.309]**	[0.291]	[0.557]	[0.692]	[0.402]
τ_{MOR_risk3}	1.48***	**1.81*** **	1.73***	2.12***	2.22***	1.95***
	[0.210]	**[0.323]**	[0.303]	[0.607]	[0.795]	[0.427]
τ_{MOR_risk4}	1.74***	**2.09*** **	2.01***	2.44***	2.56***	2.25***
	[0.222]	**[0.343]**	[0.320]	[0.665]	[0.837]	[0.457]
λ_{SEV_land}	0.66**	0.73***	0.74***	0.75***	0.71***	0.74***
	[0.244]	[0.226]	[0.241]	[0.246]	[0.238]	[0.228]
τ_{SEV_land1}	-4.42***	-4.49***	-4.50***	-4.51***	-4.49***	-4.52***
	[0.653]	[0.664]	[0.672]	[0.677]	[0.674]	[0.671]
τ_{SEV_land2}	-3.17***	-3.23***	-3.25***	-3.27***	-3.24***	-3.27***
	[0.394]	[0.407]	[0.405]	[0.412]	[0.409]	[0.409]
τ_{SEV_land3}	-1.60***	-1.64***	-1.66***	-1.68***	-1.66***	-1.67***
	[0.217]	[0.233]	[0.230]	[0.231]	[0.226]	[0.234]
τ_{SEV_land4}	-0.03	-0.06	-0.07	-0.09	-0.08	-0.08
	[0.173]	[0.184]	[0.186]	[0.183]	[0.181]	[0.191]
λ_{SEV_aval}	1.05***	1.27***	1.14***	1.11***	1.17***	1.15***
	[0.219]	[0.252]	[0.222]	[0.217]	[0.222]	[0.224]
τ_{SEV_aval1}	-1.78***	-1.93***	-1.89***	-1.90***	-1.91***	-1.91***
	[0.230]	[0.272]	[0.252]	[0.252]	[0.259]	[0.264]
τ_{SEV_aval2}	-0.48**	-0.57**	-0.57**	-0.60**	-0.59**	-0.59**
	[0.196]	[0.235]	[0.215]	[0.214]	[0.221]	[0.224]
τ_{SEV_aval3}	0.94***	0.94***	0.88***	0.83***	0.88***	0.87***
	[0.218]	[0.248]	[0.230]	[0.226]	[0.232]	[0.235]
τ_{SEV_aval4}	2.09***	2.20***	2.08***	2.02***	2.10***	2.08***
	[0.286]	[0.319]	[0.296]	[0.286]	[0.297]	[0.300]
λ_{SEV_eart}	1.21***	1.34***	1.28***	1.29***	1.32***	1.30***
	[0.249]	[0.249]	[0.231]	[0.235]	[0.235]	[0.232]
τ_{SEV_eart1}	-1.53***	-1.63***	-1.62***	-1.66***	-1.65***	-1.65***
	[0.220]	[0.273]	[0.264]	[0.263]	[0.263]	[0.270]
τ_{SEV_eart2}	0.26	0.20	0.17	0.14	0.17	0.16
	[0.206]	[0.238]	[0.229]	[0.224]	[0.226]	[0.231]
τ_{SEV_eart3}	1.35***	1.32***	1.27***	1.24***	1.28***	1.27***
	[0.241]	[0.268]	[0.260]	[0.251]	[0.257]	[0.257]
τ_{SEV_eart4}	2.50***	2.54***	2.46***	2.43***	2.49***	2.47***
	[0.342]	[0.351]	[0.342]	[0.332]	[0.337]	[0.337]
λ_{SEV_flood}	1.63***	1.66***	2.02***	2.12***	1.96***	2.00***
	[0.349]	[0.389]	[0.501]	[0.546]	[0.477]	[0.504]
τ_{SEV_flood1}	-1.89***	-1.98***	-2.17***	-2.28***	-2.17***	-2.20***
	[0.298]	[0.357]	[0.444]	[0.476]	[0.424]	[0.450]

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Table 3.6b – continued from previous page

	LV-RPL with three latent variables					
	100	1,000	2,000	5,000	8,000	10,000
τ_{SEV_flood2}	-0.49**	-0.60**	-0.64**	-0.70**	-0.65**	-0.66**
	[0.232]	[0.274]	[0.317]	[0.327]	[0.309]	[0.322]
τ_{SEV_flood3}	1.11***	1.00***	1.13***	1.12***	1.09***	1.10***
	[0.262]	[0.299]	[0.348]	[0.359]	[0.332]	[0.353]
τ_{SEV_flood4}	2.66***	2.58***	2.88***	2.91***	2.82***	2.84***
	[0.409]	[0.443]	[0.543]	[0.577]	[0.518]	[0.554]
λ_{FEA_land}	0.76**	**0.27**	**0.62**	1.64	1.42	1.09
	[0.368]	**[0.224]**	**[0.340]**	[1.560]	[2.040]	[1.670]
τ_{FEA_land1}	-2.39***	**-2.17*** **	-2.15***	-2.98**	-2.73*	-2.52**
	[0.338]	**[0.272]**	[0.293]	[1.440]	[1.620]	[1.160]
τ_{FEA_land2}	-1.02***	-0.86***	-0.83***	-1.22*	-1.09	-1.01*
	[0.236]	[0.197]	[0.208]	[0.644]	[0.747]	[0.564]
τ_{FEA_land3}	0.13	0.20	0.27	0.30	0.33	0.27
	[0.209]	[0.193]	[0.203]	[0.337]	[0.325]	[0.276]
τ_{FEA_land4}	1.33***	1.28***	1.38***	1.86*	1.78	1.59*
	[0.260]	[0.224]	[0.252]	[0.968]	[1.150]	[0.834]

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.].

Table 3.6b – Results of the model LV-RPL with three latent variables.

3.5 Conclusions

This study explored the stability of maximum simulated likelihood estimates of parameters for three LV-RPL models when the number of draws is gradually increased in estimation. The importance of testing for empirical identification is clearly supported by the findings of this study. In fact, some coefficients can be identified only when using a very large number of draws.

All the LV-RPL models provide very stable results with regard to the attributes' coefficients. However, some degrees of instability are present in the estimated coefficients of the latent variables and their estimated standard deviations. Overall, the LV-RPL model with one latent variable presents stable parameter estimates across draws. Using 10,000 draws, consistent conclusions can be drawn with regard to the presence of psychological sources of heterogeneity in the latent variable, previously undetected at a conventional number of draws. Stability discontinuity is observed when initial apparent stability is not confirmed at higher draws (as high as 8,000), suggesting that the definition of stability should be further expanded. The estimates from the model with two latent variables are quite stable when using more than 5,000 draws. Additionally, results suggest that using a low number of draws could lead to misinterpretation of the relative dominance of latent variables. Lastly, including a third latent variable in the model creates more instability in the results. Although the estimates appear to become more stable using a large number of draws, the results show that not all the parameters are indeed identified, leading to uncertain conclusions.

On the one hand, these findings stress the need for testing for empirical identification with a progressively larger set of draws. On the other hand, it is necessary to reflect on the fact that 8,000 and 10,000 draws are very large numbers of draws for this model structure, certainly higher than what is routinely used in the literature. Using more draws substantially increases estimation run time and the time for specification search.

Supplementary to the goal of exploring stability**,** this study was designed to model individuals' risk perceptions as latent constructs and to determine the impact of these psychological sources of heterogeneity, together with unobservable sources, on the baseline scenario in the context of landslide hazards.

The model specification selected provides new insights compared to the reduced version without latent variables. The results show the importance that people in mountainous areas place on reducing landslide hazards and how this is strongly connected to their underlying perceptions of risk. We formulated the hypothesis that strong risk perceptions may have a positive impact on aversion to the riskiest option. It is now possible to state that the parameter estimates for the latent variables confirm our expectation. Respondents with negative values of latent variables were less likely to choose the *status quo* option in favour of policies delivering lower landslide risks. The latent construct referring to the perception of own mortality risk has the largest magnitude, followed by the risk severity. The degree of fear of landslide is the only insignificant latent variable. It appears that the inclusion of latent variables affects respondents' utility for the riskiest scenario, a result that seems to be consistent with the PMT, with the only exception being the variable measuring landslide fear. Such fear could be seen as a general concept in the respondents' minds, which is not necessarily associated with tangible consequences of landslides. Other latent factors investigated here motivate respondents to increase safety as they more directly evoke dangerous scenarios. According to our results, there is evidence of the existence of multiple sources of heterogeneity in people's preferences for mitigation programmes based on risk perceptions. The models' specifications with latent constructs add a psychological dimension to taste variation. Generally speaking, people's perceptions of natural hazards are complex and deal with psychological and social aspects linked to the policy decisions. Thus, public protection policies play a major role in shaping the risk perception of the population and their protective behaviours. A model without the latent variables can be sensitive to policies that modify the availability of protection devices against landslides. However, a model with latent variables can, in addition, be sensitive to changes in perceptions due to different factors such as education campaigns and changes in the current scenario. All of these changes can have repercussions on the latent variables and therefore affect people's choices. Having said that, the concerns raised by Chorus and Kroesen (2014) are particularly salient in the context of protection behaviour. The issue of endogeneity of the latent variable, together with its cross-sectional nature, discourage the derivation of a policy aiming at changing the latent variable and the consequent choice behaviour. An example of this is the implementation of communication strategies that take into account subjective risk perceptions as a fundamental determinant in making people more willing to support mitigation programmes initially not perceived as necessary. In the present context of study, a landslide event may modify individuals' risk perceptions. Therefore, policy decisions may benefit from the additional information obtained from the adoption of the latent variable framework in conjunction with choice modelling, but this information should be used with caution. Caution should be used in assessing the consistency of the estimated latent variables coefficients.

Specific tried and tested guidance aiming at good practices is not yet available to persuade hesitant practitioners to adopt this model structure. That said, some recommendations can be derived from this and previous studies on the topic. First, the main goal of the policy of interest should be a driver in choosing the proper model specification, and the data quality and sample size have to be large enough to support complex modelling. Second, analysts should be careful in selecting the survey questions to include in the model through measurement equations. The questionnaires should be designed a priori, taking into account the specific investigation being performed. The formulation of the survey questions has to be clear and defined on an appropriate scale. Lastly, analysts should carefully consider the adoption of this model specification considering: *(i)* the stability of parameter estimates (with respect to simulation starting points, number of draws, old-out samples, resampling techniques, temporal and spatial transferability); *(ii)* the sensitivity to the number of latent variables; *(iii)* the issue of multicollinearity, when explanatory variables are correlated; and *(iv)* the computational complexity of the model structure in terms of estimation time and interpretation of the results. In our case, the reduced form (i.e. RPL model) provided very stable estimates, but it failed to account for psychological sources of heterogeneity. In contrast, the LV-RPL models resulted in more informative although less precise models. Moreover, as the model complexity increases so does the number of draws needed for testing empirical identification. In fact, using a low number of draws can obscure important implications in the interpretation of the estimated parameters. When interaction terms between latent variables and attributes are significant, and have substantial magnitude, this instability may be reflected in changes in WTP estimates. Another important factor for practitioners to consider is the different estimation time of these models as implied by the number of draws. In our study, from 100 to 10,000 draws, it increased from a few minutes to 10 hours when one latent variable was used. Adding more latent variables to the model resulted in an extended estimation time of one or two days. In general, computational complexity and challenging interpretation of outputs are common weak points of this group of models. A simplification of the model specification may be necessary to make estimation feasible when the multi-dimensional integral becomes too complex.

We believe that the investigation conducted can be seen as a contribution to the topic of estimates stability to an increasing number of draws and latent variables. Furthermore, the findings provide insights into respondents' decision processes in the context of risk and threats to life.

However, the study has some limitations such as the difficulty in defining suitable indicators for the latent constructs and scale of measure. Other limitations also exist, such as the measurement bias because respondents tended to engage in typically superstitious behaviour when replying to the question on perception of their own mortality risk. The difficulties in collecting completed questionnaires, together with the seasonality of tourism in the area, did not allow for a larger sample size. However, the sampled portion of residents was almost 1% of the whole population living in the area of study. Moreover, we are aware of the fact that other psychological theories than PMT could have been tested in the context of safety choices. Lastly, we acknowledge a limitation in the model structure that did not allow the latent constructs to affect implicit prices for policy attributes. This was because exploring the empirical identification with a large number of draws would have increased significantly the extended model computational time.

Further studies are still required on the issue of estimate stability for choice models with latent variables. Future and new research can be conducted on the stability of the latent variables' indicators (i.e. risk perceptions) over time, such as after a landslide event.

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3.7 Appendix

Variables	Description	Mean	St.dv.	Min	Max
Age	Age of the respondent	48	15	18	92
Gender	Dummy (0=male; 1=female)	0.47	0.50	0	1
Family members	Number of family members	2.72	1.23	1	9
Minor family members	Number of minor members	0.34	0.75	0	6
Residents	Dummy (0=visitor; 1= resident)	0.43	0.5	0	1

Table 3.7 – Demographic characteristics of the sample.

Correlations	Landslide	Avalanche	Earthquake	Flood
Landslide	1			
Avalanche	0.24	1		
Earthquake	0.06	0.34	1	
Flood	0.26	0.30	0.39	1

Table 3.8 – Correlation coefficients between natural hazards.

Attributes	Acronym	Levels
Diverging channel	CHAN	[0,1]
Retaining basin	BAS	[0,1]
Video cameras	VIDEO	[0,1]
Acoustic sensors	SENS	[0,1]
Road toll	TOLL	€1,€2,€3,€4

Table 3.9 – Attributes and attribute levels in the CE.

	RPL					
	100	1,000	2,000	5,000	8,000	10,000
Mean parameters						
β_{CHAN}	2.66***	2.95***	2.97***	2.96***	2.96***	2.96***
	[0.172]	[0.199]	[0.200]	[0.202]	[0.204]	[0.203]
β_{BAS}	2.39***	2.64***	2.67***	2.67***	2.70***	2.70***
	[0.155]	[0.195]	[0.197]	[0.197]	[0.197]	[0.200]
β_{VIDEO}	2.01***	2.27***	2.24***	2.24***	2.25***	2.26***
	[0.171]	[0.202]	[0.205]	[0.205]	[0.203]	[0.204]
β_{SENS}	1.72***	1.87***	1.86***	1.86***	1.88***	1.88***
	[0.158]	[0.187]	[0.188]	[0.189]	[0.189]	[0.190]
β_{TOLL}	-1.46***	**-1.53*** **	-1.53***	-1.53***	-1.53***	-1.53***
	[0.049]	**[0.051]**	[0.051]	[0.051]	[0.051]	[0.051]
ASC_{SQ}	0.05	-0.06	-0.08	-0.08	-0.07	-0.07
	[0.155]	[0.168]	[0.167]	[0.167]	[0.166]	[0.168]
St.dv. parameters						
σ_{CHAN}	1.86***	1.89***	1.92***	1.89***	1.90***	1.89***
	[0.200]	[0.214]	[0.209]	[0.226]	[0.220]	[0.225]
σ_{BAS}	1.96***	2.04***	2.09***	2.07***	2.03***	2.08***
	[0.173]	[0.202]	[0.215]	[0.212]	[0.212]	[0.215]
σ_{VIDEO}	1.84***	1.93***	1.97***	1.93***	1.94***	1.92***
	[0.163]	[0.193]	[0.195]	[0.192]	[0.192]	[0.194]
σ_{SENS}	1.42***	1.50***	1.47***	1.49***	1.47***	1.48***
	[0.154]	[0.176]	[0.175]	[0.179]	[0.177]	[0.180]
Model fit						
LL	-1552.4	-1522.17	-1523.73	-1524.82	-1522.34	-1522.57
AIC	3124.95	3064.49	3067.61	3069.79	3064.83	3065.28
BIC	3177.93	3117.47	3120.59	3122.77	3117.81	3118.26
cAIC	3124.96	3064.50	3067.62	3069.80	3064.84	3065.29
est. time	00h01'18"	00h09'44"	00h38'07"	00h59'29"	01h21'43"	01h42'57"
draws	100	1,000	2,000	5,000	8,000	10,000

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]

Table 3.10 – RPL model results.

Variables	Coefficient estimates																	
	LV-RPL with one latent variable						LV-RPL with two latent variables						LV-RPL with three latent variables					
	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000
Mean parameters																		
β_{CHAN}	2.90***	3.02***	3.09***	3.08***	3.13***	3.12***	2.86***	3.02***	3.09***	3.09***	3.15***	3.10***	2.88***	3.03***	3.10***	3.10***	3.14***	3.12***
	[0.148]	[0.169]	[0.178]	[0.178]	[0.184]	[0.183]	[0.146]	[0.177]	[0.187]	[0.191]	[0.196]	[0.196]	[0.153]	[0.188]	[0.196]	[0.193]	[0.205]	[0.202]
β_{BAS}	2.48***	2.55***	2.61***	2.59***	2.68***	2.66***	2.40***	2.55***	2.60***	2.62***	2.63***	2.66***	2.33***	**2.58*****	2.61***	2.65***	2.65***	2.67***
	[0.156]	[0.175]	[0.177]	[0.182]	[0.186]	[0.185]	[0.150]	[0.189]	[0.191]	[0.196]	[0.196]	[0.196]	[0.144]	**[0.201]**	[0.199]	[0.201]	[0.200]	[0.201]
β_{VIDEO}	1.92***	1.98***	2.01***	2.02***	2.07***	2.04***	1.81***	**2.00*****	2.00***	2.03***	2.05***	2.05***	1.83***	1.99***	2.01***	2.04***	2.04***	2.05***
	[0.132]	[0.146]	[0.147]	[0.151]	[0.157]	[0.156]	[0.126]	**[0.157]**	[0.158]	[0.166]	[0.166]	[0.165]	[0.133]	[0.156]	[0.162]	[0.165]	[0.166]	[0.168]
β_{SENS}	1.73***	1.78***	1.80***	1.80***	1.83***	1.82***	1.66***	1.80***	1.79***	1.81***	1.82***	1.82***	1.69***	1.80***	1.81***	1.80***	1.82***	1.83***
	[0.131]	[0.132]	[0.135]	[0.134]	[0.144]	[0.138]	[0.134]	[0.147]	[0.138]	[0.141]	[0.148]	[0.145]	[0.139]	[0.143]	[0.148]	[0.148]	[0.151]	[0.148]
β_{TOLL}	-1.44***	-1.46***	-1.48***	-1.49***	-1.50***	-1.49***	-1.39***	**-1.47*****	-1.48***	-1.49***	-1.50***	-1.49***	-1.39***	**-1.48*****	-1.49***	-1.49***	-1.50***	-1.50***
	[0.053]	[0.055]	[0.056]	[0.056]	[0.056]	[0.056]	[0.053]	**[0.057]**	[0.058]	[0.057]	[0.058]	[0.059]	[0.055]	**[0.059]**	[0.061]	[0.058]	[0.059]	[0.060]
ASC_{SQ}	-1.98***	-2.17**	-1.77**	-1.88**	-1.37**	-1.35**	-2.38***	**-1.22***	-1.75**	-1.68**	-1.62**	-1.60**	-1.29**	-1.72**	-2.49**	-2.05***	-2.08***	-1.46**
	[0.594]	[0.775]	[0.719]	[0.779]	[0.513]	[0.507]	[0.661]	**[0.632]**	[0.784]	[0.633]	[0.609]	[0.593]	[0.593]	[0.698]	[0.894]	[0.725]	[0.675]	[0.639]
θ_{MOR}	-5.38***	-5.24***	-5.22***	-5.40***	**-4.06*****	-4.25***	-5.54***	-5.04***	-5.43***	**-3.90*****	-4.23***	-3.72***	-4.88***	-5.37***	-4.66***	-4.14***	**-3.27*****	-4.15***
	[0.492]	[0.574]	[0.560]	[0.623]	**[0.815]**	[0.844]	[0.532]	[0.657]	[0.624]	**[0.864]**	[0.899]	[0.817]	[0.520]	[0.896]	[0.853]	[0.887]	**[0.830]**	[0.911]
θ_{SEV}	-	-	-	-	-	-	-0.33**	**-0.81****	-0.85*	-1.47**	-1.32**	-1.58**	-1.64***	**-0.92****	**-2.06*****	-1.99**	-1.67**	-1.65**
	-	-	-	-	-	-	[0.206]	**[0.349]**	[0.479]	[0.626]	[0.542]	[0.683]	[0.209]	**[0.361]**	**[0.641]**	[0.718]	[0.625]	[0.707]
θ_{FEA}	-	-	-	-	-	-	-	-	-	-	-	-	-0.58	**1.12**	1.72	1.00	**0.24**	0.70
	-	-	-	-	-	-	-	-	-	-	-	-	[0.424]	**[0.718]**	[1.060]	[0.759]	**[0.725]**	[1.070]
St.dv. parameters																		
σ_{CHAN}	1.40***	1.53***	1.59***	1.58***	1.63***	1.62***	1.22***	**1.54*****	1.61***	1.59***	1.63***	1.63***	1.26***	**1.57*****	1.64***	1.60***	1.63***	1.63***
	[0.181]	[0.208]	[0.211]	[0.210]	[0.216]	[0.215]	[0.172]	**[0.208]**	[0.219]	[0.221]	[0.229]	[0.224]	[0.182]	**[0.188]**	[0.231]	[0.224]	[0.230]	[0.229]
σ_{BAS}	1.73***	1.81***	1.82***	1.83***	1.86***	1.85***	1.63***	1.81***	1.84***	1.82***	1.88***	1.84***	1.53***	**1.86*****	1.86***	1.82***	1.86***	1.85***
	[0.186]	[0.210]	[0.220]	[0.214]	[0.225]	[0.221]	[0.177]	[0.211]	[0.228]	[0.214]	[0.230]	[0.226]	[0.176]	**[0.218]**	[0.233]	[0.218]	[0.228]	[0.229]
σ_{VIDEO}	1.06***	1.08***	1.09***	1.13***	1.19***	1.16***	0.90***	**1.10*****	1.10***	1.16***	1.13***	1.15***	0.98***	1.08***	1.10***	1.14***	1.12***	1.15***
	[0.163]	[0.184]	[0.181]	[0.187]	[0.183]	[0.184]	[0.175]	**[0.191]**	[0.190]	[0.195]	[0.193]	[0.194]	[0.177]	[0.185]	[0.197]	[0.197]	[0.197]	[0.203]
σ_{SENS}	0.63***	0.62***	0.69***	0.67***	0.81***	0.73***	0.53***	**0.76*****	0.63***	0.68***	0.76***	0.73***	0.55***	0.66***	0.66***	0.69***	0.75***	0.74***
	[0.192]	[0.204]	[0.192]	[0.200]	[0.182]	[0.192]	[0.189]	**[0.191]**	[0.199]	[0.195]	[0.189]	[0.195]	[0.196]	[0.206]	[0.201]	[0.190]	[0.200]	[0.201]
σ_{MOR}	<0.001	<0.001	<0.001	<0.001	**4.41*****	4.57***	<0.001	**2.22****	**<0.001**	**3.90*****	3.84***	3.77***	<0.001	**4.01*****	**1.59**	**4.14*****	4.11***	3.95***
	[a]	[a]	[<0.001]	[a]	**[0.723]**	[0.827]	[<0.001]	**[0.885]**	**[a]**	**[0.864]**	[1.050]	[0.905]	[a]	**[0.923]**	**[1.210]**	**[0.887]**	[0.806]	[0.833]
σ_{SEV}	-	-	-	-	-	-	<0.001	0.08	<0.001	**1.44****	0.85	1.54*	1.26***	**0.04**	**1.79***	1.40**	**2.27****	**0.99**
	-	-	-	-	-	-	[<0.001]	[0.782]	[<0.001]	**[0.611]**	[1.040]	[0.905]	[0.300]	**[0.934]**	**[0.952]**	[0.565]	**[0.767]**	**[1.230]**
σ_{FEA}	-	-	-	-	-	-	-	-	-	-	-	-	1.06**	**<0.001**	**1.31**	0.97*	0.97	0.30
	-	-	-	-	-	-	-	-	-	-	-	-	[0.423]	[a]	**[0.800]**	[1.450]	[1.290]	[1.790]

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Table 3.11 – continued from previous page

Variables	Coefficient estimates																	
	LV-RPL with one latent variable						LV-RPL with two latent variables						LV-RPL with three latent variables					
	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000
Structural equations																		
$\gamma_{Female,MOR}$	0.48***	0.42**	0.56***	0.49**	**0.80*** **	0.84***	0.28***	**0.60*** **	0.48**	**0.80** **	0.63**	0.75**	0.41**	**1.11*** **	1.01*	**0.72** **	0.61**	0.90**
	[0.122]	[0.164]	[0.185]	[0.188]	**[0.259]**	[0.272]	[0.113]	**[0.197]**	[0.204]	**[0.293]**	[0.271]	[0.299]	[0.181]	**[0.253]**	[0.528]	**[0.272]**	[0.252]	[0.425]
$\gamma_{Female,SEV}$	-	-	-	-	-	-	0.50***	0.49**	0.51***	0.47**	0.44**	0.49**	0.68***	0.50**	0.50**	0.47**	0.47**	0.47**
	-	-	-	-	-	-	[0.149]	[0.180]	[0.167]	[0.176]	[0.174]	[0.176]	[0.154]	[0.187]	[0.188]	[0.185]	[0.185]	[0.194]
$\gamma_{Female,FEA}$	-	-	-	-	-	-	-	-	-	-	-	-	0.69	2.30	1.81	**0.54**	0.63	0.76
	-	-	-	-	-	-	-	-	-	-	-	-	[0.484]	[1.680]	[1.26]	**[0.343]**	[0.587]	[0.860]
Measurement equations																		
λ_{MOR_risk}	0.58***	0.60***	0.62***	0.62***	1.22*	1.18**	0.54***	0.51**	0.52**	**1.11***	0.89*	0.94*	0.43**	0.66**	0.63**	1.22*	1.40	0.90*
	[0.191]	[0.200]	[0.206]	[0.209]	[0.626]	[0.600]	[0.193]	[0.223]	[0.218]	**[0.575]**	[0.462]	[0.495]	[0.204]	[0.279]	[0.291]	[0.725]	[0.899]	[0.527]
τ_{MOR_risk1}	0.60***	0.58***	0.63***	0.63***	**1.04** **	1.04**	0.56***	0.61***	0.59***	**0.98*** **	0.79***	0.85***	0.57***	**0.84*** **	0.77***	0.98**	1.02**	0.92***
	[0.157]	[0.157]	[0.165]	[0.164]	**[0.373]**	[0.374]	[0.164]	[0.185]	[0.175]	**[0.339]**	[0.276]	[0.301]	[0.179]	**[0.260]**	[0.253]	[0.392]	[0.461]	[0.314]
τ_{MOR_risk2}	1.30***	1.28***	1.34***	1.33***	**1.89*** **	1.88***	1.25***	1.30***	1.28***	**1.80*** **	1.55***	1.62***	1.24***	**1.56*** **	1.49***	1.83***	1.92**	1.69***
	[0.183]	[0.181]	[0.191]	[0.191]	**[0.519]**	[0.514]	[0.188]	[0.213]	[0.200]	**[0.465]**	[0.360]	[0.396]	[0.201]	**[0.309]**	[0.291]	[0.557]	[0.692]	[0.402]
τ_{MOR_risk3}	1.54***	1.52***	1.58***	1.57***	**2.18*** **	2.17***	1.49***	1.53***	1.51***	**2.08*** **	1.81***	1.89***	1.48***	**1.81*** **	1.73***	2.12***	2.22***	1.95***
	[0.196]	[0.196]	[0.205]	[0.205]	**[0.563]**	[0.555]	[0.200]	[0.225]	[0.210]	**[0.502]**	[0.393]	[0.421]	[0.210]	**[0.323]**	[0.303]	[0.607]	[0.795]	[0.427]
τ_{MOR_risk4}	1.81***	1.79***	1.86***	1.85***	**2.50*** **	2.49***	1.76***	1.80***	1.78***	**2.39*** **	2.10***	2.19***	1.74***	**2.09*** **	2.01***	2.44***	2.56***	2.25***
	[0.204]	[0.204]	[0.214]	[0.214]	**[0.610]**	[0.599]	[0.211]	[0.236]	[0.219]	**[0.546]**	[0.423]	[0.454]	[0.222]	**[0.343]**	[0.320]	[0.665]	[0.837]	[0.457]
λ_{SEV_land}	-	-	-	-	-	-	0.68***	0.70***	0.72***	0.72***	0.73***	0.74***	0.66**	0.73***	0.74***	0.75***	0.71***	0.74***
	-	-	-	-	-	-	[0.237]	[0.223]	[0.233]	[0.221]	[0.222]	[0.225]	[0.244]	[0.226]	[0.241]	[0.246]	[0.238]	[0.228]
τ_{SEV_land1}	-	-	-	-	-	-	-4.50***	-4.48***	-4.49***	-4.50***	-4.52***	-4.52***	-4.42***	-4.49***	-4.50***	-4.51***	-4.49***	-4.52***
	-	-	-	-	-	-	[0.633]	[0.644]	[0.641]	[0.654]	[0.644]	[0.645]	[0.653]	[0.664]	[0.672]	[0.677]	[0.674]	[0.671]
τ_{SEV_land2}	-	-	-	-	-	-	-3.25***	-3.23***	-3.24***	-3.25***	-3.27***	-3.26***	-3.17***	-3.23***	-3.25***	-3.27***	-3.24***	-3.27***
	-	-	-	-	-	-	[0.379]	[0.372]	[0.370]	[0.373]	[0.374]	[0.376]	[0.394]	[0.407]	[0.405]	[0.412]	[0.409]	[0.409]
τ_{SEV_land3}	-	-	-	-	-	-	-1.67***	-1.65***	-1.65***	-1.67***	-1.68***	-1.67***	-1.60***	-1.64***	-1.66***	-1.68***	-1.66***	-1.67***
	-	-	-	-	-	-	[0.210]	[0.218]	[0.215]	[0.217]	[0.219]	[0.220]	[0.217]	[0.233]	[0.230]	[0.231]	[0.226]	[0.234]
τ_{SEV_land4}	-	-	-	-	-	-	-0.10	-0.07	-0.07	-0.09	-0.10	-0.07	-0.03	-0.06	-0.07	-0.09	-0.08	-0.08
	-	-	-	-	-	-	[0.159]	[0.170]	[0.169]	[0.169]	[0.171]	[0.174]	[0.173]	[0.184]	[0.186]	[0.183]	[0.181]	[0.191]
λ_{SEV_aval}	-	-	-	-	-	-	1.07***	1.24***	1.16***	1.13***	1.18***	1.15***	1.05***	1.27***	1.14***	1.11***	1.17***	1.15***
	-	-	-	-	-	-	[0.222]	[0.238]	[0.231]	[0.218]	[0.228]	[0.221]	[0.219]	[0.252]	[0.222]	[0.217]	[0.222]	[0.224]
τ_{SEV_aval1}	-	-	-	-	-	-	-1.91***	-1.93***	-1.89***	-1.91***	-1.95***	-1.91***	-1.78***	-1.93***	-1.89***	-1.90***	-1.91***	-1.91***
	-	-	-	-	-	-	[0.236]	[0.272]	[0.254]	[0.252]	[0.262]	[0.256]	[0.230]	[0.272]	[0.252]	[0.252]	[0.259]	[0.264]

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Table 3.11 – continued from previous page

Variables	Coefficient estimates																	
	LV-RPL with one latent variable						LV-RPL with two latent variables						LV-RPL with three latent variables					
	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000
τ_{SEV_aval2}	-	-	-	-	-	-	-0.60***	-0.57**	-0.57**	-0.60**	-0.62***	-0.58**	-0.48**	-0.57**	-0.57**	-0.60**	-0.59**	-0.59**
	-	-	-	-	-	-	[0.192]	[0.229]	[0.211]	[0.214]	[0.219]	[0.216]	[0.196]	[0.235]	[0.215]	[0.214]	[0.221]	[0.224]
τ_{SEV_aval3}	-	-	-	-	-	-	0.83***	0.93***	0.88***	0.84***	0.84***	0.87***	0.94***	0.94***	0.88***	0.83***	0.88***	0.87***
	-	-	-	-	-	-	[0.199]	[0.238]	[0.222]	[0.223]	[0.228]	[0.225]	[0.218]	[0.248]	[0.230]	[0.226]	[0.232]	[0.235]
τ_{SEV_aval4}	-	-	-	-	-	-	2.01***	2.18***	2.08***	2.04***	2.07***	2.08***	2.09***	2.20***	2.08***	2.02***	2.10***	2.08***
	-	-	-	-	-	-	[0.268]	[0.311]	[0.294]	[0.287]	[0.295]	[0.293]	[0.286]	[0.319]	[0.296]	[0.286]	[0.297]	[0.300]
λ_{SEV_eart}	-	-	-	-	-	-	1.24***	1.34***	1.32***	1.28***	1.31***	1.31***	1.21***	1.34***	1.28***	1.29***	1.32***	1.30***
	-	-	-	-	-	-	[0.239]	[0.243]	[0.236]	[0.223]	[0.229]	[0.228]	[0.249]	[0.249]	[0.231]	[0.235]	[0.235]	[0.232]
τ_{SEV_eart1}	-	-	-	-	-	-	-1.67***	-1.64***	-1.63***	-1.65***	-1.68***	-1.65***	-1.53***	-1.63***	-1.62***	-1.66***	-1.65***	-1.65***
	-	-	-	-	-	-	[0.234]	[0.263]	[0.252]	[0.251]	[0.258]	[0.259]	[0.220]	[0.273]	[0.264]	[0.263]	[0.263]	[0.270]
τ_{SEV_eart2}	-	-	-	-	-	-	0.14	0.20**	0.18	0.14	0.13	0.17	0.26	0.20	0.17	0.14	0.17	0.16
	-	-	-	-	-	-	[0.201]	[0.231]	[0.218]	[0.218]	[0.222]	[0.224]	[0.206]	[0.238]	[0.229]	[0.224]	[0.226]	[0.231]
τ_{SEV_eart3}	-	-	-	-	-	-	1.24***	1.32***	1.28***	1.24***	1.24***	1.28***	1.35***	1.32***	1.27***	1.24***	1.28***	1.27***
	-	-	-	-	-	-	[0.231]	[0.260]	[0.246]	[0.244]	[0.248]	[0.248]	[0.241]	[0.268]	[0.260]	[0.251]	[0.257]	[0.257]
τ_{SEV_eart4}	-	-	-	-	-	-	2.41***	2.55***	2.48***	2.43***	2.45***	2.48***	2.50***	2.54***	2.46***	2.43***	2.49***	2.47***
	-	-	-	-	-	-	[0.327]	[0.346]	[0.333]	[0.325]	[0.329]	[0.330]	[0.342]	[0.351]	[0.342]	[0.332]	[0.337]	[0.337]
λ_{SEV_flood}	-	-	-	-	-	-	1.56***	1.69***	2.02***	2.14***	1.97***	1.97***	1.63***	1.66***	2.02***	2.12***	1.96***	2.00***
	-	-	-	-	-	-	[0.329]	[0.389]	[0.498]	[0.564]	[0.481]	[0.496]	[0.349]	[0.389]	[0.501]	[0.546]	[0.477]	[0.504]
τ_{SEV_flood1}	-	-	-	-	-	-	-2.02***	-2.01***	-2.16***	-2.29***	-2.22***	-2.17***	-1.89***	-1.98***	-2.17***	-2.28***	-2.17***	-2.20***
	-	-	-	-	-	-	[0.298]	[0.366]	[0.426]	[0.489]	[0.434]	[0.435]	[0.298]	[0.357]	[0.444]	[0.476]	[0.424]	[0.450]
τ_{SEV_flood2}	-	-	-	-	-	-	-0.66**	-0.60**	-0.64**	-0.70**	-0.70**	-0.65**	-0.49**	-0.60**	-0.64**	-0.70**	-0.65**	-0.66**
	-	-	-	-	-	-	[0.230]	[0.274]	[0.301]	[0.332]	[0.309]	[0.306]	[0.232]	[0.274]	[0.317]	[0.327]	[0.309]	[0.322]
τ_{SEV_flood3}	-	-	-	-	-	-	0.91***	1.01***	1.12***	1.14***	1.04***	1.10***	1.11***	1.00***	1.13***	1.12***	1.09***	1.10***
	-	-	-	-	-	-	[0.246]	[0.294]	[0.338]	[0.359]	[0.329]	[0.336]	[0.262]	[0.299]	[0.348]	[0.359]	[0.332]	[0.353]
τ_{SEV_flood4}	-	-	-	-	-	-	2.44***	2.62***	2.87***	2.95***	2.77***	2.83***	2.66***	2.58***	2.88***	2.91***	2.82***	2.84***
	-	-	-	-	-	-	[0.374]	[0.440]	[0.539]	[0.577]	[0.512]	[0.531]	[0.409]	[0.443]	[0.543]	[0.577]	[0.518]	[0.554]
λ_{FEA_land}	-	-	-	-	-	-	-	-	-	-	-	-	0.76**	**0.27**	**0.62**	1.64	1.42	1.09
	-	-	-	-	-	-	-	-	-	-	-	-	[0.368]	**[0.224]**	**[0.340]**	[1.560]	[2.040]	[1.670]
τ_{FEA_land1}	-	-	-	-	-	-	-	-	-	-	-	-	-2.39***	**-2.17*** **	-2.15***	-2.98**	-2.73*	-2.52**
	-	-	-	-	-	-	-	-	-	-	-	-	[0.338]	**[0.272]**	[0.293]	[1.440]	[1.620]	[1.160]
τ_{FEA_land2}	-	-	-	-	-	-	-	-	-	-	-	-	-1.02***	-0.86***	-0.83***	-1.22*	-1.09	-1.01*
	-	-	-	-	-	-	-	-	-	-	-	-	[0.236]	[0.197]	[0.208]	[0.644]	[0.747]	[0.564]

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Table 3.11 – continued from previous page

Variables	Coefficient estimates																	
	LV-RPL with one latent variable						LV-RPL with two latent variables						LV-RPL with three latent variables					
	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000
τ_{FEA_land3}	-	-	-	-	-	-	-	-	-	-	-	-	0.13	0.20	0.27	0.30	0.33	0.27
	-	-	-	-	-	-	-	-	-	-	-	-	[0.209]	[0.193]	[0.203]	[0.337]	[0.325]	[0.276]
τ_{FEA_land4}	-	-	-	-	-	-	-	-	-	-	-	-	1.33***	1.28***	1.38***	1.86*	1.78	1.59*
	-	-	-	-	-	-	-	-	-	-	-	-	[0.260]	[0.224]	[0.252]	[0.968]	[1.150]	[0.834]
Model fit																		
LL	-1712.98	-1699.11	-1699.19	-1696.71	-1691.48	-1691.89	-3131.61	-3099.33	-3100.82	-3090.49	-3090.69	-3090.80	-3512.04	-3476.67	-3475.13	-3470.68	-3470.13	-3471.49
AIC	3462.42	3434.68	3434.84	3429.88	3419.42	3420.24	6347.58	6283.02	6286.00	6265.34	6265.74	6265.96	7125.46	7054.72	7051.64	7042.74	7041.64	7044.36
BIC	3557.60	3529.86	3530.02	3525.06	3514.60	3515.42	6563.06	6498.50	6501.48	6480.82	6481.22	6481.44	7382.43	7311.69	7308.61	7299.71	7298.61	7301.33
cAIC	3462.45	3434.71	3434.87	3429.91	3419.45	3420.27	6347.64	6283.08	6286.06	6265.40	6265.80	6266.02	7125.53	7054.79	7051.71	7042.81	7041.71	7044.43
est. time	00h05'17"	01h16'12"	02h12'00"	04h51'02"	08h44'15"	10h45'52"	00h15'30"	03h26'45"	06h26'46"	16h09'55"	19h45'34"	21h26'05"	00h43'01"	04h44'07"	08h35'37"	11h39'57"	19h46'18"	24h13'41"
draws	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000	100	1,000	2,000	5,000	8,000	10,000

Significance at: ***1% level, **5% level,*10% level. Std.err. in [.]. [a]=1.8e+308.

Table 3.11 – LV-RPL models results.

Chapter 4

Exploring spatial sources of preference heterogeneity for landslide protection

Abstract

This paper explores the sources of preference heterogeneity for landslide protection, with a special focus on spatial determinants. The data was collected using a stated preference survey of landslide hazards in an Italian mountain valley, using a Best-Worst ranking approach, in-person interviews and site-specific choice sets. Preference heterogeneity is analysed using individual and spatial variables with a focus on the importance of geographical characteristics, spatial error components and landslide locational effects. Results from spatial choice models reveal the importance of accounting for spatial heterogeneity at different levels given that taste variations were present at both individual and municipality levels.

Keywords:

Spatial choice models, site-specific choice sets, spatial error components, best-worst ranking, landslide hazard.

4.1 Introduction

Landslide protection is considered to be an environmental service, whose benefits affect only individuals that live in a specific geographic area. The local nature of these benefits emphasises the importance of conducting spatial analysis, specifically when dealing with public preferences for landslide protection.

In recent years, spatial dimensions of preference heterogeneity for environmental goods have been the focus of a large amount of published research, especially in surveys using discrete choice experiments (DCE). During the last decade, an increasing number of studies have explored *ex-post* the relevance of spatial effects on willingness to pay (WTP) estimates for environmental outcomes. Investigating the spatial distribution of WTP estimates has been achieved by calculating individual-specific mean coefficients for respondents and then by mapping their locally averaged values to account for the spatial allocation of benefits. A two-stage modelling process was used by Campbell (2007), Campbell, Scarpa and Hutchinson (2008) and Campbell, Hutchinson and Scarpa (2009) to capture spatial determinants of marginal WTP (mWTP) estimates for rural landscape features in Ireland. They provided evidence of spatial autocorrelation of the WTP estimates as well as a significant effect of the respondent's location on the values. In this regard, several research papers have suggested the presence of spatial heterogeneity or a sensitivity of the estimates to spatial factors. Recently, in a two-stage model, Johnston and Abdulrahman (2017) accounted for response propensity linked to geographical indicators of risk exposure for coastal flooding. They reported that the characteristics related to respondents' flood risk exposure systematically affected WTP estimates for mitigation actions.

In a parametric analysis, Yao et al. (2014) investigated the determinants of mWTP estimates for enhancement of biodiversity in New Zealand forests. The values held by respondents were assumed to decrease with their distance from the biodiversity source. Their findings showed evidence of such a distance-decay effect, with respondents living closer to the forest presenting higher WTP estimates. Similarly, Abildtrup, Garcia, Olsen and Stenger (2013) pointed out that unobserved spatial factors have an impact on WTP estimates for forest features. They stressed the importance of considering the spatial heterogeneity of preferences when dealing with spatially delineated environmental goods. Czajkowski, Budzinski, Campbell, Giergiczny and Hanley (2017) further extended the two-stage approach with the introduction of a spatial latent class model to identify groups of respondents with similar preferences for forest conservation in Poland. Termansen, Zandersen and McClean (2008) studied alternative substitution patterns through MXL with spatially defined error components.

Another way to explore spatial effects is to include the spatial variables as covariates in a choice model to estimate their impacts. In a study in Denmark, Broch, Strange, Jacobsen and Wilson (2013) identified spatial patterns for farmers willing to accept compensation for afforestation programmes to provide ecosystem services. Schaafsma, Brouwer and Rose (2012) and Jørgensen et al. (2013) found evidence in support of the directional effects of distance decay on WTP values related to differences in the availability of substitutes. Bateman, Day, Georgiou and Lake (2006) asserted that distance decay functions can reflect spatial preference heterogeneity. However, Meyerhoff (2013) and Johnston and Ramachandran (2014) pointed out limits in this traditional method based on distance-decay for investigating spatial heterogeneity. Since distance-decay is not automatically associated with spatial heterogeneity, they proposed the use of local indicators of spatial association to identify welfare patchiness and to explore WTP hot spots when distance decay does not apply. This is an approach that I pursue further here. Continuing with this line of research, Johnston, Jarvis, Wallmo and Lew (2015) presented a set of methods to account for multiscale heterogeneity in stated preference (SP) studies. They pointed out difficulties faced in identifying the appropriate scale of welfare evaluation. Holland and Johnston (2017) implemented a quantity-within-distance model for the systematic identification of spatial heterogeneity. The model considered the effects of the area of affected public good at a certain distance buffer or radius for each respondent. Recently, Campbell, Budziński, Czajkowski and Hanley (2017) proposed a new latent class framework, in which spatial dependence enters through the membership function errors. The inclusion of site-specific attributes in the choice experiments design (e.g. Horne, Boxall & Adamowicz, 2005) represents another route for investigating spatial effects.

I argue in this paper that spatial dimensions are particularly important when considering preferences for protection from natural hazards. This DCE study is one of the few contributions to the literature on preferences for landslide protection in mountain regions. It is an attempt to capture and disentangle spatial patterns in the distribution of WTP estimates.

The *first objective* of this paper is to improve our understanding of the individual and spatial sources of preference heterogeneity in relation to landslide protection systems for roads and settlements, using Best-Worst (B-W) rank ordered choice data. This is motivated by the fact that, for spatially delineated goods (such as landslide protection), the omission of spatial factors may have serious repercussions on the policy outcomes. As established by previous studies (Johnston & Duke, 2009; Martin-Ortega, Brouwer, Ojea & Berbel, 2012), spatial heterogeneity is likely to be relevant for policy decisions, particularly in benefit transfer estimates. Given that mountain areas have uneven natural boundaries, every municipality presents unique spatial characteristics, inclusive of the degree of landslide hazard. These locational effects give rise to choice behaviour with spatial heterogeneity, as individual preferences change across space. This is especially true for this study that aims to estimate the effects of locating specific interventions for landslide safety measures at sites with differing degrees of vulnerability.

The *second objective* concerns the spatial scale of investigation. I assess whether spatial choice models at the municipality level provide an improved approach for policy decisions taken at the municipality scale, such as landslide protection. Here the availability of ranking data (instead of first choice data) is crucial for allowing a sufficient number of choice observations within each municipality. To the author's best knowledge, prior publications using DCE have failed to adequately account for spatial hierarchies generating common preference heterogeneity within the model structure. With a few exceptions (Morrison & Bennett, 2004; Van Bueren & Bennett, 2004; Johnston & Duke, 2009; Brouwer, Martin-Ortega & Berbel, 2010), most studies have dealt with the potential errors in a benefit transfer context, leading to overestimation or underestimation of the transferred values. Morrison and Bennett (2004) were able to show that estimates for improvements in rivers' health differ across catchments in a study in New South Wales, Australia. Similarly, in a survey on land and water degradation, Van Bueren and Bennett (2004) argued that values were highly dependent on the geographical context of analysis. Moreover, WTP estimates for farmland preservation in Johnston and Duke (2009) varied with the scale of the jurisdiction. In other environmental studies, spatial heterogeneity has been explored by fitting separate models for different locations. Among them, Brouwer et al. (2010) accounted for spatial preference heterogeneity in four river districts, finding significantly different estimates for water quality improvements between locations.

The specific context of my application is a mountain valley (the Boite Valley) in the Dolomites, a mountain range located in the north-eastern section of the Italian Alps. It hosts more than 350 potential landslide sites that threaten inhabited areas and the main road network. In the last 100 years, 64 landslide events were reported, with a recent major episode in August 2017 that caused casualties and totally destroyed a hamlet. This case study is quite unusual in that it offers the possibility to combine observables in terms of both conventional individual socio-economic covariates as well as geographical information relating to road segments travelled and the municipality of residence (i.e. a town or district that has local government). In this study, such variables are identified in separate effects via interaction factors with the *status quo* alternative and with common spatial error components, which introduce shared variation (i.e. correlation). Interactions between landslide locations and the policy cost are also included.

I end this introduction with an overview of what follows. Section 2 presents the model specifications aiming to explore sources of preference heterogeneity and their spatial distribution. The survey design and the data are described in Section 3. Section 4 reports the results of the spatial models at the individual and municipality levels and discusses the findings with a comparison of policy scenarios. Geographical representations of the estimates are also included. Finally, Section 5 concludes with policy implications.

4.2 Research questions and models

4.2.1 Research questions

In this study I address the following two research questions:

RQ4.1: Do spatial determinants contribute to explaining the patterns of preference heterogeneity for landslide protection?

I employ a choice model that examines the factors that influence whether or not an individual (resident or visitor) is in favour of the deployment of new safety devices against landslides at either a given road segment and/or residential site. People were expected to value alternative protection programmes differently depending on their socio-economic characteristics as well as the geographical features of the place of residence. So, this model specification was developed to identify and incorporate the separate effects of selected socio-economic and geographical variables, such as the specific landslide threat.

In order to explore the spatial determinants of preference heterogeneity, I identified three separate geographical effects. First, I included geographical variables that demonstrated a significant interaction with the *status quo* intercept, in the utility of the *status quo* options. This because I wanted to investigate the impact of geographical variables on the aversion to *status quo* conditions (i.e. the riskiest option). I expected people living in municipalities with similar geographical characteristics to be more likely to exhibit similar preferences, perhaps motivated by neighbourhood effects. Secondly, the variables representing six selected hazard sites were interacted with the monetary attribute to gain information on site-specific preferences. This is because taste can vary locally depending on the specific landslide location. I also investigated substitution patterns among non-*status quo* alternatives that implied a higher degree of protection than that afforded in the current situation. Lastly, I re-specified the model by introducing shared error terms for the non-*status quo* alternatives (Herriges & Phaneuf, 2002; Greene & Hensher, 2007; Scarpa, Willis & Acutt, 2007; Thiene & Scarpa, 2008) to allow correlations among their utilities. Geographical correlation in the error terms of different road segments was investigated using the three error components (EC). This was only done for visitors, based on the supposition that they may have weaker preferences for safety devices than residents.

RQ4.2: Do spatial choice models at the municipality level offer a useful tool for understanding the spatial dimensions of preference heterogeneity?

Given the geographical scale of this type of policy decision, a spatial model at the municipality level provided an alternative way of getting insights into preference heterogeneity. This model allowed the geographical distribution of preferences and the existence of spatial heterogeneity among sampled municipalities to be investigated. The motivation behind the use of a spatial model was that the distribution of preferences is likely to be spatially heterogeneous among municipalities given the geographical distribution of landslide events. As pointed out by Campbell (2007), the inclusion of locational variables, as dummies, was unsuitable for making comparisons among many municipalities. Nor was it feasible to fit separate models for each location, because of the large number of municipalities and the uneven sample sizes across them. Preliminary results on spatial heterogeneity for this case study were shown in Mattea, Franceschinis, Scarpa and Thiene (2016).

I pursued this by extending the conventional model framework based on individual heterogeneity to accommodate spatial heterogeneity among municipalities directly in the model structure. Following Revelt and Train (1998), I defined tastes in a random parameter logit model to allow variation across individuals and to remain constant across choices by the same individual. But I went further and adapted this to my spatial model, bringing it to a higher hierarchical level in which tastes varied across municipalities of residence, but remained constant across all choice observations by respondents from the same municipality. This implied a strong assumption of homogeneity of preference within the same municipality. I brought together the repeated choices made by respondents from the same municipalities, considering the municipalities as the units of observation. Since some municipalities had few respondents, the use of the rank dataset was particularly helpful to increase the number of pseudo-choice observations (from 1,500 to 9,000). Therefore, the number of observational units in the spatial model decreased from 250 (the number of those surveyed) to 48 (the number of sampled municipalities), and the panel was unbalanced.

4.2.2 Theoretical framework of the “exploded” logit model

To investigate the multiple sources of preferences’ heterogeneity, I used a set of “rank-exploded” conditional and mixed logit models to relax the underlying assumption of homogeneity of the baseline multinomial logit model.

In a repeated B-W ranking framework (Louviere et al., 2008; Louviere & Islam, 2008; Scarpa, Notaro, Louviere & Raffaelli, 2011; Marley & Flynn, 2015), the respondent repeatedly chooses the best and then the worst option among a set of alternatives. I denote the respondents by n=1,…,250; the chosen alternative by i; the generic alternatives by j=A,…,G; the ranking of choices by c=1,…,7; the ranking choice set by t=1,…,6; the number of available alternatives in the choice set by q=2,…,7; the specific attributes by k and the particular respondents' characteristics by s.

The utility function (U_{intq}) of each alternative can be represented as the sum of a systematic component (V_{intq}) and a stochastic component (ε_{intq}), all multiplied by an alternative-availability coefficient (δ_q) (Equation 4.1).

$$U_{intq} = \delta_q(V_{intq} + \varepsilon_{intq}) \qquad \text{(Eq. 4.1)}$$

where δ_q=1 when the alternative is available in the choice set q, and hence it was not previously chosen, 0 otherwise; ε_{intq} refers to the error term and represents the unobservable component of utility; the observable portion of utility is embodied by V_{intq} that depends on the characteristics of the alternatives, i.e. observable attributes (X_{ink}), and the respondent's characteristics (X_{ins}).
Generally, the systematic component of the utility is represented by the following linear function (Equation 4.2):

$$V_{intq} = \sum_k \beta_k X_{ink} + \sum_s \eta_{ns} X_{ins} \qquad \text{(Eq. 4.2)}$$

where $\sum_k \beta_k X_{ink}$ represents the sum of the coefficients associated with the k attributes that define the choice alternatives, and $\sum_s \eta_{ns} X_{ins}$ represents the sum of the coefficients related to the s individual's socio-economic characteristics.

In this specific case, I assume a Random Parameter Error Component Logit model (RPL-EC) specification with covariates. Omitting the alternative-availability coefficient, the utility of the non-*status quo* alternatives (Equation 4.3) and of the *status quo* alternative (Equation 4.4) are as follows:

$$U_{\neq SQ,n} = \sum_k \beta_{nk} X_{ink} + \sum_r \mu_{ir} X_{inr} + \varepsilon_{in} \qquad \text{(Eq. 4.3)}$$

$$U_{SQ,n} = \sum_k \beta_{nk} X_{ink} + \sum_s \eta_{ns} X_{ins} + \sum_g \lambda_{mg} X_{img} + \varepsilon_{in} \qquad \text{(Eq. 4.4)}$$

where μ_{ir} are individual-specific error components, normally distributed with zero mean and variance σ^2. They allow for correlation patterns between the stochastic portions of the non-*status quo* alternatives for the three road segments *r* (r_1, r_2, r_3). In other words, respondents sharing road segments have correlated non-*status quo* utilities. Along with the attributes and the socio-economic characteristics of the respondents, I include the term $\sum_g \lambda_{mg} X_{img}$ that represents the sum of the coefficients associated with the interaction terms between the socio-demographic variables and the g geographical characteristics of the m municipalities (m=1,…,48).

Since the residual unobserved utility term ε_{in} is assumed to follow an i.i.d. extreme value type I distribution, the unconditional probability that the respondent *n* chooses the alternative *i* as the "best" alternative is denoted by the Random Parameters Logit (RPL) model (Hensher & Greene, 2003; Train, 2009) in Equation 4.5:

$$Pr\left(U_{in} > U_{jn}\right) = \iint \frac{\exp(\ V_{in})}{\sum_{j}^{J=7} \exp(\ V_{jn})}\ f(\beta|\theta) g(\mu|\tau) d\beta d\mu \qquad \text{(Eq. 4.5)}$$

However, the probability of observing the full ranking of seven alternatives is a product of six RPL probabilities, as shown in Equation 4.6 using some approximation in the notation:

$$Pr(U_{in1} > U_{in3} > U_{in5} > U_{in7} > U_{in6} > U_{in4} > U_{in2})$$
$$= \iint \frac{\exp(V_{in1})}{\sum_{j=1}^{J=7} \exp(V_{jn1})} \frac{\exp(V_{in2})}{\sum_{j=2}^{J=7} \exp(V_{jn2})} \frac{\exp(V_{in3})}{\sum_{j=3}^{J=7} \exp(V_{jn3})} \frac{\exp(V_{in4})}{\sum_{j=4}^{J=7} \exp(V_{jn4})} \frac{\exp(V_{in5})}{\sum_{j=5}^{J=7} \exp(V_{jn5})} \frac{\exp(V_{in6})}{\sum_{j=6}^{J=7} \exp(V_{jn6})} f(\beta|\theta) g(\mu|\tau) d\beta d\mu$$

(Eq. 4.6)

where the respondent chooses 1 as the "first best" answer from the entire alternative set {1, …, 7}, then chooses 2 as the "first worst" alternative from the set {2,…,7} from which the best alternative has been excluded. The process is then iterated till the final choice is between the residual two alternatives.

4.3 Survey and data

4.3.1 Survey design and data collection

I collected the data for this study by using an in-person questionnaire administration technique. A sample of 250 people was interviewed on-site in the Boite Valley. Respondents were selected from the population of residents (1% of those were sampled) and visitors to the valley. To obtain high-quality data, door-to-door in-person interviews were also carried out, enabling elimination of missing data. Difficulties in data collection were faced due to the typical climate conditions prevailing in late summer and autumn, with frequent rainstorms, and due to the sensitivity of people to the specific topic, as many had been affected by previous landslide events.

I interviewed respondents using a structured questionnaire, which included a series of socio-economic questions and other questions related to landslide hazard. The main component of the questionnaire consisted of an experiment in which respondents were asked to rank hypothetical landslide protection scenarios with different combinations of safety devices to reduce the landslide risk in specific locations. Each respondent was presented with seven experimentally designed scenarios based on five attributes, which concerned a set of four safety devices and a payment vehicle. Expert hydrologists helped me to select the devices to be included in the experimental design as attributes.

The four safety devices tested were the diverging channel ("*CHAN*"), which is a passive device built to divide water and rocks to diminish the impact of the landslide. The retaining basin ("*BAS*") is a dam that collects the debris. Video cameras ("*VIDEO*") with night-vision allow the potential area of landslides to be under surveillance at all times; acoustic sensors ("*SENS*") consist of a system of special pipes that captures the vibrations of the moving debris. These last two measures of protection immediately activate the alarms and/or traffic lights. The monetary attribute ("*TOLL*") is a provisional payment in the form of a road toll to transit in the valley to pay for the cost of implementation of the protection programmes. The length of the toll period was eight months (from April to November of a specific year) determined based on the seasonality of landslide events. Each attribute has two levels (indicating presence or absence of the device), except the monetary attribute, which has four levels (1€, 2€, 3€ and 4€).

The optimised orthogonal fractional factorial design (Ferrini & Scarpa, 2007; Rose & Bliemer, 2007; Scarpa & Rose, 2008) adopted was fully balanced, so each level appeared the same number of times across the full dataset. The full factorial structure was 2^4x4 and provided 64 choice sets with six alternatives each. Then, the design was blocked into 10 blocks of six choice sets each. The remaining four choice sets were used to replace unrealistic combinations. The unlabelled experimental design was constructed using Ngene (ChoiceMetrics, 2012).

To make the hypothetical scenarios more realistic, each choice set referred to one of six selected landslide sites (site-specific choice sets) (Figure 4.1). Then, a site-specific *status quo* alternative was added for each of them, leading to a total of seven options per choice set. Each respondent was randomly assigned to one of the 10 blocks and evaluated one choice set per site, for a total of six choice sets per respondent. The selected sites, within the boundaries of the Boite Valley, are Cancia (hamlet of Borca), Chiapuzza (hamlet of San Vito), Acquabona (hamlet of Cortina), and three other locations in Fiames (hamlet of Cortina) at kilometre 106, 108 and 109 on highway SS51. All of these sites need continuous monitoring and prompt interventions. Decision-makers are currently defining the best strategy for risk mitigation in each of the six locations.

Site 5 – FIAMES km 108

Alternatives	A	B	C	D	E	F	Status quo
Channel	channel	-	-	channel	channel	-	-
Basin	basin	-	basin	-	basin	-	-
Video cameras	-	-	video	video	video	video	-
Acoustic sensors	sensors	sensors	sensors	-	-	sensors	-
Road toll	€1	€2	€3	€1	€1	€2	€0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Figure 4.1 – An example of a choice set for a specific landslide site.

As previously mentioned, the seven alternatives in each choice set were ranked by means of the repeated B-W ranking approach in the sequential choice process. For each choice set, respondents provided their “best” alternative (i.e. the one with the highest utility) out of seven options, the “worst” alternative (i.e. the one with the lowest utility) out of six, then the “second best” out of five, the “second worst” out of four, then the “third best” out of the remaining three, the “third worst” of the last remaining two and the last one.

To provide site-specific information to respondents to facilitate their scenario evaluations, I gave them pictures of previous landslides and of the set of safety devices together with maps of the policy sites. The maps illustrated the position of the affected locations in the valley in conjunction with the road network and the residential areas. The maps worked as a tool for allowing respondents to locate their own position in relation to the landslide hazards for the purpose of obtaining well-informed preference elicitation (Johnston, Holland, & Yao, 2016).

4.3.2 Data description

In the following subsections, I discuss the respondents' characteristics as well as geographical and socio-demographic characteristics of the municipalities in which they live.

4.3.2.1 Socio-economic variables of the respondents

The sample's descriptive statistics are reported in Table 4.1.

Variable	Description	Freq	%
Gender	Male	133	53.2
	Female	117	46.8
Age	18-30 years	29	11.6
	31-40 years	46	18.4
	41-50 years	64	25.6
	51-60 years	55	22.0
	+ 60 years	56	22.4
Education	Primary/Intermediate school	69	27.6
	High school	118	47.2
	University	63	25.2
Job	Currently working	186	74.4
	Not actively working	64	25.6
Kids	With minor members	59	23.6
	No minor members	191	76.4
Family income	€0 - €15,000	69	27.6
	€15,000 - €30,000	102	40.8
	€30,000 - €45,000	55	22.0
	€45,000 - €60,000	16	6.4
	+ €60,000	8	3.2

Table 4.1 – Descriptive statistics of the respondents.

Respondents replied to several questions on socio-economic characteristics through the interviews, including: gender, age, education level, occupation, municipality in which they live, number of individuals in the household, number of minors in the household, family income. Also, the questionnaire included a set of introductory questions assessing respondents' awareness of landslide hazard. Specifically, they stated their knowledge of previous events in the valley, their experience of landslide events, and their participation in hazardous activities (e.g. climbing, off-piste skiing, etc.). Respondents also provided additional information with regards to their recreational behaviour.

4.3.2.2 Geographical variables of the municipalities

I sampled respondents from 48 municipalities. Six of those were in the Boite Valley; the reminders were in the Belluno province, ranging in distance from 30 km to 100 km from the landslide sites. Socio-demographic variables (population size and density, mean income level, and mean age) and geographical variables of the municipalities were obtained from the Italian National Institute of Statistics (Istituto Nazionale di Statistica). Geographic variables tested were altitude, land area, distance from the Boite Valley, and landslide hazards.

The construction of the variable for landslide hazard, "*Landslide_hazard*", required a detailed analysis of the landslides layer on a GIS map for each municipality. Each landslide was coded according to the level of danger as assessed by the hydrogeological service (from 1=null landslide hazard to 4=very high hazard). The overall landslide hazard assigned to each municipality was based on the highest danger of landslides that impacted on a road or a residential area within the municipality borders.

4.4 Results

The conventional individual level model specification (Model 1) and the corresponding spatial model at the municipality level (Model 2) are discussed and presented in this section (see Table 4.2).

The RPL-EC model at the individual level (Model 1) includes the socio-economic characteristics of the respondents and municipality characteristics as covariates in the utility of the *status quo* option, with the purpose of capturing

heterogeneity in preferences towards the current safety situation. Considering just the individuals' characteristics, it emerges that having children in the household ("*Kids*"), being retired ("*Retired*"), having experienced previous landslides ("*Experienced*") and participating in certain types of recreational activities ("*Hiking*" and "*Ferrata*") are determinants of observed preference heterogeneity.
A geographical dummy variable is included in the model ("*High_hazard*", which denotes a municipality with a high landslide threat). The model specification is chosen after considering the degree of correlation of the covariates (Appendix 4.7 – Figure 4.8). Some geographical variables are highly correlated due to their spatial nature. For example, living in mountain areas such as the Boite Valley is positively correlated with a high landslide hazard. To further investigate the spatial dimension, error components for road segments are added to account for possible correlations among utilities of the non-*status quo* alternatives. The road network was divided into three segments ("r_1, r_2, r_3"). The road segments correspond approximately to natural borders, such as mountain valleys or plains. Specifically, r_1 refers to the road segment connecting to the eastern municipalities, r_2 is the segment that links with the northern areas and r_3 includes all roads coming from the southern plains. Space heterogeneity is shared across respondents transiting the above-mentioned road segments when travelling to and from the Boite Valley. Given that every choice set refers to a particular location in the Boite Valley, the model examines site-specific preference heterogeneity allowing for interactions with the attribute "*TOLL*" and each of the five locations, where site 5 is taken as a baseline. Interaction terms between safety devices and spatial variables were also tested but resulted in a lower fit in comparison to the proposed model. The model superimposes unobserved heterogeneity in the form of random taste across respondents to the set of observables and error components. I assume that the preferences for the four random attributes follow a normal distribution (Train & Sonnier, 2005). Preferences towards the monetary attribute are considered homogeneous assuming that the marginal utility of income is constant and equal for all individuals given that cost is a small fraction of individual incomes.

The RPL-EC model at the municipality level (Model 2) is the counterpart which, instead, allows for random taste across municipalities.

	Model 1 individual level		Model 2 municipality level	
	Mean	Std.err.	Mean	Std.err.
Parameters				
β_{CHAN}	2.21***	0.079	1.95***	0.088
β_{BAS}	1.84***	0.088	1.79***	0.082
β_{VIDEO}	1.41***	0.074	1.43***	0.070
β_{SENS}	1.41***	0.068	1.27***	0.063
β_{TOLL}	-0.51***	0.025	-0.49***	0.024
ASC_SQ	1.38***	0.134	1.28***	0.141
Standard deviations				
σ_{CHAN}	1.10***	0.058	0.90***	0.058
σ_{BAS}	1.15***	0.062	0.91***	0.062
σ_{VIDEO}	0.88***	0.058	0.76***	0.054
σ_{SENS}	0.71***	0.056	0.58***	0.059
Interactions with sites				
TOLL* Cancia	-0.38***	0.034	-0.34***	0.034
TOLL * Chiapuzza	-0.43***	0.038	-0.38***	0.035
TOLL * Acquabona	-0.14***	0.039	-0.12***	0.040
TOLL * Fiames_km106	-0.12***	0.038	-0.11***	0.036
TOLL * Fiames_km109	-0.36***	0.037	-0.32***	0.037
Respondent characteristics				
ASC_SQ * Kids	-0.30***	0.074	-0.24***	0.069
ASC_SQ * Retired	-0.51***	0.077	-0.49***	0.074
ASC_SQ * Experienced	-0.56***	0.082	-0.56***	0.080
ASC_SQ * Hiking	-0.59***	0.070	-0.43***	0.059
ASC_SQ * Ferrata	0.48***	0.130	0.41***	0.095
Municipality characteristics				
ASC_SQ * High_hazard	-0.29**	0.127	-0.31**	0.136
Error components (Std.)				
r_1	1.26***	0.12	0.99***	0.10
r_2	0.94	0.82	0.89	0.72
r_3	0.70***	0.18	0.55**	0.25
Model fit				
LL	-8915.06		-9155.24	
AIC	17878.25		18358.61	
BIC	18048.64		18529.00	
cAIC	17878.26		18358.62	

Table 4.2 – Models at individual and municipality levels.

In estimation, the choice probabilities are approximated by simulating the sample log-likelihood with 1,000 Halton draws (Halton, 1960), using the PythonBiogeme software (Bierlaire, 2016).

4.4.1 Results from Model 1: individual level

It emerges that the estimated attribute parameters of Model 1 are all significant and with the expected sign. The coefficient estimates of attributes related to safety devices are all positively signed, with the highest magnitude for the diverging channel, followed by the basin. Video cameras and sensors show the same estimated value. The cost attribute is negative as expected. Additionally, the significance of standard deviation estimates of the random parameters reveals that there is still a high unobservable heterogeneity in the systematic part of the utility, even after adding several sources of observables. The positive and significant alternative-specific constant (ASC) for the current situation represents a potential *status quo* effect (Scarpa, Ferrini & Willis, 2005). The sign suggests that *ceteris paribus,* there is a preference for the current situation when faced with a costly increase in safety against landslides. This, however, is confounded by the ranking nature of the data. The estimated interaction coefficients between the attribute "*TOLL*" and each of the five sites are all negative, so respondents are willing to pay more for increased protection at the reference site than for others. This is unsurprising as the reference site (site 5, i.e. Fiames km 108) is the only site without any device in place. Respondents seem to be willing to pay for some protection at a site which has none, even when the hazard is lower than at other locations. It is plausible that respondents are unaware of the degree of landslide hazard of each site since Cancia (site 1), Chiapuzza (site 2) and Acquabona (site 3) are considered to be the most dangerous sites by scientists, but display lower coefficient estimates than other locations according to the observed choices.

The sign and significance of socio-economic variables reveal whether respondents are likely to choose the *status quo* alternative. Model estimates suggest that having children ("*Kids*") in the household has a negative impact on the ASC of the *status quo* option. Respondents with children are more willing to pay for increasing landslide protection levels, probably feeling protective of their children and of themselves as caregivers. A negative coefficient is also found for retired respondents ("*Retired*"), who are often a high proportion of residents of mountain areas. Similarly, people that had previously experienced landslide events ("*Experienced*") favour more protection, and are more willing to pay for it than others. The same is true for respondents who go hiking ("*Hiking*"). Those who are likely to be more aware of mountain hazards are more willing to pay for new safety measures. People that climb protected climbing routes called ferrata ("*Ferrata*") seem to be less keen on new safety measures, perhaps because they are less risk-averse than other groups of recreationists. People living in settlements with high landslide risk ("*High_hazard*") are in favour of safety investments, as expected.

The correlation between non-*status quo* alternatives is revealed by significant estimates of the standard deviations for two of the three common error components. The high and positive correlation corroborates the existence of a substitution pattern among the utilities of the non-*status quo* options (i.e. a nesting structure among those alternatives) shared across visitors of the Alpine valley that transit on the eastern (r_1) or southern roads (r_3). These road segments are mainly located in flat areas, where the landslide hazard is low and respondents are likely to be less familiar with such threats. No significant estimate was found for the error component of the northern road network (r_2): people living in that area are perhaps more concerned about safety improvements in the Boite Valley because many of them transit those road segments on a daily basis for either family or work commitments.

4.4.2 Results from Model 2: municipality level

The same patterns are repeated for the spatial model at the municipality level. All the random parameters are significant and with the expected sign. The results of Model 2 further highlight the presence of high heterogeneity in preferences, not only across respondents but also across municipalities. The fact that preferences for safety measures vary across both suggests the relevance of spatial heterogeneity for policy actions, as discussed in the next section.

I find no significant difference between the covariates of the two models. Both models show significant interactions of the landslide sites with the monetary attribute. Also the socio-economic and geographic covariates are significant determinants of preference for the proposed protection scenario.

The high significance of the standard deviation estimates of most of the random error component coefficients provides evidence of correlation between the stochastic portions of the utility of the non-*status quo* alternatives for the visitors to the valley. The two error components with significant standard deviation estimates are those for road segments in the eastern (r_1) or the southern parts (r_3) of the region.

The model with the best fit is the one in which I included multiple sources of heterogeneity fitted at the individual level (Model 1). Even though, in this specific case, the spatial model at the municipality level has slightly inferior performance, the empirical results validate the theoretical expectation about the importance of analysing unobserved heterogeneity at higher hierarchical scale using spatial models. The fact that Models 1 and 2 show insignificant differences in results is encouraging for the adoption of the spatial approach when this is required to uncover the presence of additional heterogeneity at hierarchical levels higher than the individual.

4.4.3 Policy scenarios

In this section I compare alternative policy scenarios using individual-specific means of mWTP estimates. I illustrate the differences across the sample distributions of welfare estimates by means of kernel plots of these means. Four policy actions of potential interest for local decision-makers in the mountain valley are discussed, with a specific focus on the one associated with the highest estimated benefit (i.e. the construction of the channel).

The estimates of individual-specific means of random parameters conditional on observed choices (von Haefen, 2003; Greene, Hensher & Rose, 2005; Scarpa et al., 2005; Train, 2009) were retrieved using the estimates of the RPL-EC model at the individual level (Model 1). The computation was done using Nlogit 5 with 10,000 draws, providing the estimates as starting values and setting the iterations to zero. Given that conditioning can be only on the observed choices for each respondent, I use the mean estimate for the sub-sample that made the same set of choices in the panel (Revelt & Train, 2000; Hensher, Greene & Rose, 2006; Train, 2009). This is because conditional estimates for each respondent follow a random distribution, so only the moments of this distribution can be obtained. The calculation of individual-specific posterior distribution parameters provides information about the most likely position of a respondent on the distributions of mWTP. The estimates of individual-specific means of random mWTP for each safety device are computed as ratios of marginal rates of substitution in the indirect utility function. Details for the derivation of the individual-specific mean estimates can be found in Greene et al. (2005).

To compare policy scenarios, the distributions of the individual-specific means of mWTP estimates for each of the four safety devices are described in Figure 4.2. These kernel densities describe higher frequencies of means of mWTP for video cameras and sensors, which also show lower variance and thin upper tails. The densities for channel and basin are shifted to the right and show thicker upper tails. While mWTP for basin has a mode close to that of cameras and sensors, the distribution for the channel is bimodal, with the highest mode to the left of these values. Channel and basin, have a high standard deviation of the means of the mWTP distribution, implying heterogeneity in the amount that sample respondents are willing to spend to support these mitigation policies. I conclude that respondents gain the highest level of benefit from safety measures that include construction of diverging channels; however, this benefit is distributed heterogeneously including the presence of bimodality.

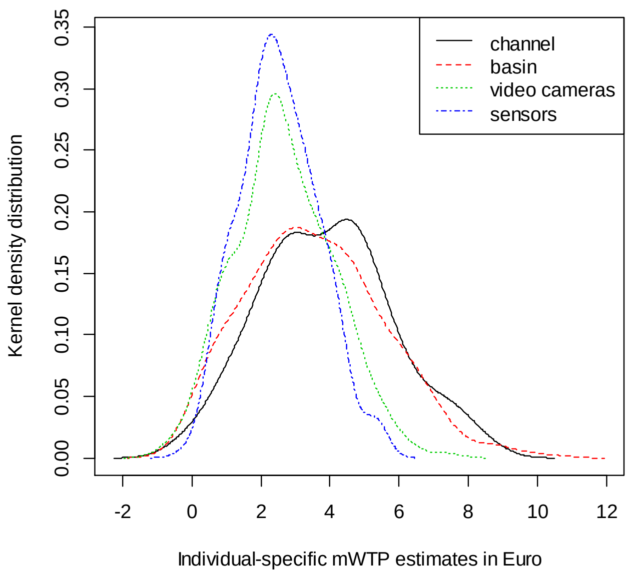

Figure 4.2 – Kernel distributions of individual-specific means of mWTP estimates for the safety devices.

Given that the channel is the attribute with the largest benefit, it is the most plausible target for policy interventions. Therefore, policy actions aiming at implementing the construction of channels are discussed in the following subsection. A special focus is given to two determinants: *(i)* personal experience of previous landslides; and *(ii)* the landslide threat in the municipality of residence. The kernel distributions of individual means for mWTP across sample respondents who had previously experienced landslide events are contrasted with those who had not (Figure 4.3). From this analysis, it appears that respondents who had never experienced a landslide event show two modal values, with the highest frequencies in this range. Instead, those who had experienced such a traumatic event present a curve shifted slightly to the right with higher frequencies at higher mWTP values. Although differences are not significant, they suggest that respondents are more in favour of the implementation of this specific policy action. Figure 4.4 illustrates the kernel distributions for those respondents living in municipalities with different hazard levels in conjunction with landslides. Similar modal values are shown for the two distributions. The distribution for respondents living in municipalities with high landslide risk is shifted more to the right side (i.e. more in favour of the implementation of the policy action) than that of other respondents. These results are in keeping with my theoretical expectations and results from previous models, providing some degree of theoretical validity to the method.

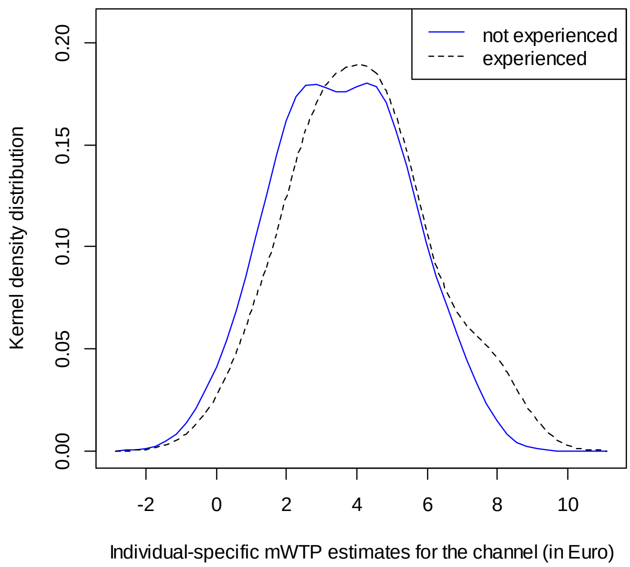

Figure 4.3 – Kernel distributions of individual-specific means of mWTP estimates for the construction of a channel by experience of previous landslides.

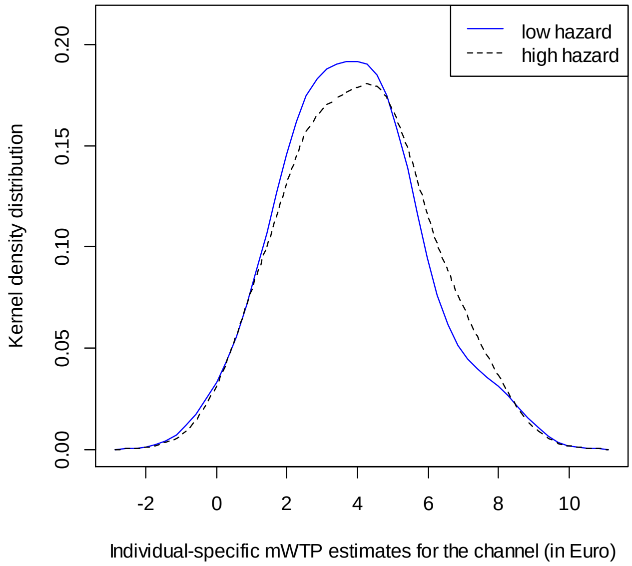

Figure 4.4 – Kernel distributions of individual-specific means of mWTP estimates for the construction of a channel by landslide hazard.

Here I discuss the differences between the distributions of means of mWTP estimates for respondents living in selected areas frequently damaged by landslides as opposed to those living in other municipalities. Hence, the kernel density distributions of means of mWTP values are obtained conditional on respondents' residency in three municipalities with high-risk exposure in the area of investigation: Cortina, San Vito, and Borca, with a fourth group with residency in other municipalities with lower risk exposure.

Figure 4.5 shows the kernel distribution of means of mWTP values for the four groups for each policy action. Overall, significant differences are found between the three municipalities with high landslide risk and other municipalities. As expected, the group of other municipalities ("*Others*") show higher frequencies for lower mWTP values for all the proposed policy actions. This is in accordance with the "beneficiary-pays principle", which says that the beneficiary of a good or service should be more willing to support the costs of its provision than others. Visitors to the valley do not benefit from risk mitigation in the same way as residents.

With regard to the construction of a channel (top left), the plot shows a high variation of individual means of the mWTP distributions across all municipalities. This implies heterogeneity in the amount respondents are willing to spend to support this mitigation programme since the benefit is distributed differently among the population from different municipalities. The highest modal value is shown for San Vito, followed by Borca and Cortina.

Instead, for the basin (top right), the distributions of individual means of mWTP present a higher modal value for the municipality of Borca, which was the scene of a deadly landslide event in 2009 that caused the breakage of the pre-existing basin. The fact that the distribution for the other municipalities is bimodal can be interpreted as very heterogeneous mean preferences for this device across municipalities with different landslide risk. Therefore, the skewness and kurtosis differ given the local modal values.

At the bottom left of Figure 4.5, similar kernel distributions among municipalities are observed for the video cameras. There are no major differences among municipalities with regard to the implementation of this policy.

The last policy scenario discussed is the installation of acoustic sensors (bottom right). For this device, Cortina shows the highest modal values, even if bimodality is present. The kernel density distribution for this location is almost symmetric to the municipalities classified as "*Others*", which have a lower mWTP value.

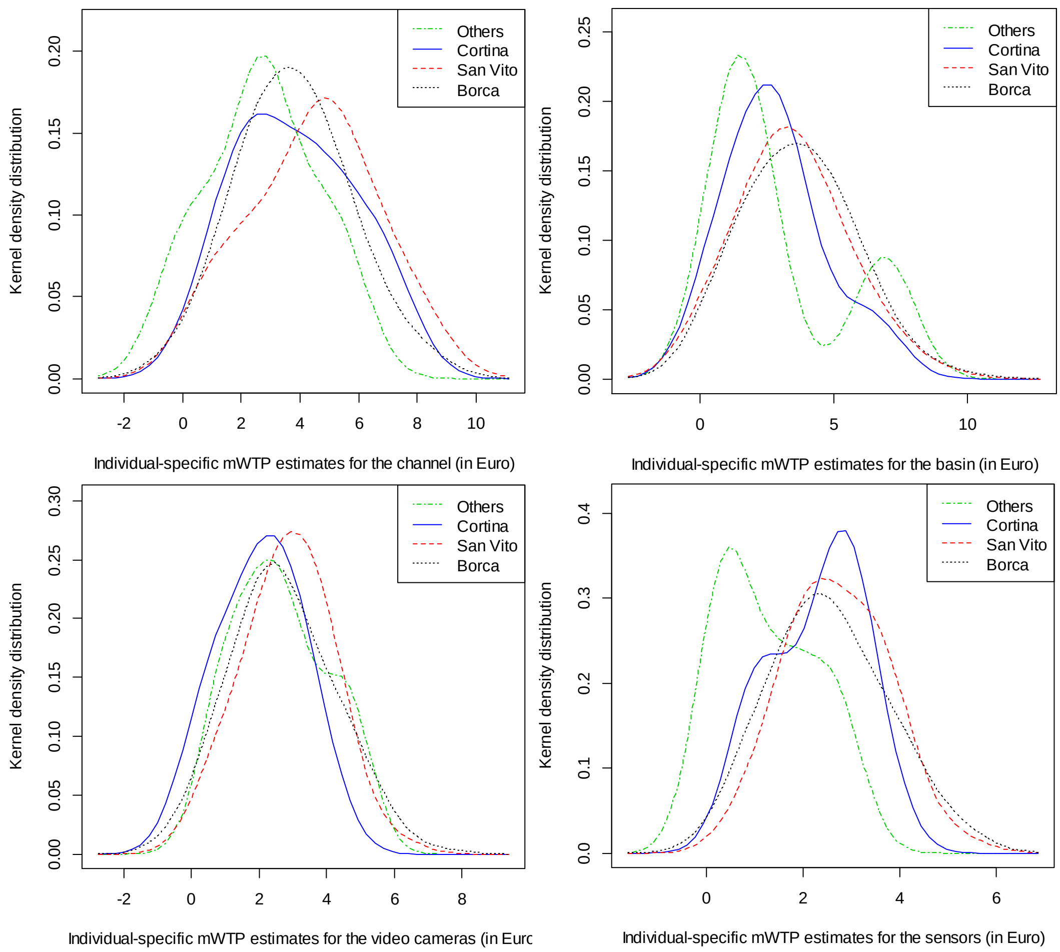

Figure 4.5 – Kernel distributions of individual-specific mWTP estimates for the four safety devices by selected municipalities.

4.4.3.1 Maps of the mean WTP values at municipality level

After examining the distributions of preferences across municipalities, the respondent-specific mean value estimates were averaged at the municipality level and then mapped across the Belluno province. Figure 4.6 shows the maps of the mean mWTP values for the four safety devices in the sampled municipalities. Each polygon represents a municipality within the borders of the province, and each colour reflects the average mWTP value in Euro. Municipalities outside the sample are in white.

The benefits are heterogeneously distributed within the province and among the different systems of protection. With regard to the Boite Valley, the six municipalities within its borders do not show a significantly higher average of mWTP value for the four devices than the municipalities in the north of the region. The highest benefit seems to be shown by the municipalities located in the north-east of the region. In fact, these municipalities are located in a mountain area, similar to the Boite Valley, and are therefore susceptible to landslides. This finding is more evident for video cameras (bottom left) and sensors (bottom right) than for channel (top left) and basin (top right). Especially for channel and basin, lower mWTP values are shown for municipalities in the central part, a flat area with low landslide hazard. The range of positive mean values covers the majority of municipalities. Only one municipality (Feltre) in the south of the region shows a negative average estimated value for the attribute channel that is close to zero, but for this location the sample count was low.

Important policy implications can be drawn from the preferences for safety devices in the three municipalities under investigation (Figure 4.7). Despite the fact that some passive devices are already in place in most of the landslide locations, respondents tend to prefer them to active measures. The municipality of Borca shows the highest mean mWTP values for all the four protection measures with a preference for channel. Channel construction is also preferred in San Vito. However, respondents living in Cortina slightly prefer basin, followed by channel and video cameras, and seem not to like sensors. An explanation can be found in the type of landslide threat in Cortina, which affects the road network more than the settlement.

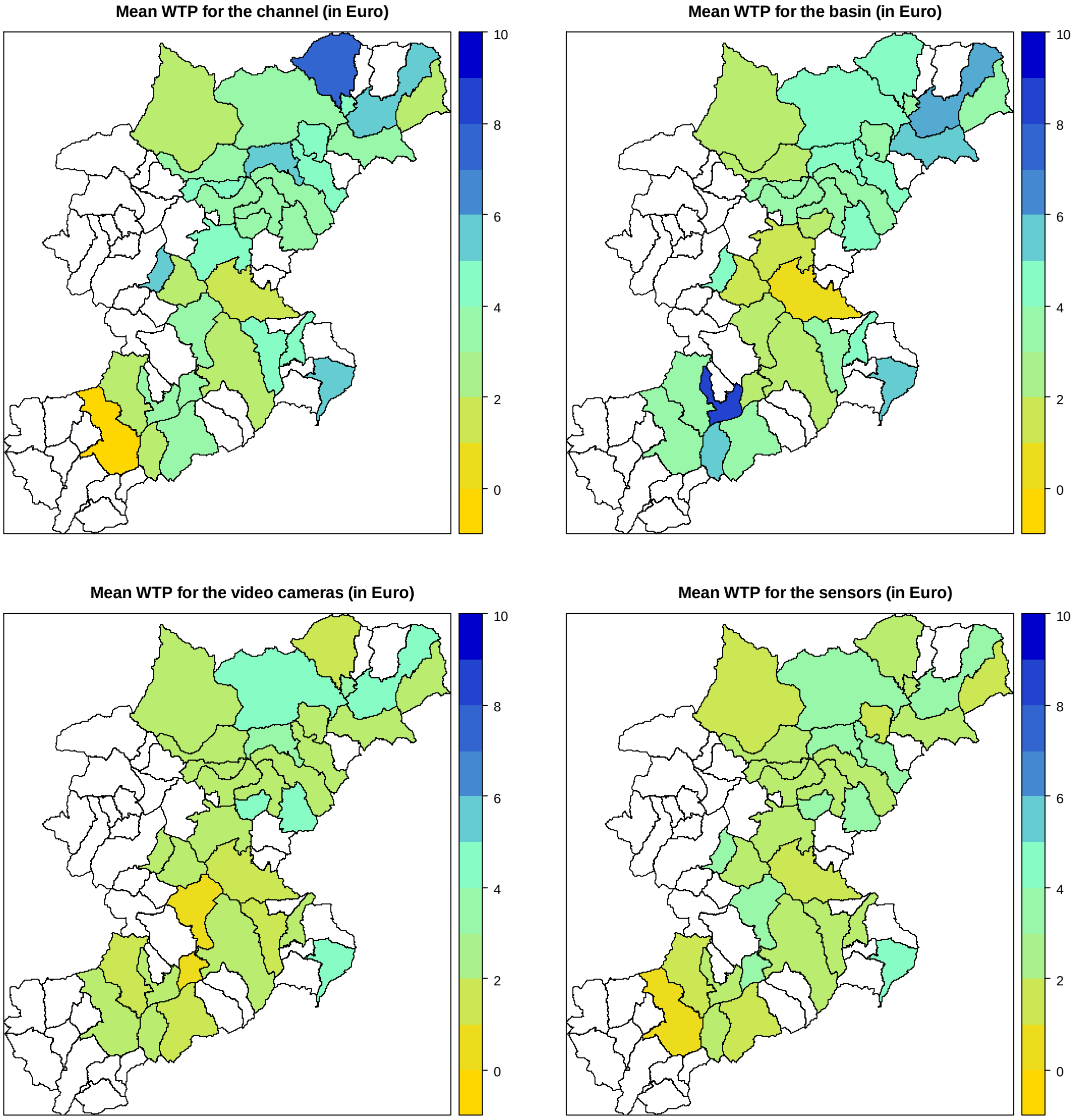

Figure 4.6 – Maps of mean WTP values for the municipalities.

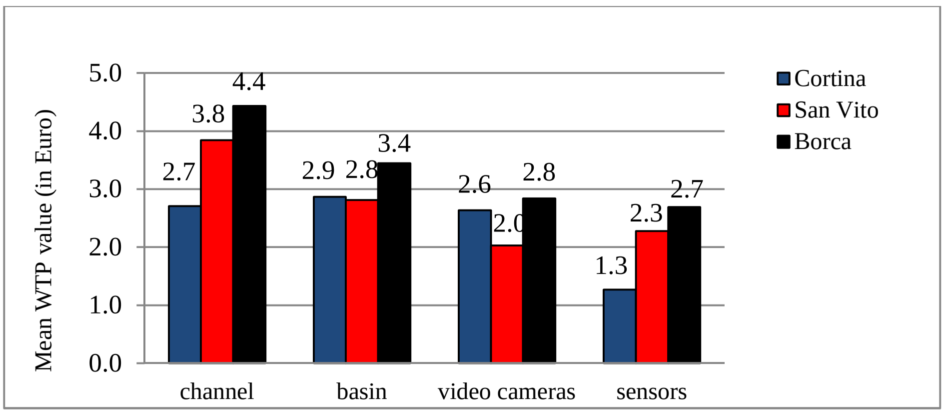

Figure 4.7 – Mean WTP values for the three municipalities of study.

4.5 Conclusions and policy implications

The main objective of this study was to explore individual and spatial sources of heterogeneity in preferences for landslide safety measures. The study explored how the inclusion of less conventional categories of observable heterogeneity, could provide insights into spatial determinants of preference heterogeneity. To do so, I augmented choice models with individual and municipality characteristics. I extended the traditional set of socio-economic variables, including geographical variables related to the municipality of residence, to provide further information on preferences towards the current level (*status quo*) of landslide protection. These variables supplemented the logit specification in a way that improved model-fit and interpretation of results. Furthermore, adding shared random components into the model revealed the presence of positive substitution patterns among the non-*status quo* alternatives for visitors driving through specific road segments. The inclusion of interaction terms between the monetary attribute and the site-specific choice sets showed that people prioritised interventions in locations without any device in place, despite these locations being at lower risk than others.

The second objective was to further investigate sources of heterogeneity through the use of a spatial model at the municipality level. In this paper, local clusters of WTP (corresponding to municipalities) are identified, in line with previous works of Meyerhoff (2013), Johnston and Ramachandran (2014), and Johnston et al. (2015). Application of the spatial model, in which tastes vary across municipalities and remain constant across choices within the same municipality, revealed the importance of accounting for spatial heterogeneity given that taste variations were present at both individual and municipality levels. The spatial model at the individual level (Model 1) seemed to fit the data better than the municipal level model (Model 2) in this specific case. However, this result is not conclusive and further investigation of the performance of spatial models at different hierarchical levels is required.

Failing to take account of spatial heterogeneity may have serious consequences on the selection of policy actions, especially in terms of cost and benefit distribution across the population of beneficiaries. This conclusion is in line with previous SP studies (Bateman et al. 2006; Johnston & Ramachandran, 2014; Johnston et al., 2015) that pointed the potential bias of individual and aggregate welfare measures when spatial patterns are ignored. The practical implications of this study may be of interest for different agents such as residents of the Boite Valley, visitors, policy makers and the Alpine mountain community overall.

Implications for beneficiaries

From a practical viewpoint, the analysis of the distribution of preferences among specific municipalities could help to prioritise policy interventions that match the preference of the public living or recreating in locations under landslide threat. Thus, policy decisions can be viewed over the system of spatial units, where the decision-makers decide in accordance with the preferences prevailing in specific locations. For spatially delineated environmental goods, different goals can be defined for each site, providing greater benefits than a uniform solution.

No substantial differences in preferences was found between residents and visitors to the valley, even though, residents benefit more than visitors from the implementation of mitigation programmes. Landslide protection measures provide respondents living in the Boite Valley with greater safety, higher house values and higher levels of income from tourism. This unexpected result could be partially explained by the fact that visitor preferences are heterogeneous. Visitors located in southern municipalities in the region are less likely to financially support the implementation of protection programmes for landslides, probably because they are less familiar with these hazards living in areas with a lower landslide risk. On the contrary, visitors coming from the northern part of the region show similar mean mWTP values to the residents of the valley. In some cases, they are willing to pay even more than the locals for the implementation of safety measures, given that most of them travel every day along the valley and are therefore more exposed than others.

The spatial information provided by this study will allow decision-makers to implement policy measures aimed at raising the awareness of natural hazards among different groups of visitors.

Implications for policymakers

Since public expenditure decisions for landslide protection are taken across multiple municipalities, these results could be of great practical interest for decision-makers. They can benefit from knowing which locations derive relatively higher values from the increase in specific safety measures for landslide protection. As an example, the municipality of Borca showed a strong preference for construction of a diverging channel, while Cortina had no clear preference but did not like sensors.

An improved understanding of the sources of heterogeneity leads to further insights into how the benefits and costs of policies are distributed across residents and visitors. This information can be of great use for local authorities interested in maintaining public support and in implementing safety policy for a broad audience. However, high preference heterogeneity may be problematic for decision-makers who have to deal with widely different views. Therefore, local authorities may opt for a policy that combines multiple safety measures to minimise disagreement.

Implications for the Alpine mountain community

The relevance of this study for the Alpine mountain community is further demonstrated by the recent increase in public concern about the consequences of natural hazards on people and property, given the increased incidence of extreme weather events. Fear of natural disasters has repercussions for where people choose to live, work, travel and recreate. This is an important consideration in the present case study, given that people in Alpine mountain valleys rely mainly on income from tourism. Generalization of these findings to other landslide contexts is unfeasible given the local geographical scale of the investigation. However, it should be noted that municipalities with high landslide risk are likely to present a stronger aversion to their current protection situation compared to municipalities with lower landslide risk. Overall, spatial preference heterogeneity matters in the consideration of landslide protection measures and should be taken into account.

This paper represents an advance over previous research through an in-depth exploration of the spatial sources of preference heterogeneity in the context of landslide hazard. The main findings illustrate how incorporating spatial variables into the model allows for better segmentation of policy preferences based on respondent and municipality characteristics. Accounting for multiple spatial dimensions in the model significantly enhances our understanding of the sources of taste variation and reveals richness in the structure of preferences, with relevant insights into the priority of intervention. Furthermore, this paper contributes to the existing literature on the implementation of spatial models that use B-W rank ordered choice data at the municipality level. The findings are of direct practical relevance and suggest that this approach could also be integrated into a benefit transfer framework due to its policy focus. The last important consideration is the observation that capturing multiple sources of preference heterogeneity is possible in the presence of good data. So, I argue that greater effort has to be devoted to collecting rich, high-quality data, since this is a necessity for better models.

Some limitations should be noted. The complexity of the B-W ranking posed some cognitive difficulties for the respondents that were asked to compare and rank a large number of alternatives, as previous studies have shown (Bradley & Daly, 1994; Scarpa et al., 2011; Marsh & Phillips, 2012). However, this was judged to be the best way of gathering the information that was necessary for the implementation of the spatial model. Another limitation of the study was the fact that the spatial model assumed homogeneity of preferences within each municipality. Future research may relax this strong assumption, allowing unobserved heterogeneity to vary over individuals and over municipalities, and further investigate hierarchical spatial models at a finer spatial resolution. Additionally, a social component may be included to account for spatial interdependencies between individuals since choices can be socially influenced by spatial variables.

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4.7 Appendix

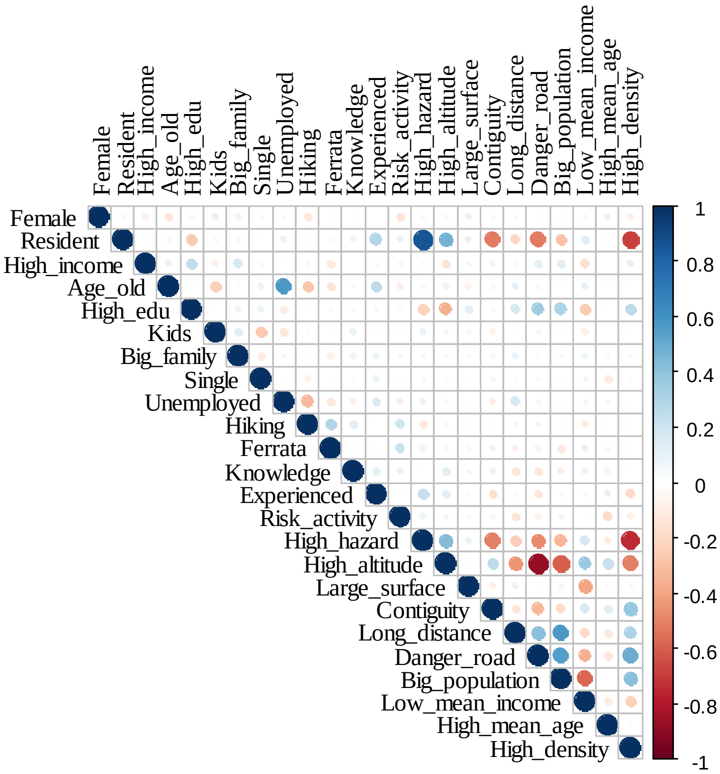

Figure 4.8 – Correlation plot between explanatory variables.

Chapter 5

Conclusions

This thesis presents nonmarket valuation research on landslide protection and contributes to the field of public and environmental economics. It addresses an important issue faced by mountain areas worldwide, which causes significant human and economic losses. The global impact of landslides is clearly evidenced by the numbers. Around 5% of the world population lives in areas under landslide threat. Over the period 2004-2010, the average number of fatalities was more than 3,000 people per year. This estimate is certainly a lower bound on the real value since it does not include landslide fatalities following other natural events. A conservative estimate of the global economic loss for landslide damage was calculated at approximately $US20 billion per year (Klose, 2015). Given the increasing number of natural disasters around the world, this estimate is expected to rise.

Therefore, landslide risk management policies are of increasing importance for the economics of adaptation to climate change. Additionally, an increase in soil fragility associated with urbanisation processes and tourism growth poses future challenges for public decision-makers in charge of landslide management. To respond to this problem, tools for evaluating efficient public expenditure targeted to social benefit are needed (Samuelson, 1954; Atkinson & Stiglitz, 2015). However, what is problematic is the quantification of intangible losses following a catastrophic event. Therefore, public economists have engaged in the analysis of social benefits and costs of public goods and services, not necessarily reflected by the market.

Landslide protection is a local public service, specific to a geographic location. It differs from a pure public good/service given its excludability due to distance. The fact that benefits of local public goods affect only individuals that belong to a particular community emphasises the importance of spatial analysis for this specific group of goods. As Samuelson (1954) stated, it is unlikely that the optimal level of a pure public good can be provided by decentralised market systems. Nevertheless, Tiebout (1956) argued that a decentralised market mechanism can work for local public goods given a self-sorting mechanism based on preference heterogeneity. Following works (e.g. Williams, 1966) pointed out that Tiebout's hypothesis is not accurate to reflect the real world, especially when governments act passively in providing local public goods. An inefficient level of provision may also result from local policies that do not represent the interests of the local population. As shown elsewhere (Stiglitz, 1977; Stiglitz, 1982), the Fundamental Theorems of Welfare Economics do not encompass economies with local public goods, unless under a restrictive set of assumptions. Given that the equilibrium will not be Pareto optimal, regulation or benefit taxation can be necessary to an efficient allocation of public resources (Stiglitz, 1982).

Starting with an application in the Italian Alps, I applied random utility theory to investigate stated preferences for hypothetical landslide protection programmes. Specifically, the study adopted a DCE method to explore the associated nonmarket benefits and to test several hypotheses related to preference heterogeneity and its determinants. The study focused on the implementation of choice models that accounted for different aspects of preference heterogeneity as well as for preference stability after additional information was provided, latent constructs and spatial sources of heterogeneity in preference.

This chapter summarises the main outcomes of the thesis and draws final conclusions. Section 5.1 offers an overview of each paper and the type of answers produced in the study for each of the research questions presented in Section 1.5. The contributions to the ex-ante literature from each of the papers that make up this thesis are discussed in Section 5.2. Implications for researchers and decision-makers are discussed in Section 5.3. Section 5.4 highlights some limitations of the study while Section 5.5 presents possible directions and recommendations for future research. The last part, Section 5.6, presents final remarks.

5.1 Summary of results

The first paper (Chapter 2) focused on heterogeneity and stability of preferences when scientifically-based information was provided to respondents. The second paper (Chapter 3) discussed the issue of the empirical identification of simulated coefficient estimates obtained by integrating choice and latent variable models, focusing on the effect of increasing the number of latent variables on the stability of results. The third paper (Chapter 4) offered a comprehensive treatment of sources of preference heterogeneity, accounting for its spatial determinants.

The following paragraphs discuss the answers to the research questions.

RQ1. Do people perceive the current level of protection from landslide hazard as inadequate? Does the provision of scientifically based information for an attribute have an impact on people's preferences? Are the distributions of the willingness-to-pay estimates and the effect of information provision spatially heterogeneous?

In the first paper, it was possible to derive the monetary value due to changes in attributes through the respondents' trade-offs for specific policy actions aimed at reducing landslide hazards. The data analysis showed that current safety measures were perceived as inadequate by respondents. In fact, the ASC for the *status quo* option was significant and negative, pointing out respondents' aversion to the current levels of protection. Additionally, passive devices, such as channels and basins, were preferred to active devices (video cameras and acoustic sensors). The specific mWTP estimates for these engineering solutions showed that the channel had the highest value of €2.12, followed by the basin (€1.83). With regard to early warning systems, the respondents slightly preferred acoustic sensors to video cameras (€1.26 and €1.19 respectively). A MXL model in WTP space was adopted to account for preference heterogeneity. This model specification outperformed the MNL and MXL in preference space models and accommodated the direct derivation of population mWTP values. The results from the data analysis showed that heterogeneity of preference existed for all protection devices. So, it should be taken into account for outlining the characteristics of the social demand for safety against landslides and for assisting policymakers in the implementation of effective mitigation policies. In the analysis reported in this paper, I further investigated the stability of preferences after scientifically-based information was provided to respondents, who were shown visual simulations of landslide events.

The information effect had a significant impact only on preference estimates for the device for which information was provided (i.e. channel Δ€0.42). Preference estimates were found to be stable for those devices for which no information was provided. The provision of information also affected the *status quo*, since the current mitigation measures were valued significantly less (Δ€-0.15) after information exposure. The geographical distribution of WTP estimates was also investigated by mapping the means of mWTP estimates at the municipality level. For landslide protection by means of a channel, the results suggested that before the information provision most municipalities had values between €1 and €2. However, after the information, values between €2 and €3 were more common. Evidence of spatial heterogeneity of WTP values was detected, but I could identify no distinctive spatial patterns across the sampled municipalities.

RQ2. How stable are the simulated parameter estimates from Integrated Choice and Latent Variable models when the number of latent variables is increased? Is heterogeneity in preference across respondents driven by underlying psychological factors such as perceptions of landslide risk? If so, may strong risk perceptions related to landslides have a positive impact on the aversion to status quo conditions (i.e. the riskiest option)?

The second paper investigated the importance of testing for the empirical identification of ICLV models. It analysed the stability of parameter estimates to the number of simulation draws and latent variables. Three LV-RPL models with respectively one, two and three latent variables were fitted using six sets of increasingly larger quasi-random draws to approximate unconditional choice probabilities. The results from each set of draws were compared within each model. Overall, the LV-RPL models provided very stable results with regard to the attributes' coefficients, but not for the estimated coefficients of latent variables and their standard deviations. It was expected that increasing the complexity of model specification (e.g. by adding more latent variables) required additional draws in the simulation process to ensure empirical identification.

I found that, with three latent variables, an unusually large number of draws (10,000 draws) was needed to discover if the coefficients can be identified. This number is much larger than what is conventionally adopted in most of the published literature (i.e. 1,000 draws). However, the number of draws is data-driven. Other papers can found different numbers and it is impossible to generalise. Using such a high number of draws allowed the detection of the presence of psychological sources of heterogeneity towards the latent variable, which went undetected when using a lower number of draws. The inclusion of more latent variables introduced instability in the order of relative magnitude across latent variables in estimates obtained at conventional draw sizes. Such instability ceased when the size of the draws was extended to these much higher than usual levels. This suggests that relative dominance among latent variables could have been misinterpreted in estimations via simulation if using a conventional number of draws.

The results also showed how preferences for the current level of protection were strongly related to the underlying perceptions of landslide risk. Such individuals' perceptions were modelled as latent psychological sources of heterogeneity that, together with unobservable sources, had a significant impact on the consideration of the baseline scenario (i.e. the riskiest option). The findings showed that two of the three latent variables were significant. The perception of own mortality risk was the latent construct with the largest marginal effect on the *status quo* (-4.15), followed by risk severity (-1.65). In contrast, the variable representing fear of landslides was insignificant. Taken together these results imply important recommendations to practitioners for the necessary computational time of ICLV models when testing for empirical identification. With an increased number of latent variables and a large number of draws, obtaining model estimates took a significant amount of time; up to two days with standard computer power (Asus Intel Core i7 1.90GHz 2.40GHz in Ubuntu 14.04).

RQ3. *Do spatial determinants contribute to explaining the patterns of preference heterogeneity for landslide protection? Do spatial choice models at the municipality level offer a useful tool for understanding the spatial dimensions of preference heterogeneity?*

The third paper explored individual and spatial sources of preference heterogeneity of residents and visitors with regard to mitigation programmes for landslides. Spatial effects were investigated in three different ways through the use of geographical characteristics related to landslide hazard, spatial error components and site-specific choice sets. In the "exploded" logit models, the inclusion of an extended set of socio-economic and geographical variables related to the respondents and their municipality of residence provided extra information on preferences for the current level of landslide safety. Furthermore, positive substitution patterns among the non-

status quo alternatives emerged for visitors driving through specific segments of the road network. The site-specific choice sets allowed investigation of the priority of interventions in six different locations in the valley under investigation. It emerged that respondents prioritised interventions to a location without any device in place, despite this area being at lower risk than others. The sources of heterogeneity were also analysed at a higher hierarchical level through the use of a spatial model at the municipality level, which found the presence of spatial heterogeneity among administrative units. Exploring multiple spatial dimensions of preference heterogeneity, as done in this paper, allowed the gathering of information on the distributional effects of increasing protection, which is of great value for policy decisions.

5.2 Contributions of the study

Overall, the thesis contributed to the existing and limited literature on public preferences for natural hazard protection policies. Additionally, the results of this research informed the contemporary debate between decision-makers and local populations on the efficiency of public spending.

The methodological and practical contributions of the thesis are listed below:

For paper 1:

1. *Preferences for landslide protection*: the paper contributed to knowledge about the value of protection against landslides in a mountain valley of the Italian Alps. This work is located in a limited literature on nonmarket valuation of natural hazards, which is of particular significance for the economies of many countries in mountain areas.
2. *Information effect*: the paper provided insights into the stability of preference estimates in the presence of additional information regarding one specific attribute. In accordance with Munro and Hanley (2002), the individual's WTP increased after positive information about the device was provided. In contrast to other studies (e.g. Oppewal et al., 2010), the information effect was only significant for the attribute for which landslide simulations were provided. The additional information did not affect the estimates of the other attributes. Also, information provision had a negative effect on the propensity to choose the current level of protection.

3. *Preference heterogeneity and representations of WTPs*: the paper found the existence of preference heterogeneity among respondents for all the attributes and made a first attempt to uncover the presence of spatial heterogeneity among municipalities, which is fleshed out in Paper 3. In addition to previous studies (e.g. Campbell et al., 2008 and 2009), mapping posterior individual specific mWTP estimates provided a visual comparison of the distribution of benefits from alternative defensive devices, before and after information provision.

For paper 2:

4. *Stability of simulated parameter estimates to the number of draws and latent variables*: the paper highlighted an issue regarding the integrated choice and latent variable models that had been largely unquestioned, i.e. the identification problem when including a progressive higher number of latent variables. This work advanced on that of Vij and Walker (2014) on the identification issue in ICLV models in conjunction with the number of draws. Given the lack of guidelines and the increasing popularity of this group of models, this paper presented a series of good practices that can be of help to practitioners when using this model framework. In addition to the critique by Chorus and Kroesen (2014), the study stressed that the empirical identification of ICLV models has to be systematically tested, especially for policy implications.
5. *Latent psychological sources of heterogeneity*: despite the downside of instability, the ICLV models provided insights into unobservable psychological sources of heterogeneity. Latent variables, such as mortality risk perception and perception of local risk severity for natural hazards, impacted the respondents' preferences for the current (and riskiest) scenario. In line with the economic theory of risk and uncertainty (e.g. Machina & Viscusi, 2014), those with higher risk perceptions were keener on increasing the safety level by mitigating the impact of landslides. A third latent construct, related to fear of landslide events but not to risk, emerged as insignificant.
6. *Psychological theory of protection*: the results of this study appeared to be fairly consistent with the threat appraisal process of the PMT (Rogers, 1975). This behavioural theory allowed for a better understanding of how people deal with protection choices under threats. It offered the opportunity to derive

three psychological constructs related to the mental processes of assessing threats. Perceived threat vulnerability, perceived threat severity and fear were included in the model with the result that two out of the three latent constructs were significant. Other studies used PMT in the context of natural hazards (e.g. Grothmann & Reusswig, 2006; Reynauld et al., 2013) proving that this psychological theory is well established in the context of health and environmental risk.

For paper 3:

7. *Spatial preference heterogeneity*: The work responded to a call for more studies into the relevance and complexity of spatial dimensions in stated preference analysis. This paper recognised the importance of distinct spatial effects, such as geographical characteristics, spatial error components and site-specific choice sets. An unusual set of geographical observables was tested. Those connected with landslide risk to settlements and roads were found to be significant. Another important finding was that residents and visitors slightly differed in their consideration of alternative scenarios of protection. Thanks to the inclusion of spatial error components in the model, substitution patterns for non-*status quo* alternatives were detected for visitors driving on specific road segments. As far as I know, the use of site-specific choice sets referring to particular locations is rare in the DCE literature.
8. *Spatial models*: the paper contributed to the existing literature on the implementation of spatial choice models (e.g. Campbell et al., 2009; Johnston & Ramachandran, 2014; Czajkowski et al., 2017). To the best of my knowledge, the adoption of a B-W rank-ordered choice dataset for spatial modelling was a totally new contribution, as was the exploration of multiple sources of preference heterogeneity in the context of natural hazards risk management using spatial models with hierarchical levels (i.e. individual and municipality levels).

5.3 Policy implications

This research is of particular relevance to local policymakers who are expected to take actions to lower the risk of current landslide hazards in the area under investigation. I argue that the inclusion of public preferences for protection programmes in the valuation of mitigation strategies is pivotal for an integrated approach that considers both the technical and the socio-economic dimensions.

Several policy implications can be derived from this research. With regard to the first paper, respondents were willing to pay to increase the level of protection against landslides. The mWTP estimates can guide decision-makers regarding the relative importance of each protection device for the public. For local policymakers, mitigation policies should focus on the implementation of passive measures, such as channels and basins, given that the beneficiaries are willing to contribute more to their realisation than to active devices. The channel was the attribute associated with the highest mWTP (around €2.1), followed closely by the basin (around €1.8), then acoustic sensors (around €1.3) and lastly video cameras (around €1.2). I found that the overall WTP equalled the value of €6.4 for a protection policy aiming to provide the highest safety (i.e. deployment of all four devices). This value seems to be acceptable as an averaged road toll to be paid for a limited time by residents and visitors passing through the Boite Valley. Also, educational campaigns can have a positive impact on the public awareness of the landslide issues, leading to a broader support for landslide mitigation programmes from better-informed respondents. The encouraging findings on the spatial heterogeneity of individuals' preferences have important practical consequences for policymakers. This is especially true in such a highly geographically differentiated context as Alpine mountain valleys.

The second paper pointed out the potential vulnerability of conclusions drawn from unstable estimated latent variables' coefficients. It was clear that a conventional number of draws in the simulation process can lead to unstable and misleading results, especially for the latent variables' coefficients. Therefore, the inclusion of more latent variables in a model poses some uncertainty for the derivation of policy implications. As the literature suggests, it is difficult to estimate several latent variables and having them all significant. The additional information provided by this group of models may be beneficial for local decision-makers aiming at increasing the public acceptance of the proposed policy actions. However, the concerns raised by Chorus and Kroesen (2014) regarding the endogeneity of the latent variable and its cross-sectional nature are plausible in this context. Therefore, communication campaigns aimed at increasing the awareness of landslide hazards through the modification of risk perceptions (i.e. latent variables) are discouraged. Another point that practitioners should consider carefully is the complexity of the model. More latent variables inevitably require more draws for the simulation process to obtain stable estimates (up to 10,000 draws), which lead to extended computational time (days with a standard processor).

The third paper stressed the importance of accounting for spatial dimensions of preference heterogeneity for spatially-delineated environmental goods. This is especially true for local decisions (e.g. taken at the municipality level) regarding public safety. The fact that visitors considered alternatives differently from residents is relevant for strategic policy decisions. It highlighted a general need by visitors for increased protection but weak preferences for specific devices. In fact, the exploration of spatial and non-spatial sources of preference heterogeneity can provide local decision-makers with a better understanding of how costs and benefits of policies are distributed across beneficiaries (i.e. residents and visitors), and hence across the relevant electorate. A way of recovering the cost of provision of landslide safety is by taxing those who receive the benefits ("beneficiary-pays principle"). This means that residents would pay more than visitors given that they receive the highest benefit from the implementation of protection policies, while visitors would contribute less based on the "use" of the protection service (e.g. through a road toll or tourism tax). This means that local policymakers can target specific policies based on the distribution of preferences among selected municipalities. Moreover, the research pointed out that failure to explore spatial heterogeneity in a land management context can potentially have severe repercussions on individual and aggregate welfare estimates (Bateman et al., 2006; Campbell et al., 2009; Johnston & Ramachandran, 2014).

5.4 Limitations of the study

Some limitations of this thesis must be reported, as follows:

- *Limitations in the data collection*: given the sampling technique, the sample did not cover some of the municipalities in the Belluno province with a very high landslide hazard. In addition, the number of respondents for each municipality was uneven. As a consequence, the mean mWTP estimates for some towns were based on relatively few respondents.

- *Limitations of the survey instrument*: the respondents might not have had the same familiarity with the selected attributes. A general explanation of each device, together with pictures, was provided before the ranking exercise. Also, the number of attributes and their levels were reduced to facilitate the trade-off among alternatives. The complexity of the B-W ranking exercise posed some cognitive difficulties, especially to older respondents. This is a common limitation of the methodology adopted, in which respondents are asked to rank many alternatives (Hanley et al., 2001; DeShazo & Fermo, 2002). However, the repeated B-W approach alleviated the cognitive effort (Scarpa et al., 2011). The number of alternatives in each choice set was judged suitable for a ranking exercise even though there are no general suggestions in this regard (Johnston et al., 2017). Given the time and resources available, it was impossible to obtain a bigger sample. Therefore, the ranking format was necessary to generate the size of sample choices for the implementation of spatial models. The use of an online survey in which the alternatives already chosen were removed could have simplified the exercise but was not applicable to the present case study. The issue of complexity and fatigue effects that can appear in ranking exercises (Scarpa et al., 2011) was addressed by randomising the choice set order.
- *Limitations of the first paper*: the difficulties in collecting completed questionnaires, together with the touristic seasonality of the area and the length of the questionnaire, did not allow scope for a control group for the information effect. Additionally, the information provided in the form of simulations of events was technical, so in some cases respondents may have incorrectly interpreted it.
- *Limitations of the second paper*: Other psychological theories could have been tested in the second paper. However, the PMT was judged the most appropriate for representing the protection behaviour of the respondents. Furthermore, it was difficult to define a proper set of indicators for the latent constructs and their scale of measure. Respondents might also have had distorted perceptions of their risk exposure. Therefore measurement bias cannot be ruled out, given that some respondents clearly displayed superstitious behaviour while replying to questions on risk perception of their own mortality. The measurement scale of the mortality perception could be criticised, as it has been shown that respondents have difficulties in dealing

with probabilities (Manski, 2004). Nevertheless, the most significant limitation faced in the second paper was the computational time for complex integrated choice and latent variable models. Additionally, I analysed the stability of the coefficients to the number of draws used in simulation-based estimation. However, stability of parameters can be analysed with respect to simulation starting points, old-out samples, resampling techniques, temporal and spatial transferability.

- *Limitations of the third paper*: the specification of the spatial models implied a strong assumption of preference homogeneity within each municipality, which might be unwarranted. Even though a large number of spatial variables were tested, only a few of these emerged as being significant. Since socio-economic effects were over-represented compared to geographical ones, this result might have penalised the performance of the spatial models in comparison to the conventional models. Also, the problem of defining jurisdictional optimality (Rubinfeld, 1987) is present, given the uncertainty over the proper geographical scale to adopt (for example neighbourhood, hamlet, municipality, high hazard settlements).

5.5 Directions for future research

The results from this investigation suggest a number of future research avenues.

From the practical point of view, future research could go in the direction of integrating the approach adopted in this thesis with a cost-benefit analysis for an effective decision-making tool for a comprehensive risk management policy. Given the local scale of the policy actions, the ranking approach could be integrated into a benefit transfer framework to infer the values for municipalities not covered by the sampling. Geographical benefit determinants, such as the landslide risk of the municipality, could act as predictors of welfare estimates in the benefit functions of non-sampled municipalities. However, the influence of policy scale on transfer validity has to be addressed (Johnston & Duke, 2009).

From a methodological point of view, future research could include a simulation study for investigating the causes of instability in the estimates of the integrated choice and latent variable models when more complexity is added into the model. In the field of numerical analysis and econometrics, other aspects of the simulation process could be investigated rather than the minimum number of draws for empirical identification. For example, the progressive order in which latent variables are included in the model may provide additional insights regarding their relative importance. Further research could also compare the performance of conventional and hierarchical spatial models with a finer spatial resolution, such as the neighbourhood. The inclusion of a social component to account for spatial interdependencies between individuals is also suggested as choices can be socially influenced. Future research could benefit from the results of a Bayesian study that accounts for landslide risk perceptions as latent variables. The investigation could provide a methodological contribution to enrich choice modelling and an alternative way to avoid the endogeneity issue present in the conventional choice models with latent variables, as suggested by Bolduc and Alvarez-Daziano (2010). In order to validate the results of the present study, an *ex-post* investigation could be conducted to test whether the deployment of landslide mitigation devices is perceived as sufficient by the population. Another *ex-post* analysis could validate the results in similar geographical contexts or where there are similarities in explanatory variables, such as individuals' risk perception. Finally, other psychological theories and approaches to incorporate spatial considerations into choice modelling can be explored for future research.

5.6 Final remarks

The *first* lesson from this study is that addressing every source of heterogeneity is unfeasible, but outlining the heterogeneous characteristics of social demand can increase public acceptability and public support for mitigation actions. The *second* lesson is related to spatial aspects. Controlling for spatial heterogeneity across respondents and municipalities can provide useful information for decision-makers and politicians who are interested in their electorate pool. However, how to convert results from complex models exploring heterogeneity into simple words understandable by local authorities is an issue that has yet to be addressed.

Finally, this research showed that nonmarket valuation techniques are under-used in the context of natural hazards. Given the high demand for tools for determining efficient public expenditure, the use of stated preferences for the assessment of the social demand for safety is expected to gain much attention in future. In fact, efficiency of public expenditure is essential when public money is considered a "scarce resource".

5.7 References

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Appendices

Appendix A – Landslide hazards in the Boite Valley

This appendix contains the chronology of landslide events since 1729 in the Boite Valley. In the last 300 years, there have been 74 recorded major landslides in the Boite Valley. However, just in the last 100 years, there have been 64 landslides. The current study is of particular relevance because six events occurred in 2015, three events in 2016 and five events in 2017 in the area under study, causing fatalities and widespread damage to roads and settlements. Table A.1 reports the most important landslide events in the history of the Boite Valley, together with the recorded consequences when available. The data was retrieved from an inventory of the areas affected by landslides (AVI project - Inventory of information on sites historically affected by landslides and floods) kept by the Italian National Research Council (CNR - Consiglio Nazionale delle Ricerche).

Date	Location	Consequences
5 Aug 2017	Cimabanche (Cortina)	Road interruption
4 Aug 2017	Rio Gere (Cortina)	Road interruption
4 Aug 2017	Alverà (Cortina)	1 victim, evacuated population, damage to houses
14 Aug 2016	Acquabona (Cortina)	Road interruption
16 Jun 2016	Acquabona (Cortina)	Road interruption
15 Jun 2016	Acquabona (Cortina)	Road interruption
14 Sept 2015	Acquabona (Cortina)	Road interruption
14 Sept 2015	Peaio (Vodo)	Evacuated population
8 Aug 2015	Acquabona (Cortina)	Road interruption
4 Aug 2015	Peaio (Vodo)	Cycle path interruption
4 Aug 2015	San Vito (San Vito)	3 victims
23 Jul 2015	Cancia (Borca)	Road interruption
7 Jul 2015	Acquabona (Cortina)	Road interruption
22 Jun 2015	Acquabona (Cortina)	Road interruption
30 Sept 2013	Cortina (Cortina)	//
18 Jul 2009	Cancia (Borca)	2 victims, damage to houses, road interruption
5 Jul 2006	Fiames (Cortina)	Damage to roads

Continued on next page

Table A.1 – continued from previous page

Date	Location	Consequences
7 Oct1998	Passo (Cibiana)	Damage to roads
7 Oct 1998	Cortina (Cortina)	Damage to roads
6 Oct 1998	Fiames (Cortina)	Damage to roads
5 Sept 1998	Fiames (Cortina)	Damage to roads
31 Jul 1998	Cortina (Cortina)	Damage to roads
3 Jul 1998	Cortina (Cortina)	Damage to roads
4 Jul 1997	Fiames (Cortina)	3 evacuated people, damage to roads
4 Jul 1997	Passo Tre Croci (Cortina)	1 victim, damage to bridges
14 Jun 1997	Cancia (Borca)	//
8 Aug 1996	Cancia (Borca)	35 evacuated people, damage to houses and roads
14 Jul 1995	Chiapuzza (San Vito)	Damage to roads
1995	Acquabona (Cortina)	Damage to roads
14 Sept 1994	Passo Tre Croci (Cortina)	Damage to roads
14 Sept 1994	Acquabona (Cortina)	Damage to roads
14 Sept 1994	Chiapuzza (San Vito)	Damage to roads
2 Jul 1994	Vallesina (Valle)	Damage to houses and roads
2 Jul 1994	Cancia (Borca)	100 evacuated people, damage to houses and roads
2 Nov 1993	Masariè (Cibiana)	Damage to houses and roads
Jul 1992	Fiames (Cortina)	//
4 Sept 1987	Acquabona (Cortina)	Damage to roads
20 Jul 1987	Acquabona (Cortina)	Damage to roads
1987	Chiapuzza (San Vito)	Damage to roads
Jul 1977	Cortina (Cortina)	Damage to roads
5 Nov 1976	Acquabona (Cortina)	Damage to roads
16 Sept 1976	Cinque Torri (Cortina)	Damage to forests
24 Jul 1972	Chiapuzza (San Vito)	Damage to roads
12 Jun 1972	Cortina (Cortina)	Damage to roads
17 Sept 1968	Masariè (Cibiana)	Damage to houses
11 Apr 1967	Passo (Cibiana)	Damage to roads
24 Nov 1966	San Martino (Valle)	Damage to houses, church and roads
4 Nov 1966	Chiapuzza (San Vito)	Damage to roads
21 Jul 1964	Acquabona (Cortina)	Damage to railway
5 Jun 1962	Acquabona (Cortina)	Damage to roads
6 Nov 1961	Zuel (Cortina)	Damage to roads

Continued on next page

Table A.1 – continued from previous page

Date	Location	Consequences
17 Feb 1960	Chiapuzza (San Vito)	Damage to forests
3 Aug 1958	Acquabona (Cortina)	Damage to roads
14 Nov 1951	Pecol (Cortina)	Damage to community buildings
9 Nov 1951	Cancia (Borca)	Damage to the railway
9 Nov 1951	Chiapuzza (San Vito)	Damage to roads
16 Jul 1950	Acquabona (Cortina)	Damage to roads
15 Jul 1950	Chiapuzza (San Vito)	Damage to roads
1946	Cancia (Borca)	//
8 Jun 1935	Alverà (Cortina)	Damage to roads and loss of agricultural land
18 Feb 1925	Passo (Cibiana)	Damage to roads
18 Feb 1925	Chiapuzza (San Vito)	Damage to roads
17 Feb 1925	Cancia (Borca)	288 victims, 44 injured people, 53 missing people, damage to houses and buildings, death of farm animals
1924	Alverà (Cortina)	Damage to roads
14 Mar 1913	Masariè (Cibiana)	Damage to houses
1882	Alverà (Cortina)	Damage to roads
27 Jul 1868	Cancia (Borca)	//
1864	Cancia (Borca)	18 victims, damage to community buildings
1 Nov 1841	Pecol (Cortina)	30 evacuated people, damage to community buildings
21 Apr 1814	Marceana, Toluen (Borca)	257 victims, damage to houses and community buildings, damage to agriculture and forests
7 Jul 1737	Chiapuzza (San Vito)	Damage to roads and agricultural land
1736	Cancia (Borca)	Damage to community buildings and historical buildings
27 Oct 1729	Borca (Borca)	Damage to community buildings
24 Nov 1729	Borca (Borca)	Damage to community buildings

Table A.1 – Major landslide events in the Boite Valley (CNR, 2017).

Table A.2 shows the number of events that have occurred in each town. Cortina d'Ampezzo had 59.4% of the events because the municipality has an extended land area (254.5 km^2, 56.5% of the total land area of the valley). The second municipality is San Vito di Cadore, with 10 events (15.6%), followed by Borca di Cadore with eight (12.5%). Cibiana di Cadore had five events (7.8%), Valle di Cadore had two events (3.1%) and Vodo di Cadore only one (1.6%).

These records further support the selection of the six sites for the ranking exercise: three of them in Cortina, one in San Vito and one in Borca.

Town	Freq	%
Cortina d'Ampezzo	38	59.4
San Vito di Cadore	10	15.6
Borca di Cadore	8	12.5
Cibiana di Cadore	5	7.8
Valle di Cadore	2	3.1
Vodo di Cadore	1	1.6
Total	64	100.0

Table A.2 – Landslide events by municipality in the Boite Valley.

Figure A.1 reports the frequency of landslide events in the last 100 years, taking into account only the year of occurrence. It can be seen that 2015 registered the highest number of landslides (6 events), followed by 2017 and 1998, each with 5 events. Despite the adoption of some mitigation measures after previous landslide events these have increased in number in recent years, which underscores the relevance of the present study.

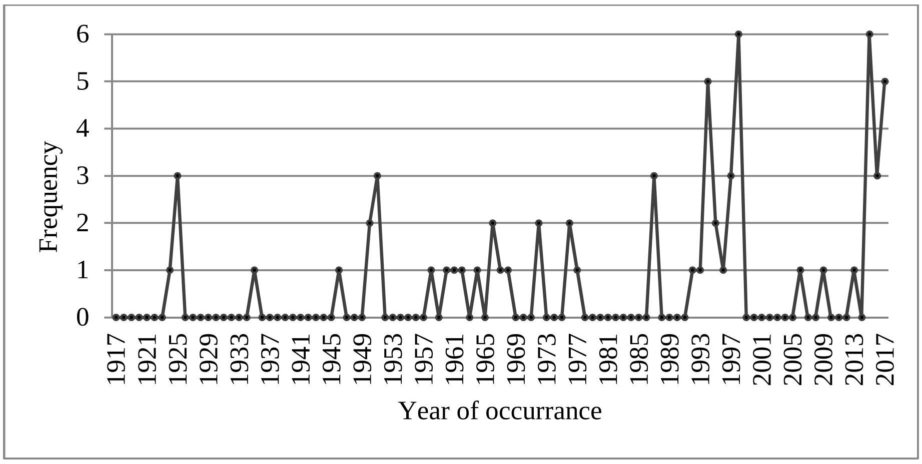


Figure A.1 – Landslide events in the Boite Valley per year (last 100 years).

Only partial historical data are available regarding the number of fatalities in the Boite Valley in the last 300 years (Table A.3). It is difficult to track fatal landslide events that happened long ago. It appears that in the last 300 years there were 623 reported victims from landslides in the valley. Most of the fatalities occurred in Borca di Cadore (99.2%).

Municipality	Freq	%
Borca di Cadore	618	99.2
San Vito di Cadore	3	0.5
Cortina d'Ampezzo	2	0.3
Vodo di Cadore	0	0.0
Cibiana di Cadore	0	0.0
Valle di Cadore	0	0.0
Total	623	100.0

Table A.3 – Number of fatalities in each municipality of the Boite Valley (1717-2017).

Regarding the year with the highest number of victims, 1925 registered 341 fatalities (54.7%), while in 1814 there were 257 deaths (41.3%) (Table A.4). A few major events caused the deaths of hundreds of people in a single town (Borca di Cadore). Considering the small number of inhabitants in this municipality (varying between 550 and 1300 people from the first census in 1871), the number of victims represent a large portion of the population that was living there. In 1925, almost 50% of the population died.

On average, approximately two people per year have died from landslide events in the Boite Valley over the last 300 years. In a total population that fluctuated between approximately 9,900 and 14,600 inhabitants (Istat, 2017) over that period, the probability of being the victim of a landslide is minimal and approximates zero. However, the findings depend heavily on the municipality, given that some towns have faced events of much greater magnitude than others. Nevertheless, this value is in line with those calculated from the data reported by Salvati, Bianchi, Rossi and Guzzetti (2010) for all the inhabitants of the Veneto region, which is 0.0009% calculated over a 50-year period from 1960 to 2010.

Year	Freq	%
1925	341	54.7
1814	257	41.3
1864	18	2.9
2015	3	0.5
2009	2	0.3
1997	1	0.2
2017	1	0.2
Total	623	100.0

Table A.4 – Victims of landslides per year (1717-2017).

Appendix B – Survey questionnaire

SURVEY on LANDSLIDE MITIGATION in the BOITE VALLEY

The University of Padua and The University of Waikato (New Zealand) would like to invite you to take part in this survey. Our purpose is to collect information on preferences for landslide risk reduction programmes among residents and visitors of the Boite Valley. The information you can contribute by completing this survey is important for us and for the Boite Valley. Your participation will help in developing landslide mitigation policies that reflect the population's needs.

Who is the researcher?

Stefania Mattea, a PhD student in the Department of Economics at the University of Waikato, supervised by Professor Riccardo Scarpa. The team leader for the project is Assistant Professor Mara Thiene, at the University of Padua.

What are we asking you to do?

The survey will require approximately 30-40 minutes of your time. You will be asked some general questions about you, your risk perceptions, and the activities you undertake in the Boite Valley. There will be also questions regarding landslide events and your preferences for different combinations of protection devices. During the survey, a map of the valley will be provided to display specific landslide locations.

What will happen to the data?

Your participation in this study is entirely **voluntary**. You have the right to decline to answer any particular questions and ask for any clarification about the study. The information you provide will be treated with **confidentially**, and your identity will not be required. The data will be released only in aggregate form. The results will be collated into a thesis and parts of it will be published in academic journals. Completion of the survey is deemed to mean consent.

This research is supported by the project: "Study of new early warning systems against hydrogeological risk and their social perception in a high valuable area for tourism and environment", funded by the University of Padova (CPDA119318).

SECTION I: Landslide and risk perception questions

Landslides, also called debris flows, are composed of a mixture of fine and coarse rock materials, water and often vegetal debris, which move towards the valley floor at high speed. These natural events represent a risk to people's safety as well as a cause of damage to private properties and public infrastructures.

Q1. Do you know of previous landslide events that have happened in the Boite Valley?

☐ Yes ☐ No

Q2. If you replied <u>yes</u> to question Q1, in which locations did the landslides happen?

☐ Cancia (Borca di Cadore)

☐ Chiapuzza (San Vito di Cadore)

☐ Acquabona (Cortina)

☐ Fiames (Cortina)

☐ Other, please specify ____________________________

Q3. What do you think are the triggers of landslides?

☐ Human activities (for example: land use change)

☐ Climate change (for example: heavy rainstorms)

☐ No triggers, just natural processes

☐ Other, please specify ____________________________

Q4. On a scale from 1 (=very low) to 5 (=very high), how much do you worry about the following consequences of landslides?

	Very low 1	2	Medium 3	4	Very high 5
Road interruption	☐	☐	☐	☐	☐
People's safety	☐	☐	☐	☐	☐
Environmental damage	☐	☐	☐	☐	☐
Property damage	☐	☐	☐	☐	☐

Q5. On a scale from 1 (=very low) to 5 (=very high), what is your fear of the following negative events?

	Very low 1	2	Medium 3	4	Very high 5
Car accident	☐	☐	☐	☐	☐
Theft/robbery	☐	☐	☐	☐	☐
Serious illness	☐	☐	☐	☐	☐
Accident at work	☐	☐	☐	☐	☐
Home fire	☐	☐	☐	☐	☐
Landslide	☐	☐	☐	☐	☐
Avalanche	☐	☐	☐	☐	☐
Earthquake	☐	☐	☐	☐	☐
Flood	☐	☐	☐	☐	☐

Q6. Have you ever been involved in past landslide events?

☐ Yes ☐ No

Q7. On a scale from 1 (=very low) to 5 (=very high), what do think is the severity of risk in the Boite Valley for the following natural events?

	Very low 1	2	Medium 3	4	Very high 5
Landslide	☐	☐	☐	☐	☐
Avalanche	☐	☐	☐	☐	☐
Earthquake	☐	☐	☐	☐	☐
Flood	☐	☐	☐	☐	☐

Q8. How many people in this region, out of about 5 million who live here, do you believe will be killed by a landslide event over the next year? (The number you choose can also include people who visit here)

☐ 0 ☐ 16-20

☐ 1-2 ☐ 21-30

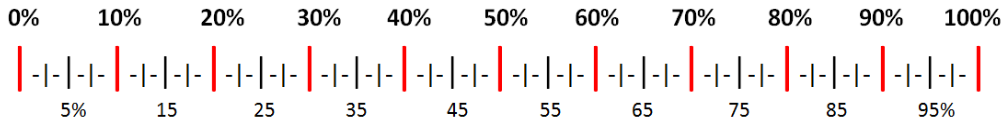
☐ 3-5 ☐ 31-40

☐ 6-10 ☐ 41-50

☐ 11-15 ☐ More than 50

Q9. On a scale from 0% (=cannot happen) to 100% (=definitely will happen), what do you believe is the chance that you might be killed by a landslide in the coming year, assuming that it is a typical year? (Please put a cross on the below line)

cannot happen *definitely will happen*



SECTION II: Recreated behaviour questions

Q10. What is the reason for your presence in the Boite Valley today?

☐ I am a resident

☐ I have a vacation home

☐ I am a one-day visitor

☐ I am an overnight visitor

☐ I work here

☐ Other, please specify ________________________

Q11. How many days, on average, do you spend per year in the Boite Valley? Days ___________

Q12. What outdoor recreational activities do you usually practice in the Boite Valley?

☐ Climbing

☐ Hiking

☐ Picnic

☐ Mountain biking

☐ Via ferratas (hiking routes with cables)

☐ Nature photography

☐ Mushroom picking

☐ Other, please specify _______________________

Q13. Do you frequently engage in activities that might be considered hazardous to your health?

☐ Yes ☐ No

Q14. If you replied yes to question Q13, which activities do you practice?

☐ Mountain climbing

☐ Off-piste skiing

☐ Fast car driving

☐ Motorcycling

☐ Other, please specify ___________________________

Q15. Suppose that you would like to visit the Boite Valley but it is not accessible due to a landslide. What would you do?

☐ I would visit other valleys nearby

☐ I would prefer to stay at home

Q16. If you replied that you would prefer to visit other valleys in Q15, please specify which valleys you would consider (more than one reply is allowed).

☐ Centro Cadore

☐ Comelico Valley

☐ Zoldo Valley

☐ Pusteria Valley

☐ Fassa Valley

☐ Belluno and Feltrino Valley

☐ Other, please specify ________________________

SECTION III: Ranking exercise (before information)

This section is a ranking exercise. You will be presented with 12 questions (choice sets) asking you to rank hypothetical landslide management options (alternatives). After the first six questions, information about landslides will be provided to you, and it will be followed by a repeated ranking exercise with the remaining six choice sets. Please consider the choice sets as **independent** and not additive choices.

The management options are described in term of protection devices that can be deployed, such as:

1. **Diverging channel**: a man-made channel built to redirect water. The water is carried off in a different direction than the sediment and rocks, mitigating the impact of the landslide;
2. **Retaining basin:** a dam where the solid and liquid mass is collected before it can damage roads and settlements;
3. **Video camera:** monitors for landslides during the night and, in case of emergency, it will activate an alarm system and traffic lights on the road;
4. **Acoustic sensor:** detects soil movement in slopes prior to landslides. The sensor consists of pipes inserted vertically in the flank of a landslide slope. It provides acoustic emissions used to give early warning of landslides and activates the traffic lights;
5. **Road toll:** is a cost to residents and visitors to the Boite Valley to be paid daily for driving in the valley over a period of eight months (April to November of one specific year).

Each choice set will refer to a specific landslide location in the Boite Valley. The current protection devices in place in each of the six locations are:

Sites	Passive devices		Active devices	
	Channel	Basin	Video camera	Acoustic sensor
Cancia	absent	insufficient	absent	absent
Chiapuzza	insufficient	insufficient	absent	absent
Acquabona	absent	present	absent	absent
Fiames Km 106	present	absent	absent	absent
Fiames Km 108	absent	absent	absent	absent
Fiames Km 109	present	insufficient	absent	absent

Please keep in mind that even though these are hypothetical scenarios, there could be real implications for your family's spending if changes in management happen. Also, please take into consideration that scientists agree with regard to the reduction in landslide risk after devices such as those presented are deployed in known hazard areas.

Please, rank the management options in each choice set in the following order:
(1) the first best alternative;
(2) the first worst alternative;
(3) the second best among the remaining five alternatives;
(4) the second worst among the remaining four alternatives;
(5) the third best among the remaining three alternatives;
(6) the third worst among the remaining two alternatives;
(7) the last alternative.

Q17. SCENARIO 1 of 12

Site 1 - **CANCIA**

Alternatives	A	B	C	D	E	F	Status quo
Channel	-	-	-	channel	channel	channel	-
Basin	-	basin	basin	basin	-	-	insuf.basin
Video camera	video	-	video	-	-	video	-
Sensor	-	-	sensor	-	sensor	sensor	-
Road toll	€3	€4	€1	€1	€3	€3	€0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q18. SCENARIO 2 of 12

Site 2 **- CHIAPUZZA**

Alternatives	A	B	C	D	E	F	Status quo
Channel	-	channel	-	channel	channel	channel	insuf. channel
Basin	-	-	basin	basin	basin	basin	insuf. basin
Video camera	video	-	-	-	-	-	-
Sensor	sensor	sensor	sensor	-	sensor	-	-
Road toll	€1	€4	€2	€1	€3	€4	€0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q19. SCENARIO 3 of 12

Site 3 - **ACQUABONA**

Alternatives	A	B	C	D	E	F	Status quo
Channel	-	channel	-	-	channel	-	-
Basin	basin	-	-	basin	-	basin	basin
Video camera	-	video	video	-	video	video	-
Sensor	-	-	-	-	sensor	sensor	-
Road toll	€3	€3	€3	€4	€1	€1	€0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q20. SCENARIO 4 of 12

Site 4 - **FIAMES km 106**

Alternatives	A	B	C	D	E	F	Status quo
Channel	-	-	channel	channel	-	channel	channel
Basin	-	-	basin	-	basin	basin	-
Video camera	-	video	-	-	-	-	-
Sensor	sensor	sensor	sensor	sensor	-	sensor	-
Road toll	€1	€2	€2	€2	€4	€1	€0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q21. SCENARIO 5 of 12

Site 5 - **FIAMES km 108**

Alternatives	A	B	C	D	E	F	Status quo
Channel	channel	-	-	channel	channel	-	-
Basin	basin	-	basin	-	basin	-	-
Video camera	-	-	video	video	video	video	-
Sensor	sensor	sensor	sensor	-	-	sensor	-
Road toll	€1	€2	€3	€1	€1	€2	€0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q22. SCENARIO 6 of 12

Site 6 - **FIAMES km 109**

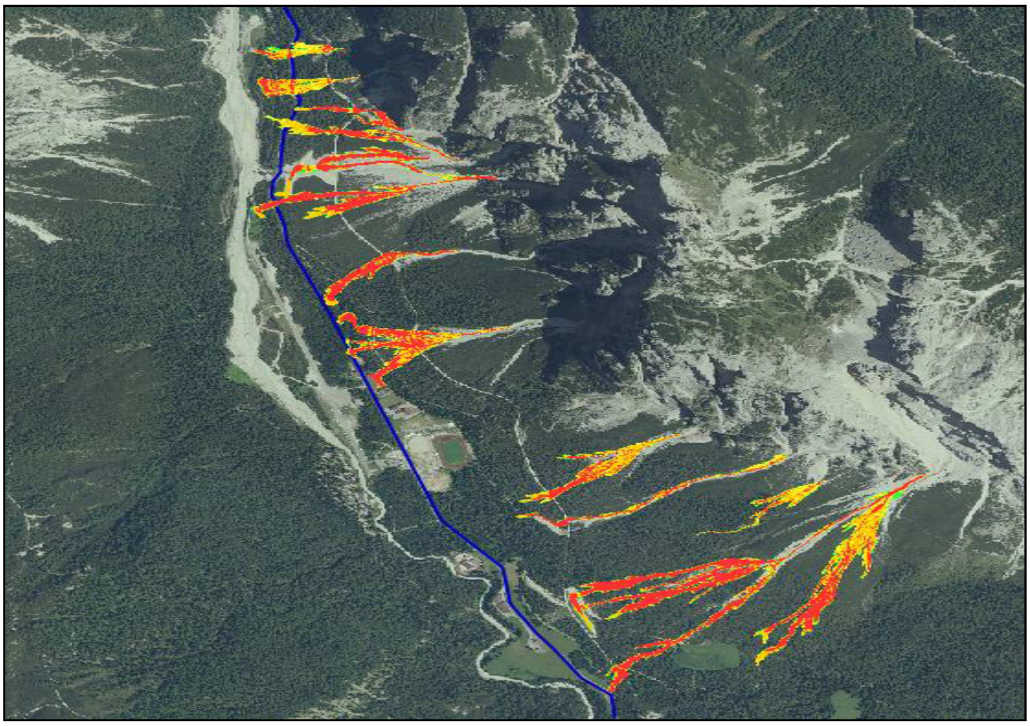
Alternatives	A	B	C	D	E	F	Status quo
Channel	-	-	-	channel	-	-	channel
Basin	basin	-	basin	-	basin	basin	insuf. basin
Video camera	video	-	-	-	video	-	-
Sensor	-	sensor	-	sensor	-	-	-
Road toll	€2	€2	€3	€3	€4	€1	€0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

SECTION VI: Ranking exercise (after information)

This section provides you with information about the landslide issue in the Boite Valley. Scientists have identified more than 350 potential landslide sites in this region that can threaten settlements and road networks. Visual science-based information in the form of hydro-geological simulations of landslide events is available for selected locations at high risk.

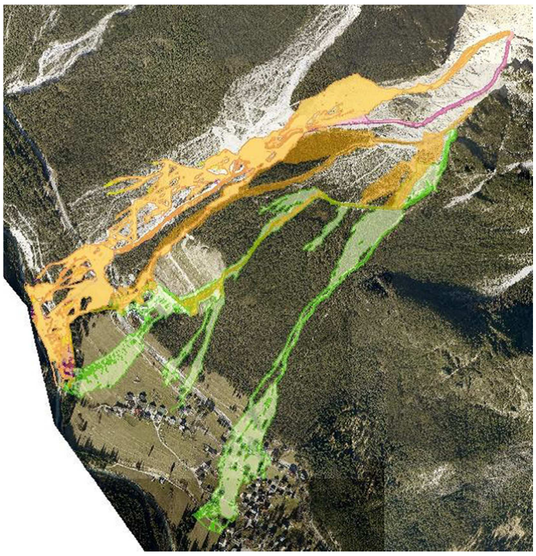
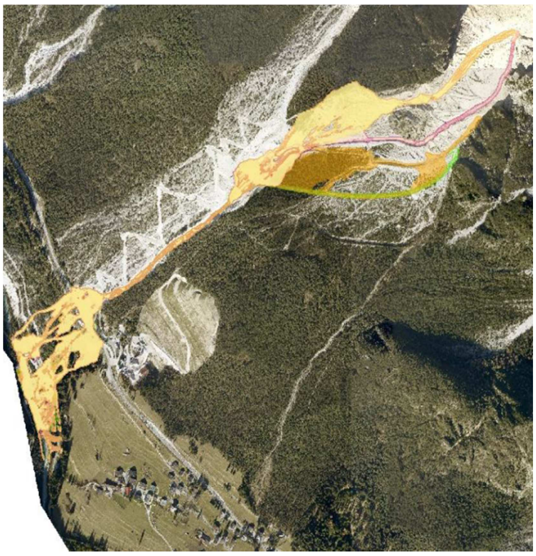
Fiames (km 106, km 108, km 109)

In Fiames, at least 12 landslide trajectories have been detected by scientists. The sliding debris may potentially reach the road and some private properties (houses, hotel and a factory). This has happened several times in the past, involving road interruptions and cycle path closures. The following map represents simulated trajectories of landslides and their associated risk from km 106 to km 109 in Fiames. The main road is represented by a blue line, while the cycle path is the white line above it. The different colours of the potential trajectories reveal the hazard class related to the magnitude of the landslide: green (lowest hazard), yellow, orange and red (highest hazard). Not all possible trajectories were included, only the most dangerous ones.



Chiapuzza

Two simulations of a landslide event in Chiapuzza are provided here, respectively before and after the implementation of a mitigation measure. The pre-intervention situation dates back to October 2013, before the deployment of a new diverging channel (channel 5bis). The settlement of Chiapuzza is situated at the bottom left of the landslide simulation area, while the main road is above it, crossing the maps diagonally.

Simulation pre-intervention in Chiapuzza (<u>without</u> the channel):	*Simulation post-intervention in Chiapuzza (<u>with</u> the channel):*
	

Please carefully consider the above information and reply to the following six questions **ranking the alternatives in the following order:**

(1) the first best alternative;

(2) the first worst alternative;

(3) the second best among the remaining five alternatives;

(4) the second worst among the remaining four alternatives;

(5) the third best among the remaining three alternatives;

(6) the third worst among the remaining two alternatives;

(7) the last alternative.

Q23. SCENARIO 7 of 12

Site 1 - **CANCIA**

Alternatives	A	B	C	D	E	F	Status quo
Channel Basin Video camera Sensor Road toll	- - video - €3	- basin - - €4	- basin video sensor €1	channel basin - - €1	channel - - sensor €3	channel - video sensor €3	- insuf.basin - - €0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q24. SCENARIO 8 of 12

Site 2 - **CHIAPUZZA**

Alternatives	A	B	C	D	E	F	Status quo
Channel Basin Video camera Sensor Road toll	- - video sensor €1	channel - - sensor €4	- basin - sensor €2	channel basin - - €1	channel basin - sensor €3	channel basin - - €4	insuf. channel insuf. basin - - €0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q25. SCENARIO 9 of 12

Site 3 - **ACQUABONA**

Alternatives	A	B	C	D	E	F	Status quo
Channel Basin Video camera Sensor Road toll	- basin - - €3	channel - video - €3	- - video - €3	- basin - - €4	channel - video sensor €1	- basin video sensor €1	- basin - - €0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q26. SCENARIO 10 of 12

Site 4 - **FIAMES km 106**

Alternatives	A	B	C	D	E	F	Status quo
Channel Basin Video camera Sensor Road toll	- - - sensor €1	- - video sensor €2	channel basin - sensor €2	channel - - sensor €2	- basin - - €4	channel basin - sensor €1	channel - - - €0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q27. SCENARIO 11 of 12

Site 5 - **FIAMES km 108**

Alternatives	A	B	C	D	E	F	Status quo
Channel Basin Video camera Sensor Road toll	channel basin - sensor €1	- - - sensor €2	- basin video sensor €3	channel - video - €1	channel basin video - €1	- - video sensor €2	- - - - €0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

Q28. SCENARIO 12 of 12

Site 6 - **FIAMES km 109**

Alternatives	A	B	C	D	E	F	Status quo
Channel Basin Video camera Sensor Road toll	- basin video - €2	- - - sensor €2	- basin - - €3	channel - - sensor €3	- basin video - €4	- basin - - €1	channel insuf. basin - - €0
Rank from 1 to 7	☐	☐	☐	☐	☐	☐	☐

SECTION V: Follow-up questions

Q29. Which payment methods do you prefer for providing your support for the realisation of landslide mitigation measures in the Boite Valley?

☐ Road toll

☐ Municipal tax

☐ Tourism tax

☐ Increase in price of tourist activities

☐ Donation

☐ Other, please specify ________________________

Q30. On a scale from 1 (=very low) to 5 (=very high), which level of security do you think will result from the following protection systems?

	Very low 1	2	Medium 3	4	Very high 5
Channel	☐	☐	☐	☐	☐
Basin	☐	☐	☐	☐	☐
Video camera	☐	☐	☐	☐	☐
Acoustic sensor	☐	☐	☐	☐	☐

Q31. On a scale from 1 (=very unimportant) to 5 (=very important), how do you rate the realisation of safety interventions in the following locations?

	Very unimportant 1	2	Medium 3	4	Very important 5
Cancia	☐	☐	☐	☐	☐
Chiapuzza	☐	☐	☐	☐	☐
Acquabona	☐	☐	☐	☐	☐
Fiames	☐	☐	☐	☐	☐

Q32. Based on the additional information provided, we ask you to reply again to the following question (as in question Q8). How many people in this region, out of about 5 million who live here, do you believe will be killed by a landslide event over the next year? (The number you choose can also include people who visit here)

☐ 0
☐ 1-2
☐ 3-5
☐ 6-10
☐ 11-15
☐ 16-20
☐ 21-30
☐ 31-40
☐ 41-50
☐ More than 50

__SECTION VI: Socio-economic questions__

To conclude, we would like to ask you a few questions about yourself. These questions allow us to check that we have a representative sample of people living in or visiting the Boite Valley.

Q33. What is your gender?

- ☐ Male
- ☐ Female

Q34. Which age group do you belong to?

☐ 18-29 ☐ 30-39 ☐ 40-49 ☐ 50-59
☐ 60-69 ☐ 70-79 ☐ 80 or over

Q35. What is the highest level of schooling you received?

- ☐ Primary school diploma
- ☐ Intermediate school diploma
- ☐ High school diploma
- ☐ Bachelor's degree
- ☐ Master's degree
- ☐ PhD degree

Q36. What is your occupation?

- ☐ Employee
- ☐ Self-employed
- ☐ Professional
- ☐ Businessman
- ☐ Student
- ☐ Retired
- ☐ Housewife/Unemployed

Q37. Where do you live? Municipality ______________________________

Province ______________________________

Q38. How many people usually live with you?

	0	1	2	3	4 or more
Adults 18 years and over	□	□	□	□	□
Children under the age of 18	□	□	□	□	□

Q39. What is your annual household income, after tax (€/year)?

□ Up to €15,000

□ €15,000 to €30,000

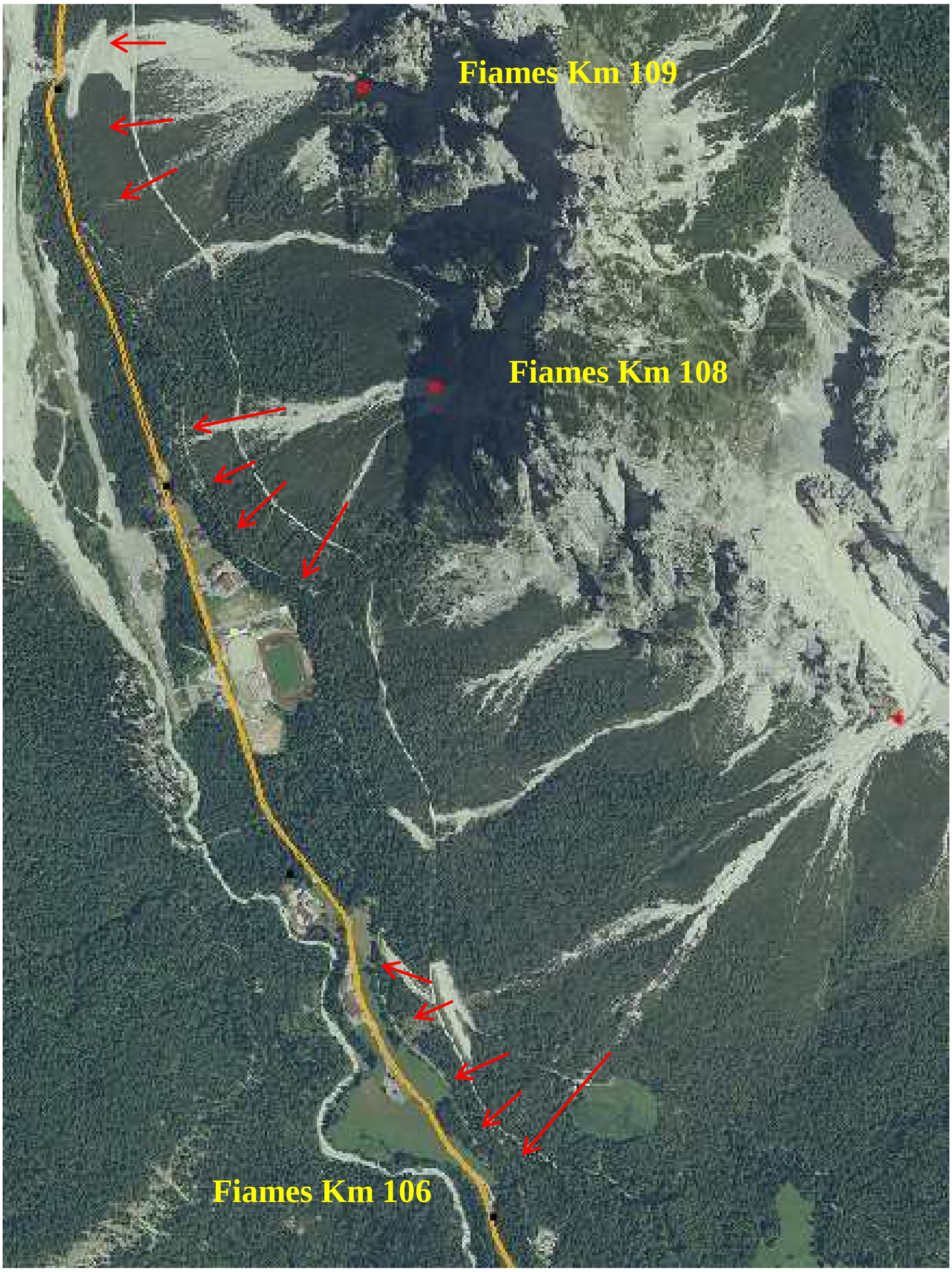
□ €30,000 to €45,000

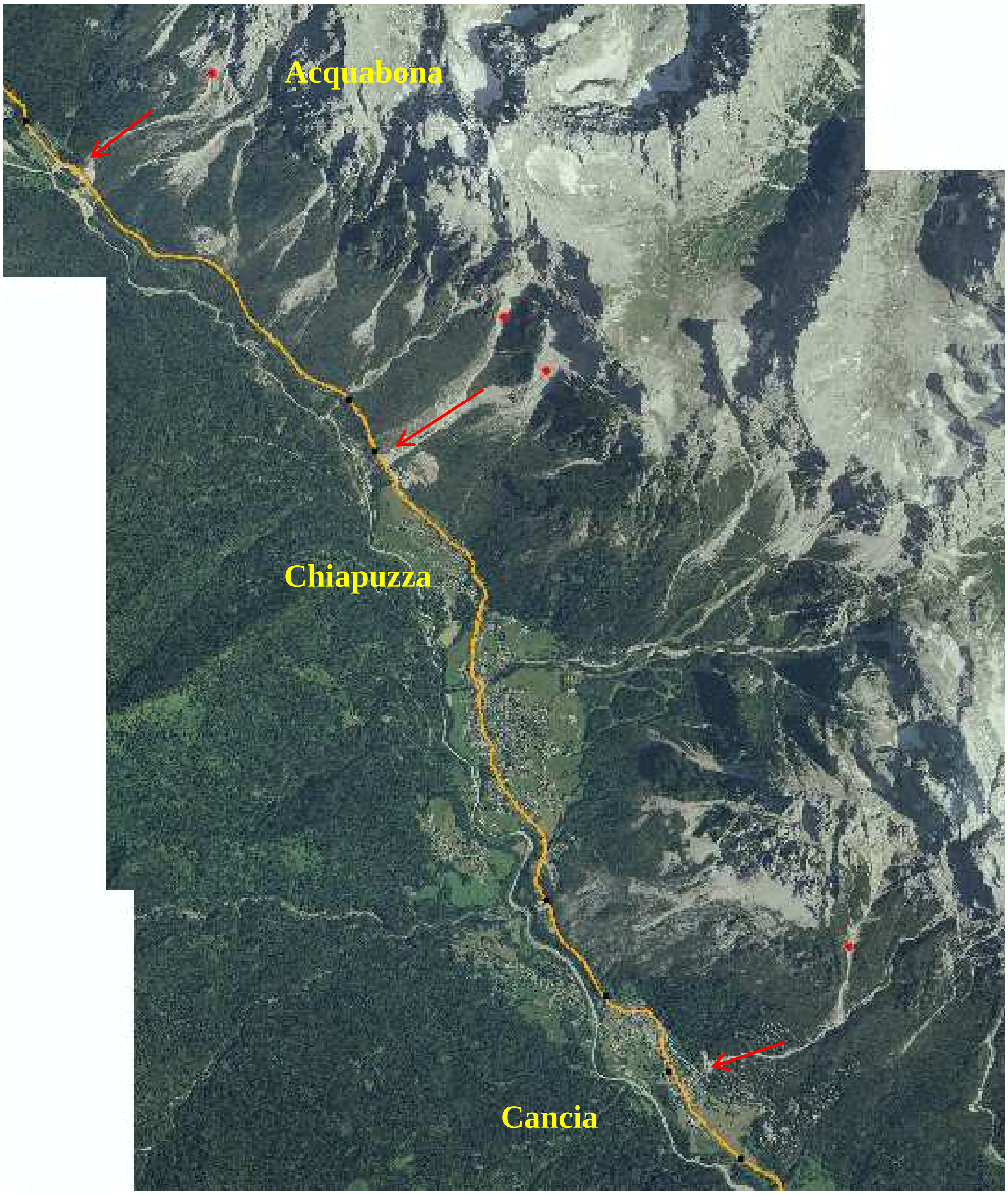
□ €45,000 to €60,000

□ Over €60,000

Thank you for your time and help to make this research possible!

Map of the Boite Valley with selected landslide sites




Acquabona
Chiapuzza
Cancia

Explanation of sources of simulation figures (not included in the questionnaire):

The simulations of landslide events in the Boite Valley were made using the model developed by Gregoretti, Degetto and Boreggio (2016).

The first block of information, showing the potential trajectories of landslides in three locations in Fiames (km 106, km 108 and km 109), was from the unpublished (at the time of the survey) work of Boreggio, Gregoretti and Degetto (2015) and was included in the survey with the authors' permission.

The second block of information, which compared two landslide simulations with and without a specific protection device in Chiapuzza, was retrieved from the unpublished (at the time of the survey) work of Degetto, Gregoretti, Mezzomo and Soppelsa (2014) and was included in the survey with the authors' permission.

The maps of the Boite Valley were retrieved and modified from Google Earth © (2014).

Appendix C – Derivation of individual-specific WTP values

Model estimates can be conditioned on the observed choices made by each respondent to obtain conditional individual-specific parameter estimates. Using Bayes' rule, the parameter estimates for each respondent *n* can be simulated from the individual's conditional distribution of the model estimates, based on observed responses (Greene, Hensher, & Rose, 2005; Campbell, Hutchinson, & Scarpa, 2009; Train, 2009). The estimator for the parameter β_n is the following:

$$E(\beta_n |\, y_n) = \int_{\beta_n} \beta_n \Pr(\beta_n | y_n) d\beta_n = \frac{\int_{\beta_n} \beta_n \Pr(y_n|\beta_n) \Pr(\beta_n)\, d\beta_n}{\int_{\beta_n} \Pr(y_n|\beta_n) \Pr(\beta_n)\, d\beta_n} \quad \text{(Eq. C.1)}$$

where β_n is the vector of estimated random coefficients from the model and $\Pr(\beta_n|y_n)$ is the marginal density of β_n. The observed sequence of choices (y_n) made by each respondent *n* is used for conditioning the individual-specific parameter estimates.

Since the integrals in Equation C.1 do not have a closed form, it cannot be computed analytically. Therefore, the conditional mean for β_n for individual *n* can be simulated as in Equation C.2:

$$E(\beta_n |\, n) = \frac{\frac{1}{R}\sum_{r=1}^{R} \beta_{nr}\, L(\beta_{nr}|y_n)}{\frac{1}{R}\sum_{r=1}^{R} L(\beta_{nr}|y_n)} \quad \text{(Eq. C.2)}$$

where R is the number of draws to be used in the simulation process, and $L(\beta_{nr}|y_n)$ is the likelihood of an individual's sequence of choices computed at the r^{th} draw.

However, as stated by Hensher, Rose and Greene (2005) and Train (2009), the conditional parameter estimates are not individual-specific but more generally are same-choice-specific parameters. This means that the conditional estimates are more correctly the means of the parameters of the sub-population of respondents who made the same choices when facing the same choice sets.

Despite the recent interest in obtaining individual estimates, little software is currently available. The software Nlogit (Econometric Software, 2007) gives the possibility of obtaining conditional parameter estimates, providing the starting values and setting the iteration equal to zero. An alternative approach is the software developed by Hess (2010).

The individual-specific marginal WTP (mWTP) values for an attribute k are calculated as the negative ratio of the estimated parameter for the specific attribute β_{nk} and the cost parameter estimate for the monetary attribute β_{cost}, as in Equation C.3:

$$WTP_{nk} = -\left(\frac{\beta_{nk}}{\beta_{cost}}\right) \qquad \text{(Eq. C.3)}$$

Appendix D – Codes for choice models

Code - paper 1

The following code exemplified for the MXL model in WTP space in Chapter 2 was programmed in Biogeme 2.0 (Bierlaire, 2003) (installed the 14/12/2014; http://biogeme.epfl.ch/install.html). The data processor used was an Asus Intel Core i7 1.90GHz 2.40GHz with a Windows 8.1 operating system.

```
// Model: MXL model in WTP space (interaction effect for information)
// Report file: MXL_WTPspace.mod
// Sample file:  Data_FirstChoice_BeforeAfter_Landslide.dat

[Choice]
// Define dependent variable
   Choice

[PanelData]
// Id is the identifier for respondents
// List of random parameters, constant for all observations of the same
individual
   Id
   B_S_B
   B_BA_S_BA
   B_CH_S_CH
   B_VI_S_VI
   B_SE_S_SE

[Beta]
// Each line corresponds to a parameter of the utility functions
// Name       Value   LowerBound  UpperBound   status(0=variable, 1=fixed)
   ASC_SQ     -0.016       -10         10             0
   B_BA         1.59       -10         10             0  // Basin
   B_CH         1.89       -10         10             0  // Channel
   B_VI         1.46       -10         10             0  // Video
   B_SE         1.21       -10         10             0  // Sensor
   B_CO           -1       -10          0             1  // Cost
   S_SQ       -0.152         0         10             0
   S_BA        -0.81         0         10             0
   S_CH        0.752         0         10             0
   S_VI        0.086         0         10             0
   S_SE        -0.92         0         10             0
   D_SQ       -0.052       -10         10             0
   D_BA         0.15       -10         10             0
   D_CH         0.52       -10         10             0
   D_VI         0.04       -10         10             0
   D_SE        0.123       -10         10             0
   D_CO        0.022       -10         10             0
   B          -0.121       -10         10             0
   S_B        -0.204         0         10             0
```

```
[Utilities]
// Each row corresponds to an alternative. There are seven alternatives
// Id: as defined in the choice variable
// Name: alternative's name
// Avail: indicates if the alternative is available or not
// Id  Name      Avail  linear-in-parameter expression
   1   alt1      one    $NONE   // NONE because specified as non-linear
   2   alt2      one    $NONE
   3   alt3      one    $NONE
   4   alt4      one    $NONE
   5   alt5      one    $NONE
   6   alt6      one    $NONE
   7   alt7      one    $NONE

[GeneralizedUtilities]
//  Utility function for each alternative specified in the WTP space, so
    nonlinear
    1   exp(B [ S_B ] ) * ( B_BA [ S_BA ] * bas1 + B_CH [ S_CH ] * cha1 +
        B_SE [ S_SE ] * sen1 + B_VI [ S_VI ] * vid1 + B_CO * cos1 + D_BA
        * dbas1 + D_CH * dcha1 + D_SE * dsen1 + D_VI * dvid1 + D_CO *
        dcos1 )

    2   exp(B [ S_B ] ) * ( B_BA [ S_BA ] * bas2 + B_CH [ S_CH ] * cha2 +
        B_SE [ S_SE ] * sen2 + B_VI [ S_VI ] * vid2 + B_CO * cos2 + D_BA
        * dbas2 + D_CH * dcha2 + D_SE * dsen2 + D_VI * dvid2 + D_CO *
        dcos2 )

    3   exp(B [ S_B ] ) * ( B_BA [ S_BA ] * bas3 + B_CH [ S_CH ] * cha3 +
        B_SE [ S_SE ] * sen3 + B_VI [ S_VI ] * vid3 + B_CO * cos3 + D_BA
        * dbas3 + D_CH * dcha3 + D_SE * dsen3 + D_VI * dvid3 + D_CO *
        dcos3 )

    4   exp(B [ S_B ] ) * ( B_BA [ S_BA ] * bas4 + B_CH [ S_CH ] * cha4 +
        B_SE [ S_SE ] * sen4 + B_VI [ S_VI ] * vid4 + B_CO * cos4 + D_BA
        * dbas4 + D_CH * dcha4 + D_SE * dsen4 + D_VI * dvid4 + D_CO *
        dcos4 )

    5   exp(B [ S_B ] ) * ( B_BA [ S_BA ] * bas5 + B_CH [ S_CH ] * cha5 +
        B_SE [ S_SE ] * sen5 + B_VI [ S_VI ] * vid5 + B_CO * cos5 + D_BA
        * dbas5 + D_CH * dcha5 + D_SE * dsen5 + D_VI * dvid5 + D_CO *
        dcos5 )

    6   exp(B [ S_B ] ) * ( B_BA [ S_BA ] * bas6 + B_CH [ S_CH ] * cha6 +
        B_SE [ S_SE ] * sen6 + B_VI [ S_VI ] * vid6 + B_CO * cos6 + D_BA
        * dbas6 + D_CH * dcha6 + D_SE * dsen6 + D_VI * dvid6 + D_CO *
        dcos6 )

    7   exp(B [ S_B ] ) * ( ASC_SQ [ S_SQ ] * one + B_BA [ S_BA ] * bas7
        + B_CH [ S_CH ] * cha7 + B_SE [ S_SE ] * sen7 + B_VI [ S_VI ] *
        vid7 + B_CO * cos7 + D_SQ * dsq + D_BA * dbas7 + D_CH * dcha7 +
        D_SE * dsen7 + D_VI * dvid7 + D_CO * dcos7 )

[ParameterCovariances]
// Elements of Cholesky
//     Par_i         Par_j      Value    LowerBound    UpperBound status
       B_BA_S_BA     B_CH_S_CH    0      -10           10           0
       B_BA_S_BA     B_SE_S_SE    0      -10           10           0
       B_BA_S_BA     B_VI_S_VI    0      -10           10           0
       B_CH_S_CH     B_SE_S_SE    0      -10           10           0
       B_CH_S_CH     B_VI_S_VI    0      -10           10           0
       B_SE_S_SE     B_VI_S_VI    0      -10           10           0

[Expressions]
// Define arithmetic expressions for name that are not directly available
   from the data
   one = 1
```

```
// Interactions
   dbas1 = ( bas1 * aft )
   dbas2 = ( bas2 * aft )
   dbas3 = ( bas3 * aft )
   dbas4 = ( bas4 * aft )
   dbas5 = ( bas5 * aft )
   dbas6 = ( bas6 * aft )
   dbas7 = ( bas7 * aft )
   dcha1 = ( cha1 * aft )
   dcha2 = ( cha2 * aft )
   dcha3 = ( cha3 * aft )
   dcha4 = ( cha4 * aft )
   dcha5 = ( cha5 * aft )
   dcha6 = ( cha6 * aft )
   dcha7 = ( cha7 * aft )
   dsen1 = ( sen1 * aft )
   dsen2 = ( sen2 * aft )
   dsen3 = ( sen3 * aft )
   dsen4 = ( sen4 * aft )
   dsen5 = ( sen5 * aft )
   dsen6 = ( sen6 * aft )
   dsen7 = ( sen7 * aft )
   dvid1 = ( vid1 * aft )
   dvid2 = ( vid2 * aft )
   dvid3 = ( vid3 * aft )
   dvid4 = ( vid4 * aft )
   dvid5 = ( vid5 * aft )
   dvid6 = ( vid6 * aft )
   dvid7 = ( vid7 * aft )
   dcos1 = ( cos1 * aft )
   dcos2 = ( cos2 * aft )
   dcos3 = ( cos3 * aft )
   dcos4 = ( cos4 * aft )
   dcos5 = ( cos5 * aft )
   dcos6 = ( cos6 * aft )
   dcos7 = ( cos7 * aft )
   dsq = ( one * aft )

[Model]
// Specified which model is to be used
   $MNL

[Draws]
// Specified the number of draws
   500
```

Code – paper 2

The following code exemplified for the LV-RPL model with three latent variables in Chapter 3 was programmed in PythonBiogeme 2.3 (Bierlaire, 2016) (installed the 10/05/2015; http://biogeme.epfl.ch/install.html). The data processor used was an Asus Intel Core i7 1.90GHz 2.40GHz with an Ubuntu 14.04 operating system.

```
#######################################
# Model: LV-RPL with three random latent variables (10,000 draws)
# LVs: perception of risk mortality (MOR),
# perception of natural hazards’ severity (SEV) and fear of landslides
(FEA)
# Report file:  LV-RPL_3LVrandom_10000.html
# Sample file:  Data_FirstChoice_Before_Landslide.dat
######################################

from biogeme import *
from headers import *
from distributions import *
from loglikelihood import *
from statistics import *

###
# A. LATENT VARIABLE MODEL
#
###
# A1. Structural model
###

#Define variables:
female = DefineVariable ('female', sex==1)

# Coefficients of the socio-economics characteristics
b_fem_MOR = Beta('b_fem_MOR',0.347,-10000,10000,0)
b_fem_SEV = Beta('b_fem_SEV',0.614,-10000,10000,0)
b_fem_FEA = Beta('b_fem_FEA',-0.0473,-10000,10000,0)

# Error term of the structural model
omega_MOR = bioNormalDraws('omega_MOR','Id')
omega_SEV = bioNormalDraws('omega_SEV','Id')
omega_FEA = bioNormalDraws('omega_FEA','Id')

# Latent variable (Z=risk perception) is modelled as follows
MOR = b_fem_MOR * female + omega_MOR
SEV = b_fem_SEV * female + omega_SEV
FEA = b_fem_FEA * female + omega_FEA

###
# A2. Measurement model: ordered logit
###

# Measurement equations:
# For the latent variable MOR:
# I_MOR_risk (CL_PR_MORTI) represents the mortality risk estimate stated
# by each respondent. The ordinal variable takes the following values:
# 1=0-5% (correct measure), 2=6-10% double the correct measure, 3=11-15%
# three times, 4=16-20% four times, 5≥20% more than four time the
# objective measure of risk.
# For the latent variable SEV:
# I_SEV_land (B_FRANA) represents the estimate of severity of landslide
# severity) to 5(high severity) in the Boite Valley. The ordinal
# variable takes values from 1(low # I_SEV_aval (B_VALAN) represents the
```

```
# estimate of severity of avalanche in the Boite Valley. The ordinal
# variable takes values from 1(low severity) to 5(high severity).
# I_SEV_eart (B_TERR) represents the estimate of severity of earthquake
# in the Boite Valley. The ordinal variable takes values from 1(low
# severity) to 5(high severity).
# I_SEV_flood (B_ALLUV) represents the estimate of severity of flood in
# the Boite Valley.
# The ordinal variable takes values from 1(low severity) to 5(high
# severity).
# For the latent variable FEA:
# I_FEA_frana (FRANA) represents the estimate of respondent’s fear of
# landslide. The ordinal variable takes values from 1(very low fear) to
# 5(very high fear).

#MOR
lambda_risk = Beta('lambda_risk', 0.654, -10000,10000, 0)
tau_risk1 = Beta ('tau_risk1', 0.603, -10000, 10000, 0)
tau_risk2 = Beta ('tau_risk2', 1.31, -10000, 10000, 0)
tau_risk3 = Beta ('tau_risk3', 1.55, -10000, 10000, 0)
tau_risk4 = Beta ('tau_risk4', 1.83, -10000, 10000, 0)

ME_MOR_RISK = {
1: 1/ (1+exp(MOR * lambda_risk - tau_risk1)),
2: 1/ (1+exp(MOR * lambda_risk - tau_risk2)) - 1/ (1+exp(MOR *
lambda_risk - tau_risk1)),
3: 1/ (1+exp(MOR * lambda_risk - tau_risk3)) - 1/ (1+exp(MOR *
lambda_risk - tau_risk2)),
4: 1/ (1+exp(MOR * lambda_risk - tau_risk4)) - 1/ (1+exp(MOR *
lambda_risk - tau_risk3)),
5: 1 - 1/ (1+exp(MOR * lambda_risk - tau_risk4))}

#SEV
lambda_land = Beta('lambda_land', 0.748, -10000, 10000, 0)
tau_land1 = Beta ('tau_land1', -4.42, -10000, 10000, 0)
tau_land2 = Beta ('tau_land2', -3.17, -10000, 10000, 0)
tau_land3 = Beta ('tau_land3', -1.59, -10000, 10000, 0)
tau_land4 = Beta ('tau_land4', -0.0119, -10000, 10000, 0)

ME_SEV_LAND = {
1: 1/ (1+exp(SEV * lambda_land - tau_land1)),
2: 1/ (1+exp(SEV * lambda_land - tau_land2)) - 1/ (1+exp(SEV *
lambda_land - tau_land1)),
3: 1/ (1+exp(SEV * lambda_land - tau_land3)) - 1/ (1+exp(SEV *
lambda_land - tau_land2)),
4: 1/ (1+exp(SEV * lambda_land - tau_land4)) - 1/ (1+exp(SEV *
lambda_land - tau_land3)),
5: 1 - 1/ (1+exp(SEV * lambda_land - tau_land4))}

lambda_aval = Beta('lambda_aval', 1.09, -10000, 10000, 0)
tau_aval1 = Beta ('tau_aval1', -1.75, -10000, 10000, 0)
tau_aval2 = Beta ('tau_aval2', -0.481, -10000, 10000, 0)
tau_aval3 = Beta ('tau_aval3', 0.914, -10000, 10000, 0)
tau_aval4 = Beta ('tau_aval4', 2.09, -10000, 10000, 0)

ME_SEV_AVAL = {
1: 1/ (1+exp(SEV * lambda_aval - tau_aval1)),
2: 1/ (1+exp(SEV * lambda_aval - tau_aval2)) - 1/ (1+exp(SEV *
lambda_aval - tau_aval1)),
3: 1/ (1+exp(SEV * lambda_aval - tau_aval3)) - 1/ (1+exp(SEV *
lambda_aval - tau_aval2)),
4: 1/ (1+exp(SEV * lambda_aval - tau_aval4)) - 1/ (1+exp(SEV *
lambda_aval - tau_aval3)),
5: 1 - 1/ (1+exp(SEV * lambda_aval - tau_aval4))}

lambda_eart = Beta('lambda_eart', 1.24, -10000, 10000, 0)
tau_eart1 = Beta ('tau_eart1', -1.48, -10000, 10000, 0)
tau_eart2 = Beta ('tau_eart2', 0.267, -10000, 10000, 0)
tau_eart3 = Beta ('tau_eart3', 1.33, -10000, 10000, 0)
tau_eart4 = Beta ('tau_eart4', 2.47, -10000, 10000, 0)
```

```
ME_SEV_EART = {
1: 1/ (1+exp(SEV * lambda_eart - tau_eart1)),
2: 1/ (1+exp(SEV * lambda_eart - tau_eart2)) - 1/ (1+exp(SEV *
lambda_eart - tau_eart1)),
3: 1/ (1+exp(SEV * lambda_eart - tau_eart3)) - 1/ (1+exp(SEV *
lambda_eart - tau_eart2)),
4: 1/ (1+exp(SEV * lambda_eart - tau_eart4)) - 1/ (1+exp(SEV *
lambda_eart - tau_eart3)),
5: 1 - 1/ (1+exp(SEV * lambda_eart - tau_eart4))}

lambda_flood = Beta('lambda_flood', 1.91, -10000, 10000, 0)
tau_flood1 = Beta ('tau_flood1', -1.90, -10000, 10000, 0)
tau_flood2 = Beta ('tau_flood2', -0.468, -10000, 10000, 0)
tau_flood3 = Beta ('tau_flood3', 1.21, -10000, 10000, 0)
tau_flood4 = Beta ('tau_flood4', 2.87, -10000, 10000, 0)

ME_SEV_FLOOD = {
1: 1/ (1+exp(SEV*lambda_flood - tau_flood1)),
2: 1/ (1+exp(SEV*lambda_flood - tau_flood2))- 1/(1+exp(SEV * lambda_flood
- tau_flood1)),
3: 1/ (1+exp(SEV*lambda_flood - tau_flood3))- 1/(1+exp(SEV * lambda_flood
- tau_flood2)),
4: 1/ (1+exp(SEV*lambda_flood - tau_flood4))- 1/(1+exp(SEV * lambda_flood
- tau_flood3)),
5: 1 - 1/ (1+exp(SEV*lambda_flood - tau_flood4))}

#FEA
lambda_frana = Beta('lambda_frana', -1.59, -10000, 10000, 0)
tau_frana1 = Beta ('tau_frana1', -4.33, -10000, 10000, 0)
tau_frana2 = Beta ('tau_frana2', -3.55, -10000, 10000, 0)
tau_frana3 = Beta ('tau_frana3', -2.05, -10000, 10000, 0)
tau_frana4 = Beta ('tau_frana4', -0.219, -10000, 10000, 0)

ME_FEA_FRANA = {
1: 1/ (1+exp(FEA*lambda_frana - tau_frana1)),
2: 1/ (1+exp(FEA*lambda_frana - tau_frana2))- 1/(1+exp(FEA * lambda_frana
- tau_frana1)),
3: 1/ (1+exp(FEA*lambda_frana - tau_frana3))- 1/(1+exp(FEA * lambda_frana
- tau_frana2)),
4: 1/ (1+exp(FEA*lambda_frana - tau_frana4))- 1/(1+exp(FEA * lambda_frana
- tau_frana3)),
5: 1 - 1/ (1+exp(FEA*lambda_frana - tau_frana4))}



###
# B. CHOICE MODEL
###

# Parameters of the choice model to be estimated
ASC_SQ = Beta('ASC_SQ',-2.03,-10,10,0)
B_CH = Beta('B_CH',2.73,-1000,1000,0 )                          # betas
B_BA = Beta('B_BA',2.35,-1000,1000,0 )
B_VI = Beta('B_VI',1.90,-1000,1000,0 )
B_SE = Beta('B_SE',1.62,-1000,1000,0 )
B_CO = Beta('B_CO',-1.37,-1000,1000,0 )
B_MOR = Beta('B_MOR',-5.58,-1000,1000,0 )
B_SEV = Beta('B_SEV',-0.0855,-1000,1000,0 )
B_FEA = Beta('B_FEA',-0.615,-1000,1000,0 )
S_CH = Beta('S_CH',1.28,0,10,0)                                 # sigmas
S_BA = Beta('S_BA',1.58,0,10,0)
S_VI = Beta('S_VI',1.03,0,10,0)
S_SE = Beta('S_SE',0.317,0,10,0)
S_MOR = Beta('S_MOR',0.1,0,10,0)
S_SEV = Beta('S_SEV',0.1,0,10,0)
S_FEA = Beta('S_FEA',0.1,0,10,0)
```

```
# Define random parameters, normally distributed.
# Note that the draws are generated for individuals,
# and they are the same for all observations of the same individual.
B_R_CH = B_CH + S_CH * bioNormalDraws('B_R_CH','Id') # random parameters
B_R_BA = B_BA + S_BA * bioNormalDraws('B_R_BA','Id')
B_R_VI = B_VI + S_VI * bioNormalDraws('B_R_VI','Id')
B_R_SE = B_SE + S_SE * bioNormalDraws('B_R_SE','Id')
B_R_MOR = B_MOR + S_MOR * bioNormalDraws('B_R_MOR','Id')
B_R_SEV = B_SEV + S_SEV * bioNormalDraws('B_R_SEV','Id')
B_R_FEA = B_FEA + S_FEA * bioNormalDraws('B_R_FEA','Id')

# Utility functions for choice model
# The utilities depend on the attributes: channel (CH), basin (BA),
# video cameras (VI), sensors (SE), and cost (CO). The latent variables
# are MOR, SEV and SAF.

V1 = B_R_CH * cha1 + B_R_BA * bas1 + B_R_VI * vid1 + B_R_SE * sen1 + B_CO
     * cos1
V2 = B_R_CH * cha2 + B_R_BA * bas2 + B_R_VI * vid2 + B_R_SE * sen2 + B_CO
     * cos2
V3 = B_R_CH * cha3 + B_R_BA * bas3 + B_R_VI * vid3 + B_R_SE * sen3 + B_CO
     * cos3
V4 = B_R_CH * cha4 + B_R_BA * bas4 + B_R_VI * vid4 + B_R_SE * sen4 + B_CO
     * cos4
V5 = B_R_CH * cha5 + B_R_BA * bas5 + B_R_VI * vid5 + B_R_SE * sen5 + B_CO
     * cos5
V6 = B_R_CH * cha6 + B_R_BA * bas6 + B_R_VI * vid6 + B_R_SE * sen6 + B_CO
     * cos6
V7 = ASC_SQ * one + B_R_MOR * MOR + B_R_SEV * SEV + B_R_FEA * FEA +
     B_R_CH * cha7 + B_R_BA * bas7 + B_R_VI * vid7 + B_R_SE * sen7 + B_CO
     * cos7

# Associate utility functions with the numbering of alternatives
V = {1: V1,
     2: V2,
     3: V3,
     4: V4,
     5: V5,
     6: V6,
     7: V7}


# Associate the availability conditions with the alternatives
av = {1: one,
      2: one,
      3: one,
      4: one,
      5: one,
      6: one,
      7: one}

# Iterator on individuals, that is on groups of rows
metaIterator('personIter','__dataFile__','panelObsIter','Id')

# For each item of personIter, iterates on the rows of the group
rowIterator('panelObsIter','personIter')

# Iterator on draws for Monte-Carlo simulation
drawIterator('drawIter')

# The choice model is a logit, with availability conditions
prob = bioLogit(V,av,Choice)

# Conditional probability for the sequence of choices of an individual
indivCondProb = Prod(prob,'panelObsIter')
```

```
# Conditional likelihood
condLikelihoodOneObs = (indivCondProb *
Sum(Elem(ME_MOR_RISK,cl_Pr_mort),'panelObsIter')/ Sum(1,'panelObsIter') *
Sum(Elem(ME_SEV_LAND,B_frana),'panelObsIter') / Sum(1,'panelObsIter') *
Sum(Elem(ME_SEV_AVAL,B_valan),'panelObsIter') / Sum(1,'panelObsIter') *
Sum(Elem(ME_SEV_EART,B_terr),'panelObsIter') / Sum(1,'panelObsIter') *
Sum(Elem(ME_SEV_FLOOD,B_alluv),'panelObsIter') / Sum(1,'panelObsIter') *
Sum(Elem(ME_FEA_frana,frana),'panelObsIter') / Sum(1,'panelObsIter'))

# The sample likelihood function for estimation
likelihoodOneObs = Sum(condLikelihoodOneObs,'drawIter')

BIOGEME_OBJECT.ESTIMATE = Sum(log(likelihoodOneObs),'personIter')
BIOGEME_OBJECT.PARAMETERS['optimizationAlgorithm'] = "CFSQP"
BIOGEME_OBJECT.PARAMETERS['numberOfThreads'] = "4"
BIOGEME_OBJECT.PARAMETERS['RandomDistribution'] = "HALTON"
BIOGEME_OBJECT.PARAMETERS['NbrOfDraws'] = "10000"
```

Code – paper 3

The following code exemplified for the RPL-EC model (Model 6) in Chapter 4 was programmed in PythonBiogeme 2.3 (Bierlaire, 2016) (installed the 10/05/2015; http://biogeme.epfl.ch/install.html). The data processor used is an Asus Intel Core i7 1.90GHz 2.40GHz with an Ubuntu 14.04 operating system.

```
#######################################
# Model: RPL-EC with covariates at individual level
# (observed and unobserved heterogeneity) (1,000 draws)
# Report file:  RPL-EC-cov_heter_mod6_1000.html
# Sample file:  Data_Rank_Before_Landslide_Spatial.dat
######################################

from biogeme import *
from headers import *
from distributions import *
from loglikelihood import *
from statistics import *

# Create additional variables
kids = n_min>0
coinvol_land = (eventi==6)
retired = profes>5
high_hazard = geohazard>3

# Parameters of the choice model to be estimated
ASC_SQ = Beta('ASC_SQ',1.18,-10,10,0)
ASC_coinvol_land = Beta('ASC_coinvol_land',-0.477,-10,10,0)
ASC_kids = Beta('ASC_kids',-0.225,-10,10,0)
ASC_esc = Beta('ASC_esc',-0.408,-10,10,0)
ASC_ferr = Beta('ASC_ferr',0.290,-10,10,0)
ASC_retired = Beta('ASC_retired',-0.345,-10,10,0)
ASC_high_hazard = Beta('ASC_high_hazard',-0.309,-10,10,0)
#ASC_dang_road = Beta('ASC_dang_road',-0.278,-10,10,0)
B_CH = Beta('B_CH',1.60,-1000,1000,0)                        # betas
B_BA = Beta('B_BA',1.41,-1000,1000,0)
B_VI = Beta('B_VI',1.10,-1000,1000,0)
B_SE = Beta('B_SE',1.04,-1000,1000,0)
B_CO = Beta('B_CO',-0.392,-1000,1000,0)
S_CH = Beta('S_CH',0.2,0,10,0)                               # sigma
S_BA = Beta('S_BA',0.2,0,10,0)
S_VI = Beta('S_VI',0.2,0,10,0)
S_SE = Beta('S_SE',0.2,0,10,0)
I_cost_site1 = Beta('I_cost_site1',-0.341,-1000,1000,0)      # sites
I_cost_site2 = Beta('I_cost_site2',-0.347,-1000,1000,0)
I_cost_site3 = Beta('I_cost_site3',-0.130,-1000,1000,0)
I_cost_site4 = Beta('I_cost_site4',-0.131,-1000,1000,0)
#I_cost_site5 = Beta('I_cost_site5',-0.302,-1000,1000,0)
I_cost_site6 = Beta('I_cost_site6',-0.302,-1000,1000,0)

S_T1 = Beta('S_T1',0,0,10,0)                                 # sigma ec
S_T2 = Beta('S_T2',0,0,10,0)
S_T3 = Beta('S_T3',0.2,0,10,0)

# Define random parameters and error components, normally distributed.
# Note that the draws are generated for individuals,
# and they are the same for all observations of the same individual.
B_R_CH = B_CH + S_CH * bioNormalDraws('B_R_CH','Id') # random parameters
B_R_BA = B_BA + S_BA * bioNormalDraws('B_R_BA','Id')
B_R_VI = B_VI + S_VI * bioNormalDraws('B_R_VI','Id')
B_R_SE = B_SE + S_SE * bioNormalDraws('B_R_SE','Id')
```

```
B_R_T1 = S_T1 * bioNormalDraws('B_R_T1','Id')        # ECs road segments
B_R_T2 = S_T2 * bioNormalDraws('B_R_T2','Id')
B_R_T3 = S_T3 * bioNormalDraws('B_R_T3','Id')

# Utility functions
# The utilities depend on the attributes: channel (CH), basin (BA),
# video cameras (VI), sensors (SE), and cost (CO).

V1 = B_R_CH * cha1 + B_R_BA * bas1 + B_R_VI * vid1 + B_R_SE * sen1 + B_CO
* cos1 + I_cost_site1 * cos1 * site1 + I_cost_site2 * cos1 * site2 +
I_cost_site3 * cos1 * site3 + I_cost_site4 * cos1 * site4 + I_cost_site6
* cos1 * site6 + B_R_T1 * seg1 + B_R_T2 * seg2 + B_R_T3 * seg3

V2 = B_R_CH * cha2 + B_R_BA * bas2 + B_R_VI * vid2 + B_R_SE * sen2 + B_CO
* cos2 + I_cost_site1 * cos2 * site1 + I_cost_site2 * cos2 * site2 +
I_cost_site3 * cos2 * site3 + I_cost_site4 * cos2 * site4 + I_cost_site6
* cos2 * site6 + B_R_T1 * seg1 + B_R_T2 * seg2 + B_R_T3 * seg3

V3 = B_R_CH * cha3 + B_R_BA * bas3 + B_R_VI * vid3 + B_R_SE * sen3 + B_CO
* cos3 + I_cost_site1 * cos3 * site1 + I_cost_site2 * cos3 * site2 +
I_cost_site3 * cos3 * site3 + I_cost_site4 * cos3 * site4 + I_cost_site6
* cos3 * site6 + B_R_T1 * seg1 + B_R_T2 * seg2 + B_R_T3 * seg3

V4 = B_R_CH * cha4 + B_R_BA * bas4 + B_R_VI * vid4 + B_R_SE * sen4 + B_CO
* cos4 + I_cost_site1 * cos4 * site1 + I_cost_site2 * cos4 * site2 +
I_cost_site3 * cos4 * site3 + I_cost_site4 * cos4 * site4 + I_cost_site6
* cos4 * site6 + B_R_T1 * seg1 + B_R_T2 * seg2 + B_R_T3 * seg3

V5 = B_R_CH * cha5 + B_R_BA * bas5 + B_R_VI * vid5 + B_R_SE * sen5 + B_CO
* cos5 + I_cost_site1 * cos5 * site1 + I_cost_site2 * cos5 * site2 +
I_cost_site3 * cos5 * site3 + I_cost_site4 * cos5 * site4 + I_cost_site6
* cos5 * site6 + B_R_T1 * seg1 + B_R_T2 * seg2 + B_R_T3 * seg3

V6 = B_R_CH * cha6 + B_R_BA * bas6 + B_R_VI * vid6 + B_R_SE * sen6 + B_CO
* cos6 + I_cost_site1 * cos6 * site1 + I_cost_site2 * cos6 * site2 +
I_cost_site3 * cos6 * site3 + I_cost_site4 * cos6 * site4 + I_cost_site6
* cos6 * site6 + B_R_T1 * seg1 + B_R_T2 * seg2 + B_R_T3 * seg3

V7 = ASC_SQ * one + B_R_CH * cha7 + B_R_BA * bas7 + B_R_VI * vid7 +
B_R_SE * sen7 + B_CO * cos7 + ASC_kids * kids + ASC_coinvol_land *
coinvol_land + ASC_retired * retired + ASC_esc * esc + ASC_ferr * ferr +
ASC_high_hazard * high_hazard

# Associate utility functions with the numbering of alternatives
V = {1: V1,
     2: V2,
     3: V3,
     4: V4,
     5: V5,
     6: V6,
     7: V7}

# Associate the availability conditions with the alternatives
# Important for ranked data
av = {1: av1,
      2: av2,
      3: av3,
      4: av4,
      5: av5,
      6: av6,
      7: av7}

# The choice model is a logit, with availability conditions
prob = bioLogit(V,av,Choice)

# Iterator on individuals, that is on groups of rows
metaIterator('personIter','__dataFile__','panelObsIter','Id')

# For each item of personIter, iterates on the rows of the group
rowIterator('panelObsIter','personIter')
```

```
#Iterator on draws for Monte-Carlo simulation
drawIterator('drawIter')

#Conditional probability for the sequence of choices of an individual
condProbIndiv = Prod(prob,'panelObsIter')

# Integration by simulation
probIndiv = Sum(condProbIndiv,'drawIter')

# Sample Log-Likelihood function
loglikelihood = Sum(log(probIndiv),'personIter')

BIOGEME_OBJECT.ESTIMATE = loglikelihood
BIOGEME_OBJECT.PARAMETERS['numberOfThreads'] = "4"
BIOGEME_OBJECT.PARAMETERS['NbrOfDraws'] = "1000"
BIOGEME_OBJECT.PARAMETERS['RandomDistribution'] = "HALTON"
BIOGEME_OBJECT.PARAMETERS['optimizationAlgorithm'] = "CFSQP"

# Statistics
nullLoglikelihood(av,'panelObsIter')
choiceSet = [1,2,3,4,5,6,7]
cteLoglikelihood(choiceSet,Choice,'panelObsIter')
availabilityStatistics(av,'panelObsIter')
```

Appendix E – Co-authorship forms

THE UNIVERSITY OF WAIKATO

Co-Authorship Form

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Student and Academic Services Division
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Phone +64 7 858 5096
Website: http://www.waikato.ac.nz/sasd/postgraduate/

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in all copies of your thesis submitted for examination and library deposit (including digital deposit), following your thesis Abstract.

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter II:
Valuing landslide risk reduction programs in the Italian Alps: The effect of visual information on preference stability

Nature of contribution by PhD candidate	survey design, data collection, database construction, analysis, writing, reviewing
Extent of contribution by PhD candidate (%)	70

CO-AUTHORS

Name	Nature of Contribution
Cristiano Franceschinis	analysis, writing
Riccardo Scarpa	reviewing
Mara Thiene	writing

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and
- in cases where the PhD candidate was the lead author of the work that the candidate wrote the text.

Name	Signature	Date
Cristiano Franceschinis		11/01/18
Riccardo Scarpa		19/01/2018
Mara Thiene		11/01/18

THE UNIVERSITY OF WAIKATO

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Co-Authorship Form

This form is to accompany the submission of any PhD that contains research reported in published or unpublished co-authored work. **Please include one copy of this form for each co-authored work.** Completed forms should be included in all copies of your thesis submitted for examination and library deposit (including digital deposit), following your thesis Abstract.

Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work.

Chapter III:
Exploring the stability of simulated parameter estimates in the context of risk perceptions: good practices in an Integrated Choice and Latent Variable framework

Nature of contribution by PhD candidate	survey design, data collection, database construction, analysis, writing, reviewing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Riccardo Scarpa	reviewing
Mara Thiene	reviewing

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and
- in cases where the PhD candidate was the lead author of the work that the candidate wrote the text.

Name	Signature	Date
Riccardo Scarpa	Riccardo Scarpa	5th January 2018
Mara Thiene	Mara Thiene	9 January 2018

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