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Abstract

Over the last years, Choice Experiment (CE) methodology has increased its diffusion in several environmental contexts. Despite the increasing popularity of the method, there are still aspects that are not fully explored yet. In particular, the research areas explored in the thesis are:

i) the analysis of the effect of information treatments in CEs;
ii) the development of frameworks to include spatial variables in discrete choice models;
iii) the analysis of the effect of individuals' psychological traits on preferences towards environmental goods and services;
iv) the comparison of existing model specifications which allow to account for preference heterogeneity.

Most of the research questions were investigated by applying discrete choice modeling to data collected in two case studies: i) the analysis of social demand for landslide protection in Val del Boite (Veneto region), ii) the analysis of the demand of different heating system of households of the Veneto region. The remaining part of the analysis, instead, involved data generated by means of a simulation study.

The thesis is organized in five chapters. Chapter 1 introduces the Choice Experiment method, outlines the research objectives and illustrates the case studies. Chapter 2 focuses on the exploration of the effect of information treatments on the stability of preference estimates and it is based on data analysis carried out from the first case study. Preferences were retrieved before and after providing respondents with scientific-based information, based on visual simulations of possible landslide events. This enabled to measure information effects. Choice data were used to estimate a Mixed Logit model (MXL) in WTP space to obtain robust estimates of marginal willingness-to-pay estimates and control for the effect of information. Overall, it was found that mWTP estimates are dependent on information. The geographical distribution of such effects was illustrated by means of maps of willingness to pay values. Chapters 3-4 illustrate analysis carried out on data retrieved from the second case study. Chapter 4 aims to analyze how geographical variables influence individuals' sensitivity to key features of heating systems. A MXL model was estimated to spatially characterize preference heterogeneity. The results showed that geographical variables are in fact significant sources of variation of individual's sensitivity to the investigated attributes of heating systems. Thematic maps were produced to illustrate the distribution of willingness to pay to avoid CO_2 emissions across the region and to validate the estimates ex-post. Chapter 5 roots on previous theoretical evidence which suggests that beliefs and attitudes of individual consumers play a crucial role in the diffusion of innovative products. A Latent Class-Random Parameter (LC-RPL) model was estimated to analyze preferences of households for key features of ambient heating systems. The model specification allowed to evaluate the coherence of the underlying preference structure using as criteria psychological constructs from the Theory of Diffusion of Innovation by Rogers. The results broadly support this theory by providing evidence of segmentation of the population consistent with the individuals' propensity to adopt innovations. It was also found that preferences for heating systems and respondents' willingness to pay for their key features vary across segments. Chapter 6 illustrates the results of a Monte-Carlo experiment aimed at retrieving the required number of parameters and sample sizes to obtain good approximations of true distributions with Logit-mixed logit (LML) models. These models were recently introduced by Train (2016) and are a key

advancement in methods to represent the random taste heterogeneity in logit-type models as they generalize many previous parametric and seminonparametric specifications. The performance of LML models are also compared with those of parametric specifications based on normal mixing distributions. The results suggest that LML models outperform parametric models only at large sample sizes. LML Mmdel specifications with large number of parameters outperformed those with small number parameters only at large sample sizes as well. Finally, chapter 8 draws the conclusions of the thesis.

Contents

1. Introduction

The estimation of the economic-monetary value of environmental goods and services is complicated due to the lack of market prices, as well as the multifunctional role that characterizes most such goods or services. The monetary indicator usually adopted to express the value of such goods and services is the Willingness to Pay (WTP), that is the amount of money individuals are willing to pay to benefit from a given environmental resource. To estimate WTP values, economists have developed a set of tools known as non-market valuation techniques. Among such techniques, Choice Experiments (CE hereafter) (Louviere and Hensher, 1982; Louviere and Woodworth, 1983) have become increasingly popular in environmental valuation studies over the last decade and have been adopted in a wide range of environmental fields, such as recreational demand in protected areas (e.g. Juutinen et al., 2011; Mejía and Brandt, 2015; Browuer et al. 2016), energy resources (e.g. Rouvinen and Matero, 2013; Yoo and Ready, 2014, Henser et al., 2014; Yamamoto, 2015), ecosystems services (Ohdoko and Yoshida, 2012; Thiene et al., 2012; Tyrväinen et al., 2014) and water services (Thiene et al., 2015).

In CEs, respondents are presented with a number of choice scenarios consisting of two or more alternatives and are asked to choose their preferred one. Each alternative is described in terms of its characteristics (attributes), which can take different values (levels). Alternatives are built by means of experimental designs, which create combinations of attributes and levels. Respondents' choices are analyzed by means of discrete choice models which are rooted on the Random Utility Theory (Luce, 1959; McFadden, 1974). Among monetary valuation approaches, CEs are appropriate for environmental goods and services because they allow the estimation not only of the value of the item as a whole but also the implicit values of its different attributes. This is particularly important for policy plans aimed at achieving multiple objectives and for the evaluation of multifunctional environmental resources.

Despite the popularity of the CE approach, there are still research questions to be answered. The aim of the thesis is to disentangle some of these issues to improve the usefulness of the CE approach in estimating the value of environmental goods and services and in providing policy advices. Specifically, the thesis explores two main areas of the methodology, these being CE surveys and discrete choice modeling adopted to analyze choice data. As far as to concerns for the first area, the thesis focuses on the investigation of the effect of information treatments on the perceived benefits of environmental goods and services.

As far as it concerns discrete choice modelling, considerable improvements have been made through the past decade with respect to correctly modelling the preferences displayed through observing the choices of decision markers. Great effort has been devoted to develop discrete choice models that allow for the recovery of preference heterogeneity. Investigating heterogeneity of preferences is particularly important for environmental goods and services, where management is often controversial, relying on individuals who often display very different opinions and tastes. Over the last few years, an increasing number of model specifications have been proposed in the literature. The thesis aims to compare statistical features of these specifications and to contribute to identifying those more appropriate to capture preferences heterogeneity.

Increasing attention has been also dedicated to the investigation of the sources of preference heterogeneity. In particular, over the last few years, an increasing number of studies has analyzed the effects on preferences of spatial factors (e.g. Campbell et al., 2007; Czajkowski et al., 2015) and individuals' psychological traits (e.g. Nosetti et al., 2013; Farizo et al., 2014). The literature on spatial effects has mainly focused on post-hoc analysis, so the thesis aims to explore frameworks to include geographical variables directly on model specifications. In addition, studies on the influence of psychological traits highlighted the advantages of incorporating constructs of psychological theories in applied economics. Among those, the Diffusion of Innovation theory (Rogers, 2003) has still received little attention in empirical studies. The theory seeks to explain the diffusion of new technologies and describe the factors that drive it. The thesis aims to relate the theory to the preference structure of choice models and to provide empirical evidence of its constructs. This could be useful to better understand the demand of environmental friendly technologies.

Most of the research objectives outlined above were investigated by applying discrete choice modeling to data collected in two case studies: the first deals with the analysis of social demand for landslide protection in Val del Boite (Veneto region) and the second one concerns the analysis of the demand of different heating system of households of the Veneto region. The remaining part of the analysis, instead, involved data generated by means of a simulation study.

1.1 Thesis Structure

The rest of this chapter is dedicated to the analysis of existing literature, to outline the thesis objectives and to provide an overview of the case studies. Paragraph 1.2 outlines the current state of art of discrete choice modeling with a focus on the areas that are still not fully explored. The paragraph also highlights the gaps in the existing literature that motivated this research. Paragraph 1.3 outlines the research objectives which root on the literature gaps and provides an overview on how the research questions have been investigated. Paragraph 1.4 introduces the two case studies. The first case study concerns the analysis of the social demand of landslide protection in Val del Boite (Veneto region), whereas the second case study deals with the analysis of preferences of households of the Veneto region. Both empirical applications have been chosen due to their strong policy implication.
Chapter 2 focuses on the results of the first case study, that is the inclusion of information treatments in CE studies. This chapter is an edited version of a paper currently in press in *Land use Policy*.
Chapter 3 and 4 present the results from the second case study, focusing on model specifications that include ancillary variables aimed at investigating the sources of preference heterogeneity. Chapter 3 investigates the inclusion of spatial variables in discrete choice models, whereas chapter 4 focuses on the inclusion of variables related to psychological traits of respondents. Chapter 3 is an edited version of a paper published in *Energies* and chapter 4 is an edited version of a paper revised and resubmitted to *Energy*. Chapter 5 roots in the analysis of preference heterogeneity as well. It describes a Monte Carlo simulation study aimed at comparing statistical features of different model specifications. Finally, chapter 6 is dedicated to the conclusions.

1.2 Literature review and gaps

Although the literature related to discrete choice models is wide and consolidated, in the last few years, new directions of research emerged that are not fully explored, such as a) the inclusion of information treatments in surveys, b) the analysis of the effects of the adoption of different experimental designs, c) the analysis of spatial effects on individuals' preferences, d) the inclusion in model specifications of variables related to attitudinal and psychological aspects; e) the comparison of statistical features of different choice models specifications. Accounting for such aspects in CE studies is important as it allows for a better understanding of individual decision-making process and more accurate estimates of WTP. In what follows an overview of the state of the art will is provided for each research area and the gaps existing in the literature are highlighted.

1.2.1 Inclusion of information treatments in surveys

For many years, stated preference researchers have been interested in information effects on WTP estimates. In the context of environmental goods, Munro et al. (2002) found that information about an environmental good could lead to changes in the variance of WTP estimates, depending on how individuals responded to this information. They also showed that an individual's WTP increased if positive information about the good was provided. Alberini et al. (2005) explored the impacts of providing information to a sub-sample of residents of the Veneto region on the benefits and costs of a project to restore beaches in San Erasmo, an island in the Venice lagoon. They found that this information had a significant effect on WTP only when it was interacted with education. MacMillan et al. (2006) used Contingent Valuation (CV) to value two environmental goods which differ in terms of familiarity, namely reintroductions of a bird of prey, and expansion of renewable energy. They found that almost half of respondents changed their WTP over successive rounds of information provision, with more pronounced effects for the good with which people were less familiar. Czajkowski and Hanley (2012) investigated the effects of information on preferences for biodiversity conservation using a CE. Their results suggested that respondents were more deterministic in their choices when provided with additional information. They also found that changes in information provision affected WTP estimates. The provision of additional information was also investigated by O'Brien and Teisl (2004) regarding environmental certification and labelling. They found out that additional information on the labels of forest products considerably altered the importance of specific environmental attributes in the CE and the consumers' WTP for certified forest products.

Information effects have been studied also in non-environmental fields. For instance, Protière et al. (2004) undertook a valuation study for three health programs amongst French citizens. They employed three levels of information provision, and found that WTP increased according to the different levels. Oppewal et al. (2010) studied preferences towards different DVD recorders, comparing choice models estimated from discrete choice responses before and after respondents were exposed to additional product information. Their results suggest that if respondents are unfamiliar with an attribute, providing explanatory information about the attribute not only results in parameter shifts for the particular attribute but it also affects the estimates of the remaining attributes and the scale unit of the utility function. Chanel et al. (2006), in a CV study about the health risk of air pollution, found out that respondents are positively influenced by scientific information and not by public opinion. They showed that information can have an impact on the respondents' WTP. Overall the existing empirical evidence as not clear yet as to whether providing information about an attribute lead to a change of perceived benefits only for that attribute or also for the other attributes included in the study. Furthermore, to the best of our knowledge, there are no empirical studies investigating information effects within the field of natural hazards. 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. Furthermore, uninformed respondents may underestimate benefits of protection projects for the community and therefore they could not be willing to support the implementation of such projects.

1.2.2 The analysis of spatial effects on individuals' preferences

An expanding literature addresses the relevance of spatial factors for the estimation of WTP. Spatial distributions of WTP estimates from CE surveys have been investigated in several studies, starting from the seminal work by Campbell (2008, 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. Broch et al. (2012) estimated the spatial pattern of the willingness to provide ecosystem services in agricultural landscapes. Abildtrup et al. (2013) investigated spatial heterogeneity in WTP for forest attributes in a sample of residents in Lorraine, France. Termansen et al. (2008) combined recreational choice modelling and economic valuation with GIS based techniques to allow an assessment of the spatial diversity of the value of forest recreation services. The spatial predictions, however, revealed a considerable difference in the spatial pattern of economic benefits from recreation between the two models. Similarly, Yao et al. (2014) used data on forest distance from respondent's homes to capture spatial effects in WTP for enhancement of biodiversity forests in New Zealand. This study found evidence that respondents tend to have a higher WTP if living closer to the environmental good evaluated. Johnston and Ramachandra (2014) used local indicator of spatial association to explore WTP for hot spots. Duke et al. (2014) mapped the outcomes of targeting using four different strategies for spatial provision of environmental services in Sussex County, Delware. Czajkowski et al. (2015) identified spatial effects on WTP for forest attributes in Poland. They found that respondents' WTP was higher the closer they were living to their nearest forest, and the scarcer forests were in the area where they were living. Furthermore, they pointed out that respondents from different regions had different WTP for each attribute. The above-mentioned studies support the hypothesis of existence of spatial effects on preferences for environmental goods, but mainly focused on addressing the relevance of spatial factors through post hoc analysis on the WTP estimated from choice models. There is only limited work (e.g. Thiene and Scarpa, 2008; Smirnov, 2010; Czajkowski et al., 2015) on the inclusion of spatial variables in the utility structure behind choice, which is instead common practice in studies based on linear models (e.g. spatial regressions).

1.2.3 The inclusion in model specifications of variables related to attitudinal and psychological aspects

The issue of preference heterogeneity has been one of the key areas of interest in the nonmarket valuation literature. To tackle the issue, researchers incorporated in the econometric models explanatory variables such as attitudes and psychological traits. Morey et al. (2006) estimated a Latent Class model defining the class membership function only using answers to a set of attitudinal questions. Their survey was addressed to a sample of anglers and included several attitudinal questions, including the importance of boat fees, species catch rates, and fish consumption advisories on site choice. Similarly, Morey et al. (2008) used a latent class model to identify preference classes for landscape preservation in the Ibleo, a rural part of Sicily. They performed the estimation of classes using only attitudinal data consisting of answers to Likert-scale questions about the importance of preservation. Using this method, they defined four distinct preference classes with different level of importance attached to preservation. Spash (2006) reported a CV study which included a psychometric scale on pro-social environmental attitudes to test for non-economic motivations for WTP. The multi-item scale adopted by the author aimed at measuring biospheric, altruistic, and egoistic motives, and analyzed and the relationships between such factors and WTP. He found that environmental attitudes are significant in explaining intended WTP. Similarly, Ojea and Loureiro (2007) measured general attitudes and ethical beliefs towards preservation, as well as the importance of three value orientations (biospheric, egoistic and altruistic) in WTP estimates. They carried out a CV exercise to estimate the WTP for the recovery of the common murre in Galicia (Spain). They concluded that ethical aspects affect individuals' decision making process, and that value orientations play an important role in the pro-environmental attitude formation. They also found that value orientations affect WTP estimates for environmental goods. Lopez-Mosquera and Sanchez (2011) explored the ability of place attachment to predict place-specific and general pro-environment behavioural intentions, and linked such factors to WTP for conservation plans in two suburban natural areas in Spain. They found that place attachment has a significant effect on WTP. Solino and Farizo (2014) analysed the influence of the big five personality dimensions (extraversion, agreeableness, conscientiousness, neuroticism and openness) in a discrete CE aimed at investigating preferences for the development of an environmental program for forest management in Spain. They found a positive effect of openness and extraversion and a negative effect of agreeableness and neuroticism in consumers' preferences for this environmental program. Several studies investigated the empirical relationship between environmental attitudes measured by the New Ecological Paradigm (NEP henceforth) scale and conservation-related WTP estimates. Aldrich et al., 2007 reported a significant role of environmental attitudes (measured by NEP scores) as a predictor of mean WTP estimates for the protection of endangered species. They employed dichotomous-choice CV questions whereas Cooper et al. (2004) used an open-ended CV question and found a contradictory result that showed no significant relationship between NEP scores and contingent values of water quality improvements. Choi and Fielding (2013) investigated the influence of environmental attitudes on WTP for the protection of endangered species in a choice modelling context. They measured pro-environmental attitudes using the NEP scale and found significant attitude-WTP association. Psychological aspects are also accounted in the study of Scarpa and Thiene (2011), in which preferences in organic food choice are linked to the Protection Motivation Theory. Expecting that organic food choices are correlated with PMT constructs, they used the latter for the definition of the classes of a latent class model and for the validation and interpretation of the results.

1.2.4 Comparison of statistical features of different Choice models specifications

Over the past decades one of the main research areas in the field of discrete Choice Modeling has been the development of model specifications that account for preference heterogeneity. Among these, the Mixed Logit Model (MXL) with normally distributed random parameters is the most common one. However, over the last years, an increasing body of literature (e.g. Louviere and Eagle, 2006; Fosgerau and Hess, 2007; Louviere and Meyer, 2007) argued that the normal mixing distributions may introduce problems of misspecification if the assumed distribution is not appropriate for the data. The estimation of MXL models is generally a nonlinear optimization problem, but Bajari et al. (2007) proposed a method that is fast and easy to code that takes advantage of a linear regression-type specification. The authors assume that the population can be sorted into finite classes or clusters (i.e. discrete number of preference parameters) and assert that their estimator is non-parametric because any mixing distribution can be approximated by making the number of classes large enough. However, this linear regression method may violate some necessary constraints on the model parameters. To handle this issue, Fox et al. (2011) reparametrized MXL and derived a specification very similar to that of Bajari et al. (2007), but used inequality constrained linear least squares. Fosgerau and Bierlaire (2013) further proposed a method to approximate any continuous distribution using a Legendre polynomial. The use of polynomials is a very flexible method to retrieve preference heterogeneity because different distributions can be recovered simply by adding more terms to the series expansion. Train (2016) recently proposed a seminonparametric logit-mixed logit (LML) model, which generalizes many previous parametric and seminonparametric logit model. As the name suggests, this model contains two logit formulations: one for the decision maker's probability to choose an alternative and a second one for the probability of selecting a parameter from a finite parameter space. The exponential terms in the latter logit formulation ensure a positive probability and the denominator ensures normalization, that is all probabilities sum to one. In addition, the shape of the logarithm of the mixing distribution can be defined by different types of functions such as polynomials, step functions, and splines. Despite the theoretical advantages of such models, there is still little empirical evidence whether they allow to retrieve better approximation of the underlying distribution of tastes than traditional models based on normal distributions. Furthermore, the sample sizes and number of parameters need to retrieve good approximations with such models has yet to be fully explored.

1.3 Research objectives

The overall objective of the thesis is to contribute to the advancement of CE surveys and choice modeling, by focusing on research areas that are still not fully explored in the literature. The first specific objective is related to CE surveys, whereas the remaining three concern data analysis by means of discrete choice models. Specifically, the first objective is related to information treatments in CEs, whereas. the remaining three objectives seek to contribute to the well-established literature on preferences heterogeneity. In particular, the thesis focuses on developing frameworks to include spatial variables in discrete choice models (third objective), on relating the preference structure to psychological theories (fourth objective) and on comparing existing model specifications which account for preferences heterogeneity (fifth objective). In what follows a detailed explanation of each objective is provided.

1) **Analysis of the effect of information treatments on individual's preferences.**
   Although there is compelling evidence that information treatments can affect individuals' decision process, there remain mixed results as far as it concerns the effect of providing information for only a subset of the attributes. The thesis aims to fill this gap by investigating whether information treatments focused on one attribute affect preferences only for that attribute or for all the others included in the survey as well. The analysis related to this objective was carried out on data from the first case study (analysis of social demand for landslide protection) and is described in Chapter 2.

2) **Development of frameworks to include geographical variables in choice modeling.**
   Previous work investigating spatial effects on individuals' preferences for environmental goods and services mainly focused on the post hoc analysis on the WTP estimated from choice models. Limited work exists on literature on the inclusion of spatial variables in choice

models. Therefore, the thesis aim to propose a choice model specification which includes both geographical variables and socio-demographical variables related to individuals place of living. The analysis on this subject has been carried out on data collected from the second case study (analysis of preferences towards heating systems) and it is illustrated in chapter 3.

3) **Relating individuals' psychological traits to their preferences towards environmental goods and services.**

   There exists compelling evidence in literature that individuals' decisions regarding environmental goods are influenced by personal aspects, such as attitudinal and psychological traits. It is also clear that including in the econometric analysis theories derived from other disciplines (such as psychology and sociology) can enrich the explanatory power of choice modeling. Motivated by such evidence, the thesis aims to contribute to the literature which proposes econometric frameworks to provide empirical evidence of psychological theories. Specifically, it focuses on test empirically the Diffusion of Innovation theory (Rogers, 2003). This theory has still received little attention in economic studies concerning environmental goods, yet its constructs can help understanding the drivers of the demand of environmental friendly technologies. This has been explored in the second case study (analysis of preferences towards heating systems) and is reported in chapter 4.

4) **Comparison of statistical features of different choice models specifications**

   Over the last years the literature on choice models increasingly focused on model specifications with flexible distributions of random parameters. Recently Train (2016) proposed the LML model which generalizes previous flexible specifications. The theoretical expectation is that this model outperforms those based on normal distributions, however there is still little empirical evidence corroborating it. This thesis aims to contribute to fill this gap by comparing statistical features of LML models with those of model specifications based on normal distributions. In particular, it aims to explore the number of parameters and the sample size which are required to retrieve more accurate approximations of the underlying distribution of population parameters with LML models. Those research questions were not explored in the case studies, but by means of the Monte Carlo simulation which will be described in Chapter 5.

1.4 The case studies

This chapter is dedicated to a brief description of the case studies adopted in my thesis work. Paragraph 1.4.1 provides an overview of the case study of the analysis of the social demand for safety improvements in risk mitigation projects in Val del Boite (Veneto region). Paragraph 1.4.2 introduces the case study related to of preferences householders of the Veneto region towards different heating systems. My involvement in the first case study was limited to data analysis, whereas for the second case study I carried out the entire CE, from data collection to data analysis, except for experimental designs and the web implementation of the survey. The experimental designs were provided by Prof. John Rose. Given that the details of the questionnaire for data collection are not covered in the published papers, paragraph 1.4.3 will be dedicated to its description. Paragraph 1.4.4 describe the CE by illustrating its attribute and levels. The description of the CE was included in both papers written for this case study, so it is reported in this chapter and omitted in the following ones, to avoid unnecessary repetitions. Finally, paragraph 1.4.5 focuses on the description of the experiment design adopted in the case study.

1.4.1 The case study of the analysis of the social demand for safety improvements in risk mitigation projects in Val del Boite (Veneto region)

This study involved the use of a CE to investigate the WTP of a sample of residents and visitors of the Boite Valley for different technical and engineering solutions to increase safety from landslides. In the steep mountain areas of the Dolomites (North-East of Italy), there is substantial evidence of recent and past debris flow occurrence. This region is highly vulnerable to landslides, specifically debris flows. People living in mountain areas suffer serious socio-economic consequences from these natural events. Several times such events resulted in fatalities, homelessness, damaged buildings and interrupted road traffic (Sterlacchini et al., 2007; Salvati et al., 2010), which affect the major local industry, which are largely based on tourism. Due to the high hydrogeological risk level, several landslide events occurred in the Boite Valley and caused deaths and damage to houses and other property. In 1814, a massive debris flow destroyed two villages, killing 257 people. The biggest event occurred in 1925, causing 288 victims, with an additional 53 people missing. In the last decade, this area has suffered a series of devastating debris-flows. In 2009, another disaster produced two victims and significant damage to properties. Recently, in the summer of 2015, intense rainfall over a short period of time triggered eight events, causing significant damage to public infrastructure, and the death of three tourists. Geologists believe that there are approximately 350 potential and active debris flows that can be highly dangerous for the population living in the valley (Guidoboni and Valensise, 2014). Based on these data, it is clear that risk mitigation is still a major safety issue for local authorities. However, potential interventions are expensive to implement. Our case study was therefore justified by the need for better understanding of public acceptability of landslide risk management for an efficient allocation of funds. The inclusion of social preferences in the decision process allows policy makers to take into account of the importance and the value (expressed in terms of WTP values) placed on a range of mitigation devices by the local population and by tourists.

1.4.2 The case study of the analysis of preferences towards different heating systems among the householders of the Veneto region

The general aim of the study was to explore how different types and key attributes of residential heating systems affect private homeowners' choices in renovations. This was done by adopting the CE approach. The analysis of the demand of heating system has strong policy implications, as the residential heating sector is strictly linked to global environmental issues such as pollution, climate change and use of renewable resources. To tackle these issues, the European Union promulgated the Renewable Energy Directive 2009/28/EC which established a policy framework aimed at promoting energy production from renewable sources. The directive sets for Italy a target of at least 20 percent of total energy to be covered by renewables by 2020. To meet the EU targets, in 2010 Italy submitted to the European Commission the Italian Renewable Energy Action plan. The plan includes specific measures aimed at promoting the uptake of pellet fired heating systems, which consist mostly in monetary incentives to support their installation, such as subsidies and tax detractions. However, such measures only partially achieved the goals, as the diffusion of pellet fired heating systems in Italy is still limited. According to ISTAT (2015) only four percent of Italian households possess a pellet based heating system. The analysis of the demand of these technologies and of the factors that drive their diffusion are therefore particularly interesting from a policy perspective.

1.4.3 Survey and questionnaire

The data were collected by means of a web-based questionnaire involving a sample of 1,451 residents from the Veneto region. The full questionnaire is illustrated in Appendix 1.

The questionnaire was structured in five sections: the first section aimed at collecting data about the heating system and the energy resources used by respondents; the second section included the CE; the third section provided some follow-up questions linked to the alternatives chosen in the previous section; the fourth section presented attitudinal questions and other questions related to the Theory of the Diffusion of Innovations and to the maximize-scale. The Diffusion of innovations (Rogers 2003) is a theory that seeks to explain the diffusion of new technologies and relates it to features such as the perception of the characteristics of the innovation, the information channels and time. The maximization-scale (Schwartz 2002) aims to capture the distinction between decision makers who tend to maximize the outputs of their choices and those who tend to satisfice.

The five sections are described in details below.

<u>First section (respondents' current heating system)</u>

After welcoming respondents and explaining the purpose of the research, the first question asked respondents about their current heating system, as well as providing them with information about different heating systems available in the Veneto region. Then, for those respondents who owned a firewood fueled heating system, a general question about the value they assign to wood was asked: *"The Veneto region is planning to introduce a law denying common property of estovers. If this happens, how much would you be willing to pay in order to be able to access to the forest to cut".* This question was on purpose at the beginning of the questionnaire, to avoid being influenced with the answers obtained from following sections. The aim of this question was to capture not only the market value of the wood, but also the social and traditional value associated with wood.

If respondents possess a firewood fuel heating system, information about wood quantity used along the year, cost of the purchased wood, source of the wood (purchase or direct cut) was collected.

Second section (choice experiment)

The second section included the CE. The list of alternatives and attributes was shown to respondents, along with detailed information about each of them prior to undertaking the experiment. Respondents were asked to imagine they had to renovate their heating system and hence they were asked to choose a system from amongst those available in the choice sets. After each choice-set respondents were asked to indicate when they would adopt the system chosen and how many hours per year they thing they would use it. Details of the CE will be provided in the following chapters.

Third section (factors influencing respondent’s choices)

The third section aimed at collecting additional information about respondent’s choices, along with asking questions about pellet certification and incentives. In case the pellet alternative was never chosen in the provided choice sets, respondents were asked why they systematically excluded the adoption of pellet based system, and if they would reconsider their choice in the future and why. The next question regarded the Forest Stewardship Council certification for the wood pellet, which certifies that wood pellet is made from wood from forest sustainably managed, both from the environmental and social point of view. In particular, respondents were asked whether such certification would influence their renovation choices. The last question dealt with incentives, asking respondents the minimum amount of money they would consider to undertake the procedures to obtain them. The incentives provided by the Italian state and by the Veneto region are a combination of a tax deduction and a contribution to the purchase of the system, and are usually limited to technologies with low environmental impacts, such as biomass based heating systems.

Fourth section (attitudinal questions)

In this section, a series of attitudinal questions were presented. These questions aimed at understanding the role of factors such as the influence of the community and individual psychological treats in households' decision making. The first question of this section presents agree/disagree statements measuring the value of the direct cut activity (Table 2.1). It is important to collect such information, because in some areas, especially the mountain ones, such activity is strictly linked to tradition and social habits. The following question aimed at collecting information about some psychological treats of respondents, according to the theory of the Diffusion of innovation. They were meant to investigate respondents’ perceptions towards pellet fired heating system, the role of the source of information and its influence on their propensity to adopt such heating system. Details about such questions will be provided in Chapter 4. The last question of the section investigates respondents’ maximization propensity, by means of the 6-item Maximization-scale proposed by Nenkov et al. (2008).

Fifth section (socio-demographic questions)

The last section contained some socio-demographic questions, referring to age, sex, education, and average yearly income.

1.4.4 The Choice Experiment

The CE was conducted by presenting respondents with a series of choice sets, each of which presented three hypothetical alternative fuels for heating systems taken from 1) fire wood, 2) chip wood, 3) wood pellet, 4) methane, 5) LP Gas, and 6) oil. Each heating system varied in terms of attributes’ levels. The attributes are: 1) investment cost, 2) investment duration, 3) annual operating cost, 4) CO_2 emissions, 5) fine particle emissions, and 6) required own work. The respective levels are reported in Table 1.1, and a description of each is provided in the text below.

Investment cost is the cost of purchasing and installing the heating device. Possible public subsidies from the state or the region are not considered. *Investment duration* refers to the lifespan of the heating device, from installation to dismantling. *Operating costs* include fuel price, maintenance and repair costs as well as costs of the system's electricity consumption. Energy cost depends on the unit cost of fuel and the operating efficiency. *CO_2 emissions* refers to the quantity of CO_2 released by the fuel combustion processes, and the same goes for *fine particle emissions*. Finally, *required own work* refers to the time required to ensure the faultless operation of the heating system (e.g., cleaning and adding fuel). The choice of attributes and their levels was based on earlier technical studies and on feedback from experts. The annual operating cost, CO_2 and fine particle emissions were calculated based on the energy consumption of an average detached house (120 m^2), the efficiency of each heating system and unit price/emission of a fuel. Respondents were asked to select within each choice set their preferred option if they had to renovate their system.

Table 1.1 Attributes and levels of the CE

Attributes	Firewood	Wood Chip	Wood Pellet	Methane	Oil	LP Gas
Investment cost (€)	9,500, 11,000, 12,500	11,500, 13,000, 14,500	13,000, 15,000, 17,000	4,000, 4,800, 5,600	4,500, 5,500, 6,500	4,000, 5,000, 6,000
Investment duration (years)	15, 17, 19	17, 20, 23	16, 19, 22	16, 18, 20	16, 18, 20	14, 17, 20
Operating cost (€/year)	1200, 2000, 2800	2000, 2800, 3600	2,500, 3,750, 5,000	4,000, 5,500, 7,000	6,000, 8,000, 10,000	9,000, 12,500, 16,000
CO_2 Emissions (kg/year)	150, 225, 300	300, 375, 450	375, 450, 525	3,000, 3,750, 4,500	3,900, 4,575, 5,250	3,525, 4,125, 4,725
Fine particle emissions (g/year)	4500, 6000, 7500	2250, 3750, 5250	750, 1500, 2250	15, 30, 45	150, 450, 750	15, 30, 45
Required own work (h/month)	5, 10, 15	1, 2, 3	1, 2, 3	-	0.5, 1, 1.5	0.5, 1, 1.5

1.4.5 Experimental design

The experimental design adopted in the CE is a variant of the efficient availability design proposed by Rose et al. (2013). According to this design, only three alternatives were shown in each choice set, despite the total number of labelled alternatives being six. The master design – the design which determines which alternatives are shown in each choice set – was a fixed master design, that produced 20 choice sets. The design was repeated three times (for a total of 60 choice sets) to ensure the balance of the attribute levels of the sub designs, which appear 20 times for each attribute. The combination of levels that appeared in each choice set was defined according to three different sub designs, namely near orthogonal, D-efficient (Ferrini and Scarpa, 2007; Scarpa and Rose, 2008; Rose and Bliemer, 2009; Bliemer and Rose, 2011), and a serial design (Rose and Bliemer, 2009). For the serial design, an orthogonal design was used for the first respondent. After completion of the choice set by this first respondent, the parameters were estimated by the purpose design software in the background using a multinomial logit model based on his or her observed choices. Statistically significant parameters were then used as priors in determining the next design whilst parameters that were not statistically significant were assumed to be zero. From these new priors, a new efficient design was generated and given to the next respondent. The data from each additional respondent was then pooled with the data from previously surveyed respondents and new models were estimated, in order to generate a new, gradually more efficient design. This new design was then assigned to the next respondent. All this was programmed in the background of the web-survey. The design generated a total of 60 choice sets that were blocked into six groups, so that each respondent faced a sequence of 10 choice sets. Examples of the choice sets are included in Appendix 1.

2[1]. Valuing landslide risk reduction programs in the Italian Alps: the effect of visual information on preference stability

This chapter illustrates the analysis related to the first specific objective of this thesis, that being the investigation of the effect of information treatments. Data used for the analysis were retrieved from the first case study (analysis of social demand for landslide protection).

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 CE 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 WTP estimates and control for the effect of information. Mapping posterior individual specific WTP estimates provide additional policy implications. Overall, we found the WTP estimates to be dependent on information.

2.1 Introduction

Climate change has increased the frequency of geo-hydrogeological calamities, over both time and space. Worldwide a growing number of people is 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 probability of occurrence. In the engineering literature, there have been several proposals of technical solutions aimed to reduce the impacts of landslide events (Berti et al., 1999; Gregoretti and Dalla Fontana, 2008; D'Agostino et al., 2010). Most solutions consist of specific safety devices to mitigate the risk in pre-existing landslides' trajectories. However, few studies address individuals' preferences to 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 non-market 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 et al., 2015; Thiene et al., 2016 and Vlaeminck et al., 2016). However, there is still limited work carried out in the investigation on the social acceptability of risk mitigation programs, and on their specific demand.

[1] This chapter is an edited version of: Mattea, S., Franceschinis, C., Scarpa, R., Thiene. M. (2016). Valuing landslide risk reduction programs in the Italian Alps: the effect of visual information on preference stability. *Land Use Policy*. Article in Press.

This study reports the results of a CE study 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 for the alternative solutions, the population during the debate should be exposed to scientific-based information such as hydro-geological simulations of possible events. As such, 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 and Hanley, 2002; Chanel et al., 2006; MacMillan et al., 2006; Oppewal et al., 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 in four sections. Section 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 3 describes the survey design and the modelling approach used for the data analysis and the hypotheses' tests. In section 4 we discuss the results, including the geographical representations of the respondent-specific marginal WTP estimates. Finally, our conclusions are reported in section 5 along with the policy implications for landslide risk mitigation in the Boite Valley.

2.2 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 result in fatalities, homelessness, damage to buildings, and interruption to road traffic (Sterlacchini et al., 2007; Salvati et al., 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 event happened in 1925, causing 288 victims, with an additional 53 people missing. In the last decade, this area suffered a series of devastating landslides. Recently, in the summer of 2015, intense rainfall over a short period of time triggered eight events, causing significant damage to public infrastructure alongside three victims amongst visitors to the area. Geologists believe that there are approximately 350 potential and active landslides that can be highly dangerous for the population living in the valley (Guidoboni and 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) realization 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.

2.3 Hypotheses

This paper specifically investigates the following three hypotheses:

H1: People would benefit from the increase of the current level of protection from landslide hazard.

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 policy makers to take into account the economic dimension (expressed in terms of WTP), in addition to the other dimensions that feed into such debate. 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 positively shift the WTP for the specific attribute for which the information was provided as well as for the other attributes.

Many stated preference researchers have investigated information effects on WTP estimates. 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 WTP 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. A study conducted by Czajkowski and Hanley (2012) found that respondents were more deterministic in their choices when provided with additional information. In a CV 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 have 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 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. We expect a stronger information impact on individuals living far from the Boite Valley, as they are likely to be less aware of the landslide problem of the area.
It is a theoretically well-established expectation that welfare changes display spatial heterogeneity, and that this heterogeneity can be policy relevant in empirical applications. An expanding literature addresses the relevance of spatial factors for the estimation of WTP. Spatial distributions of WTP estimates from DCE surveys have been investigated in several studies, starting from the seminal work by Campbell et al. (2008, 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 et al. (2013), Broch et al. (2013) and Termansen et al. (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. Additionally, Czajkowski et al. (2016) 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.

2.4 Survey design and data

2.4.1 Choice experiment attributes

We developed a CE consisting of alternatives described by five attributes, with the specific attributes and their levels 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 access 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.

Table 2.1. Attributes and levels of the DCE.

Attribute	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	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

2.4.2 Experimental design and questionnaire development

The generic DCE used an optimised orthogonal experimental design (Ferrini and Scarpa, 2007; Scarpa and Rose, 2008; Rose and Bliemer, 2009; Bliemer and Rose, 2010 and 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 sixty choice sets that were blocked into ten groups of six each. Each respondent could reply to six choice sets from one of the ten blocks to which s/he was randomly assigned. Each choice set comprised seven alternatives among which to choose the preferred option (Table 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.

Table 2.2. An example of a choice set for a specific site.

Site 1 - CANCIA

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

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. 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 2.3 reports the actual situation of safety devices in each location.

Table 2.3 *Status quo* in each site.

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

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 CE in the third part and a "repeated" CE 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 CEs 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 2.1) 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 2.2. The yellow and green areas describe all possible landslide trajectories without the channel.

Alternatively, were the channel built, the yellow areas does not constitute possible landslide trajectories.

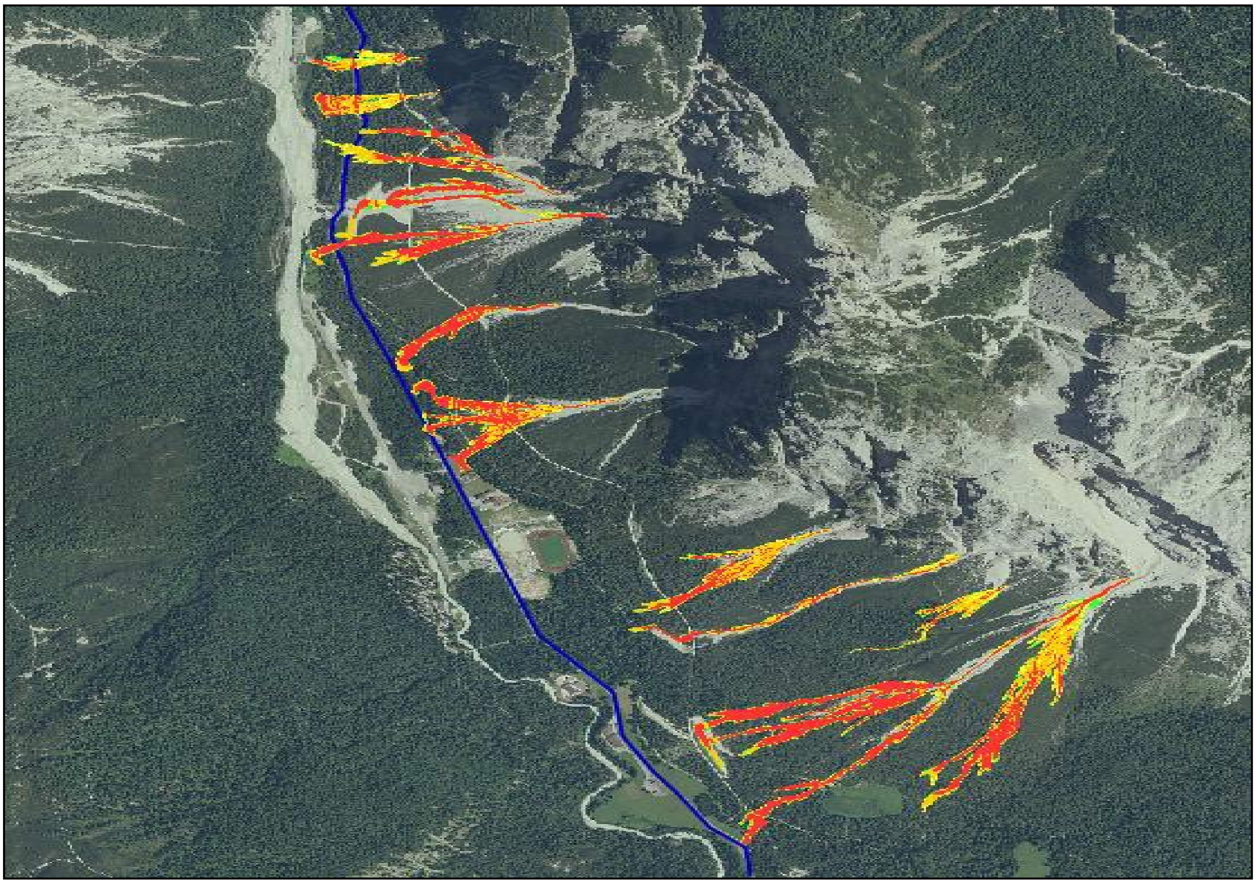

Figure 2.1. First simulation: possible landslide events in the upper part of the Boite Valley (Gregoretti, 2014).

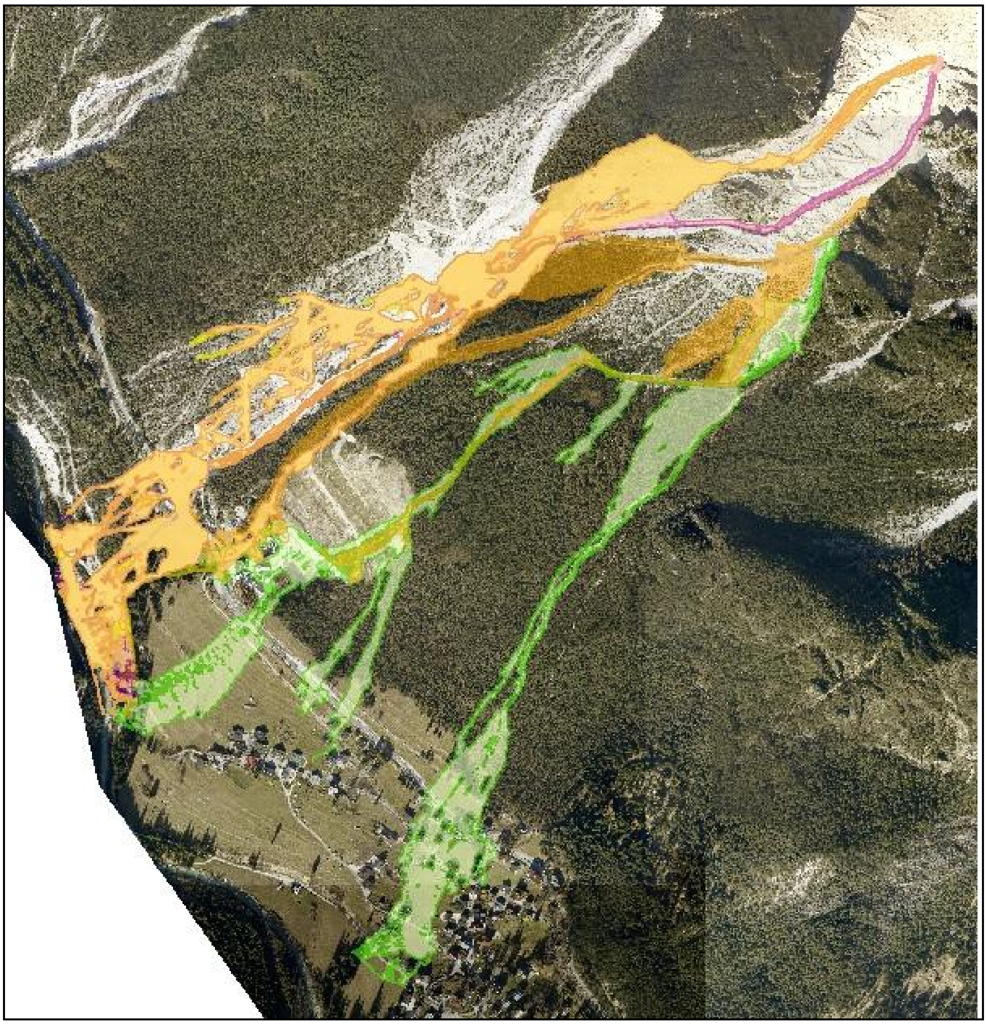

Figure 2.2. Second simulation: a possible landslide with (only yellow area) and without channel (yellow and green areas) in site 2 – Chiappuzza (Gregoretti, 2014).

2.4.3 Sampling procedure

An initial version of the questionnaire was tested on a sample pilot of 30 respondents. After the necessary amendments, the full-scale data collection was carried out in September-October 2014 by in-person surveys. The sample included 250 respondents randomly sampled on-site among the residents and 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 percent) and 117 women (46.8 percent). 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 percent, 108 respondents out of 250) and the other half was composed of different types of visitors (56.8 percent, 142 respondents). However, almost 90 percent 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.

2.5 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 alternatives from best to worst using a reiterated best-worst approach, in the analysis reported here we only use data on the most prefered 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 literature, and most recently focussed has been placed on those able to relax the independence of irrelevant alternative assumption, such as Mixed Logit models (Train, 1998; Revelt and Train, 1998). In this paper we adopt a Mixed Logit specification in WTP space (Train and Weeks, 2005; Scarpa et al., 2008). The utility function for alternative *i* in choice occasion *t* is specified as:

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

where X is a vector of non-monetary attributes, p_{it} is the cost attribute and ω_n is a 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 hypothesis that visitors and residents would benefit from an increase of the current level of protection from landslide hazard, we included in our model the alternative specific constant (ASC) for status quo alternative. A negative sign of the ASC would support our hypothesis.

To investigate the substitution pattern of different protection devices a covariance structure was estimated to account for correlation across the elements of the vector ω_n:

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

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). In order to test such hypothesis, one can estimate 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, which is defined as equal to 1 for data collected after the exposure to information. The generic linear utility function for the alternative i in the pooled data can be expressed as:

$$V_{nit} = \omega_n{}' X_{nit} + \Delta_n{}'(X_{nit} \times I) \qquad \text{(Eq. 2.3)}$$

where X_i is the vector of attributes. A statistically significant element Δ_n of vector Δ_n' would 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 WTP across the region. We first simulated WTP_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 and 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.

2.6 Results and discussion

2.6.1 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 et al., 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, beside the price/scale coefficient which is assumed to follow a lognormal 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 a MXL 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.

Table 2.4 Models comparison.

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

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 are generally benefitting from improved protection, and are ready to pay to achieve it. 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 negative perception of status quo and positive WTP values for implementation of new devices support our first hypothesis.
We investigated the effect of the information provided by simulation scenarios by means of interaction terms between each attribute and post-treatment indicator variable, which took the value 1 for choices collected after the information treatment. The coefficients of the interaction terms with the attributes are all insignificant, with the exception of 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 a positive 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. We did not find evidence, instead, of information effect for devices for which additional information was not provided. Therefore, hypothesis 2 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 change 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.

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

	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	0.2	<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 2.6 reports the estimated correlation terms amongst the attribute coefficients, which illustrates the perceived substitution pattern of protection devices. Most of the correlation terms (four out of six) are statistically significant and all of them are positives. This suggests that different devices are considered substitutes of each other. We note that the highest correlation is found to be between protection devices of the same class. In particular, the highest degree of substitution has been found between channel and basin (0.68) which are both passive devices.

Table 2.6. Correlation among the random coefficients associated with non-monetary attributes. Standard errors are reported in brackets.

	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)	

2.6.2 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 percent (89.6 percent; 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 2.3 illustrates the average WTP for the construction of a channel, before and after information provision according to different geographical areas. 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 illustrates the values after such treatment. 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.

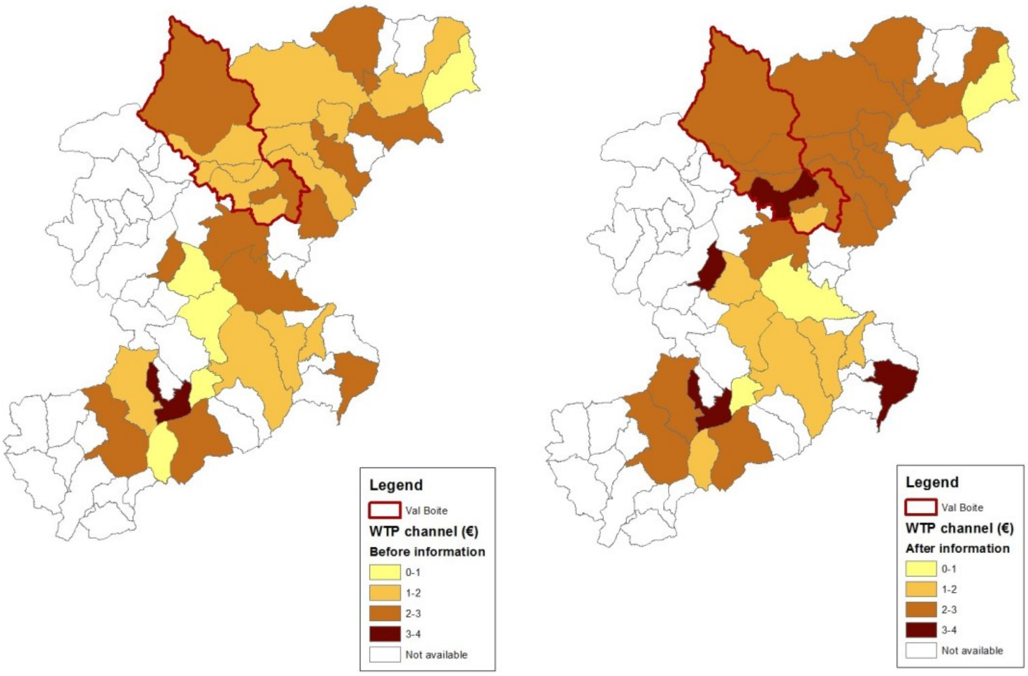

Figure 2.3 Mean WTP for the attribute "channel" (before on the left, after on the right).

2.7 Conclusions

In this study we presented the results 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 positively affects individuals WTP for safety measures; iii) there exists spatial heterogeneity of both WTP 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 are preferred to active ones. Results show evidence of nested substitution effects among protection measures, within the categories of passive and active devices. 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 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 showed which municipalities are to benefit most from increased awareness. In particular, the information effect appears to be substantial in areas located far from the Boite Valley, in which respondents are more likely to be least familiar with the local landslide issue.

With regards to the policy implications, the estimated mean values of marginal WTPs offer insight on the relative importance of each protection device. Having information about individual preference of local 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, as passive devices seem to be strong substitutes, it seems appropriate to promote the construction of channels as it is associated with the highest WTP values, even before information provision. With regards 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 a public intervention and support (i.e., cost-sharing) over a broader 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.

Acknowledgements

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3[2]. Exploring the Spatial Heterogeneity of Individual Preferences for Ambient Heating Systems

This chapter relates to the third specific objective of the thesis, that is the introduction of model specification which allow to include geographical variables in the econometric analysis. Data were retrieved from the second case study (analysis of preferences towards heating systems)

Abstract
The estimation and policy use of spatially explicit discrete choice models has yet to receive serious attention from practitioners. In this study we aim to analyze how geographical variables influence individuals' sensitivity to key features of heating systems, namely investment cost and CO_2 emissions. This is of particular policy interest as heating systems are strongly connected to two major current environmental issues: emissions of pollutants and increased use of renewable resources. We estimate a MXL model to spatially characterize preference heterogeneity in the mountainous North East of Italy. Our results show that geographical variables are significant sources of variation of individual's sensitivity to the investigated attributes of the system. We generate maps to show how the willingness to pay to avoid CO_2 emissions varies across the region and to validate our estimates ex-post. We discuss why this could be a promising approach to inform applied policy decisions.

3.1 Introduction

The European Union Renewable Energy Directive 2009/28/EC establishes a policy framework for the production and promotion of energy from renewable sources for the half billion Europeans living in the 28 EU member states. The directive requires that at least 20 percent of total energy needs in the EU be produced using renewables by 2020, to be achieved in the aggregate by defining various state-specific targets. Such targets are set by taking into account the respective starting points and overall potential for renewables in each member state. The quota of renewable energy in the power mix ranges from 10 percent in Malta to 49 percent in Sweden. In Italy the target is set to 17 percent, starting from a base of 5.7 percent share of renewable energy in 2005. To meet the EU targets, in 2010 Italy submitted to the European Commission the Italian Renewable Energy Action plan. The plan sets a 2020 target share for renewables across energy sectors as follows: 25.39 percent in the electricity sector, 17.09 percent in the heating/cooling sector, and 10.14 percent in the transport sector. Of relevance to our study is the large potential to increase the share of renewables in heating systems. Nearly 85 percent of the Italian households still use fossil fuel-based heating systems.

Government authorities are hence concerned about collecting information that can help them design and implement policy instruments that may promote a switch from fossil-based to renewable systems. Given the great diversity of territorial features across the Italian peninsula, geographical factors are likely to determine substantial variation in the propensity to adopt renewables across the population of residential homes. This study aims to systematically explore such heterogeneity of preferences by means of a geographically explicit choice model estimated from CE data. This study reports the results from a CE investigating household preferences toward different heating systems in Veneto, a

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region in the North-east of Italy with a substantial amount of mountainous territory. The survey data explores preferences for six heating systems: three based on traditional fuels and three based on renewables.

Over the last few years research applications in the field of residential heating based on CEs has increased in popularity amongst researchers (e.g. Banfi et al., 2008; Scarpa et al., 2010, Rouvinen and Matero, 2013). This method enables analysts to investigate preference heterogeneity for different heating systems in terms of energy savings, environmental benefits, comfort considerations, compatibility with daily routines, personal habits and cost. Discrete choice model estimates from the analysis of CEs data show how subjects in the sample weight salient aspects in their stated choices. In the presence of a cost for alternatives the data be used to infer the marginal rate of substitutions of attributes with income. This, in our case, is interpreted as the WTP for the various heating characteristics described in the experiment. Banfi et al. (2008) estimated the WTP for energy-saving measures in residential buildings in Switzerland. Jaccard and Dennis (2006) used key parameters (discount rate, intangible costs and degree of heterogeneity) to simulate various energy policies. Scarpa and Willis (2010) focused on microgeneration adoption in the UK and Willis et al. (2010) examined the role age plays in terms of behavioral responses towards energy efficiency, in particular whether older individuals are less likely to adopt micro-generation renewable energy technology. Achtnicht (2011), Michelsen and Madlener (2013) investigated the choice of energy retrofits in Germany. Achtnicht focused on CO_2-saving measures (heating systems and insulation) and WTP for CO_2 savings, whereas Michelsen and Madlener examined driving factors of choice of residential heating systems. Rouvinen and Matero (2013) examined how different attributes of residential heating systems affect private homeowners' choice of heating system following renovations.

Whilst several studies have explored group decision making in choice analysis (see Beck 2012 for a reviews of such papers), a common assumption in the stated choice literature is that survey respondents make choices independently of preferences of others. For example, Bartels et al. (2004, 2006) examined the preferences of plumbers and consumers for water heater systems using CEs, but treated both samples as if they were independent of each other. Where interdependence between agents has been considered, the assumption has been that the relationship exists between household members (e.g. Rungie et al., 2014), immediate family or close friends. There exists, however, an established literature (e.g. Billè and Arbia, 2013; Bhat et al., 2015) accounting for a wider range of spatial interdependencies between individuals, which may induce interdependence of preferences. This induces the phenomenon of socially influenced decision-making: individuals neither act fully independently, nor reach decisions jointly, but they decide based on a mix of social interaction factors, which might be best represented in a succinct manner as geographical determinants.

Over the last ten years or so an increasing body of literature has dealt with the study of spatial effects on welfare changes. Previous studies on this topic mainly focused on addressing the relevance of spatial factors through *post hoc* analysis on the WTP estimated from choice models (e.g. Campbell et al., 2008, 2009; Termansen et al., 2008; Czajkowski et al., 2015). However, there remains only limited work on the inclusion of spatial variables in the utility structure behind choice (e.g. Thiene and Scarpa, 2008; Smirnov, 2010). This paper contributes to the filling of this gap: it proposes MXL model specifications to explore how individuals' sensitivity to key features of heating systems varies in the different geographical areas of the study region. We include not only variables referring to respondents' geographical location, but also to socio-demographic characteristics of the area in which they live. This allows us to gain further insight on both spatial and social effects on heating systems preferences. To explore the *post hoc* validity of our results, we also map the mean values of marginal WTP estimates at the individual level within each area. Detecting if the distribution of benefits is both spatially and socially uneven is useful as it helps policy makers to design geographically targeted programs that are coherent with public preferences.

This is of particular interest in the Veneto region, as both national and local governments have the mandate to design and implement policy measures to foster households' adoption of energy-efficient and sustainable heating systems, based on renewable resources. These measures can be categorized into economic (e.g. capital grants, tax exemptions, price subsides) and awareness (e.g. education) measures. The latter aim at making households aware of the benefits of energy efficiency, and they attempt to change households' behavior with respect to fossil fuel consumption. Although financial measures are usually introduced at the national or regional scale, awareness measures can have a local nature (e.g. meeting with citizens, lectures, etc.). Knowing in which areas households are generally less prone to pay a premium to install more sustainable systems would allow policymakers to direct more efficiently their efforts using geographical criteria. This may result in a broader awareness of the importance of the use of renewable resources and in a support over a broader geographical area of government intervention.

The remainder of this paper is organized in four sections. Section 2 provides an overview of previous studies in the context of spatially explicit discrete choice models. Section 3 describes the methodology we adopted and motivates the model specification used for the data analysis. In section 4 we report and discuss the results. Finally, conclusions are reported in section 5.

3.2. Spatially explicit discrete choice models: empirical applications

There is now compelling evidence that preferences for some environmental goods follow spatial patterns. This may be due to the spatial configuration of such goods and the availability of substitutes (Munro and Hanley, 1999) or to residential sorting. People's preferences for environmental goods can influence where they choose to live, so that measures of preferences tend to be correlated with measures of environmental quality or with distance to environmental amenities (Timmins and Murdock, 2007). Recent developments in Geographical Information Systems (GIS) allow researchers to investigate spatial patterns in preferences for environmental goods. Amongst most common approaches is that of investigating spatial distribution of WTP estimates derived from CE studies. Campbell et al. (2008, 2009) used this approach to map WTP estimates for rural landscape features in Ireland. They found evidence of significant global spatial clustering and spatial autocorrelation of the WTP estimates with landscape features that were prevalent in given areas and iconic for local identity being more valued by locals. Abildtrup et al. (2013) investigated spatial heterogeneity in WTP for forest attributes in France. Yao et al. (2014) used data on forest distance from respondent's homes to capture spatial effects in WTP for enhancement of biodiversity in forests of New Zealand. They found evidence of distance-decay effects, that is, respondents living closer to the environmental good being evaluated tend to have a higher WTP for it. Duke et al. (2014) mapped the outcomes of targeting agricultural land preservation by using four different strategies for spatial provision of environmental services in Delaware. Johnston and Ramachandra (2014) used local indicators of spatial association to explore WTP hot spots. Czajkowski et al. (2015) found evidence of distance decay on WTP estimates for forest attributes in Poland. Spatial effects on WTP estimates have been also investigated including spatial variables in discrete choice models. Hanley et al. (2003) included a distance parameter in a CV study to estimate distance-decay functions for a reduction in low flow problems on the River Mimram, England. Schaafsma et al. (2012) included in discrete choice models spatial variables aimed at investigating directional effects on distance decay of WTP values, related to the availability of substitute sites across the region. Broch et al. (2013) included spatial variables as covariates in a discrete choice model to estimate the spatial pattern of the willingness to provide ecosystem services in agricultural landscapes.

Other studies investigated spatial effects including spatial attributes in stated preferences scenarios. Horne et al. (2005) examined visitors' preferences for forest management at five adjacent municipal recreation sites in Finland, using a spatially explicit CE. They included site specific levels of attributes to evaluate whether preferences towards management options differed across sites. Lanz and Provins (2011) used CE to examine preferences for the spatial provision of local environmental improvements in the context of regeneration policies. They included the spatial scope of the policy as an attribute, making the trade-off between environmental amenity and its spatial provision explicit. Luisetti et al. (2011) included the distance from respondents' home as an attribute to investigate distance decay effects on preferences towards cost management programs in UK. Schaafsma et al. (2012) evaluated WTP for improvements in the provision of environmental services of eleven lakes in a lake district in the Netherlands. They included the lakes as different labelled alternatives in choice sets. Finally, spatial effects on preferences for wind power are commonly investigated by including in the CE attributes describing the distance between wind farms and residential areas or shores to account for visual intrusion (see Knapp and Ladenburg, 2015 for a review).

3.3. The Model

Within the CE approach each respondent's choice is modelled as a function of the attributes using Random Utility Theory (Luce, 1959; McFadden, 1974). According to the theory, for and individual n facing a set of J alternatives, denoted by $j=1,\ldots,J$ the utility of choosing the alternative i is a function of the K attributes used to describe alternative j. The utility function has a systematic part V_{ni} (indirect utility) and a random part ε_{ni}, for all unobserved variables, such that

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad \forall\, i \text{ in } j. \qquad \text{(Eq 3.1)}$$

The systematic part of the utility function of individual n associated with the selected alternative i is modeled as a linear function of the vector of the attributes $\mathbf{x}_i$ and associated parameters β_n. If the unobserved error term ε_{ni} is assumed to follow a Gumbel distribution, the probability of individual n choosing alternative i out of J alternatives can be defined by the MNL model:

$$\Pr\left(U_{ni} > U_{nj}, \forall J\right) = \frac{\exp(V_{ni})}{\sum_{j=1}^{J} \exp(V_{nj})} \qquad \text{(Eq. 3.2)}$$

A property of the MNL model is the Independence of Irrelevant Alternatives (IIA), which is most often undesirable as it implies constant share elasticities. The MXL model (see Revert and Train, 1998; Train, 1998) allows for a relaxation of the IIA assumption, whilst continuing to assume the residual error term is i.i.d. extreme value type I distributed. The MXL model allows for un-attributable heterogeneous preferences (i.e., unlike interaction effects, preferences are assumed to be randomly distributed over the population). Different interpretations have been given to the MXL in various empirical work, the two most common interpretations being the Random Parameter Logit (RPL) and Error Component Logit (ECL) models. Whilst mathematical equivalent (Train, 2003), the respective behavioural interpretations of the two models are motivated by distinct analytical interests (Brownstone, 2001). More specifically, RPL appeals to the analysis of taste variation, whilst the ECL interpretation is more amenable to the analysis of complex substitution patterns and variance-covariance structure. Behaviourally sound models often mix the RPL and ECL features to achieve flexible specifications that are suitable for the problem at hand. In this spirit we use two separate sources of randomness, one linked to diversity across respondents, the other shared across respondents from the same geographical area.

The utility structure is specified as

$$V_{ni} = \beta'\mathbf{x}_{ni} + \mu_n{}'\mathbf{z}_{ni}, \qquad \text{(Eq. 3.3)}$$

where $\mathbf{x}_{ni}$ and $\mathbf{z}_{ni}$ are vectors of observed variables relating to alternative i, β is a vector of fixed coefficients, μ_n is a vector of random terms with mean μ and stochastic components that, along with ε_{ni} define the stochastic portion of utility as well as the manner in which utility is correlated across respondents via the unobserved portion of utility.

What makes this model explicit in its geographical variables is that μ_n has a stochastic component ϵ_n with standard deviation that is in part constant and in part shifted by $\alpha_h z_h$, linked to the h^{th} place of residence via the indicator vector z_h. The parameter α_h expands or shrinks the total standard deviation tailoring it to the place of residence indicated by z_h. In essence:

$$\mu_{nh} = \mu + \epsilon_{nh} = \mu + (\sigma + \alpha_h z_h)\eta_n \qquad \text{where } \eta_n \sim N(0,1) \qquad \text{(Eq. 3.4)}$$

The aim of the study is to investigate how the variance of the random parameters changes according to different areas of the region. In particular, we focus on the variance shift of key random taste parameters: the coefficient for the cost of heating system and that for the CO_2 emission. The first relates to the marginal utility of income, the second to the marginal utility of emission abatement. Importantly for a geographical tailoring of the subsidy policies, geographical differences in the random cost parameter allow us to better investigate how the marginal WTP estimates vary across the region.

Under this basic specification each person has her own parameter μ_{nh}, which deviates from the population mean μ by ϵ_{nh}. The idiosyncratic random term ϵ_{nh} is normally distributed and has standard deviation $\sigma + \alpha_h z_h$ with mean 0. Variance reducing sites will have $\alpha_h < 0$, while variance increasing ones $\alpha_h > 0$.

To define the geographical areas affecting the variance of ϵ_{nh} we used three different criteria to capture both spatial and social effects. We grouped the municipalities of the region according to three criteria: 1) altitude, i.e. being located in low land (plain or valley), hilly or mountainous area, 2) average income in the municipality, 3) population size. Accordingly, we estimated three MXL models. The first criterion produced three different areas, the second and the third ten areas each. Average income was divided in ten classes of €1,000 width, ranging from €15,000 to €25,000. The population size classes are move in steps of 5,000 people, with boundary classes being less than 5,000 and over 40,000.

Model identification was ensured by keeping as baseline hilly areas for the first criterion, the lowest average income segment (less than 15,000€) and the lowest population size (less than 5,000 people).

3.4 Expected results and rationale

We now turn to our expected results for selected features of the investigation and the rationale behind each expectation. From the altitude-related model we expect individuals living in mountainous areas to be relatively more homogenous in their views on cost of heating system. The motivation would be that populations in these areas are traditionally quite careful with resource use and management because of their harsh living conditions and close-nit societies who often openly disapprove of profligacy. We do not have a clear expectation with respect to residents in hills and plains, although we suspect that there would be a gradient of heterogeneity with the largest being associated with lower altitude. With respect to preference variation of CO_2 emissions, we expect that people in the plains be more homogeneous since they are more exposed to air pollution than people in the hills or mountains, especially during the periodical winter fogs that impede speed of transport, often dramatically. Even though fogs are not directly caused by CO_2 emissions, smog (smoke+fog) is strongly correlated with CO_2.

We now turn our attention to the effect of segregating sites on the basis of average income. For the heterogeneity of cost coefficient, we expect that as income increases the variation of taste intensity for income should also increase as income has been found to be a typical source of heteroscedasticity in economic datasets. The cost coefficient in linear utility specifications is equivalent to the (negative of) marginal utility of income. Relatively poorer residents have little choice in the way they value their last unit of income, while those relatively better off can choose from a wider range of behaviors. A rich person can behave as a miser, but a poor person has no choice. Turning to heterogeneity for the CO_2 coefficient we hold much weaker expectations. It can be argued that in richer sites there might be more disposable income and in as much as fewer emissions and a cleaner environment are a luxury good (as the literature on Environmental Kuznets curve suggests) a higher consensus in favor of renewables should be found in richer locations.

The population gradient criterion should suggest that for both coefficients there should be a higher heterogeneity the higher the population, if anything because population size correlates with diversity. Extreme views on utility of income and CO_2 emissions ought to be more common in larger size locations. However, it might also be that higher density induces more homogeneity of views against higher levels of pollution. In any case, we do not hold strong expectations along this segregation criterion and which feature will prevail remains an empirical question the outcome of which has weak theoretical basis.

3.5 Ex-post validation

The sequence of choices made by each respondent contains additional information that may help improve the accuracy of estimates derived from the latent utility, such as individual specific marginal WTP estimates. These can be used to assess the theoretical validity of the stated choice method by exploring how WTP estimates correlate with theoretically meaningful independent variables, as suggested in the early literature of validation of hypothetical choice statements (Mitchell and Carson 1989, Bishop et al. 1995). In practice, one can use visual inspection and regression analysis, we opt for both and use geographical mapping and kernels densities. The technical details are as follows. We simulated the population distributions of individual specific estimates of WTP_n by generating 10,000 pseudo-random draws from the unconditional distribution of the estimated parameters and we calculated individual-specific estimates for each draw as explained in the seminal literature of panel choice models (Train, 1998; von Haefen, 2003; Scarpa and Thiene, 2005). The formula employed (Greene et al., 2005) is

$$\widehat{WTP}_n = \frac{1/R\sum_{r=1}^{R}\mu_{n,r}^{c}/\mu_{n,r}^{€}L(\mu_{n,r}|data_n)}{1/R\sum_{r=1}^{R}L(\mu_{n,r}|data_n)} \quad \text{(Eq. 3.5)}$$

where R is the number of replications (i.e., draws of μ_n), $\mu_{n,r}^{c}$ is the r^{th} draw for the CO_2 attribute, $data_n$ is the observed sequence of choice data by respondent n, $L(\mu_{n,r}|data_n)$ is likelihood of an individual's sequence of choices computed at draw $\mu_{n,r}$ and $\mu_{n,r}^{€}$ is the r^{th} draw for the investment cost attribute, that is the payment vehicle used to compute the WTPs.

The individual value estimates are averaged by geographical polygon of each municipality, colour-coded and mapped with ArcGIS to obtain the geographic distribution of the estimates. Kernel density distributions of WTP from the best performing model are obtained conditional on income levels, altitudes of place of residence and population size of the place of residence.

3.5. Results

All MXL estimates were obtained by simulated maximum likelihood using Pythonbiogeme software (Bierlaire, 2003). The choice probabilities are simulated in the sample log-likelihood with 1,000 pseudo-random draws. We estimated three specifications, one for each criterion by using different $\alpha_h\, z_h$ in the standard deviation for the random parameters for cost and CO_2 emissions.

In the first MXL model, which relates to altitude of place of residence of the respondent, α_1 denotes the coefficient for mountain areas associated with z_1, while α_2 is the analogue for low land. So, the baseline standard deviation is for intermediate altitude areas (hilly). The second (average income) and third (population size) models have 10 ordinal groupings each, so nine $\alpha_h\, z_h$ are used. In all models, error components η_n are assumed to have a standard normal distribution. As the aim of the study is to investigate the heterogeneity of sensitivities for the investment cost and the CO_2 emissions, we kept all other coefficients fixed. All models include six alternative specific constants (ASCs) for all heating systems except for LP Gas, which is the baseline.

Table 3.1 shows the estimates for the MNL and the three MXL models. Each of the three MXL models substantially improves the fit to the data. Across the three MXL models, the specification based on population size seems to perform best, according to all criteria. In all the models, the investment and operating cost coefficients are significant and negative, as expected. The other significant determinants of preferences towards heating systems are the emission of CO_2 and required own work. The negative sign for emissions coefficient (FP and CO_2) are as expected, but that for FP is never significant, while the one for CO_2 always is, suggesting a different sensitivity to the type of pollutant caused by heating systems and a preference for technologies that target CO_2 emissions. The coefficient for required own work is also negative, suggesting an expected preference for low maintenance systems.

The alternative specific constants (ASCs) reflect the average system-specific impacts of unobserved factors associated with each system and measured with respect to LPG. These estimates are always statistically significant except for chip wood. The signs of the ASCs for firewood, wood pellet, and methane are positive, thus suggesting that those heating systems are preferred to the LPG fueled ones. Only the ASC for the oil based systems is negative, suggesting that it is the least preferred heating system. The standard deviations of the random components are significant in each of the three models, thus suggesting heterogeneity of cost sensitivity in the sample for both investment cost and CO_2 emissions. The estimated values for α_h show the sensitivity of the variance of the random coefficients for investment cost and CO_2 emissions across the geographical indicators of interest, which we now examine in turn.

In the "altitude" model, all estimates for α_h are significant, suggesting that density of coefficient values differs across the three altitude categories. α_{1cos} is associated with the variance of investment cost for respondents in mountain areas (-0.019) and α_{2cos} is its analogue for the plains (0.025). The alternate sign suggests a monotonic relationship between preference heterogeneity and altitude: the lower the latter the higher the former. In other words, these value estimates are consistent with a lower variance among respondents living in mountainous areas compared to those living in the low land, with those in the hills having an intermediate degree of heterogeneity thus confirming our expectation: preferences for marginal utility of money are more homogeneous in high altitude areas than elsewhere.

The pattern reverses for heterogeneity of taste for emissions, which displays a positive, rather than negative, monotonic relationship with altitude. People living in mountainous areas are more diverse in preference (0.033) compared to those living in the hills and plains. The latter show a higher homogeneity (-0.025) of taste in their view on CO_2 emissions. This differences in spread of taste parameters may be explained by considering that Veneto mountainous areas are less urbanized and populated (and therefore with more diffuse pollution), as compared to the hills and plains. So, extreme views are more prevalent in mountain areas where you might have a wider diversity of perceptions on the emission problem, whereas residents in the plains display higher converge in opinion. This may induce respondents living in the mountains to consider heating systems' emissions with a broader difference of opinion, thereby requiring a higher policy effort from the viewpoint of education and generally adopt more sustainable heating systems.

The seventh to eighth columns of Table 3.1 show coefficient estimates for the "average income" model. The lowest segment of income (less than €15,000) was defined as the baseline; eight out of nine investment cost coefficients and five out of nine CO_2 emissions coefficients show significant estimates. All α coefficients associated with investment cost are positive, and their relative values confirm the theoretical expectation of a gradual increase in heterogeneity with respect to marginal utility of money as average income increases. We take this result as a strong endorsement of theoretical validity of this stated preference data.

Finally, turning to the "population size" estimates (columns 10-12), four of the nine investment cost coefficients are significant and these show a monotonic set of relative values with respect to population size. A similar pattern, albeit with inverse correlation, is found for the eight coefficients with good significance for CO_2 emissions. The values of heterogeneity coefficients decrease as we move from less to more populated areas, thereby suggesting that in bigger cities people are more heterogeneous in their preferences towards CO_2 emissions. As expected, more populated cities are usually more urbanized and therefore more polluted. This may explain why individuals living in those areas are more sensitive to the issue of CO_2 emissions, even those produced by heating systems.

Table 3.1: Parameters estimates

	MNL			MXL - Altitude			MXL - Income			MXL - Inhabitants		
Variable	Coeff.	St. Err	|t|	Coeff.	St. Err	|t|	Coeff.	St. Err	|t|	Coeff.	St. Err	|t|
ASC Firewood	0.495	0.187	2.8	0.734	0.187	1.9	0.822	0.158	2.0	0.601	0.133	1.9
ASC Chip wood	0.201	0.199	1.0	0.512	0.199	0.6	0.469	0.204	0.7	0.333	0.201	0.6
ASCWood pellet	0.711	0.166	4.7	0.888	0.166	2.1	0.934	0.174	2.0	0.812	0.231	2.1
ASC Methane	0.944	0.212	9.8	1.023	0.212	7.7	1.026	0.157	8.6	1.001	0.234	5.0
ASC Oil	-0.311	0.071	5.0	-0.398	0.071	5.5	-0.411	0.055	5.7	-0.402	0.06	5.5
Inv. duration	0.07	0.051	1.3	0.021	0.051	1.1	0.014	0.028	1.2	0.021	0.029	1.3
CO2 emissions	-0.207	0.032	1.0	-0.101	0.032	2.5	-0.121	0.021	2.4	-0.146	0.041	2.5
FP emission	-0.012	0.19	0.9	-0.002	0.19	0.5	-0.003	0.01	0.5	-0.003	0.012	0.5
Req. own work	-0.133	0.099	0.6	-0.144	0.099	2.0	-0.101	0.081	1.9	-0.109	0.099	2.0
Investment cost	-0.321	0.123	3.6	-0.525	0.123	8.0	-0.567	0.091	7.0	-0.531	0.086	7.9
Operating cost	-0.059	0.024	8.0	-0.068	0.024	4.6	-0.099	0.013	4.6	-0.061	0.021	4.6
η_{cos}	-	-	-	0.371	0.131	3.2	0.421	0.098	4.2	0.391	0.115	3.8
η_{co2}	-	-	-	0.053	0.024	2.1	0.091	0.042	4.0	0.088	0.034	4.7
$\alpha 1_{cos}$	-	-	-	-0.019	0.006	2.4	0.006	0.002	2.8	-0.031	0.043	0.6
$\alpha 2_{cos}$	-	-	-	0.025	0.019	2.1	0.009	0.004	2.8	-0.012	0.031	0.8
$\alpha 3_{cos}$	-	-	-	-	-	-	0.016	0.032	0.6	0.009	0.006	1.9
$\alpha 4_{cos}$	-	-	-	-	-	-	0.013	0.01	1.9	-0.015	0.034	1.0
$\alpha 5_{cos}$	-	-	-	-	-	-	0.024	0.014	2.9	0.013	0.041	1.5
$\alpha 6_{cos}$	-	-	-	-	-	-	0.025	0.012	1.8	0.013	0.026	0.3
$\alpha 7_{cos}$	-	-	-	-	-	-	0.031	0.011	2.4	0.023	0.008	3.2
$\alpha 8_{cos}$	-	-	-	-	-	-	0.044	0.019	2.6	0.025	0.019	2.1
$\alpha 9_{cos}$	-	-	-	-	-	-	0.056	0.017	3.2	0.039	0.018	3.1
$\alpha 1_{co2}$	-	-	-	0.033	0.018	2.6	0.051	0.066	1.7	-0.001	0.036	1.8
$\alpha 2_{co2}$	-	-	-	-0.025	0.009	-2.8	-0.002	0.001	1.9	0.009	0.01	1.5
$\alpha 3_{co2}$	-	-	-	-	-	-	0.091	0.112	0.9	-0.011	0.004	2.0
$\alpha 4_{co2}$	-	-	-	-	-	-	-0.015	0.032	1.1	-0.012	0.005	2.6
$\alpha 5_{co2}$	-	-	-	-	-	-	-0.004	0.003	2.6	-0.017	0.016	1.8
$\alpha 6_{co2}$	-	-	-	-	-	-	0.014	0.01	0.2	-0.019	0.006	2.9

$\alpha7_{co2}$	-	-	-	-	-	-	-0.006	0.003	2.4	-0.019	0.004	3.1
$\alpha8_{co2}$	-	-	-	-	-	-	0.041	0.02	2.2	-0.029	0.012	2.8
$\alpha9_{co2}$	-	-	-	-	-	-	-0.009	0.005	3.3	-0.036	0.015	2.2

3.7 Individual WTP estimates

Figures 3.1 to 3.3 describe the sample distributions of individual-specific WTP, retrieved from the best MXL specification: the one with heterogeneity by population size. The reported kernel densities uncover differences between the distributions of WTP values to avoid the emission of 1kg/year of CO_2 for respondents from the mountains, hills and plains (Figure 3.1). Note that because WTP is computed as a function of both random coefficients, the relatively higher homogeneity of preferences for residents in the mountain for the random cost coefficient is offset by the relatively lower homogeneity of the random coefficient for CO_2 emissions. As such, we cannot expect the distribution of these values to display the pattern of kurtosis previously revealed in the values of estimates for $\hat{\alpha}_h$. By inspecting the figure it is apparent that residents in the plains and the hills have higher frequencies for lower WTP values for emission reduction, while residents of the mountains have higher frequency in the higher range (in absolute terms) of WTP values. This suggests that in the mountains there is preference for being able to emit less. Residents of the plains have lower modal values of WTP with higher frequency around the mode.

Figure 3.2 shows the kernel distributions for those respondents characterized by different income levels. We aggregate respondents in three segments: low yearly income (less than €18,000), intermediate income (€18,000 - €21,000) and high income (more than €21,000). The distributions show very similar modal values. However, the skewness varies and so does the kurtosis and the presence of local modal values. It is interesting to note that the only income group with higher density of positive values (i.e. in favor of emission increase) is the one with highest income, which also displays the highest variance and bi-modality. They are the only group with high density for WTP to avoid emission higher than €8. The distribution with stronger positive skewness is that of lowest income, which also displays highest homogeneity of preference (low variance and range) with none being willing to pay more than €5. The intermediate income group displays features in between the other two.

Figure 3.3 shows the kernel distributions for town residents separated by population size, with towns with small (less than 10,000), intermediate (between 10,000 and 25,000) or large (more than 25,000) populations. Interestingly, this plot shows a higher degree of heterogeneity, as compared to the previous ones. Small town residents have no frequency in positive values, which implies no propensity to increase emissions. They also display largest variation and bimodality, with a modal value strongly shifted to the left of the modes of the other two town size, which overlap. This implies a much higher WTP for emission reduction. The largest population size towns show the highest degree of homogeneity.

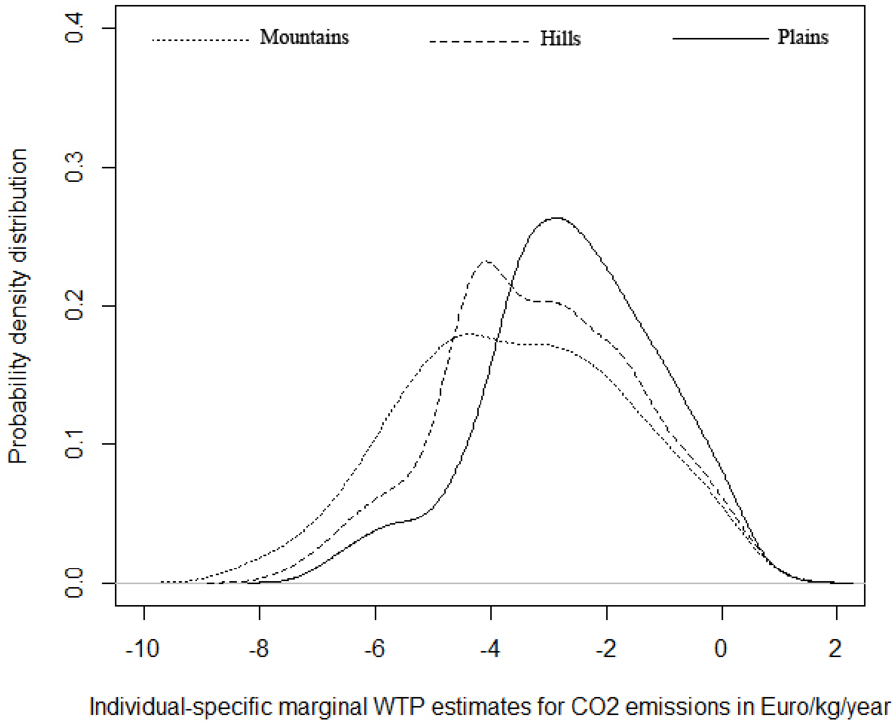


Figure 3.1: Density distributions of individual-specific WTP estimates for CO_2 by altitude levels (estimates from the "population size" model)

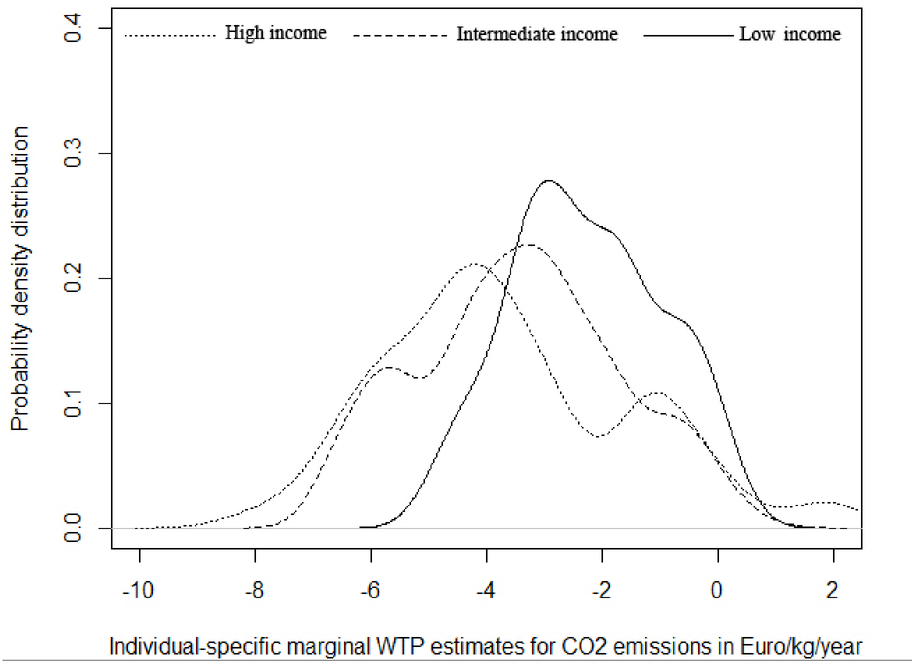


Figure 3.2: Density distributions of individual-specific WTP estimates for CO_2 by income levels (estimates from the "population size" model)

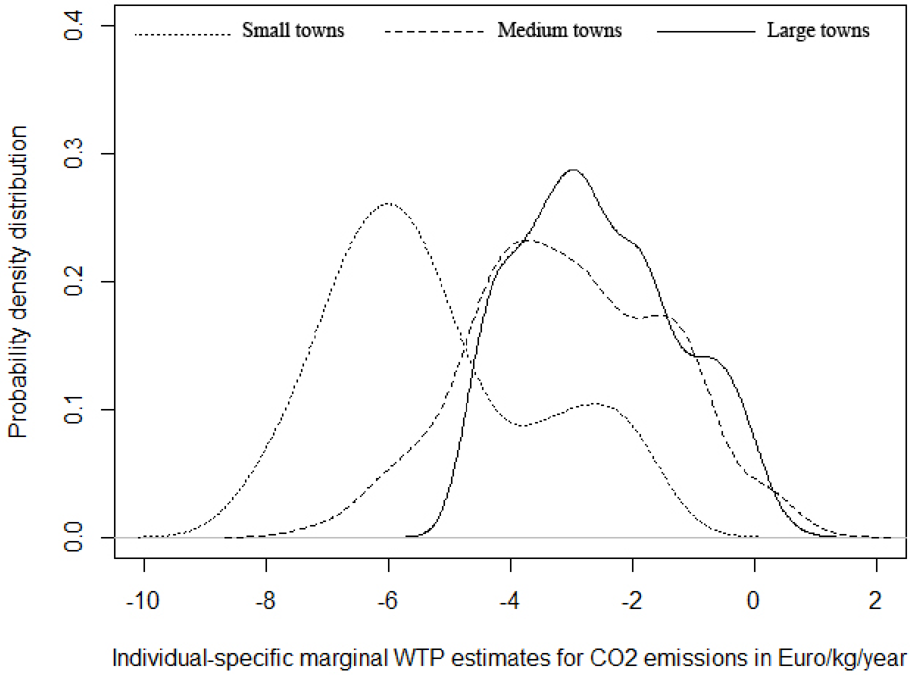


Figure 3.3: Density distribution of individual-specific WTP estimates for CO_2 by population sizes levels (estimates from the "population size" model)

3.8 Validation and calibration of WTP estimates

Estimates of individual specific $\widehat{WTP}_n$ to avoid CO_2 emissions should be meaningfully related to those variables that are—at least in theory—determining WTP. In order to establish if this is so in our case we report the results of an OLS regression of $\widehat{WTP}_n$ on a selected sub-set of socio-economic covariates, which include also indicators for altitude and population size. Instead of average income of the location of residence we prefer to include personal income of the respondent, and because of missing data on this variable, the sample is somewhat smaller (223 fewer respondents) than that used for estimation of the choice models. Table 3.4 reports the OLS estimates, whose signs support the validity of the $\widehat{WTP}_n$ estimates. Increased education attainment is progressively related to higher values of $\widehat{WTP}_n$, as is personal income and being resident in the plains and in larger towns. Being a male respondent or of different age has no significant effect on $\widehat{WTP}_n$ while being from the mountains, everything else being equal, shows a significantly lower $\widehat{WTP}_n$. This seems in contrast with the unconditional distribution displayed in Figure 3.1, but the marginal effect of altitude, obtained while controlling for other variables, is obviously different from its unconditional effect.

Table 3.4. OLS regression estimates for $\widehat{WTP}_n$

	Estimate	Std. Err.	t-value	Pr(>|t|)	Signif.
Intercept	0.995	0.802	1.24	0.215	
Middle School	-0.108	0.377	-0.29	0.775	
High School	0.584	0.164	3.57	<0.001	***
Graduate	1.010	0.186	5.43	<0.001	***
Post-graduate	1.848	0.300	5.16	<0.001	***
Man	-0.043	0.101	-0.43	0.667	
ln(age)	-0.153	0.174	-0.88	0.378	
income	0.017	0.004	4.50	<0.001	***
Plains	0.329	0.120	2.74	0.006	**
Mountains	-0.576	0.110	-5.25	<0.001	***
ln(population)	0.174	0.048	3.64	<0.001	***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Adjusted R-squared: 0.1232					
Multiple R-squared: 0.1304,					
F-statistic: 18.24 on 10 and 1217 DF,					
p-value: < 2.2e-16					
Descriptive Stats of WTP (dependent var.)					
Mean	St. dev.	Median	25 q.tle	75 q.tle	
3.045	1.741	2.974	1.796	4.229	

In order to use estimates obtained by hypothetical statements for policy analysis it is necessary to calibrate them in order to reduce hypothetical bias. WTP estimates from hypothetical statements are typically larger than equivalent estimates obtained from revealed preference data. Several studies have investigated the regularity of such discrepancy and derived calibration factors (Murphy et al., 2005; Stefani et al., 2014). In the context of environmental goods, with which respondents seldom have familiarity, calibration is obviously particularly important. A comprehensive meta-analysis study of environmental nonmarket estimates is that of Murphy et al. (2005), in which they find *"a median ratio of hypothetical to actual value of only 1.35, and the distribution has severe positive* *skewness"*. So, in our calibration, the median value serves as the anchoring point which is deflated so that the hypothetical estimate is 1.35 times the calibrated estimate. We then impose a positive skewness on the calibrated values. Hypothetical value estimates falling in percentiles above the median are deflated in increments of seven percent every steps of five percentile points, while values below the median are deflated in decrements of five percent for the same percentile steps.

3.9 Geographical distributions of WTP for CO_2 emissions

In this section we explore the geographical distribution of benefits that would derive if all respondents changed to more sustainable (lower CO_2 emitting) heating systems. The assumption is that respondents move from the current heating system—the data for which were collected in during the interviews—to the nearest system with lower emissions. So, for example, a respondent who reported to be currently using an oil-based system emitting 4575 kg of CO_2/year would move to a more sustainable system within the oil-based group emitting only 3,900 kg/year. Someone else that was already at the lowest range of emission within a category (i.e. methane with 3,000 kg/year) would lower emissions by switching to the worse emitter in the more sustainable system in the renewable category (i.e. a pellet based system emitting 525 kg/year of CO_2). In this manner we can approximate linearly the monetary change by using the individual specific estimates of marginal WTP obtained from the best performing mode, after suitable calibration for reducing hypothetical bias (include citations on bias here).

The computation of the WTP per kg of CO_2 used the following formula:

$$\Delta\widehat{WTP}_n = g(\widehat{WTP}_n)\Delta_n, \qquad \text{(Eq. 3.6)}$$

where $g(.)$ is the calibration function (a coefficient consistent with the median value and skewness from Murphy et al. 2005) that adequately deflates the estimate, and Δ_n is the marginal reduction in CO_2, conditional on the heating system currently employed by the respondent (in kg of CO_2/year). These were developed by assuming that the length of time respondents signalled to be away from the next adoption decision was an indication of pollution emission levels, with longer times indicating more sustainable current systems (with lower emissions).

To explore the geographical distribution of the benefits from such hypothetical emission reduction we mapped the values across the territory of the target population (Figure 3.4). The map describes the municipality boundaries and the colouring reflects the averaged values from respondents within each boundary. It is apparent that the highest benefits from emission reduction occur in the low land in the south part of the map, and it is especially high in the large municipalities, such as the city of Verona and Padua. The lowest benefits, instead, occur in the mountainous north and along the hilly regions along the foot of the mountains. This might be counter-intuitive if compared with the distributions reported in figures 3.1 and 3.2, but it is mostly due to higher deflation values of $g(.)$ that apply to higher $\widehat{WTP}_n$, which are more prevalent at higher altitudes.

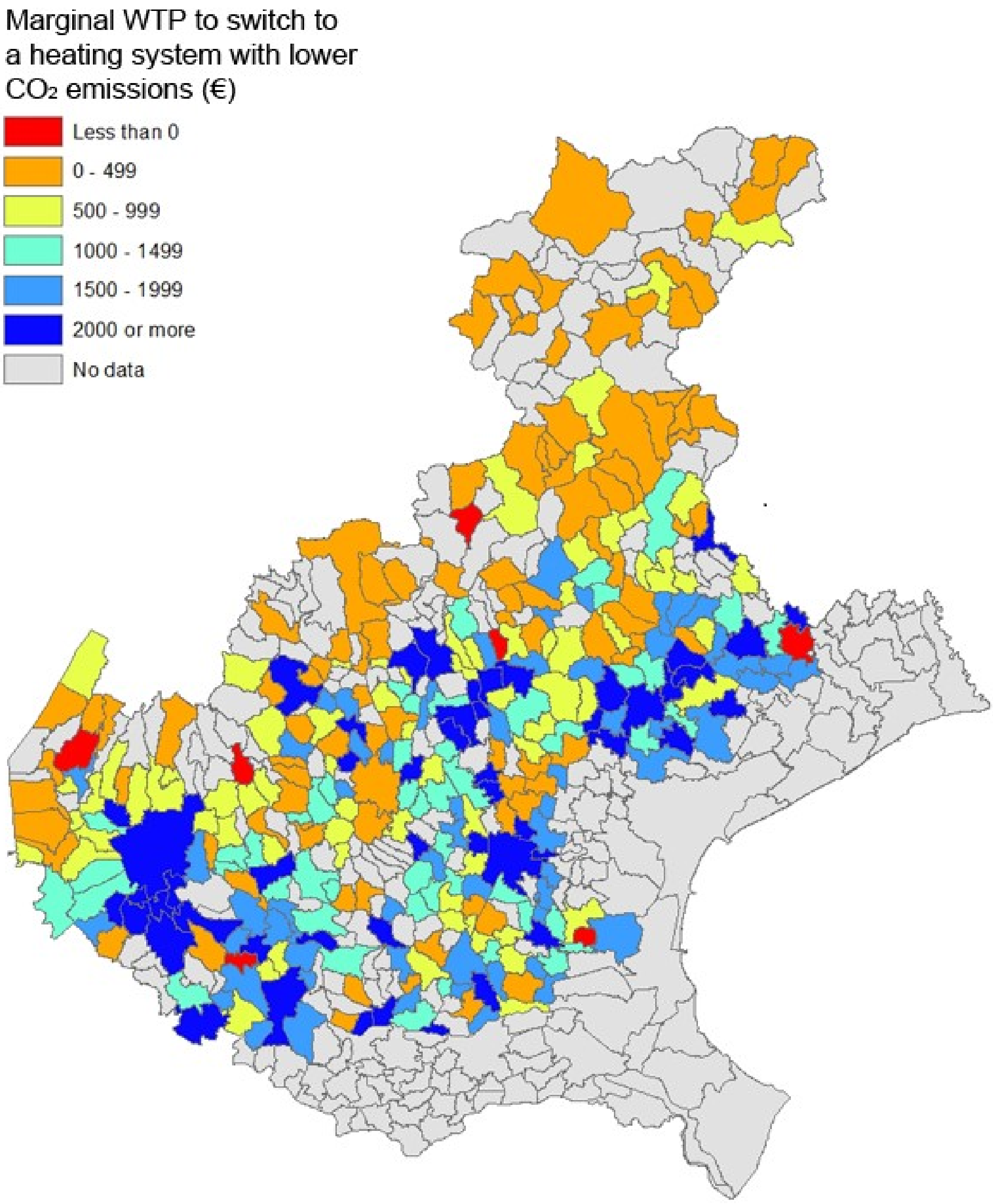


Figure 3.4: Distribution of WTP for marginally reducing CO_2 emissions from heating system

3.10 Conclusions

Emissions from heating systems are large contributors to the level of stock pollutants of the greenhouse gas type. Climate change is responsible for severe damage in high altitude areas, in the form of faster landslides, change in the snowfall patterns and topsoil erosion. However, in the plains air pollution is often more visible for the prevalence of winter fogs and low altitude haze. Respiratory problems are also more common in the lowlands. These factors, along with different patterns of population structure across these areas make geographical factors important in effective policy design. Stated preference methods are increasingly common in exploring nonmarket benefits associated with environmental policies. In this study we collect data on choice of heating systems across the population of Veneto in North-Eastern Italy. This densely populated region covers a wide range of altitudes, from the Alps to the lowlands of the rivers. Such diversity of microclimates induces a differentiated demand in terms of heating systems. As such it lends itself to studying the geographical distribution of policy actions aimed at a more sustainable pattern of adoption of heating systems and its nonmarket benefits.

We developed a CE survey to explicitly address the geographical dimension of taste heterogeneity across residents for the existing heating systems and potential adoptions of more sustainable ones. In particular, from the methodological viewpoint, we proposed an MXL model specification to account for the role of spatial and socio-demographical factors in respondents' heterogeneity of preferences towards key features of heating systems. Although our model cannot be considered a proper spatial model, it represents a way to inform discrete choice models with variables related to geographical features. This is important as the existence of spatial effect on welfare changes is well established in literature, but poorly explored in empirical studies. The estimation of spatial discrete choice models has still received little attention in literature, and our paper is an explorative work in such direction.

The hypothesis that justified our work is that spatial variables such altitude, average income and population size of the municipality are sources of heterogeneity of preferences towards key features of heating systems. Our results show that the variables we consider are in fact a source of variation in the spread of sensitivity to cost and CO_2 emissions. In particular, we found that respondents living at higher altitudes display a wider range of preferences than those in the lowlands. We validated our structural model as well as its ex-post values at the individual level by developing theoretical expectation with regards to key variables, such as income and education that are confirmed by the results. We hence argued that the model and data are theoretically valid.

From a policy viewpoint, our results are of particular interest considering that both local and national governments are providing financial incentives to encourage the installation of energy-efficient and more sustainable heating systems. Being able to account for spatial differences in the perception of the benefits of such measures is useful to design programs that are coherent with public preferences. Furthermore, as some of these measures have a strong local connotation, our results can be useful to help policy maker in addressing their action locally. In particular, our findings suggest that geographical features matter for the adoption of sustainable heating systems and that government intervention should be developed taking this into serious account.

4[3]. Adoption of Renewable heating systems: an empirical test of the diffusion of innovation theory.

This chapter reports a study that focuses on the fourth thesis specific objective, that is the empirical application of the Diffusion of Innovation theory. Data used in the study were retrieved from the second case study (analysis of preferences towards heating systems).

Abstract

The implementation of heating technologies based on renewable resources is an important part of Italy's energy policy. Yet, despite efforts to promote the uptake of such technologies, their diffusion is still limited while heating systems based on fossil fuels are still predominant. Theory suggests that beliefs and attitudes of individual consumers play a crucial role in the diffusion of innovative products. However, empirical studies corroborating such observations are still thin on the ground. We use a CE and a Latent Class-Random Parameter model to analyze preferences of households in the Veneto region (North-East Italy) for key features of ambient heating systems. We evaluate the coherence of the underlying preference structure using as criteria psychological constructs from the Theory of Diffusion of Innovation by Rogers. Our results broadly support this theory by providing evidence of segmentation of the population consistent with the individuals' propensity to adopt innovations. We found that preferences for heating systems and respondents' WTP for their key features vary across segments. These results enabled us to generate maps that show how WTP estimates vary across the region and can guide local policy design aimed at stimulating adoption of sustainable solutions.

4.1 Introduction

The residential sector is estimated to produce 17 percent of global CO_2 emissions (Nejat et al. 2015), 60 percent of which is due to ambient heating. Increasing the use of efficient heating systems based on renewable fuel represents an effective way to reduce the rate of carbon dioxide production as a stock pollutant. Interestingly, the uptake of innovative heating systems based on renewables, such as pellet-fuelled stoves, provides a testing ground for the study of innovation adoption. In accordance with the Theory of Diffusion of Innovation by Rogers (1962, 2003), the premise of the present study is that innovation diffuses amongst end users as a function of their preferences and attitudes. This comprises an empirical case study supporting the stylised features theorized to characterize the diffusion of innovation). In particular, we explore how the measurable structure of preference diversity across households relates to the adoption of heating systems based on a renewable fuel (wood pellets) and observed to what degree they aligned with Rogers' theory.

Since the pioneering work by Shumpeter (1934) the economic study of innovation diffusion has primarily focussed on the behaviour of firms (see also Nelson and Winter 1982, Dosi et al. 1988, Freeman and Soete 1997 and more recently Fagenberg 2004). Despite the early intuition and evidence provided by Hippell (1988) and Lundval (1988), who emphasized the role of end-users as drivers of innovation, few economic studies have specifically focussed on households. The theory of innovation

[3] This paper is an edited version of the paper: Franceschinis, C., Thiene, M., Scarpa, R., Rose, J., Cavalli, R., Moretto, R. Adoption of Renewable heating systems: an empirical test of the diffusion of innovation theory. Revised and resubmitted to *Energy*.

adoption formulated by Rogers seems more appropriate in the context of households and it is still prevalent in sociology at large. However, there is still a relative paucity of empirical studies providing corroborating evidence for this theory. Like most studies in innovation, it can be useful to take a multidisciplinary approach. Here we used econometric tools to analyse choice data obtained with a market research survey based on an experimental design informed by heating engineers and derived using operation research and Bayesian methods.

Environmental problems, such as climate change and pollution are prominent issues. The question of how to meet present needs without sacrificing the ability of future generations to satisfy their needs is a central topic in the debate over sustainable development. The convergence toward a sustainability path depends, to a great extent, on the speed of diffusion of environmentally friendly technologies. However, the diffusion of these technologies is often slow and difficult due to the inherent inertia in the system (what Shumpeter termed "resistance to new ways"). The diffusion of wood-pellet heating systems in Italy provides us with such an example. There are a number of advantages to using pellets as a fuel such as: limited emission of CO_2 and fine particles, at least when use is sufficiently prolonged (Toscano et al. 2014); automation on both ignition and combustion, with the possibility of remote control, even via internet; high combustion efficiency; and low price fluctuation. Despite such advantages and the policy measures currently adopted to promote the diffusion of such a technology, the size of the pellet market in Italy is currently quite small (a niche market), and its application is mostly limited to small-scale ambient heating by households.

This study reports the results of a stated choice survey implemented using the CE method. This is an increasingly popular method used to systematically and quantitatively explore respondent preferences over qualitative features of mutually exclusive alternatives. In our case, the alternatives are six heating systems: three based on traditional fuels and three based on renewables. The population of interest consists of households in Veneto, a region in the northeast of Italy that covers a geographical area of great diversity: from mountain peaks in the Alps to agricultural plains and scenic hills popular with tourists. Two provinces were excluded from the target population, Venice and Rovigo, on account of them being the only two provinces which are completely in the plains.

Over the last few years, there has been a growing number of research applications in the field of preference analysis of residential heating systems based on household CEs (e.g., Scarpa and Willis, 2010; Willis et al., 2010; Michelsen and Madlener, 2013; Rouvinen and Matero, 2013). Other energy-related applications include investigating household preferences for power supply outages; Blass, et al. (2010), Abdullah and Mariel (2010) and Hensher et al. (2014) used the method to study the reliability of electricity supply. Ndebele (2016) explored household preferences for green electricity, along with Huh et al. 2015, who also considered other service factors. There are fewer CE studies focusing on adoption diffusion at the household level. One of these is by Yamamoto (2015) who studied the specific field of photovoltaic energy adoption and found support for the hypothesis that opinion-leaders are influential. However, he does not test other aspects of the theory of innovation diffusion.

We have exploited recent advances in econometric analysis of discrete choices that have enabled researchers to use CE data to investigate specifically the structure of preference heterogeneity in a given population and the systematic effects of ancillary variables, such as attitudes and personal beliefs. In our context, taste heterogeneity is the manner with which taste intensities for various features of heating systems vary across the population of households; either in a latent or an observable manner. For example, variations of taste are expected in terms of energy savings, environmental benefits, comfort considerations, compatibility with daily routines, personal habits and cost. Discrete choice model estimates from the analysis of CEs show the relative weight respondents assign to such aspects throughout their stated choices. In the presence of a cost attribute and appropriate assumptions these can also be used to infer marginal rates of substitution and marginal WTP estimates for various heating characteristics described in the experiment.

Behind the variation of taste, one can expect there to be some latent structure corresponding to Rogers' theory. Some of this structure escapes measurement by standard economic variables, but emerges in its latent form in the underlying variation. For example, published research on the adoption and diffusion of sustainable energy technologies has often disregarded the impact of personal-sphere elements. It has focused on behaviour by a rational (or "boundedly" rational, Simon 1955) agent with perfect or even limited (Claudy et al., 2011) information. The traditional economic perspective sees cost-benefit considerations and utility maximization as the main determinants of an individual's decision of whether or not to adopt energy technology (Faiers et al., 2007). However, the adoption of sustainable energy systems can also be seen as the result of personal or private sphere factors, which concur with economic considerations, and may even include behavioural elements as well (Stern, 1999). It is indeed broadly recognized that the specific behavior of adopters is conditioned by individual factors (Fishbein and Azjen, 1975; Solino and Farizo, 2014), home-site factors (Solino et al., 2009) and a set of formal rules along with socially accepted informal rules (North, 1990), such as those of family or culture. Personality also plays a role in human behaviour as regards consumer decisions on environmental goods and services (Grebitus et al., 2013).

Rogers' theory of diffusion of innovation provides a persuasive organizational framework to combine the effect of standard and ancillary variables behind the heterogeneous adoption behaviour of households. Our results offer an unexpected degree of empirical support to this theory.

The remainder of this chapter is organized in five sections. Section 2 illustrates the essential features of Rogers' theory of diffusion of innovations and lays out the hypotheses to be tested. Section 3 describes the method used in the data analysis and hypothesis tests. Section 4 describes the design of the survey instrument, the sampling procedure and the data. Section 5 discusses the results, while section 6 draws conclusions from the study.

4.2 Rogers' theory of diffusion of innovations

In this section, we present a succinct overview of Rogers' theory tailored to our application, but we will use only selected elements of it as organizational principles for our specific empirical application.

4.2.1 Definitions and stages of innovation diffusion

Following Rogers (2003), in this household study we broadly define innovation as "an idea, practice or object perceived as new by the individual". This definition clearly emphasizes the role of perception of potential adopters as a key criterion for defining the degree of "newness" of a product that acts as a factor input in the household production function (Becker, 1981). As long as a technology is perceived to be as new, it can be labelled as an innovation. Wood pellet fired heating systems have been on the market for a number of years, but their diffusion in our study area (the Veneto region in north-eastern Italy) is still low. As such, most consumers may regard pellet-fueled burners as an innovative technology. The definition indirectly suggests that a technological invention in itself cannot be considered an innovation without the widespread perception of being “new”. Only when consumers become aware of a new technology (e.g., through marketing efforts or public information campaigns) can an invention be defined as an innovation. In other words, “a discovery that goes no further than the laboratory remains an invention” (Garcia and Calantone, 2002).

From a consumer's perspective, the innovation decision process thus begins when an “individual (or other decision-making unit) is exposed to an innovation's existence and gains an understanding of how it functions” (Rogers, 2003). According to Rogers' model of the innovation decision process, this first stage is referred to as the *knowledge* stage and is followed by four further stages: *persuasion*, *decision*, *implementation* and *confirmation*.

Gaining *knowledge* about innovation is generally mediated by personality variables and socioeconomic characteristics such as education or age. Some consumer segments appear to be generally more open to new ideas and “often function as strategically important target groups for marketers and policy makers to stimulate the diffusion of innovations like microgeneration technologies” (Claudy et al., 2011).

Persuasion is the next stage at which consumers, once aware of the innovation, evaluate its characteristics such as relative advantages, complexity or price. Based on their assessment, consumers form a favourable or unfavourable attitude to the new product, which ultimately results in a high or low intention to buy or willing to pay for the innovation. The perception of a product’s characteristics is likely to vary across subjects (e.g., households), depending on subject characteristics and the attributes of the product.

Next, this subjective evaluation of product characteristics leads to a *decision* on whether to adopt or reject the innovation. If persuaded, consumers decide “to make full use of an innovation as the best course available” (Rogers, 2003). At the *implementation* stage, consumers actually purchase the innovation and assess its usefulness. This assessment leads to the *confirmation* stage, at which consumers decide whether to continue using the innovation or to discontinue.

Note that throughout the adoption-decision process, consumers can be exposed to communication in the form of information or public policy campaigns. Ours empirical application is a static analysis and we will not concern ourselves with the above stages, which would require a dynamic dataset.

4.2.2 Dimensions of innovation diffusion

Rogers’ theory proposes four main *diffusion dimensions* for a new technology:

a) perception of the characteristics of the innovation,
b) communication channels,
c) timing of adoption, and
d) the social system.

In our empirical application, we will focus on the first three.

Rogers provides an articulated description of the first dimension (*characteristic's perception*). The empirical literature shows that these can be further and insightfully decomposed into the following measurable *functional constructs*:

1. *Complexity*: the degree to which an innovation is perceived as being difficult to use or understand (see Li and Buhalis, 2006; Alam et al., 2007);
2. *Compatibility*: the degree to which an innovation is perceived as being consistent with *existing practices or habits and routines* (see Vijayasarathy, 2002; Schwarz and Ernst, 2008)*;*
3. *Trialability:* the degree to which an innovation may be experimented with before adoption (see Moore and Benbasat, 1991);
4. *Relative advantage*: the degree to which the innovation is perceived to be superior to current practice (see Limayem et al., 2000; Cho, 2004; Bjørnstad, 2012);

To the above, the following functional constructs have been added drawing from contributions to the literature independent of Rogers' work:

5. *Performance risk*: performance uncertainties of a new product (see Shim et al., 2001; Claudy et al., 2011);
6. *Social risk*: uncertainty as to how adopting the innovation might be perceived by relevant others (see Claudy et al., 2011);
7. *Knowledge*: the degree of familiarity with the innovation. For example, households may be asked to express their subjective knowledge, in relative terms to others (higher, lower, as much as others) (see Bang et al., 2000; Pavlou and Fygenson, 2006);
8. *Environmental friendliness*: the degree to which an innovation is perceived as not harmful for the environment (see Schwarz and Ernst, 2008; Claudy et al., 2011).

In a survey context all of the above constructs can be explored using answers to adequately developed attitudinal questions (e.g., Ben-Akiva et al., 1999; Ojea and Loureiro, 2007; Scarpa and Thiene, 2011; Morey and Thiene, 2012; Hess et al., 2013; Solino and Farizo, 2014; Yoo and Ready, 2014).

The second diffusion dimension identified by Rogers concerns *communication channels* and it is less structured. Rogers sees communication as "a process in which participants create and share information with one another in order to reach a mutual understanding". Communication occurs through channels connecting sources to receivers. Rogers states that "a source is an individual or an institution that originates a message. A channel is the means by which a message gets from the source to the receiver". Diffusion requires at least the following communication elements: an innovation, two subjects (source and receiver) or other units of adoption, and a communication channel between them. For example, mass media and interpersonal communication are two communication channels. While mass media channels include TV, radio, or newspaper, interpersonal channels consist of a two-way communication between two or more subjects. Interpersonal channels are often more effective at creating or changing strong attitudes held by subjects.

The third diffusion dimension is *relative timing of adoption*. Rogers argues that the timing of adoption of an innovation is determined mostly by the degree of innovativeness of the individual adopter. This measures how early a given subject adopts new ideas *relative* to other members of her/his social system. With respect to this, members of a social system are classified by Rogers, as follows:

i) *innovators*,
ii) *early adopters*,
iii) *early majority*,
iv) *late majority*, and
v) *laggards* (see Figure 4.1).

Innovators are those who belong to the very first 2.5th percentile of adopters. *Early adopters* make up the following 13.5th percentile, the *early* and *late majorities* split the 34th percentile at both sides of the median; finally, the *laggards* belong to the last 16th percentile. According to Rogers, innovators are willing to experience new ideas. Thus, they are prepared to cope with the risk of unprofitable and unsuccessful innovations. They may not be respected by other members of the social system because of their unusual risk-loving preferences. Rogers argues that since early adopters are more likely to hold leadership roles in the social system (The Keep-up with the Joneses' effect), other subjects tend to generally seek their advice with regards to innovation. Thus, as role models, early adopters' attitudes toward innovations are extremely important. Rogers claims that although the early majority have a good interaction with other members of the social system, they do not have the same leadership role of early adopters. However, their interpersonal networks are still important in the innovation-diffusion process. Although members of the late majority are sceptical about the innovation and its outcomes, economic necessity and peer pressure may eventually lead them to adopt the innovation. Laggards hold the most conservative views and they are most sceptical about innovations and changes. As the least mobile group within the gradient of innovation time, their interpersonal networks tend to mainly consist of other members of their own social system.

4.2.3 Operationalizing the theory, hypotheses and policy implications

We investigate household stated choices between alternative heating systems with a focus on renewable fuel heating system adoption. In order to implement the above theoretical framework in our context of study, we developed a series of questions to ask of respondents, drawing from the existing literature and adapting them to our case. The specifics of these are described later in the data section.

From the above theory the following hypotheses can be derived and tested. Firstly, adopters (in our case households) should show a preference structure consistent with a segregation into groups with different propensity to adopt innovation. Secondly, the propensity to belong to each group should be associated with determinants suggested by the theory as well as the nature of the innovation, which in our case concerns lower environmental impact on carbon as a stock pollutant. More specifically, the signs of the coefficients in the membership probability equation for each group should be consistent with theoretical expectations, which in the context of innovation diffusion should be some proxy of propensity to adopt innovation. Thirdly, group sizes (in terms of relative dimensions of membership probabilities) should reflect theoretical expectations. This implies the expectation of a small group of early adopters a larger group of intermediate and again a smaller group of late adopters (or "laggards"). A fourth hypothesis suggested by the theory and consistent with the business lifecycle of all new products is that the WTP for the innovative features of the product should be higher the earlier households tend to adopt the innovation. This implies a relative magnitude in the estimated

WTPs across the different groups. Finally, communication channels should matter in the probability of selection of innovative systems.

From the policy perspective, preference analysis can provide some significant insights to public authorities interested in promoting and speeding up the rate of adoption. In particular, public decision-makers have specific aggregate targets to achieve. For example, the reduction of fossil fuel emissions at the regional level below specific thresholds within a given deadline. An adequate market-based policy, such as one based on adoption subsidies, can be designed within a given administrative region by knowing the mapping of household preferences of incentivizing factors. Prominent amongst these are the degree of innovativeness and the WTP for various associated factors.

In the following section we describe the method with which we set-up our data collection and conduct its analysis to obtain a structural model of household preference that allows us to test the above hypotheses and inform public decision makers.

4.3 Model and its policy implications

To empirically test the above theory, we use preference measures of alternative heating systems from stated choice data $\{\mathbf{y}\}$ collected via a household survey, along with attitudinal statements $\{\mathbf{s}\}$, intended to measure various dimensions relevant to Rogers' theory. Stated choices are elicited through an experimental design used to arrange heating system attributes $\{\mathbf{x}\}$ into a sequence of choice sets t to be evaluated by each surveyed household h according to efficiency-maximizing criteria. To characterize preference heterogeneity, we identify separate latent groups, called "classes" and denoted by c. The expectation is that these relate to **s** in a manner suggesting a different propensity to innovate. Household grouping takes place endogenously during estimation as we use a finite mixture of preferences, in which the mixture is defined over a finite set of probabilities. Within each probabilistic group households are clustered by similarity of preference (similar patterns of $\mathbf{y}|\mathbf{x}$ are clustered in the same preference group). All households, however, are assumed to choose according to a random utility approach, which is consistent with the maintained assumption of rational choice behaviour (Luce, 1959; McFadden, 1974).

According to the random utility maximization theory, an individual n facing a set of J alternatives of heating systems, denoted by j=1,…,J, chooses alternative i as a function of the K attributes used to describe the alternative. The respondent's utility function has a systematic part observable to the researcher V_{ni} and a random unobservable and stochastic part ε_{ni}, which is intended to collect all unobserved variables, such that total utility for alternative i in the J choice set is:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \quad \forall\, i \text{ in } j. \qquad \text{(Eq. 4.1)}$$

The systematic and observable part of the utility function V_{ni} of individual n is associated with the selected alternative i and modeled as a linear function of the k-dimensional vector of attributes $\mathbf{x}_i$ and the k-dimensional vector of taste parameters β_n associated with household n. If the unobserved error term ε_{ni} is assumed to be i.i.d. extreme value type I, the probability of individual n choosing alternative i out of J alternatives as a consequence of utility maximization can be defined by the well-known Conditional Logit (CL) model:

$$\Pr\left(U_{ni} > U_{nj}, \forall j\right) = \frac{\exp(V_{ni})}{\sum_{j=1}^{J} \exp(V_{nj})}. \qquad \text{(Eq. 4.2)}$$

Household preference heterogeneity is assumed to take the form of C classes or groups in the sample of N respondents, where C is exogenously defined by the analyst, but the probability of households being a member of each class is endogenous. As these preference classes are latent (i.e., unobserved), a probabilistic equation explaining the assignment of individual n to class C must be defined. The membership probability equation can take on a semi-parametric form only dependent on a constant term (Scarpa and Thiene, 2005). However, when possible, it is desirable to specify a class membership probability model using respondents' characteristics, as these are more informative for profiling (Boxall and Adamowicz, 2002; Provencher et al., 2002; Hynes et al., 2008; Hess et al., 2011). Typically, these characteristics are socio-demographic variables, such as income, sex and age. In our case, given our focus, we make class membership a function of a variable measuring propensity to innovate in our population. We use a logit specification for the class membership model, with $\mathbf{z}_n$ being the average score for innovativeness and α_c its associated class-specific coefficient. The probability that individual n belongs to preference class C is given by (Bhat, 1997):

$$\pi_{nc} = \frac{\exp(\alpha_c' \mathbf{z}_n)}{\sum_{c=1}^{c=C} \exp(\alpha_c' \mathbf{z}_n)} \,. \qquad \text{(Eq. 4.3)}$$

Given membership to group c, the probability that individual n chooses alternative i at choice set t in the sequence and conditional on belonging to taste group c, also takes a logit form (Hensher and Greene, 2003) and it is hence consistent with random utility:

$$\pi_{nit|c} = \frac{\exp(\beta_{nc}' \mathbf{x}_{it})}{\sum_{j=1}^{j=J} \exp(\beta_{nc}' \mathbf{x}_{jt})} \,, \qquad \text{(Eq. 4.4)}$$

where $\mathbf{x}_{it}$ represents the vector of heating system attributes associated with each alternative and β_{nc} is the vector of coefficients for class c. The joint unconditional probability for the T panel of choices by respondent n is weighted by the class membership probability is:

$$\Pr_n = \sum_{c=1}^{c=C-1} \pi_{nc} \prod_{t=1}^{t=T} \pi_{nit|c} \,. \qquad \text{(Eq. 4.5)}$$

At the single class level, an undesirable property of the CL model is the Independence of Irrelevant Alternatives (IIA). The IIA property assumes that the choice probability of alternatives A and B are not influenced by the addition or exclusion of any additional alternative in the choice set. In general, this is a strong assumption that may be unrealistic. It implies that introducing another heating system alternative would proportionally draw from all existing alternatives in a similar manner independent of its degree of substitutability with each of them, which instead is likely to matter. For example, a new renewable fuel system may encroach more on options from a similar category of sustainable systems than on fossil fuel-based systems. To relax such a maintained assumption, we allowed for random taste variation within each class and estimated a Panel Latent Class-Random Parameters Logit model (LC-RPL) (Bujosa et al., 2010; Greene and Hensher, 2013; Campbell et al., 2013; Campbell et al., 2014; Solino and Farizo, 2014; Yoo and Ready, 2014; Boeri et al. 2014) accounting for the series of T choices made by each respondent.

The resulting latent-class random parameter logit (LC-RPL) is a hybrid modelling approach combining discrete and continuous descriptions of random preferences. The assumption is that, for selected heating system attributes, respondents' preferences vary randomly and continuously within each class C according to class-specific hyper-parameters following a normal distribution (e.g. mean

μ_c and st. dev. σ_c). We denote these with random coefficients $\tilde{\beta}_{nc}$. For other heating system features, such as the alternative specific constants, cost and interaction variables, coefficients are fixed within each class and denoted by β_c as they vary across classes, but by respondents within each class. However, in what follows the separate vectors $<\beta_c : \tilde{\beta}_{nc}>$ are condensed into β_{nc}.

Taste heterogeneity across households is therefore accounted for in two ways: (i) by identifying different behavioural classes as a function of the average score of the innovativeness scale $\mathbf{z}_n$ and (ii) by considering continuous taste variation among individuals in the same group (within-group heterogeneity) (Bujosa et al., 2010).

Allowing for continuous random parameters following a separate distributional law within each class requires the modification of equation (6.4) above into the following probability integral:

$$\pi_{nit|c} = \int \frac{\exp(\beta'_{nc}\mathbf{x}_i)}{\sum_{j=1}^{j=J}\exp(\beta'_{nc}\mathbf{x}_j)} f(\beta_{nc}) d\beta_{nc} \qquad \text{(Eq. 4.6)}$$

as it is necessary to integrate the logit formula in expression (4.4) over all possible values of β_{nc} (Train, 2003). In estimation, the integral in (4.6) is approximated by averaging over 500 pseudo-random draws of β^R:

$$\pi_{nit|c} \cong \tilde{\pi}_{nit|c} = \frac{1}{R} \frac{\exp(\beta^{R\prime}_{nc}\mathbf{x}_i)}{\sum_{j=1}^{j=J}\exp(\beta^{R\prime}_{nc}\mathbf{x}_j)}. \qquad \text{(Eq. 4.7)}$$

At this point, the researcher has to assume a distribution for $\tilde{\beta}_{nc}$ and estimate its parameters μ_c and σ_c (Train, 1998; McFadden and Train, 2000). Finally, the LC-RPL unconditional probability that individual n chooses i can be written from equations (4.3) and (4.5) as:

$$\pi_{ni} = \sum_{c=1}^{c=C} \pi_{nc}\pi_{ni|c} \; . \qquad \text{(Eq. 4.8)}$$

Therefore, the sample log-likelihood reduces to a weighted average of simulated choice probabilities, where the weights are membership probabilities of the C latent classes:

$$LL = \sum_{n=1}^{N} \ln\left[\sum_{c=1}^{c=C} \pi_{nc}\left(\prod_{t=1}^{t=T}(\tilde{\pi}_{nit|c})^{y_{nit}}\right)\right], \qquad \text{(Eq. 4.9)}$$

where π_{nc} and $\tilde{\pi}_{nit|c}$ are respectively the class membership and approximated choice probabilities from equations (4.3) and (4.7) and y_{nit} equals one when the n^{th} individual chooses alternative i at choice set t, zero otherwise. As the solution involves the evaluation of a multiple-dimensional integral with no closed-form, the estimation of this model requires approximation by numerical simulation methods (Bhat, 1998; Revelt and Train, 1998).

Perhaps the most useful post-estimation tool for policy design is the implied WTP to pay estimates for the heating system attributes. Marginal WTP estimates are computed as ratios of marginal rates of substitutions in the indirect utility function. Estimates can be conditioned on the specific sequence of observed responses by each respondent using Bayes' theorem, so as to obtain individual-specific estimates. We simulate the population distributions of individual specific estimates of WTP_n by generating 10,000 pseudo-random draws from the unconditional distribution of the estimated parameters and we calculate individual-specific estimates for each draw as explained in the seminal literature of panel choice models (Train, 1998; von Haefen, 2003; Scarpa and Thiene, 2005).

To obtain a mapping of these over the sampled area, the individual value estimates are averaged by geographical polygon of each municipality, colour-coded and mapped with ArcGIS. Finally, Kernel density distributions of WTP are obtained conditional on class membership.

4.4 Theoretical expectations

One of the main hypotheses emerging from Rogers' theory is that perception of the characteristics and sources of information about heating systems using wood pellets influence the individual's preference toward such technology. In order to test the hypothesis we included in the model interaction terms between attitudinal variables $\{\mathbf{s}\}$ referring to the constructs of the theory and the Alternative Specific Constant of the wood pellet alternative. The generic linear utility function for the wood pellet alternative p (ignoring irrelevant subscripts related to classes and choice set) can be expressed as:

$$V_p = ASC_p + \beta'_{np}\mathbf{x}_p + \gamma' \ \mathbf{s} + \ \delta' \ \mathbf{i}, \qquad \text{(Eq. 4.10)}$$

where ASC_p is the Alternative Specific Constant for the wood pellet alternative, $\mathbf{x}_p$ is the vector of attributes of the wood pellet alternative, **s** is a vector of the average scores of the attitudinal questions related to the perception of wood pellet technologies' characteristics and $\mathbf{i}$ is a vector of dummy variables related to the source of information about wood pellet technologies. Note that for all other alternative fuels $\gamma = \ \delta = 0$.

We expect compatibility, relative advantage, knowledge, and environmental friendliness to have a positive effect on preferences toward wood pellet technologies in all preference groups. This would be confirmed by positively signed coefficient estimates. For complexity, we expect a negative effect among all segments of the population, and therefore a negative sign. For trialability, performance risk and social risk we expect different effects in different segments. In particular, we expect trialability to have a positive effect on preferences associated with the group likely to be late adopters of wood pellet technologies, and a lower influence on early adopters. Performance and social risk, instead, should have negatively signed coefficients on laggards, whereas early adopters, who are described by Rogers as highly risk tolerant, should not be influenced by such aspects.

With regards to communication channels, we expect information sourced from other people to influence positively preferences of all segments of population, as "word of mouth" counts in social systems. This would be confirmed by a positive δ in all classes. Information from mass media, according to Rogers, is particularly influent in the first period of the adoption, during which early adopters buy into new technologies. Therefore, we expect δ to be significant and positive for the segment of individuals with preference structure with the highest tendency to adopt innovations, and a lesser effect on the other segments. Finally, information provided by organizations is the least influential, according to the theory. We expect the coefficient estimate associated with this communication channel to be smaller than those of the other sources in each class.

4.5 Results

Simulated maximum likelihood estimates for the LC-RPL model are obtained by maximizing equation (4.9) over the parameter space $\{\alpha, \beta, \gamma, \delta, \mu, \sigma\}$ using Pythonbiogeme software (Bierlaire, 2003) in Ubuntu 15.10 Wily Werewolf. Choice probabilities are simulated in the sample log-likelihood with 500 quasi-random draws using modified Latin hypercube sampling (MLHS). The model takes account of five ASCs for all the heating systems with the exclusion of LPG. The specification includes interaction terms between the ASC for wood pellet and the average score of the perception the characteristics of such technology. The dummy variables referring to the channels of communication were interacted with the ASC for wood pellet as well, with the exclusion of the "no information" variable, which is hence to be considered as the baseline.

Following previous research (Akaiki, 1974; Bozdogan, 1987; Hurvich and Tsai, 1989), the BIC, AIC, and the CAIC information criteria were used as indicators of fit to evaluate the optimal number of classes. The information criteria values are reported in Table 4.1 and indicate that the specification with three classes is best as it minimizes all the information criteria. Therefore, the search over the ideal number of classes for our sample suggests that the sample of inhabitants of the Veneto region is best characterized in terms of three distinct preference classes.

For identification purposes in the class membership model we set class 3 as the baseline class. The average score of the innovativeness scale is associated with a significant coefficient estimate in each class (Table 4.2), thus suggesting that such a factor is a determinant of preference heterogeneity in our sample. The positive estimate for the innovativeness coefficient (0.12) in class 1 suggests that respondents with a high average score are more likely to belong to this class. This class can therefore be meaningfully associated with the classes of adopters identified by Rogers as "Innovators and Early Adopters", i.e., the first households to adopt new innovations. In class 2, instead, the average score is associated with a negative coefficient (-0.08), thus suggesting that this preference class is least prone to quickly adopt innovation. This class is hence consistent with the group identified by Rogers as "laggards", with households averse to changes and with low propensity to adopt innovations. Finally, class 3 could be linked to the two classes that Rogers named as "Early and Late Majority", which we term here as "intermediate" as they lie in the middle of the adoption curve timing. The sizes of class probabilities are also, by and large, consistent with this interpretation, as Class 3 is the largest one (44 percent) and the other two have lower and similar probabilities (26.9 for class 1 and 29.1 for class 2), as expected according to Rogers' theory.

We now move to the interpretation of the signs and magnitudes of preference coefficients (the betas) in each class. Preferences of Class 1 have stronger affinity towards pellet fired heating systems compared to the other two classes, as suggested by the higher value of the wood pellet ASC. It is interesting to note that the ASC for wood pellet is negative in Class 2, thus suggesting an aversion of those belonging to this class for wood pellet systems. The values of the ASCs for the other two biomass based systems (chip wood and firewood) are higher in Class 1 as well. The ASC for methane, which is the heating system most common in the region, is significant in all classes, and the value of its marginal rate of substitution is highest in Class 3 (1.56/0.07=22.29) as compared to the other two classes. Overall, the values of ASCs are consistent with Rogers' theory, as they highlight that innovators are more interested in biomass technologies, whereas intermediate adopters (class 3) have a stronger preference for traditional heating systems, such as the methane-based ones. Intermediate and late adopters, as expected, have intermediate values for renewable fuels, and do not show the same degree of preferences towards the innovative technology of innovators. No class show preference for oil-based systems. The coefficients of investment and operating cost are statistically significantly different from zero and negative in every class, as expected. Individuals in Class 1 show the lowest sensitivity to investment costs (the marginal rate of substitution (MRS) with operating cost is 1.56, compared to 3 for Class 3 intermediates and 1.92 Class 2 laggards). This is consistent with Roger's theory, as it states that early adopters are households with better financial resources, and hence lower marginal cost of investment. Unlike fixed coefficients, random coefficients must be interpreted as distributions. We focus on two aspects, the first is the coefficient of variation, which is the ratio of $c_v=\sigma/\mu$. A larger value indicates larger spread with respect to the mean. The second is the cumulative distribution at zero, which indicates the probability of a negative coefficient in the population belonging to that class.

The first thing to note is that the standard deviation estimates are all significant for all classes, which supports the hypothesis of heterogeneous preferences for these heating system attributes. Investment duration shows that 83 percent of the early adopters see this attribute positively, while the other two groups show that the near totality (98 percent) does so. It makes sense that a larger fraction of early adopters is inclined to consider negatively investment duration, perhaps because being inclined to innovate they would feel tied up for too long, albeit their distribution is twice as dispersed around the mean, compared to the other two classes. This suggests that early adopters are least worried about the risk linked to the sunk cost of a heating system investment.

All three classes have negative means for CO2 emissions, with early adopters showing the largest fraction (90 percent) of negative values, followed by intermediate (87) and laggards (69). In terms of spread around the mean intermediate show the largest variation (c_v=-2).

A similar pattern is shown for the other pollutant, fine particulate matter, where the early adopters show the highest fraction with negative coefficients (73 percent), which is consistent with the expectation of a stronger environmentalism amongst early adopters. The other two classes are both around little more than 50 percent. However, intermediate and laggards show much higher dispersion around the means.

Required own-work is an attribute that shows similar preferences across classes, in terms of both dispersion around the mean and fraction of negative coefficients.

Most of the coefficients of interactions terms between the ASC for wood pellet heating systems and the perception of its characteristics are significant in every class. In particular, it is interesting to note some differences between the coefficients in different classes. As far as compatibility is concerned, for example, the coefficients are significant and positive in every class, as suggested by Roger's theory.

The difference among the classes is evident when accounting for trialability: as expected, being able to try or see an operating wood pellet technology before adoption has a positive influence on Laggards (MRS/op. cost = 0.92) and intermediates (1.14), whereas it has a negative effect on innovators (-0.44). Rogers argues that individuals less prone to innovations need to be reassured about their characteristics before adopting them. Innovators, instead, according to Rogers, are more adventurous. This is also demonstrated by the fact that they are unaffected by performance and social risk, while the other two classes see them negatively. This is consistent with Rogers' description of innovators as individuals with high risk tolerance.

Knowledge is positive and significant for both early adopters and intermediates, but not so for laggards, whose level of knowledge is therefore not associated with the probability of selecting pellet fired systems. Private and public environmental concerns affect positively the selection of pellet fired systems in the early adopter class, but not in the other two. In this context, it makes sense that an innovation that alleviates environmental externalities motivates more those that tend to adopt it sooner.

The analysis of the influence of communication channels on preferences highlights that having received information from other people or mass media has a significant and positive effect on the probability of selection of pellet fired systems amongst early adopters, whereas only the information from other people affects the other two classes. Rogers states that early adopters typically have greater exposure to mass media and strong interaction with other early adopters. Rogers also suggests that information diffused by opinion leaders (that are often well represented amongst early adopters) is the most influencing factor during the evaluation stage of the innovation-decision process on late adopters. Finally, he argues that information from organization is the less relevant for the diffusion of an innovation, and this is consistent with our results as well, as the coefficients associated with this source are not significant in any of the classes.

4.5.1 Individual-specific WTP estimates

Examining the plots of kernel smoothed functions of individual-specific WTP distributions for selected attributes offers some additional insight. We focus on those for CO_2 emissions (Figure 4.2) and investment duration (Figure 4.3) and report them for the three latent classes.

Examining the plots for WTP for CO_2 increase (€/kg/year), it is interesting to note that the class with distribution most shifted to the positive side (i.e., least adverse emissions reduction) is Class 2 (Late adopters) and none of the individuals of class 2 is willing to pay more than 2€/kg/year to avoid emissions. Instead, Class 1 (Early Adopters) is the one most shifted to the left, with highest density around -1.5€/kg/year and slowest rate of decline. Class 3 (Intermediates) has intermediate values, both in terms of modal value and density of positive values and values lower than -€1/kg/year. These results are in perfect order with what expected from the theory.

Figure 4.3 shows the distribution of individual-specific WTP for 1 additional year of investment duration between individuals belonging to different classes. The distributions for Class 1 and Class 3 (Early Adopters and Intermediate) show very similar modal values (around €6) and overlap for most of the interval to the positive side of their modes. However, the degree of skewness, kurtosis and the presence of local modal values all vary. The distribution for Class 2 has modal value around 4€ and has both the highest density of values below €2 and the lowest density above €8. Individuals in Class 2 seem also to have the highest homogeneity of preferences. Overall, it seems that Innovators and Intermediate are willing to pay more to increase the duration of their investment as compared to Late Adopters. This may be due to their higher sensitivity to investment cost, which is consistent with Rogers' theory, as he describes Late Adopters as the segment of population with the lowest financial liquidity.

Public decision-makers would be interested in geographical profiling those administrative districts with similar scores for relative timing of adoptions and their sensitivity to the size of a potential subsidy. We mapped these over the area of interest in Figure 4.4. The values covering the largest area are those between €3.00 and €3.99. This is consistent with Rogers's theory, as it states that individuals in the middle of the adoption curve (Early majority and Late majority or "intermediates" in our terminology) are the majority of the population. Those with a high average score (>4) are mostly found in highly urbanized area. These are the big cities and their surrounding municipalities. Examples are the areas of Verona (on the left) and Treviso (at centre). In mountain areas, which are located in the North of the region, average scores below 3 are frequent, suggesting a low propensity to adopt innovations of inhabitants of these areas. Household living in this part of the region use traditionally firewood-based technologies, and are likely to be averse to the adoption of a new technology.

The same mapping is produced in Figure 4.5 (bottom left) for the WTP to avoid an increase of CO_2 emissions. High values of these geographically correlate with high scores for relative timing of adoptions. An example is provided by Verona, in which the average WTP to avoid the increase of 1kg/year of emission is between €1.50 and €1.99. In mountain areas, instead, where traditions prevail, several municipalities have values close to zero, suggesting that households in regions are generally not willing to pay a premium to adopt technologies to lower emissions. Finally, Figure 4.6 (bottom right) illustrates the geographical distribution of the average values of WTP for lengthening the investment duration by 1 year. Again, the distribution correlates well with that for relative timing of adoptions, as high values are more common on the plains than in the mountains. In general, in most of the municipalities, individuals are willing to pay for an increase in the lifespan of the heating system, and values below zero are rather uncommon.

4.6 Conclusions

E. M. Rogers' theory of innovation diffusion (1962, 2003) is supported by our results. It can be used as an organizational framework to rationalize observed variation of choice behaviour across households in the context of choice of innovative heating systems. The issue of population heterogeneity in preferences has been one of the key areas in choice modelling for the last 20 years or so. As a way to tackle the issue, researchers have tried to incorporate explanatory variables as sources of heterogeneity. In particular, in applied economics, different attitudinal and psychological theories have been used: for example, the implementations of Ajzen's theory of planned behaviour (1985) (Nocella et al., 2012; López-Mosquera and Sánchez, 2012 and Greiner et al., 2015); of Stern's Value-Belief-Norm theory (2000) (López-Mosquera and Sánchez, 2012); and of Rogers' protection motivation theory (1975) (Scarpa and Thiene, 2011) to rationalize differences in stated choice behaviour and how this correlates with real choice. The present contribution demonstrates, yet again, the advantages of bringing into applied economics theories derived from other disciplines to enrich the explanatory power of more conventional approaches by means of theoretically meaningful constructs.

From a policy point of view, our results can be used to improve the effectiveness of support schemes currently in place in Italy to promote the uptake of wood pellet fired heating systems (green certificates, feed-in tariffs, and premium tariffs). Under existing measures, only about four percent of Italian households have a pellet-based heating system (ISTAT 2015), which we identify as early adopters. More seems necessary to entice others. Our results showed that, compared to early adopters, intermediate adopters and laggards were found to be more sensitive to cost. The slow down in uptake of heating technologies based on wood pellet suggests that the current grant schemes of feed-in tariffs are not enough to bridge the existing gap between households' WTP and market prices. This might be exacerbated by the lack of adequate information among the population. Knowledge about wood pellet technologies was found to influence positively probabilities of adoption for both intermediate and laggards. Several studies have highlighted the advantages of wood pellet technologies (e.g. Di Giacomo and Taglieri, 2009; Toscato et al., 2014). It would seem appropriate for policymakers to increase their efforts to promote the diffusion of information about this innovation among the general population. On the other hand, we find that intermediate adopters and laggards seem to also be strongly averse to both social and performance risks associated with this innovation. Assuaging such concerns could also promote diffusion. Overall, our study suggests that future research and policy measures should focus on refining specific constructs that can be operationalized in a policy setting at the adequate geographical level to calibrate subsidies to specific segments of the population.

Table 4.1: Criteria for the selection of the number of classes

N = 1451					
Number of classes	Parameters	lnL	AIC	BIC	AICc
2	56	-13652	27360	27712	27369
3	78	-13452	26981	27471	26993
4	100	-13441	26982	27610	26997

Table 4.2.: Parameter Estimates of the LC-RPL model	Class 1 – Early adopters (26.9%)			Class 2 - Laggards (29.1%)			Class 3 - Intermediate (44.0%)		
CLASS MEMBERSHIP PROBABILITY FUNCTION	**Coeff.**	**|t|**	**MRS/op.cost**	**Coeff.**	**|t|**	**MRS/op.cost**	**Coeff.**	**|t|**	**MRS/op.cost**
CONSTANT	-0.31	1.7	3.44	0.16	6.6	-1.33	---	--	---
INNOVATIVENESS	0.12	3	-1.33	-0.08	2.2	0.67	---	--	---
FIXED PARAMETERS β									
ASC FIREWOOD	1.55	3.1	-17.22	0.68	2.4	-5.67	0.99	2.7	-14.14
ASC CHIPWOOD	0.67	2.1	-7.44	0.41	0.7	-3.42	0.55	3.4	-7.86
ASC WOOD PELLET	1.68	4.9	-18.67	-0.15	2.8	1.25	1.02	4.2	-14.57
ASC METHANE	1.43	5.8	-15.89	1.88	14	-15.67	1.56	14	-22.29
ASC OIL	-0.48	2.2	5.33	-0.3	4.8	2.50	-0.36	4.8	5.14
INVESTMENT COST	-0.14	2.2	1.56	-0.23	3.9	1.92	-0.21	3.9	3.00
OPERATIONAL COST	-0.09	6.1	1.00	-0.12	5.6	1.00	-0.07	5.2	1.00
RANDOM COEFFICIENTS (HYPERPARAMETERS)									
μ INVESTMENT DURATION	0.21	2.5	-2.33	0.31	3.8	-2.58	0.33	4.1	-4.71
σ INVESTIMENT DURATION	0.22	2.5	-2.44	0.15	4.4	-1.25	0.16	2.6	-2.29
μ CO_2 EMISSIONS	-0.16	3.9	1.78	-0.03	3.3	0.25	-0.09	3.6	1.29
σ CO_2 EMISSIONS	0.12	10.1	-1.33	0.06	6.6	-0.50	0.08	18.2	-1.14
μ FINE PARTICLES EMISSIONS	-0.11	-1.9	1.22	-0.04	0.8	0.33	-0.02	1.3	0.29
σ FINE PARTICLES	0.18	9.9	-2.00	0.19	12.4	-1.58	0.21	8.8	-3.00
μ REQUIRED OWN WORK	0.01	0.2	-0.11	-0.02	0.2	0.17	-0.05	1.1	0.71
σ REQUIRED OWN WORK	0.11	7.5	-1.22	0.23	11.3	-1.92	0.31	10.5	-4.43
INTERACTION TERMS FUNCTIONAL CONSTRUCTS γ									
PELLET × COMPLEXITY	-0.14	2.1	1.56	-0.22	1.9	1.83	-0.12	2.5	1.71
PELLET × COMPATIBILITY	0.17	0.2	-1.89	0.22	4.8	-1.83	0.13	1.7	-1.86
PELLET × TRIALABILITY	-0.04	5.8	0.44	0.11	4.2	-0.92	0.08	4.3	-1.14
PELLET × RELATIVE ADVANTAGE	0.18	2.4	-2.00	0.24	5.4	-2.00	0.15	1.9	-2.14
PELLET × PERFORMANCE RISK	-0.04	1.2	0.44	-0.31	7.7	2.58	-0.23	4.1	3.29
PELLET × SOCIAL RISK	0.02	2.1	-0.22	-0.09	3.8	0.75	-0.05	4.2	0.71
PELLET × KNOWLEDGE	0.22	4.3	-2.44	0.14	1.2	-1.17	0.28	4	-4.00
PELLET × ENVIRONMETAL FRIENDLINESS	0.28	5.2	-3.11	0.06	2.3	-0.50	0.22	2.4	-3.14
INTERACTION TERMS INFORMATION SOURCES δ									
PELLET × FROM OTHER PEOPLE	0.05	6.2	-0.56	0.12	7.6	-1.00	0.19	9.6	-2.71
PELLET × FROM MEDIA	0.05	5.8	-0.56	0.05	0.9	-0.42	0.03	1	-0.43
PELLET × FROM ORGANIZATIONS	0.09	0.5	-1.00	0.08	0.6	-0.67	0.04	0.5	-0.57

Table 4.3: Attitudinal questions included in the survey

A. Perception of characteristics

Questions were scored on a scale from 1 to 5, where 1 means *"I completely disagree"* and 5 means *"I completely agree"*.

Complexity

A1 It is hard to install a pellet-fired heating system.

A2 It is hard to use a pellet-fired heating system.

Compatibility

A3 The use of a pellet-fired heating system is compatible with my habits.

A4 To install a pellet fired heating system in my house would require minor changes.

Trialability

A5 I know someone who could give me information about pellet-fired heating system.

A6 I know buildings where I can see pellet-fired heating system in function.

Relative advantage

A7 A pellet-fired heating system requires less maintenance than my current system.

A8 A pellet-fired heating system is more convenient than my current system.

A9 A pellet-fired heating system can heat adequately my house.

Performance risk

A10 I am concerned about the maintenance required by a pellet-fired heating system.

A11 Compared to other heating systems, pellet-fired heating system has more risks.

Social risk

A12 I am afraid the purchase of a pellet-fired heating system could be badly considered by people I know.

Knowledge

A13 I have the necessary knowledge to evaluate the purchase of a pellet-fired heating system.

A14 I am aware of the installation requirements of a pellet-fired heating system.

Environmental friendliness

A15 The installation of a pellet-fired heating system would improve my local environment.

A16 The installation of a pellet-fired heating system would reduce greenhouse gases.

B. Communication channels

B1 Before starting the survey, did you have any information about pellet fired heating system? (yes or no)

B2 What is the main sources of such information? (choose only one)

B2.1 People I know who possess a pellet fired heating system

B2.2 Mass media (web, newspapers, television, radio)

B2.3 Organizations (local associations, energy agencies)

C. Timing of adoption

Questions were scored on a scale from 1 to 5, where 1 means *"I completely disagree"* and 5 means *"I completely agree"*.

C1 I love to use innovations that impress others.

C. I like to own an innovative product that distinguishes me from others who do not own this new product.

C3 I prefer to try innovative products with which I can present myself to other people.

C4 If a new product gives me more comfort than my current product, I would not hesitate to buy it.

C5 If a new product makes my work easier, then this new product is a "must" for me.

C6 If a new time-saving product is launched, I will buy it right away.

C. Acquiring innovative products makes me happier.

C8 Innovative products make my life exciting and stimulating.

C9 I find innovations that need a lot of thinking intellectually challenging and therefore I buy them instantly.

C10 I often buy new products that I consider hard to use.

C11 People I know often consult me to help choose the best innovative product available on the market.

C12 People I know think it is important that I like the products they buy.

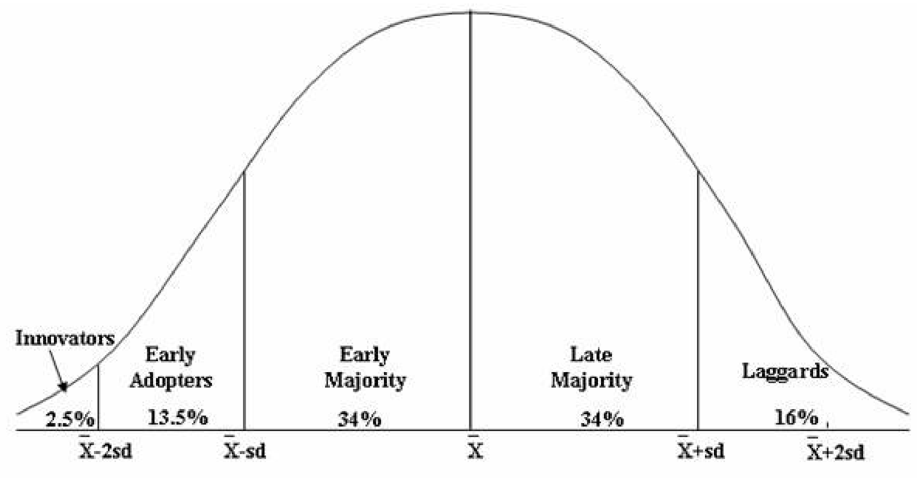


Figure 4.1: Adoption curve (Rogers, 2003)

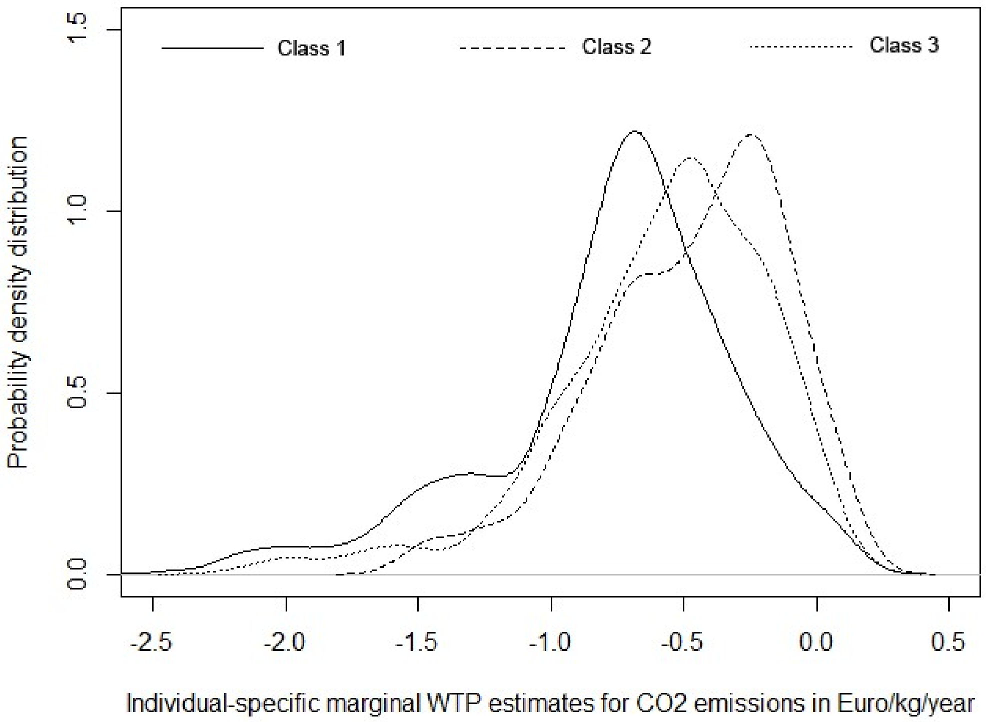


Figure 4.2: Kernel distribution of individual-specific WTP for CO_2 emissions among the 3 classes

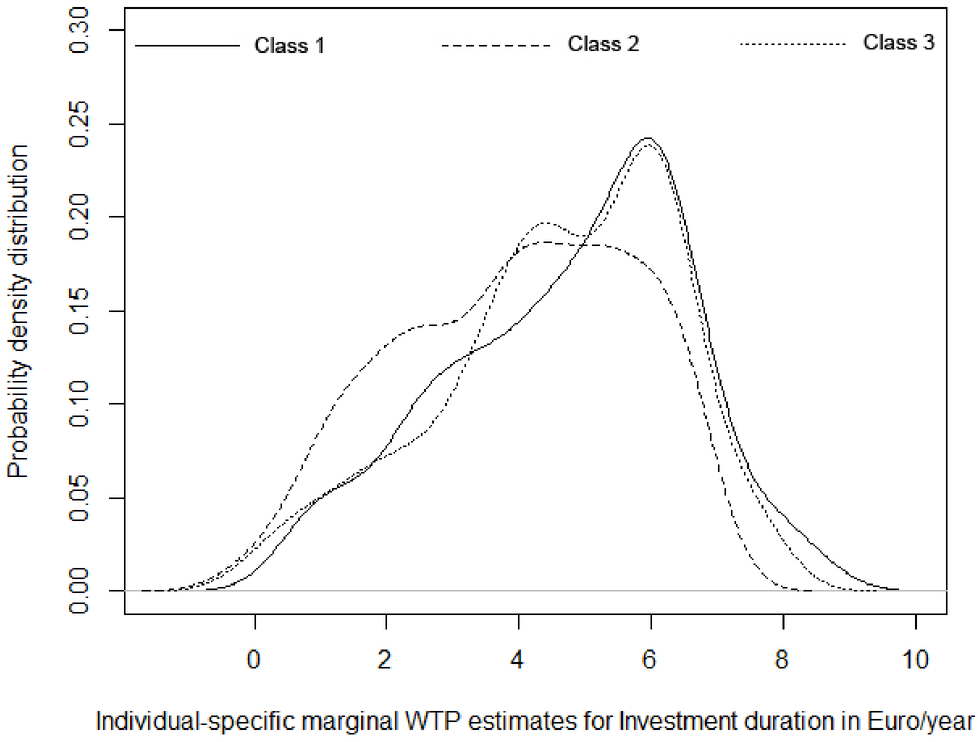


Figure 4.3: Kernel distribution of individual-specific WTP for investment duration among the 3 classes

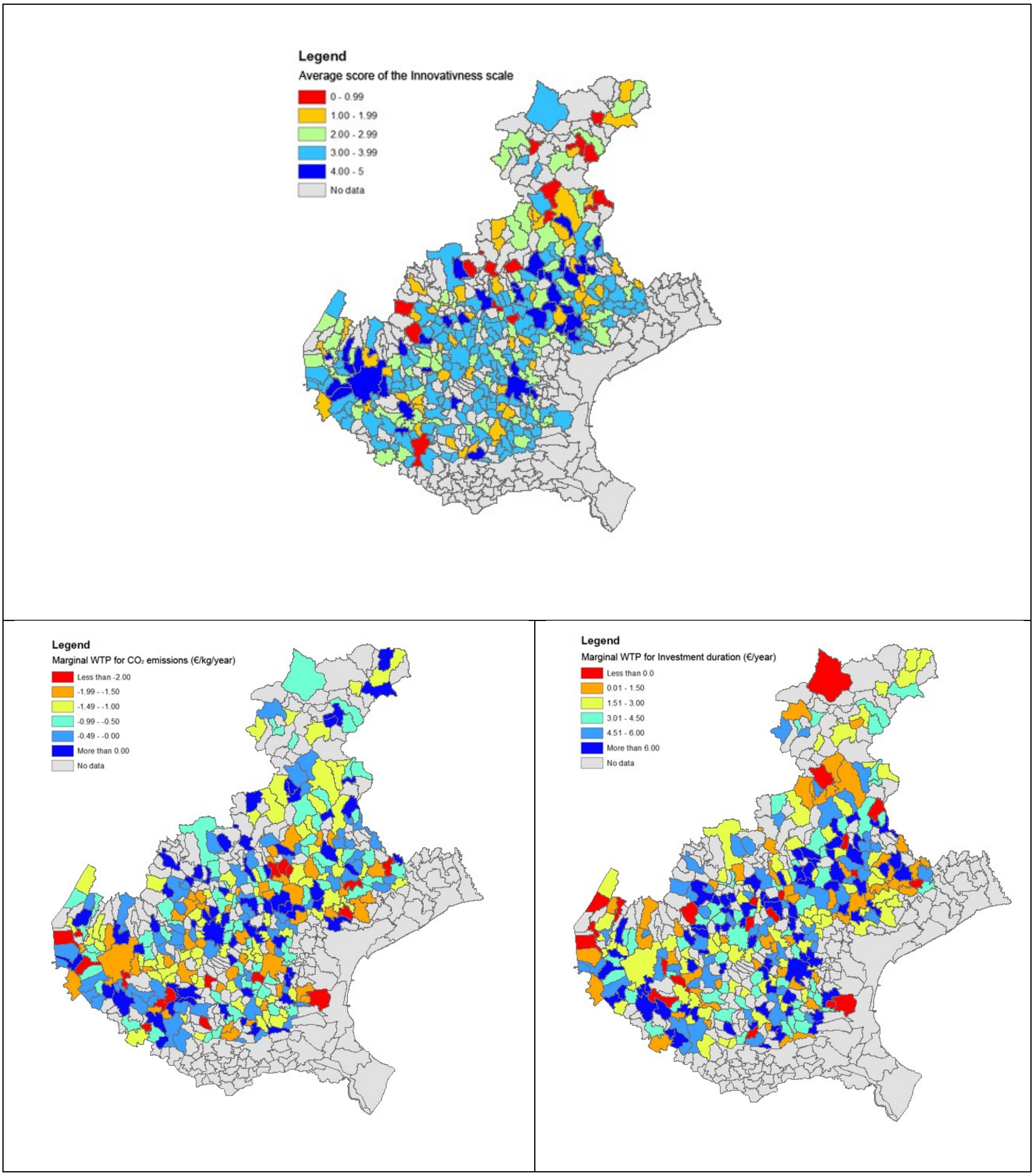


Figure 4.4: Geographical distribution of the average score of the timing of adoption (top), of the marginal WTP for CO_2 emission (bottom left) and of the marginal WTP for investment duration (bottom right).

5. Comparison of statistical features of different choice models specifications

This chapter explores the last research question of the thesis, that is the comparison of statistical features of different choice models specification. The analysis was based on the Monte Carlo simulation study, which is described in detail in the following paragraphs.

5.1 Introduction and objectives

Over the past few decades, one of the main research areas in the field of discrete choice modeling has been the development of model specifications which account for taste heterogeneity. Among these, the mixed logit model with normally distributed random parameters (MXL-N) is the most commonly adopted in practice. However, the normal distribution may not be appropriate for all empirical situations and may create misspecification issues and lead to erroneous results. To overcome this issue, several model specifications based on flexible mixing distributions have been recently proposed (e.g., Bujari at al., 2007; Fosgerau and Bierlaire, 2013). Train (2016) recently proposed a semi-nonparametric logit-mixed logit (LML) model which generalizes previous flexible models and consists of two logit formulations: one for the decision makers' probability to choose an alternative and the other for the probability of selecting a parameter from a finite parameter space. The shape of the logarithm of the mixing distribution can be defined by different types of functions such as polynomials, step functions and splines. In theory, LML models should be able to describe more accurately preference heterogeneity when tastes follow complex distributions. To investigate whether this may be true in practice, we designed a Monte Carlo Simulation study to test whether LML models are able to approximate parameters distributions better than standard MXL models. Additionally, we investigate the required number of parameters (i.e., order of polynomial, levels in step function, and knots in spline) to retrieve good approximations of the distributions of random parameters with LML models. Our hypothesis, based on the findings of previous studies on choice models with flexible mixing distributions (e.g. Fosgerau and Hess, 2009), is that increasing the number of parameters yields a better approximation of the true distribution. Finally, we investigate the issue of the number of observations needed to retrieve good approximations of parameters distributions with LML models. To do so, we compare the results retrieved from such models with those retrieved from MXL-N models at different sample sizes. The remaining chapter is organized as follows: section 2 illustrates MXL-N and LML models, section 3 describes the Monte Carlo experiment design, Section 4 discusses simulation results and Section 5 draws the conclusions of the study.

5.2 MXL-N and LML models

The MXL model represents random taste heterogeneity by allowing for different preference parameters for each decision-maker (McFadden and Train, 1998). The utility derived by individual n from choosing alternative i in choice situation t is:

$$U_{nit} = x_{nit}\ '\beta_n + \varepsilon_{nit} \qquad \text{(Eq. 5.1)}$$

where $'\beta_n$ is a vector of parameters for decision-maker n modeled as having a continuous mixing distribution in the population; x_{nit} is a column vector of observed attributes of alternative i; ε_{nit} is the error term assumed to follow a Gumbel distribution. The conditional probability $P_{nit}(\beta_n)$ of individual n choosing alternative i in choice situation t is:

$$P_{nit}(\beta_n) = \frac{\exp(x_{nit}{}'\beta_n)}{\sum_{j=1}^{J}\exp(x_{njt}{}'\beta_n)} \quad \text{(Eq. 5.2)}$$

Different variations of MXL models can be obtained by assuming different mixing distributions of the random parameters, such the MXL-N that imposes a multivariate normal mixing distribution, i.e., $\beta_n \sim N(\beta, \Sigma)$. Let y_{nit}= 1 if individual n chooses alternative i in choice situation t, and otherwise. The unconditional probability Pn(β, Σ) of the sequence of alternatives chosen by individual *n* is:

$$P_n(\beta, \Sigma) = \int \left\{ \prod_{t=1}^{T} \prod_{i=1}^{J} \left[\frac{\exp(x_{nit}{}'\beta_n)}{\sum_{j=1}^{J}\exp(x_{njt}{}'\beta_n)} \right]^{y_{nit}} \right\} f(\beta_n|\beta, \Sigma) d\beta_n \quad \text{(Eq. 5.3)}$$

where $f(\beta_n|\beta, \Sigma)$is a probability density function of random parameter vector β_n.

In LML models, the joint mixing distribution of the random parameters β_n is assumed to be discrete over a finite support set S. Discretization is not a constraint because the support set is essentially a multidimensional grid that can be made larger and denser by considering a broader domain of parameters and a higher number of grid points. The joint probability mass function of random parameters in LML is specified following the following logit-type expression:

$$W_n(\beta_r|\alpha) = P(\beta_n = \beta_r) = \frac{\exp(z(\beta_r)'\alpha)}{\sum_{s\in S}\exp(z(\beta_s)'\alpha)} \quad \text{(Eq. 5.4)}$$

where α is a vector of parameters and $z(\beta_r)$ defines the shape of the mixing distribution. This study considers $z(\beta_r)$ to be polynomial, step function, and spline. The unconditional probability $P_n(\alpha)$ of the sequence of choices of individual *n* is:

$$P_n(\alpha) = \sum_{r\in S} \left\{ \prod_{t=1}^{T} \prod_{i=1}^{J} \left[\frac{\exp(x_{nit}{}'\beta_r)}{\sum_{j=1}^{J}\exp(x_{njt}{}'\beta_r)} \right]^{y_{nit}} \right\} W_n(\beta_r|\alpha) \quad \text{(Eq. 5.5)}$$

In LML models, the vector α is estimated using maximum likelihood estimation procedure. Inclusion of all the points of the support set in the estimation of LML is unnecessary and computationally expensive. Therefore, a random subset of points is drawn within S. The logit formula to compute probability mass of random parameters (Eq. 5.4) results into an efficient computation of likelihood gradient.

5.3 Design of the Monte Carlo simulation

The Monte Carlo simulation was based on three attributes, each having two levels. Attribute 1 and attribute 2 were assumed to be non-monetary attributes, whereas the third was assumed to be the price. Attributes and level are reported in Table 7.1.

Table 7.1: Attributes and levels

Attributes	Level 1	Level 2
Attribute 1	0	1
Attribute 2	0	1
Cost	1	2

Attributes and levels were combined by means of a *d*-efficient design. The design consisted of four choice scenarios each having two alternatives.

We adopted a data generation process in WTP space, based on the assumption that a respondent chooses the alternative with maximum utility between the two alternatives. The utility of respondent *n* for alternative *i* in choice occasion *t* was specified as:

$$U_{nit} = \lambda_n^*(\omega_{1n}x_{1nit} + \omega_{2n}x_{2nit} - p_{it}) + \epsilon_{nit} \quad \text{(Eq. 5.6)}$$

WTPs for attribute 1 and 2 (ω_{1n} and ω_{2n}) were assumed to follow a mixing distribution of two normal distributions, whereas the price/scale coefficient λ_n^* was assumed to follow a mixture of two log-normal distributions. The price coefficient was assumed to be fixed to -1. The error term ϵ_{nit} was assumed to follow a standard Gumbel distribution. The distributions were specified as:

$\omega_{1n} \sim N(1.2, 0.64)$ with probability 0.3 and $N(0.5, 0.25)$ with probability 0.7

$\omega_{2n} \sim N(-1.5, 1)$ with probability 0.4 and $N(-3, 1.25)$ with probability 0.6

$\lambda_n^* \sim \exp(Y_1)\ where\ Y_1 \sim N(0.5, 0.25)$ and $\sim \exp(Y_2)\ where\ Y_2 \sim N(1,1)$, both with probability 0.5

Correlations among attributes' coefficients were assumed to be zero.

To investigate the research question concerning sample sizes needed to retrieve accurate approximations of true distributions, we generated five panel datasets with increasing number of simulated respondents: 50, 100, 250, 500, 1000. Each respondent faced four choice scenarios, resulting in 200, 400, 1000, 2000, 4000 observations. The process was repeated 1000 times for each sample size, resulting in 1000 datasets for each.

For each simulated dataset, 13 models were estimated. These models consist of MXL in WTP space with normally distributed coefficients for attribute 1 and attribute 2 and lognormally distributed price/scale coefficient, four LML-Polynomial models with varying number of parameters (12, 24, 36, 48), four LML-Step models with varying number of parameters (12, 24, 36, 48), and four LML-Spline models with varying number of parameters (12, 24, 36, 48). Data generation process and models estimation was performed in MATLAB. Choice probabilities were simulated in the sample log-likelihood with 250 Halton draws.

To compare the performances of different model specifications we computed the mean squared error of the estimated parameters, according to the formula:

$$MSE = \frac{1}{R}\sum_{r=1}^{R}(\omega^r - \omega)^2 , r = 1, \dots, 1000 \quad (14)$$

where ω is the real WTP value and ω^r is the r^{th} value estimated in the experiment.

5.4 Results and discussion

Table 5.2 reports the mean squared errors for estimates of the mean values of the two simulated attributes. For small dataset (100 and 200 simulated respondents) the best performing model (that is the one with the lowest mean squared error) is the Mixed Logit in WTP space (MSE = 0.152 for attribute 1 and MSE = 0.333 for attribute 2), which outperforms all the LML models. At small sample sizes, there are no clear patterns as far as it concerns the optimal number of parameters of LML models. As far as it concerns attribute 1, among the LML models based on polynomials the best specification is the one with 24 parameters (MSE = 0.176), followed by the specification with 48 parameters (0.199). Moving to LML models based on step function, the best performing models are those with high number of parameters (MSE = 0.192 for the model specification with 48 parameters, MSE = 0.211 for the model specification with 36 parameters). Finally, among LML models based on spline, the best performing model specification is the one with 24 parameters (MSE = 0.188), followed by the one with 36 parameters LML (MSE = 0.241). As far as it concerns the coefficients for attribute 2, among model specification based on polynomials the best performing ones are those with 24 (MSE = 0.391), and 48 (MSE = 0.402) parameters. For step function LML models, the best results were obtained with 48 (MSE = 0.356) and 36 (MSE = 0.365) parameters. The best performing model specification based on splines was the one with 36 parameters. At intermediate sample sizes (500 and 1000 simulated respondents) some of the LML specifications outperformed the MXL in WTP space, but only at large sample sizes (2500) LML models performed consistently better. For datasets with 2500 respondents there is also a clear improvement of LML models performance at increasing number of parameters. Among LML models based on step functions and splines the best model specifications were those with 48 parameters (MSE = 0.004 and MSE = 0.005 for attribute 1; MSE = 0.074 and 0.048 for attribute 1), whereas the best model specification among LML polynomial models was the one with 36 parameters (MSE = 0.006 for attribute 1 and MSE = 0.061 for attribute 1. Table 7.3 reports the mean squared errors for estimates of the standard deviation of coefficients associated with the two simulated attributes. The results are similar to those retrieved for mean values, in that the MXL in WTP space outperforms the LML specifications for small sample sizes, whereas LML models produce more accurate estimates in datasets with large dimensions. Overall the results suggest that LML models are capable outperform the MXL in WTP space only for datasets with large number of observations. As far as it concerns the optimal number of parameters to be estimated in LML models, it seems that a high number of parameters can be adopted only for large datasets. In such datasets, there is also evidence of an improvement of model performance at increasing number of parameters.

Table 5.2 Mean squared errors for mean coefficients

		100		250		500		1000		2500	
Model		ω1	ω2	ω1	ω2	ω1	ω2	ω1	ω2	ω1	ω2
MXL WTP	6	0.152	0.333	0.108	0.312	0.054	0.235	0.021	0.135	0.012	0.096
LML Polynomial	12	0.631	0.912	0.609	0.837	0.525	0.775	0.121	0.246	0.056	0.138
	24	0.176	0.391	0.113	0.338	0.028	0.239	0.039	0.121	0.008	0.084
	36	0.231	0.541	0.181	0.502	0.063	0.414	0.051	0.102	0.006	0.061
	48	0.199	0.402	0.126	0.321	0.040	0.229	0.022	0.096	0.007	0.072
LML Step	12	0.545	0.888	0.520	0.807	0.425	0.724	0.133	0.252	0.048	0.152
	24	0.612	0.437	0.541	0.398	0.480	0.299	0.051	0.128	0.015	0.099
	36	0.211	0.365	0.185	0.295	0.116	0.217	0.022	0.105	0.007	0.074
	48	0.192	0.356	0.147	0.325	0.087	0.249	0.009	0.096	0.004	0.045
LML Spline	12	0.612	0.792	0.551	0.716	0.466	0.627	0.091	0.212	0.061	0.142
	24	0.188	0.401	0.121	0.315	0.055	0.413	0.018	0.144	0.014	0.059
	36	0.241	0.371	0.203	0.435	0.133	0.343	0.031	0.126	0.009	0.056
	48	0.287	0.764	0.262	0.743	0.207	0.213	0.014	0.101	0.005	0.048

Table 5.3 Mean squared errors for standard deviations

		100		250		500		1000		2500	
Model		σ1	σ2	σ1	σ2	σ1	σ2	σ1	σ2	σ1	σ2
MXL WTP	6	0.370	0.559	0.319	0.562	0.255	0.475	0.258	0.376	0.246	0.346
LML Polynomial	12	0.867	1.139	0.816	1.072	0.761	1.023	0.342	0.487	0.284	0.384
	24	0.384	0.628	0.341	0.551	0.270	0.487	0.238	0.329	0.245	0.297
	36	0.449	0.765	0.419	0.714	0.305	0.614	0.225	0.317	0.22	0.278
	48	0.411	0.645	0.329	0.561	0.267	0.495	0.246	1.193	0.25	0.307
LML Step	12	0.778	1.097	0.734	1.034	0.668	0.958	0.363	0.469	0.252	0.373
	24	0.839	0.644	0.747	0.638	0.725	0.516	0.295	0.36	0.223	0.346
	36	0.424	0.533	0.425	0.505	0.330	0.440	0.255	0.333	0.222	0.289
	48	0.408	0.556	0.367	0.551	0.299	0.489	0.245	0.313	0.228	0.275
LML Splyne	12	0.823	1.018	0.775	0.949	0.674	0.834	0.331	0.449	0.282	0.378
	24	0.424	0.651	0.324	0.56	0.269	0.413	0.234	0.352	0.241	0.263
	36	0.467	0.718	0.449	0.664	0.334	0.582	0.262	0.342	0.252	0.288
	48	0.488	1.003	0.489	0.965	0.426	0.882	0.253	0.345	0.218	0.248

5.5 Conclusions

This chapter focused on Monte-Carlo experiments conducted to investigate the ability of different variants of the recently proposed Logit-mixed Logit (LML) in retrieving the underlying heterogeneity distributions of random parameters. In the simulation experiments, we estimated 13 models using datasets created with a data generation process in WTP space. To ensure the stability of the parameter estimates, all models were estimated for 1000 datasets and key conclusions were derived based on mean values. The first objective of this study was to investigate the performance of LML models at different sample sizes. Our findings suggest that LML models require large sample sizes to outperform traditional MXL models. At small sample sizes, LML models performed worse than the traditional specifications based on the assumption of normally distributed coefficients. The second objective was to identify the optimal number of parameters to be adopted in LML model specification. Our hypothesis, based on previous findings of studies on flexible choice models (e.g., Fosgerau and Hess, 2009) was that increasing the number of parameters yields better approximations of the true distributions of the parameters. Our findings support only partially this hypothesis, in that LML specifications with large number of parameters outperformed those with small number of parameters only at large sample sizes. The results from LML models estimated from datasets with low number of observations were mixed, and in many cases model specifications with small number of parameters outperformed those with larger number of parameters. Overall, the results of our study do not support the blind use of very flexible mixing distributions, as at times LML models with a large number of parameters performed worse as compared to both LML specifications with low number of parameters and MXL models. Thus, as a general guideline, we suggest to adopt LML model specifications with large number of parameters only when a large number of observations is available. While this study provides some insights about LML performance, additional simulation experiments are needed to evaluate the robustness of these conclusions. Additional experiments can include a variety of data settings such as variation in the number of alternatives, number of choice situations in the panel data, number of explanatory variables in the utility equation, and correlation among parameters.

6. Conclusions

Despite the popularity of the CE approach in evaluation studies, there are still research areas explored only partially by previous literature. The aim of the thesis was to explore these areas to improve the usefulness of the CE approach in estimating the value of environmental goods and services and in providing policy advices.
This thesis was based on a series of objectives concerning both CE surveys and discrete choice modeling. Specifically, the objectives were: 1) analysis of the effect of information treatments on individual's preferences; 2) analysis of the effects of the adoption of different experimental designs; 3) development of frameworks to include geographical variables in choice modeling; 4) relating individuals' psychological traits to their preferences towards environmental goods and services; 5) comparison of statistical features of different choice models specifications. The analysis related to the first objective were carried out on choice data from a case study focused on the analysis of social demand from protection devices in Val del Boite (Veneto region). Research areas referred to objectives two to four were instead explored by adopting discrete choice modeling on a dataset collected from the case study of the analysis of preferences of the household of the Veneto region towards different heating systems. Finally, a Monte Carlo simulation was carried out to conduct the analysis referred to the last objective.

As far as it concerns the first objectives, the thesis focused on the case of information provided for only one attribute, as previous similar studies obtained contrasting results. It investigated this issue in a case study concerning the analysis of social demand for protection devices in Val del Boite (Veneto region). This case study involved the provision of scientific information about one of the protection devices included in the CE. By including in the model specification interaction terms between the information treatment and each attribute, it was investigated whether the treatment had a significant effect only for the selected protection device or for the others as well. The results supported the hypothesis that information affects only the attribute on which it is focused, as significant effects were not found on the others. Furthermore, it was investigated how the information effect varies spatially, by mapping WTP values for the attribute affected by information treatment before and after information provision. The maps revealed that the information effect is stronger in areas far from the Valley, where individuals are likely to have lesser knowledge of the landslide problem. In a way, this can be interpreted as a confirmation that information effect is stronger for individuals that are less familiar with the good or service under evaluation.
The second objective was motivated by the lack of empirical evidence on this subject and was investigated carrying out choice analysis in the second case study. The CE included choice scenarios generated with alternative experimental designs, namely near orthogonal, d-efficient and serial designs. By estimating separated models for datasets generated with each design, the effects of design were investigated. The results provided evidence of better model performance for datasets generated with efficient and serial design, thus corroborating the theoretical expectations.
For the third objective, the thesis proposed a Mixed Logit model specification which included variables related to altitude, average income and population size of respondents' place of living. Model estimates suggested that such factors are indeed cause of preference heterogeneity and post hoc analysis provided validation for the proposed model. Although the proposed model cannot be considered a proper spatial model, it represents a way to inform discrete choice models with variables related to geographical features and it is an explorative work in such direction. This is particularly

important given the theoretical evidence of spatial effects and the paucity of empirical works on this subjects. The fourth objective involved a LC-RPL model specification to relate the preferences of householders of the Veneto region for pellet heating systems to the diffusion of innovation theory (Rogers, 2003). This work represented the first empirical application of the theory in a CE study investigating heating choices. The results supported the theory, which suggests than it can be used as an organizational framework to rationalize observed variation of choice behavior across households in the context of choice of innovative heating systems. Furthermore, the results confirm, the advantages of bringing into applied economics theories derived from other disciplines to enrich the explanatory power of more conventional approaches by means of theoretically meaningful constructs. Finally, the fifth objective of the thesis tackled the issue of the description of preference heterogeneity by comparing statistical features of alternative model specifications. Specifically, it focused on the LML model recently introduced by Train (2016). Although such model – according to the theory - should allow to retrieve more accurate approximation of parameters distributions as compared to parametric models, there is still no evidence in literature about the number of parameters and sample size needed to obtain better approximations. To investigate these research questions, a Monte Carlo simulation was carried out, which allowed to generated choice data with varying number observation. Using such datasets LML models with varying number of parameters were estimated, along with mixed logit models with normal distributions. The results suggest that LML models are indeed capable to outperform parametric models and to retrieve more accurate parameters distributions, but only when both sample size and number of parameters are large.

References list

Abildtrup, J., Garcia, S., Olsen, S. B., and Stenger, A. (2013). Spatial preference heterogeneity in forest recreation. *Ecological Economics*, *92*(C):67–77.

Achtnicht, M. (2011). Do environmental benefits matter? Evidence from a choice experiment among house owners in Germany. *Ecological Economics*, 70(11):2191-2200.

Ahlheim, M., Frör, O., Heinke, A., Keil, A., Nguyen, M. D., Pham, V. D., Saint-Macary, C. and Zeller, M. (2008). Landslides in mountainous regions of Northern Vietnam: Causes, protection strategies and the assessment of economic losses. University of Hohenheim. Retrieved from: https://www.uni-hohenheim.de/RePEc/hoh/papers/298.pdf

Anderson, D.A. and Wiley, J.B. (1992). Efficient Choice Set Designs for Estimating Cross-Effects Models, *Journal of Marketing Research*, 3:357-370.

Banfi, S., Farsi, M., Filippini, M., and Jakob, M. (2008). Willingness to pay for energy-saving measures in residential buildings. *Energy Economics, 30*(2):503-516.

Bartels, R., Fiebig, D.G., and McCabe, A. (2004). The value of using stated preference methods: A case study in modelling water heater choices. *Mathematics and Computers in Simulation*, 64(3-4):487-495.

Bartels, R., Fiebig, D.G., and van Soest, A. (2006). Consumers and experts: An econometric analysis of the demand for water heaters. *Empirical Economics*, 31(2):369-391.

Batsell, R.R. and Polking, J.C. (1985). A New Class of Market Share Models. *Marketing Science*, 4:177-198.

Berti M., Genevois R., Simoni A., and Tecca P.R. (1999). Field observations of a debris-flow event in the Dolomites. *Geomorphology*, *29* (3–4):265-274.

Bhat, C.R., Paleti, R., and Castro, M. (2015). A new utility-consistent econometric approach to multivariate count data modeling. *Journal of Applied Econometrics, 30*(5):806-825.

Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models. In Chevroulet, T., Sevestre, A. (Eds.), *Proc. 3rd Swiss Transportation Research Conf.*, March 19–21, 2003, Monte-Verita, Ascona, Switzerland. Retrieved from: http://www.strc.ch/conferences/2003/bierlaire.pdf

Billé, A.G. and Arbia G. (2013). Spatial Discrete Choice and Spatial Limited Dependent Variable Models: a review with an emphasis on the use in Regional Health Economics. Working paper.

Bliemer, M.C. and Rose, J.M. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. *Transportation Research Part B*, 44:720-734.

Bliemer, M. C. and Rose, J. M. (2011). Experimental design influences on stated choice outputs: An empirical study in air travel choice. *Transportation Research Part A: Policy and Practice*, *45*:63 – 79.

Bliemer, M.C.J.; Rose, J.M. Serial choice conjoint analysis for estimating discrete choice models. In Proceedings of the International Choice Modelling Conference, Yorkshire, UK, 30 March–1 April 2009.

Broch, S. W., Strange, N., Jacobsen, J. B., and Wilson, K. A. (2013). Farmers' willingness to provide ecosystem services and effects of their spatial distribution. *Ecological Economics*, *92*(0):78-86.

Brownstone, D., and Kenneth, T. (1999). Forecasting new product penetration with flexible substitution patterns, University of California Transportation Center. Working Papers, University of California Transportation Center.

Campbell, D., Hutchinson, W. G. and Scarpa, R. (2009). Using choice experiments to explore the spatial distribution of willingness to pay for rural landscape improvements. *Environment and Planning A*, *41*: 97-111.

Carpio, M.; Zamorano, M.; Costa, M. Impact of using biomass boilers on the energy rating and CO_2 emissions of Iberian Peninsula residential buildings. *Energy Build.* 2013, *66*, 732–744.

Chanel, O., Cleary, S. and Luchini, S. (2006). Does public opinion influence willingness-to-pay? Evidence from the field. *Applied Economics Letters, Taylor & Francis*, *13*: 821-824.

ChoiceMetrics (2012). Ngene 1.1.1 User manual & reference guide, Australia.

Czajkowski, M. and Hanley, N. (2012). More random or more deterministic choices? The effects of information on preferences for biodiversity conservation. Economics Discussion Paper, 06. Stirling Management School. Retrieved from: http://hdl.handle.net/1893/6360

Czajkowski, M., Budzinski, W., Campbell, D., Giergiczny, M., and Hanley, N. (2015). Spatial heterogeneity of willingness to pay for forest management. Working Papers 2015-07, University of St. Andrews, Department of Geography and Sustainable Development.

D'Agostino, V., Cesca, M. and Marchi, L. (2010). Field and laboratory investigations of runout distances of debris flows in the Dolomites (Eastern Italian Alps). *Geomorphology*, *115*:294-304.

Duke, J.M., Dundas, S.J., Johnston, R.J., and Messer, K.D. (2014). Prioritizing payment for environmental services: Using nonmarket benefits and costs for optimal selection. *Ecological Economics*, 105: 319-329.

ESRI (2010). ArcGIS 10, http://www.esri.com/.

Ferrini, S. and Scarpa R. (2007). Designs with a priori information for nonmarket valuation with choice-experiments: A Monte Carlo study. *Journal of Environmental Economics and Management*, *53*(3):342-63.

Fiedler, F.; Persson, T. Carbon monoxide emissions of combined pellet and solar heating systems. *Applied Energy* 2009, *86*, 135–143.

Flügel, S., Rizzi L., I., Veisten, K., Elvik, R. and De Dios Ortúzar, J. (2015). Car drivers' valuation of landslide risk reductions. *Safety Science*, *77*:1-9.

Greene, W.H., Hensher, D.A., and Rose J.M. (2005). In Scarpa, R. and Alberini, A. eds. Applications of Simulation Methods in Environmental and Resource Economics. Dordrecht, The Netherlands: Springer Publisher, chapter 2: 17-33.

Gregoretti, C. and Dalla Fontana, G. (2008). The triggering of debris flow due to channel-bed failure debris flow in some alpine headwater basins of the Dolomites: analyses of critical runoff. *Hydrological Processes*, *22*:2248-2263.

Guidoboni, E. and Valensise, G. (2014). L'Italia dei disastri. Dati e riflessioni sull'impatto degli eventi naturali 1861-2013. Bononia University Press.

Hackbarth, A. and Madlener, R. (2013). Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment,* 25:5-17.

Hanley, N., Schläpfer, F., and Spurgeon, J. (2003). Aggregating the Benefits of Environmental Improvements: Distance-Decay Functions for Use and Non-Use Values. *Journal of Environmental Management*, 68:297-304.

Herriges, J.A. and Phaneuf, D.J. (2002). Inducing Patterns Correlation and Substitution in Repeated Logit Model of Recreation Demand. *American Journal of Agricultural Economics*. 84(4):1076-1090.

Hess, S. Conditional parameter estimates from Mixed Logit models: Distributional assumptions and a free software tool. *J. Choice Model.* 2010, *3*, 134–152.

Hess, S., Train, K.E. and Polak, J.W. (2006). On the use of a modified latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice. Transportation Research Part B: Methodological *40*(2):147-163.

Horne, P. Boxall, P.C., and Adamowicz, W.L. (2005). Multiple-use Management of Forest Recreation Sites: A Spatially Explicit Choice Experiment. *Forest Ecology and Management*, 207:189-199.

Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, 65:340-350.

Jaccard, M. and Dennis, M. (2006). Estimating home energy decision parameters for a hybrid energy economy policy model. *Environmental Modeling and Assessment*, 11(6):91-100.

Johnston, R.J. and Ramachandran, M. (2014). Modeling spatial patchiness and the hot spots in stated preference willingness to pay. *Environmental and Resource Economics*, 59(3):363-387.

Juutinen, A., Kosenius, A.K., Ovaskainen, V. (2014): Estimating the benefits of recreation-oriented management in state-owned commercial forests in Finland: A choice experiment. Journal of Forest Economics, 20(4):396-412.

Knapp, L. and Ladenburg, J. (2015). How Spatial Relationships Influence Economic Preferences for Wind Power—A Review. *Energies*, *8:*6177-6201.

Lanz, B. and Provins, A. (2011). Valuing Local Environmental Amenity with Discrete Choice Experiments: Spatial Scope Sensitivity and Heterogeneous Marginal Utility of Income. N. 11-79, CEPE Working paper series, Center for Energy Policy and Economics, ETH Zurich.

Lazari, A.G. and Anderson, D.A. (1994). Designs of Discrete Choice Experiments for Estimating Both Attribute and Availability Cross Effects, *Journal of Marketing Research*, 31:375-383.

Louviere, J.J. and Hensher, D.A. (1982). On the design and analysis of simulated or allocation experiments in travel choice modelling. Transportation Research Record, 890:11-17.

Louviere, J.J. and Woodworth, G. (1983). Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research*, *20*(4):350-367.

Luce, R. D. (1959). Individual choice behavior. A theoretical analysis. New York: Wiley.

Luisetti, T., Bateman, I.J., and Turner, R.K. (2011). Testing the fundamental assumptions of choice experiments: are values absolute or relative? *Land Economics*, 87(2):284-296.

MacMillan, D., Hanley, N. and Lienhoop, N. (2006). Contingent valuation: Environmental polling or preference engine? *Ecological Economics*, *60*(1):299-307.

Marre, J., Brander, L., Thebaud, O., Boncoeur, J., Pascoe, S., Coglan, L., and Pascal, N. (2015). Non-market use and non-use values for preserving ecosystem services over time: A choice experiment application to coral reef ecosystems in New Caledonia. *Ocean & Coastal Management,* 105:1-14.

McFadden, D and Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics, 15*(5):447-470.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In Zarembka P. (ed), *Frontiers in econometrics*. Academic Press, New York, pp 105–142.

Mejía, C.V. and Brandt, S. (2015). Managing tourism in the Galapagos Islands through price incentives: A choice experiment approach, Ecological Economics, 117(C):1-11
Michelsen, C.C. and Madlener, R. (2012). Homeowners' preferences for adopting innovative residential heating systems: A discrete choice analysis for Germany. *Energy Economics, 34*(5):1271-1283.

Mitchell, R.C. and Carson, R.T. (1989). Using Surveys to Value Public Goods: The Contingent Valuation Method. Johns Hopkins University Press, Baltimore, MD.

Mori, M., Hosoda, T., Ishikawa, Y., Tuda, M., Fujimoto, R. and Iwama, T. (2006). Landslide management by community based approach in the Republic of Armenia. Japan International Cooperation Agency, Government of Armenia. Retrieved from: http://www.interpraevent.at/palmcms/upload_files/Publikationen/Tagungsbeitraege/2006_2_657.pdf

Munro, A. and Hanley, N. (1999). Information, Uncertainty and Contingent Valuation. In: Contingent Valuation of Environmental Preferences: Assessing Theory and Practice in the USA, Europe, and Developing Countries, Bateman, I. J. and Willis, K.G., eds., Oxford University Press.

Murphy, J., Allen, G., Stevens, T., and Weatherhead, D. (2005). A Meta-Analysis of Hypothetical Bias in Stated Preference Valuation. *Environmental and Resource Economics*, 30:313-325.

O'Brien, K.A. and Teisl, M.F. (2004). Eco-information and its effect on consumer values for environmentally certified forest products. *Journal of Forest Economics*, *10*: 75-96.

Ohdoko, T., Yoshida, K. (2012): Public preferences for forest ecosystem management in Japan with emphasis on species diversity. *Environmental Economics and Policy Studies*, 14 (2), pp. 147-169.

Oppewal, H., Morrison, M., Wang, P. and Waller, D. (2010). Preference stability: Modeling how consumer preferences shift after receiving new product information. In S. Hess and A. Daly, *Choice Modelling: The State-of-the-Art and the State-of-Practice: Proceedings from the Inaugural International Choice Modelling Conference*, Emerald Group Publishing Limited, Bingley UK, pp. 499-516.

Raghovarao, D. and Wiley, J.B. (1986) Testing Competing Effects Among Soft Drink Brands, in *Statistical Design: Theory and Practice: Proceedings of a Conference in Honour of Walter T. Federer*, McCulloch, C.E., Shwager, S.J., Gasella, G. and Searle, S.R., eds, Ithaca, NY, Cornell University, 161-176.

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

Rose, J. M. and Bliemer, M. C. J. (2009). Stated preference experimental design strategies. *Transport Reviews*, *295*: 587-617.

Rose, J.M.; Louviere, J.J.; Bliemer, M.C.J. Efficient stated choice designs allowing for variable choice set sizes. In Proceedings of the International Choice Modelling Conference, Sydney, Australia, 3–5 July 2013.

Rouvinen, S. and Matero, J. (2013). Stated preferences of Finnish private homeowners for residential heating systems: A discrete choice experiment. *Biomass and Bioenergy,* 57:22-32.

Rungie, C., Scarpa, R., and Thiene, M. (2014). The influence of individuals in forming collective household preferences for water quality. *Journal of Environmental Economics and Management*, 68(1):161-174.

Salvati P., Bianchi C., Rossi M., and Guzzetti F. (2010). Societal landslide and flood risk in Italy. *Natural Hazards and Earth System Sciences, 10*:465–483.

Scarpa, R. and Rose, J.M. (2008). Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why. *Australian Journal of Agricultural Resource Economics*, *52*: 253–282.

Scarpa, R. and Thiene, M. (2005). Destination choice models for rock climbing in the Northeastern Alps: a latent class approach based on intensity of preferences. Land Economics, 81(3):426–444.

Scarpa, R. and Willis, K.G. (2010). Willingness-to-pay for renewable energy: Primary and discretionary choice of British households' for micro-generation technologies. *Energy Economics*, 32(1):129-136.

Scarpa, R., Thiene, M. and Train, K. (2008). Utility in willingness to pay space: A tool to address confounding random scale effects in destination choice to the Alps. *American Journal of Agricultural Economics*, *90*(4):994-1010.

Scarpa, R.; Rose, J.M. Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why. *Australian. Journal of Agricultural. Resource Economics.* 2008, *52*, 253–282.

Scarpa, R.; Thiene, M. Destination choice models for rock climbing in the Northeastern Alps: A latent class approach based on intensity of preferences. *Land Economics.* 2005, *81*, 426–444.

Schaafsma, M., Brouwer, R., and Rose, J.M. (2012). Directional heterogeneity in WTP models for environmental valuation. *Ecological economics*, 79:21-31.

Stefani, G., Scarpa, R., and Lombardi, G.V. (2014). An addendum to: a meta-analysis of hypothetical bias in stated preference valuation. *Bio-based and Applied Economics*, 3(2):175-184.

Sterlacchini, S., Frigerio, S., Giacomelli, P. and Brambilla, M. (2007). Landslide risk analysis: a multi-disciplinary methodological approach. *Natural Hazards and Earth System Science*, *7*(6): 657-675.
Termansen, M., Zandersen, M. and McClean, C.J. (2008). Spatial substitution patterns in forest recreation. *Regional Science and Urban Economics*, *38*:81-97.

Thiene, M., Meyerhoff, J., De Salvo, M. (2012): Scale and taste heterogeneity for forest biodiversity: Models of serial nonparticipation and their effects. *Journal of Forest Economics*, 18 (4), pp. 355-369.

Thiene, M., Scarpa, R and Shaw, W.D. (2016). Perceived risks of mountain landslides in Italy: Stated choices for subjective risk reductions. Forthcoming *Landslides*.

Thiene, M., Scarpa, R. and Louviere,J . (2015). Addressing preference heterogeneity, multiple scales and attribute attendance with a correlated finite mixing model of tap water choice. Environmental and Resource Economics, 62(3):637-656.

Timmins, C. and Murdock, J. (2007). A revealed preference approach to the measurement of congestion in travel cost models. *Journal of Environmental Economics and Management*, 53(2):230-249.

Train, K.E. (1998). Recreation demand models with taste differences over people. *Land Economics*, *74*(2): 230–239.

Train, K.E. (2003). Discrete choice methods with simulation. Cambridge University Press, Cambridge.

Train, K.E. and Weeks, M. (2005). Discrete choice models in preference space and willingness-to-pay space. In: Scarpa, R., Alberini, A. (eds), *Application of simulation methods in environmental and resource economics*. Springer, Dordrecht, pp 1–16.

Train, K.E. Recreation demand models with taste differences over people. *Land Economics.* 1998, *74*, 230–239.

Turner, R.K., Morse-Jones, S., Fisher, B. (2010): Ecosystem valuation: A sequential decision support system and quality assessment issues. *Annals of the New York Academy of Sciences*, 1185, pp. 79-101.

Tyrväinen, L., Mäntymaa, E., Ovaskainen, V. (2014): Demand for enhanced forest amenities in private lands: The case of the Ruka-Kuusamo tourism area, Finland. *Forest Policy and Economics*, 47, pp. 4-13.

Vlaeminck, P., Maertens, M., Isabirye, M., Vanderhoydonks, F., Poesen, J., Deckers, J. and Vranken, L. (2016). Coping with landslide risk through preventive resettlement. Designing optimal strategies through choice experiments for the Mount Elgon region, Uganda. *Land Use Policy*, *51*: 301-311.
von Haefen, R. (2003). Incorporating observed choice into the construction of welfare measures from random utility models. *Journal of Environmental Economics and Management*, 45(2):145-165.

Willis, K., Scarpa, R., Gilroy, R., and Hamza, N. (2011). Renewable energy adoption in an ageing population: Heterogeneity in preferences for micro-generation technology adoption. *Energy Policy, 39*(10):6021-6029.

Yamamoto, Y. (2015). Opinion leadership and willingness to pay for residential photovoltaic systems. Energy Policy, 83:185-192.

Yao, R.T., Scarpa, R., Turner, J.A., Barnard, T.D., Rose, J.M., Palma, J.H. and Harrison, D.R. (2014). Valuing biodiversity enhancement in New Zealand's planted forests: Socio-economic and spatial determinants of willingness-to-pay. *Ecological Economics*, *98*(C):90–101.

Yoo, J., Ready, R.C. (2014). Preference heterogeneity for renewable energy technology. Energy Economics, 42:101-114.

Appendix 1: Questionnaire adopted in the case study "Analysis of preferences of households of the Veneto region for different heating systems"

SEZIONE 1

1. Quale combustibile utilizzi per riscaldare la tua abitazione? (ti è possibile indicare più di un'alternativa) (per informazioni clicca sul punto di domanda)

2. Indica la percentuale di famiglie della regione Veneto che, secondo te, ha adottato i diversi sistemi di riscaldamento.

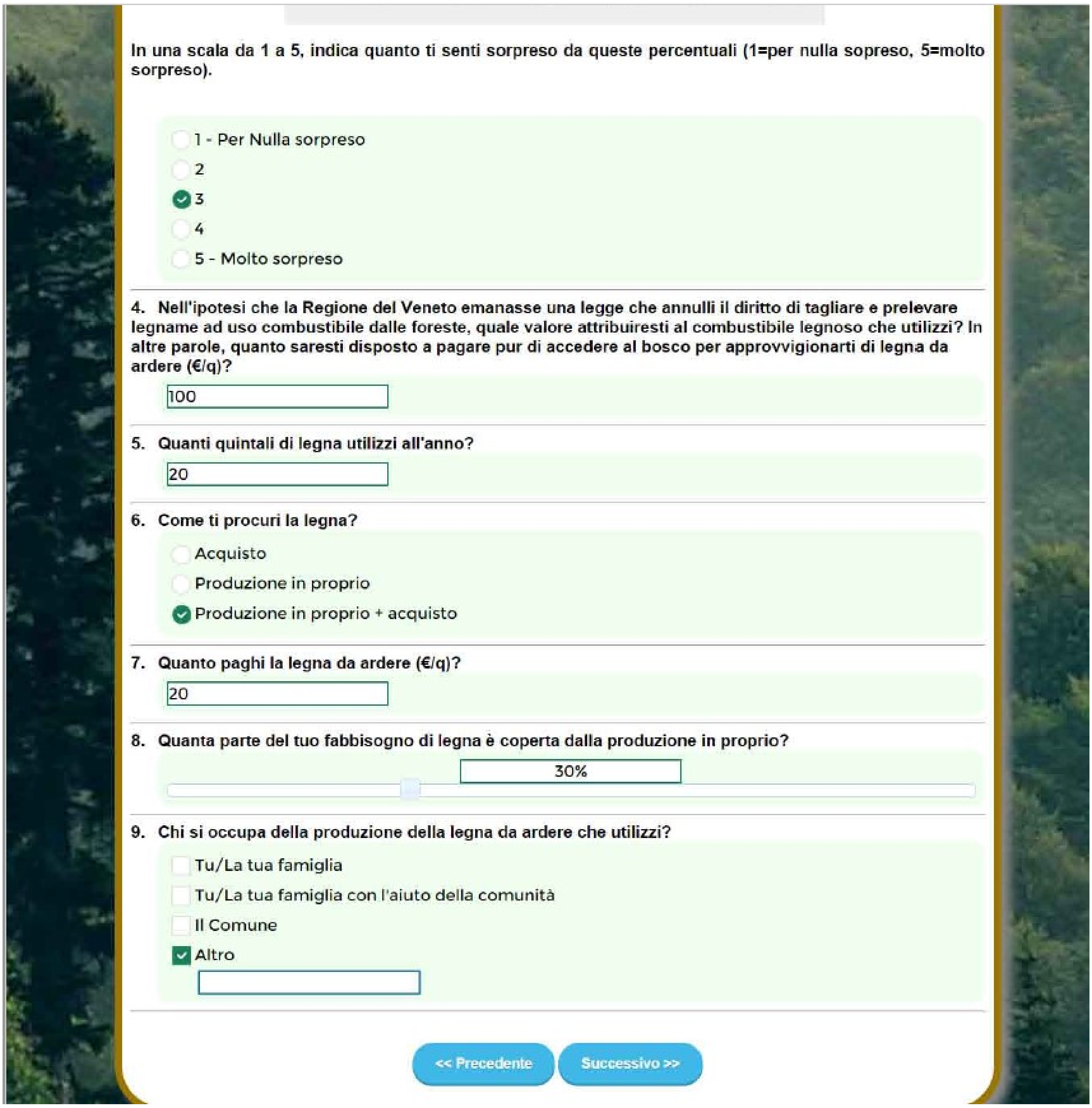
Legna da ardere	100	%
Cippato	0	%
Pellet	0	%
Metano	0	%
Gasolio	0	%
GPL	0	%
Totale	100	%

3. Nella tabella sottostante sono riportate le reali percentuali di adozione dei diversi sistemi di riscaldamento.

Legna da ardere	Cippato	Pellet	Metano	Gasolio	GPL
14,6%	1,1%	2,6%	72,3%	4,2%	3,9%

In una scala da 1 a 5, indica quanto ti senti sorpreso da queste percentuali (1=per nulla sopreso, 5=molto sorpreso).

- 1 - Per Nulla sorpreso
- 2
- 3
- 4
- 5 - Molto sorpreso



In una scala da 1 a 5, indica quanto ti senti sorpreso da queste percentuali (1=per nulla sopreso, 5=molto sorpreso).

- 1 - Per Nulla sorpreso
- 2
- 3 ✓
- 4
- 5 - Molto sorpreso

4. Nell'ipotesi che la Regione del Veneto emanasse una legge che annulli il diritto di tagliare e prelevare legname ad uso combustibile dalle foreste, quale valore attribuiresti al combustibile legnoso che utilizzi? In altre parole, quanto saresti disposto a pagare pur di accedere al bosco per approvvigionarti di legna da ardere (€/q)?

   100

5. Quanti quintali di legna utilizzi all'anno?

   20

6. Come ti procuri la legna?

   - Acquisto
   - Produzione in proprio
   - Produzione in proprio + acquisto ✓

7. Quanto paghi la legna da ardere (€/q)?

   20

8. Quanta parte del tuo fabbisogno di legna è coperta dalla produzione in proprio?

   30%

9. Chi si occupa della produzione della legna da ardere che utilizzi?

   - Tu/La tua famiglia
   - Tu/La tua famiglia con l'aiuto della comunità
   - Il Comune
   - Altro ✓

<< Precedente | Successivo >>

SEZIONE 2

Nell'ipotesi di una sostituzione del tuo attuale sistema di riscaldamento, ti chiederemo di indicare il sistema che preferisci tra quelli di seguito elencati, assumendo che NON ve ne siano altri disponibili:

1) Legna da ardere

2) Cippato

3) Pellet

4) Metano

5) Gasolio

6) GPL

Queste sono le principali caratteristiche dei sistemi di riscaldamento proposti. Per ciascuna caratteristica sono riportati più valori plausibili (ad esempio, il costo di investimento di un sistema di riscaldamento a legna può variare tra 9.500, 11.000, 12.500€).

1) Costo di installazione (€)

Costo di impianto e messa in opera.

Legna da ardere (€)	Cippato (€)	Pellet (€)	Metano (€)	Gasolio (€)	GPL (€)
9.500	11.500	13.000	4.000	4.500	4.000
11.000	13.000	15.000	4.800	5.500	5.000
12.500	14.500	17.000	5.600	6.500	6.000

2) Durata dell'investimento (anni)

Numero di anni da installazione a dismissione.

Legna da ardere (anni)	Cippato (anni)	Pellet (anni)	Metano (anni)	Gasolio (anni)	GPL (anni)
15	17	16	16	16	14
17	20	19	18	18	17
19	23	22	20	20	20

3) Costo di esercizio (€/anno)

Spesa per combustibile, elettricità e manutenzione impianto.

Legna da ardere (€/anno)	Cippato (€/anno)	Pellet (€/anno)	Metano (€/anno)	Gasolio (€/anno)	GPL (€/anno)
1.200	2.000	2.500	4.000	6.000	9.000
2.000	2.800	3.750	5.500	8.000	12.500
2.800	3.600	5.000	7.000	10.000	16.000

4) Emissioni CO_2 (kg/anno)

Quantità di anidride carbonica emessa dal processo di combustione.

Legna da ardere (kg/anno)	Cippato (kg/anno)	Pellet (kg/anno)	Metano (kg/anno)	Gasolio (kg/anno)	GPL (kg/anno)
150	300	375	3.000	3.900	3.525
225	375	450	3.750	4.575	4.125
300	450	525	4.500	5.250	4.725

5) Emissioni particolato fine (g/anno)

Piccoli frammenti di combustibile che possono causare malattie.

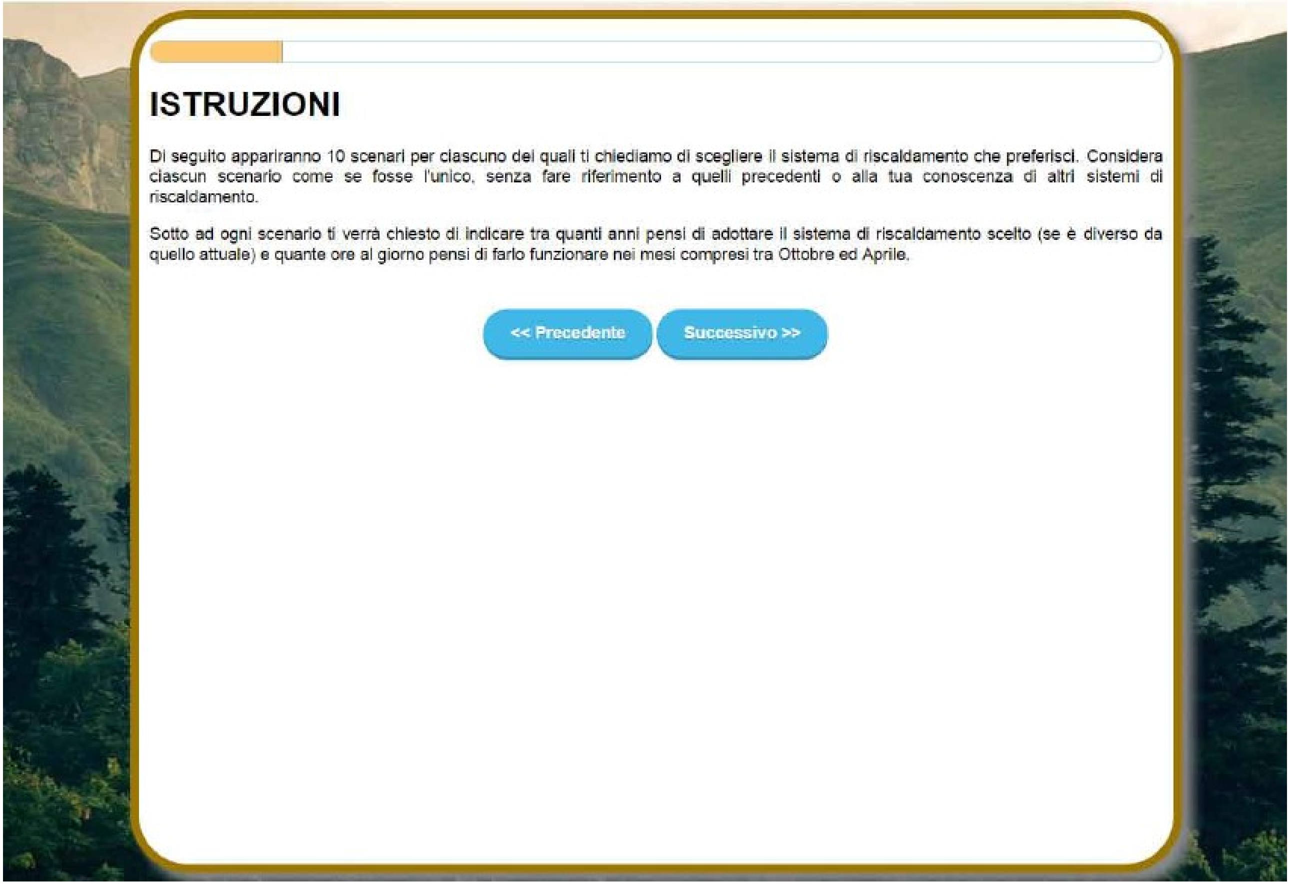
Legna da ardere (g/anno)	Cippato (g/anno)	Pellet (g/anno)	Metano (g/anno)	Gasolio (g/anno)	GPL (g/anno)
4.500	2.250	750	15	150	15
6.000	3.750	1.500	30	450	30
7.500	5.250	2.250	45	750	45

6) Lavoro richiesto (ore/mese)

Tempo richiesto per alimentazione, manutenzione e pulizia.

Legna da ardere (ore/mese)	Cippato (ore/mese)	Pellet (ore/mese)	Metano (ore/mese)	Gasolio (ore/mese)	GPL (ore/mese)
5	1	1		0,5	0,5
10	2	2	-	1	1
15	3	3		1,5	1,5

<< Precedente   Successivo >>



ISTRUZIONI

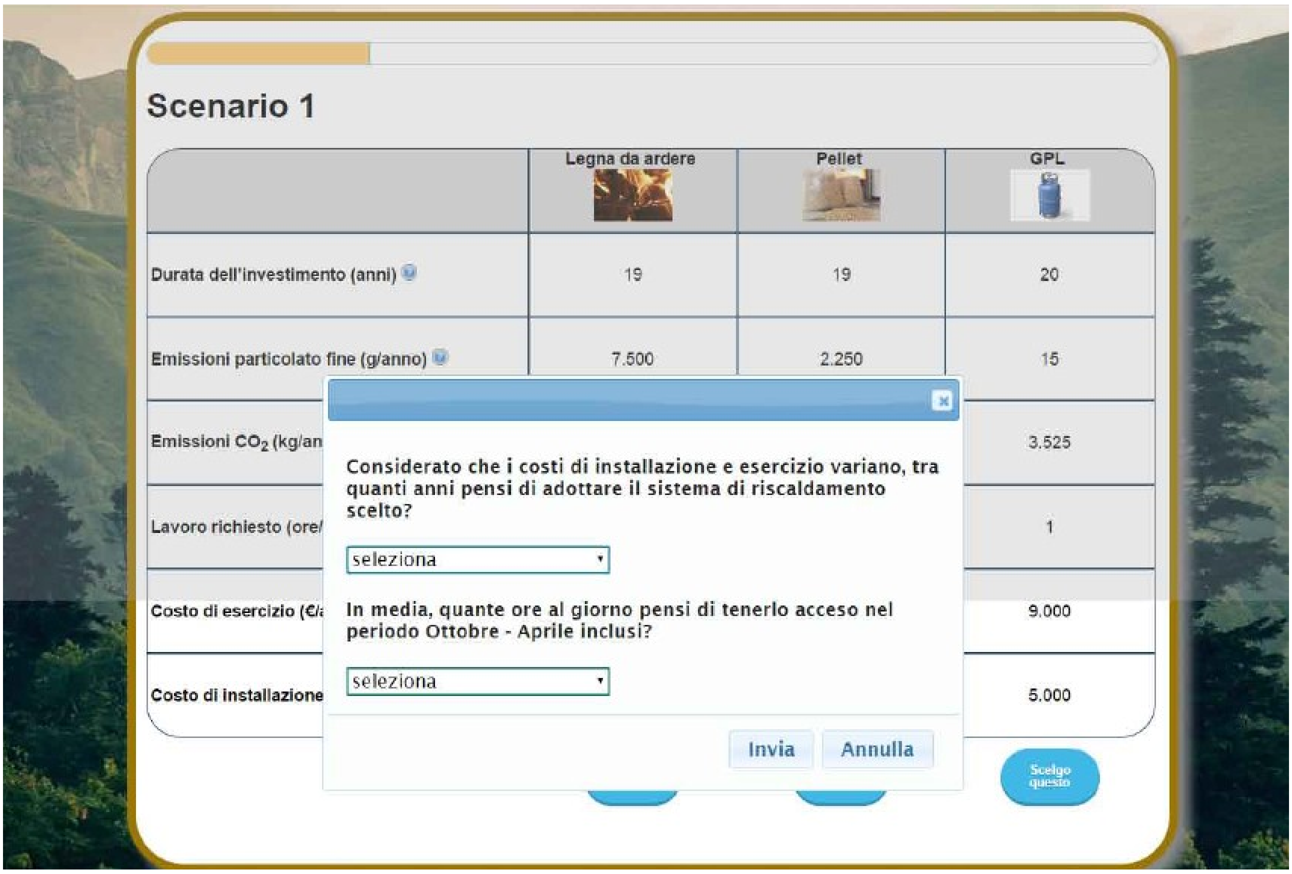
Di seguito appariranno 10 scenari per ciascuno dei quali ti chiediamo di scegliere il sistema di riscaldamento che preferisci. Considera ciascun scenario come se fosse l'unico, senza fare riferimento a quelli precedenti o alla tua conoscenza di altri sistemi di riscaldamento.

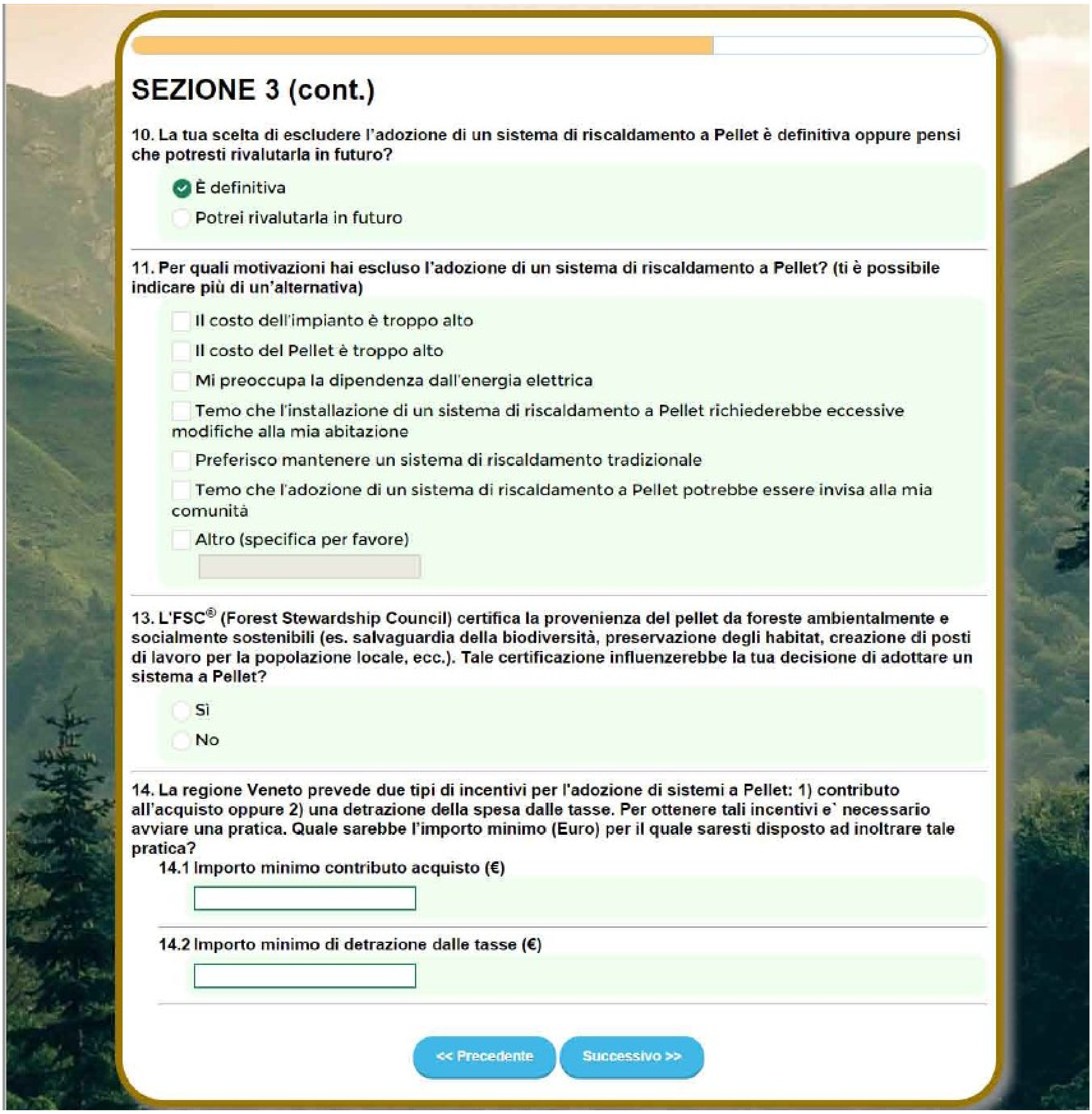
Sotto ad ogni scenario ti verrà chiesto di indicare tra quanti anni pensi di adottare il sistema di riscaldamento scelto (se è diverso da quello attuale) e quante ore al giorno pensi di farlo funzionare nei mesi compresi tra Ottobre ed Aprile.

<< Precedente Successivo >>

Scenario 1

	Pellet 	GPL 	Legna da ardere 
Durata dell'investimento (anni)	19	20	19
Emissioni particolato fine (g/anno)	2.250	15	7.500
Emissioni CO_2 (kg/anno)	375	3.525	150
Lavoro richiesto (ore/mese)	1	1	15
Costo di esercizio (€/anno)	3.750	9.000	1.200
Costo di installazione (€)	17.000	5.000	12.500
	Scelgo questo	Scelgo questo	Scelgo questo


Scenario 1
Legna da ardere
Pellet
GPL
Durata dell'investimento (anni)
19
19
20
Emissioni particolato fine (g/anno)
7.500
2.250
15
Emissioni CO2 (kg/an
3.525
Lavoro richiesto (ore/
1
Costo di esercizio (€/a
9.000
Costo di installazione
5.000
Considerato che i costi di installazione e esercizio variano, tra quanti anni pensi di adottare il sistema di riscaldamento scelto?
seleziona
In media, quante ore al giorno pensi di tenerlo acceso nel periodo Ottobre - Aprile inclusi?
seleziona
Invia
Annulla
Scelgo questo



SEZIONE 3 (cont.)

10. La tua scelta di escludere l'adozione di un sistema di riscaldamento a Pellet è definitiva oppure pensi che potresti rivalutarla in futuro?

- [x] È definitiva
- [ ] Potrei rivalutarla in futuro

11. Per quali motivazioni hai escluso l'adozione di un sistema di riscaldamento a Pellet? (ti è possibile indicare più di un'alternativa)

- [ ] Il costo dell'impianto è troppo alto
- [ ] Il costo del Pellet è troppo alto
- [ ] Mi preoccupa la dipendenza dall'energia elettrica
- [ ] Temo che l'installazione di un sistema di riscaldamento a Pellet richiederebbe eccessive modifiche alla mia abitazione
- [ ] Preferisco mantenere un sistema di riscaldamento tradizionale
- [ ] Temo che l'adozione di un sistema di riscaldamento a Pellet potrebbe essere invisa alla mia comunità
- [ ] Altro (specifica per favore)

13. L'FSC® (Forest Stewardship Council) certifica la provenienza del pellet da foreste ambientalmente e socialmente sostenibili (es. salvaguardia della biodiversità, preservazione degli habitat, creazione di posti di lavoro per la popolazione locale, ecc.). Tale certificazione influenzerebbe la tua decisione di adottare un sistema a Pellet?

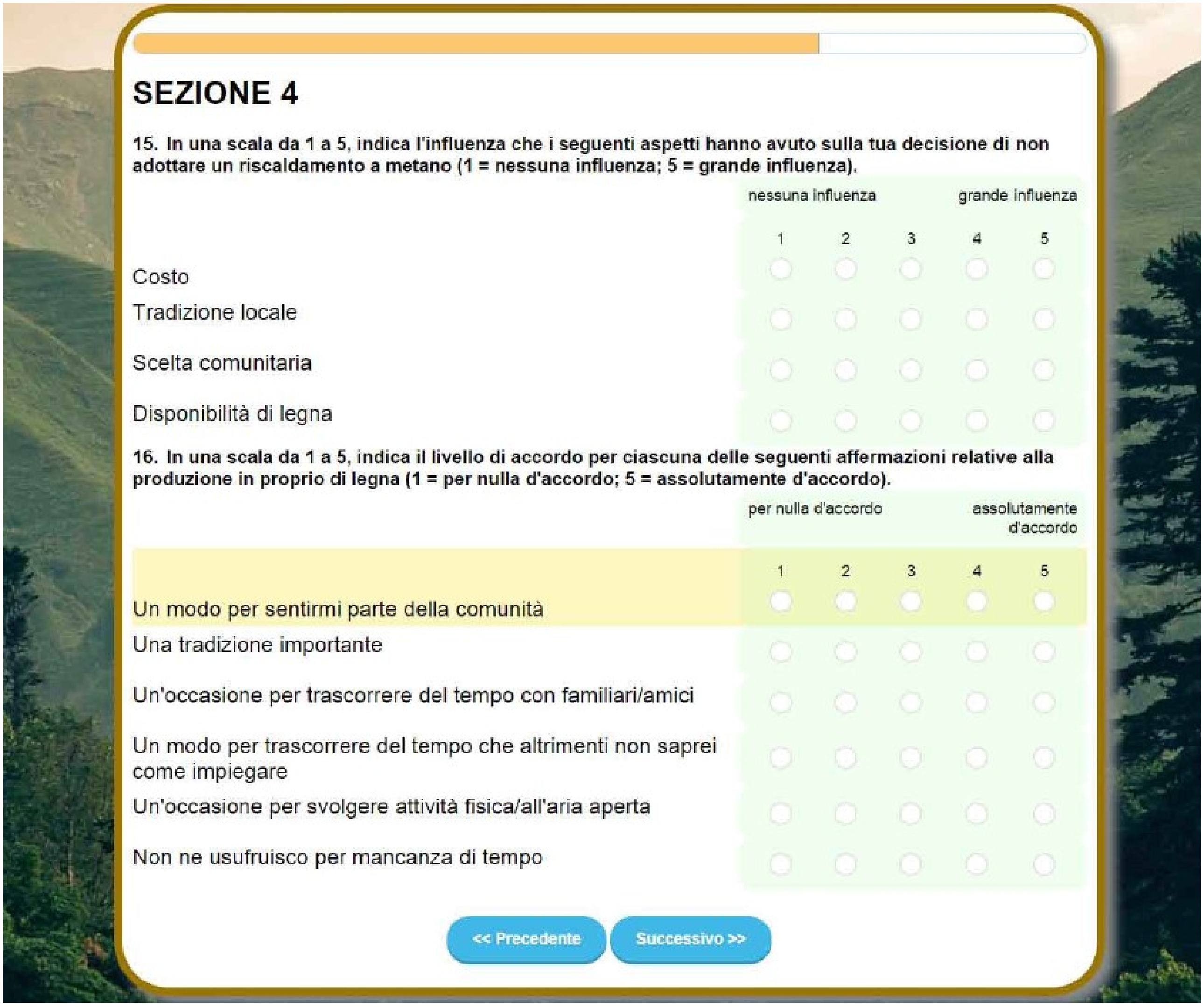
- [ ] Sì
- [ ] No

14. La regione Veneto prevede due tipi di incentivi per l'adozione di sistemi a Pellet: 1) contributo all'acquisto oppure 2) una detrazione della spesa dalle tasse. Per ottenere tali incentivi e` necessario avviare una pratica. Quale sarebbe l'importo minimo (Euro) per il quale saresti disposto ad inoltrare tale pratica?

14.1 Importo minimo contributo acquisto (€)

14.2 Importo minimo di detrazione dalle tasse (€)

<< Precedente | Successivo >>



SEZIONE 4

15. In una scala da 1 a 5, indica l'influenza che i seguenti aspetti hanno avuto sulla tua decisione di non adottare un riscaldamento a metano (1 = nessuna influenza; 5 = grande influenza).

	nessuna influenza				grande influenza
	1	2	3	4	5
Costo					
Tradizione locale					
Scelta comunitaria					
Disponibilità di legna					

16. In una scala da 1 a 5, indica il livello di accordo per ciascuna delle seguenti affermazioni relative alla produzione in proprio di legna (1 = per nulla d'accordo; 5 = assolutamente d'accordo).

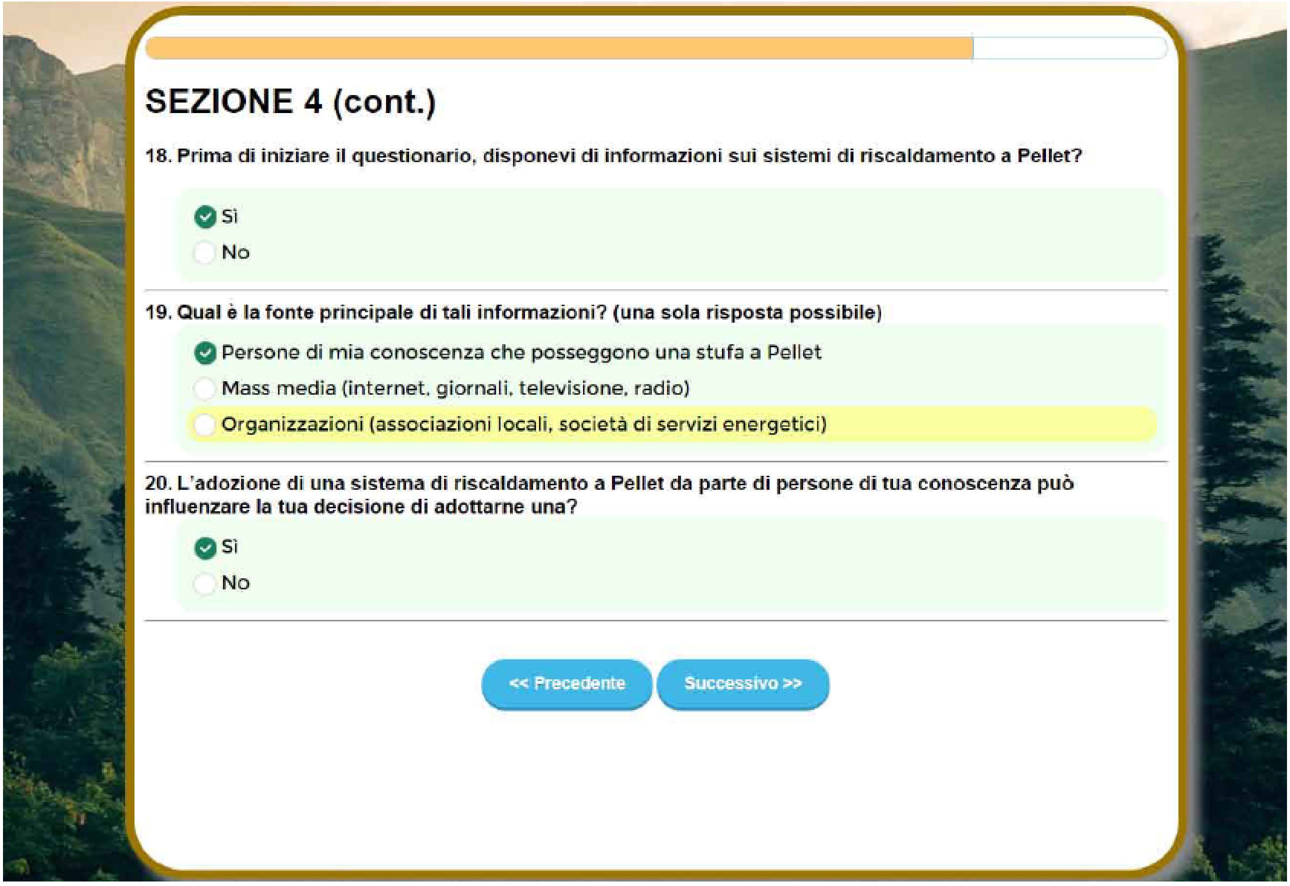
	per nulla d'accordo				assolutamente d'accordo
	1	2	3	4	5
Un modo per sentirmi parte della comunità					
Una tradizione importante					
Un'occasione per trascorrere del tempo con familiari/amici					
Un modo per trascorrere del tempo che altrimenti non saprei come impiegare					
Un'occasione per svolgere attività fisica/all'aria aperta					
Non ne usufruisco per mancanza di tempo					

<< Precedente   Successivo >>

SEZIONE 4 (cont.)

17. In una scala da 1 a 5, indica quanto sei d'accordo con ciascuna delle seguenti affermazioni (1 = per nulla d'accordo; 5 = completamente d'accordo).

	per nulla d'accordo 1	2	3	4	completamente d'accordo 5
E' difficile installare un sistema di riscaldamento a pellet					
E' difficile utilizzare un sistema di riscaldamento a pellet					
L'utilizzo di un sistema di riscaldamento a pellet è compatibile con i miei ritmi quotidiani					
Installare un sistema di riscaldamento a pellet richiederebbe grosse modifiche alla mia abitazione					
Conosco qualcuno che possiede un sistema di riscaldamento a pellet che potrebbe fornirmi informazioni in merito					
Conosco edifici in cui posso vedere un sistema di riscaldamento a pellet in funzione					
Un sistema di riscaldamento a pellet richiede meno manutenzione del mio impianto attuale					
Adottare una sistema di riscaldamento a pellet mi permetterebbe di abbassare le mie attuali spese per il riscaldamento					
Una sistema di riscaldamento a pellet riscalda adeguatamente l'abitazione					
Mi preoccupa la manutenzione che i sistemi di riscaldamento a pellet richiedono					
Rispetto ad altri sistemi di riscaldamento, i sistemi di riscaldamento a pellet comportano maggiori rischi					
Temo che l'acquisto di un sistema di riscaldamento a pellet possa essere considerato negativamente dai miei vicini					
Ho le conoscenze necessarie per decidere circa l'acquisto di un sistema di riscaldamento a pellet					
Sono a conoscenza di ciò che è necessario per installare un sistema di riscaldamento a pellet					
L'installazione di un sistema di riscaldamento a pellet migliorerebbe l'ambiente in cui vivo					
Installando un sistema di riscaldamento a pellet ridurrei le emissioni di gas serra					



SEZIONE 4 (cont.)

18. Prima di iniziare il questionario, disponevi di informazioni sui sistemi di riscaldamento a Pellet?

- [x] Sì
- [ ] No

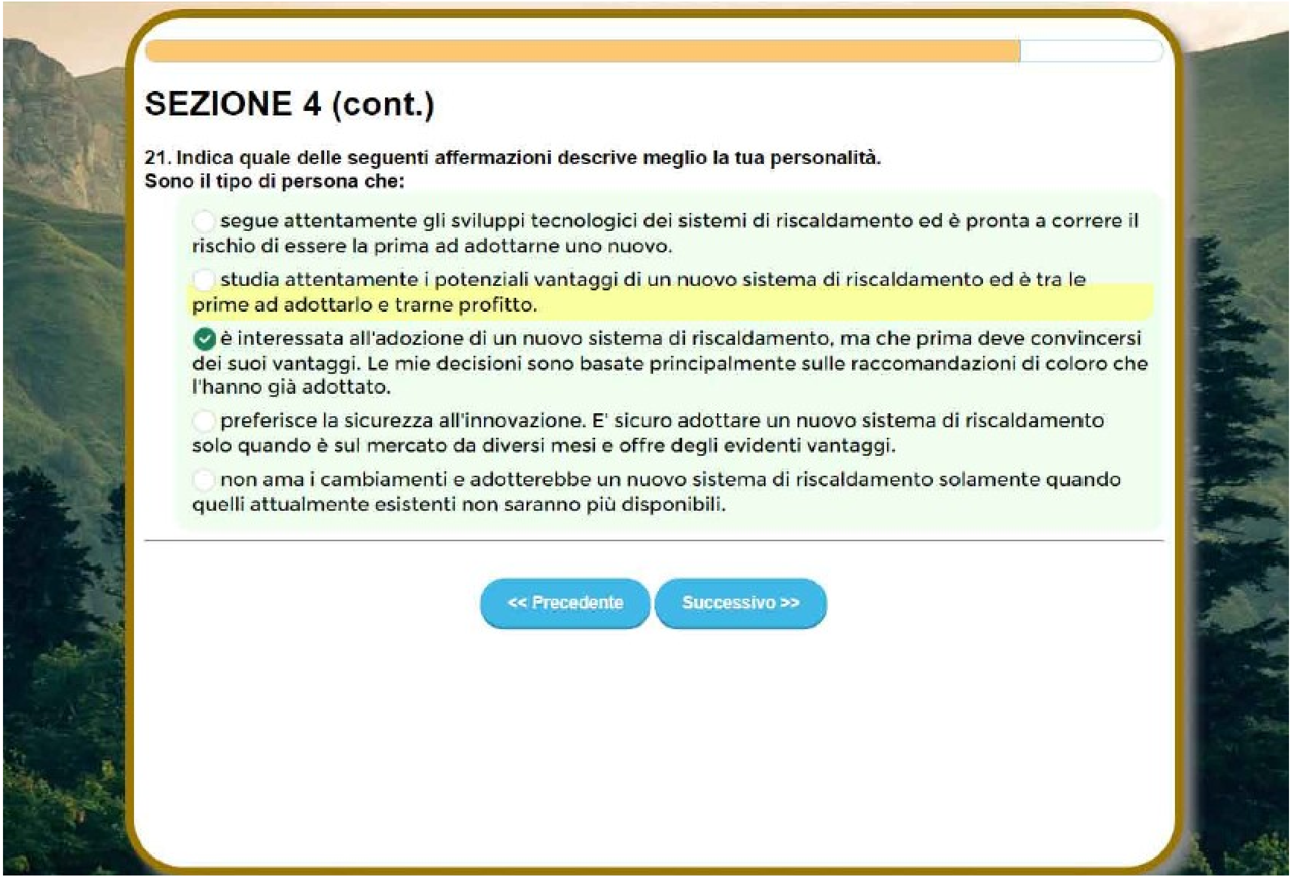
19. Qual è la fonte principale di tali informazioni? (una sola risposta possibile)

- [x] Persone di mia conoscenza che posseggono una stufa a Pellet
- [ ] Mass media (internet, giornali, televisione, radio)
- [ ] Organizzazioni (associazioni locali, società di servizi energetici)

20. L'adozione di una sistema di riscaldamento a Pellet da parte di persone di tua conoscenza può influenzare la tua decisione di adottarne una?

- [x] Sì
- [ ] No

<< Precedente | Successivo >>

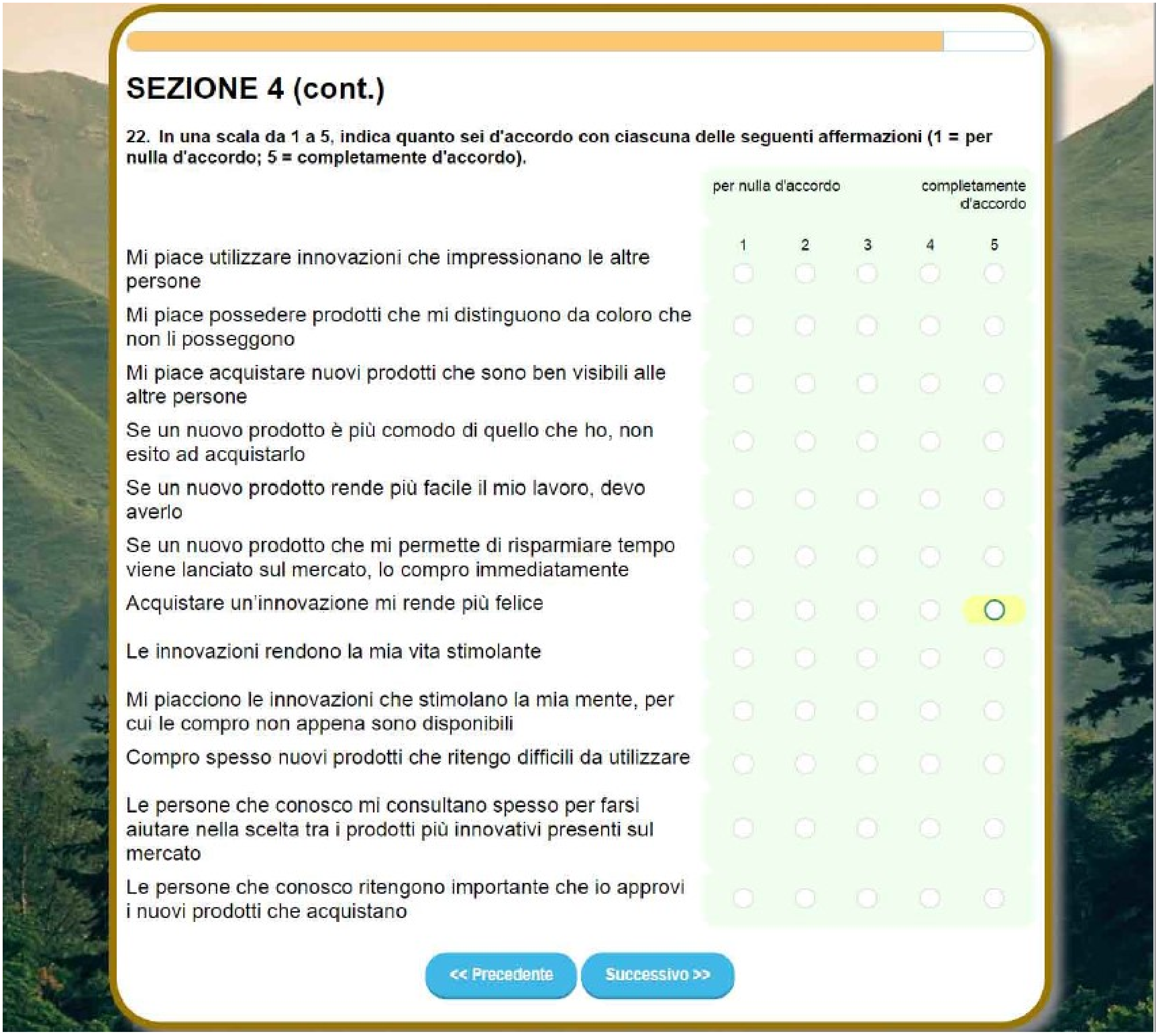


SEZIONE 4 (cont.)

21. Indica quale delle seguenti affermazioni descrive meglio la tua personalità.
Sono il tipo di persona che:

- segue attentamente gli sviluppi tecnologici dei sistemi di riscaldamento ed è pronta a correre il rischio di essere la prima ad adottarne uno nuovo.
- studia attentamente i potenziali vantaggi di un nuovo sistema di riscaldamento ed è tra le prime ad adottarlo e trarne profitto.
- è interessata all'adozione di un nuovo sistema di riscaldamento, ma che prima deve convincersi dei suoi vantaggi. Le mie decisioni sono basate principalmente sulle raccomandazioni di coloro che l'hanno già adottato.
- preferisce la sicurezza all'innovazione. E' sicuro adottare un nuovo sistema di riscaldamento solo quando è sul mercato da diversi mesi e offre degli evidenti vantaggi.
- non ama i cambiamenti e adotterebbe un nuovo sistema di riscaldamento solamente quando quelli attualmente esistenti non saranno più disponibili.

<< Precedente   Successivo >>

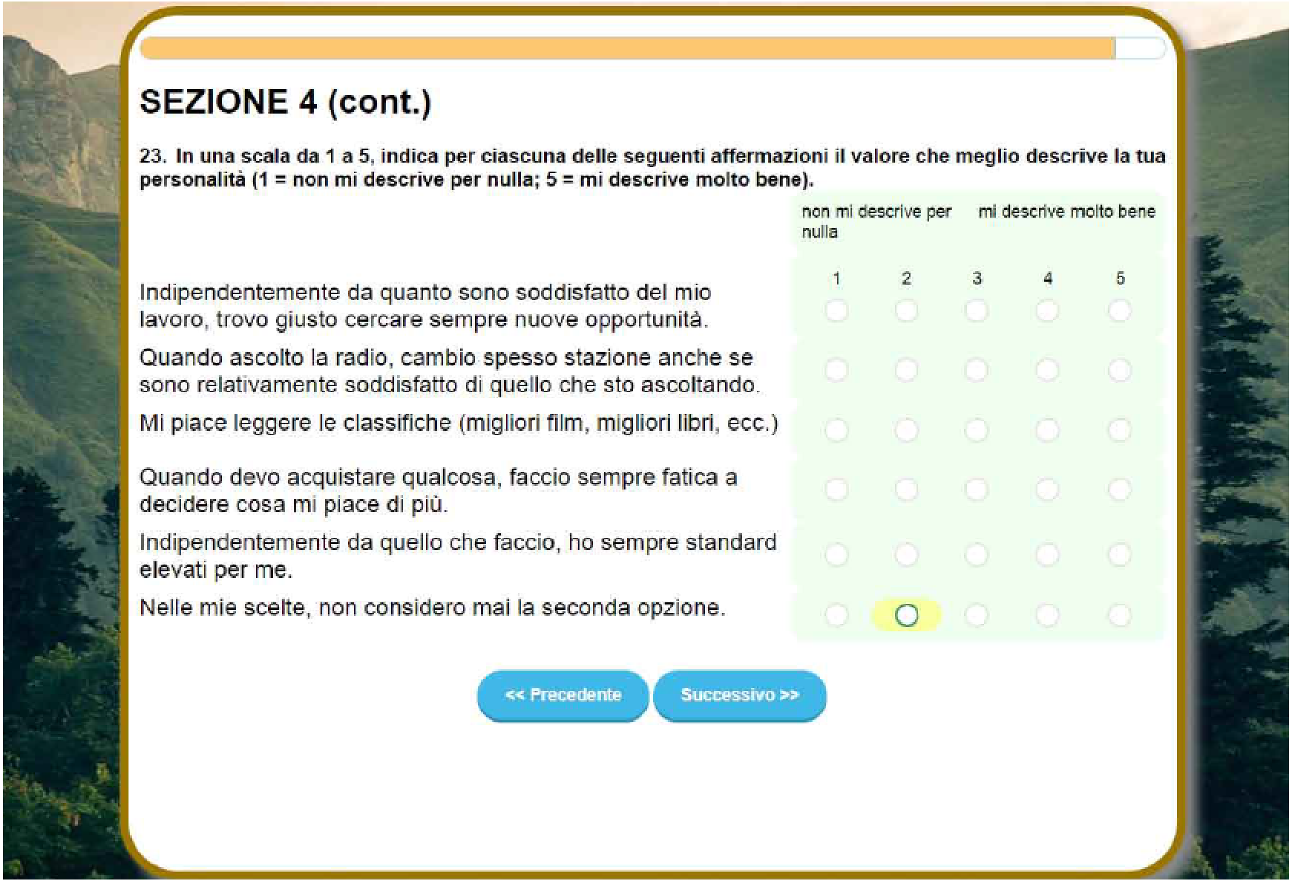


SEZIONE 4 (cont.)

22. In una scala da 1 a 5, indica quanto sei d'accordo con ciascuna delle seguenti affermazioni (1 = per nulla d'accordo; 5 = completamente d'accordo).

	per nulla d'accordo 1	2	3	4	completamente d'accordo 5
Mi piace utilizzare innovazioni che impressionano le altre persone					
Mi piace possedere prodotti che mi distinguono da coloro che non li posseggono					
Mi piace acquistare nuovi prodotti che sono ben visibili alle altre persone					
Se un nuovo prodotto è più comodo di quello che ho, non esito ad acquistarlo					
Se un nuovo prodotto rende più facile il mio lavoro, devo averlo					
Se un nuovo prodotto che mi permette di risparmiare tempo viene lanciato sul mercato, lo compro immediatamente					
Acquistare un'innovazione mi rende più felice					
Le innovazioni rendono la mia vita stimolante					
Mi piacciono le innovazioni che stimolano la mia mente, per cui le compro non appena sono disponibili					
Compro spesso nuovi prodotti che ritengo difficili da utilizzare					
Le persone che conosco mi consultano spesso per farsi aiutare nella scelta tra i prodotti più innovativi presenti sul mercato					
Le persone che conosco ritengono importante che io approvi i nuovi prodotti che acquistano					

<< Precedente | Successivo >>

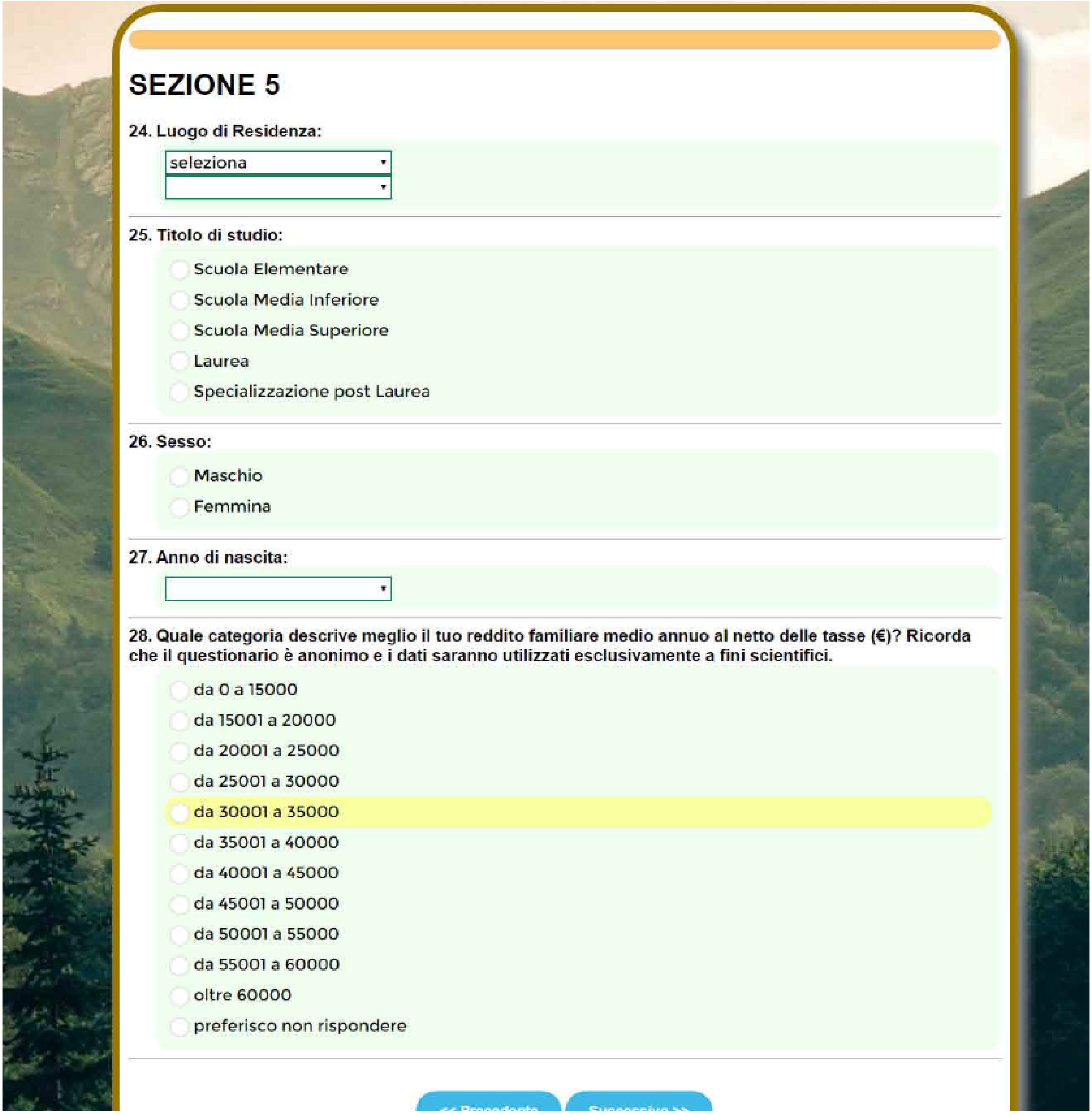


SEZIONE 4 (cont.)

23. In una scala da 1 a 5, indica per ciascuna delle seguenti affermazioni il valore che meglio descrive la tua personalità (1 = non mi descrive per nulla; 5 = mi descrive molto bene).

	non mi descrive per nulla				mi descrive molto bene
	1	2	3	4	5
Indipendentemente da quanto sono soddisfatto del mio lavoro, trovo giusto cercare sempre nuove opportunità.	○	○	○	○	○
Quando ascolto la radio, cambio spesso stazione anche se sono relativamente soddisfatto di quello che sto ascoltando.	○	○	○	○	○
Mi piace leggere le classifiche (migliori film, migliori libri, ecc.)	○	○	○	○	○
Quando devo acquistare qualcosa, faccio sempre fatica a decidere cosa mi piace di più.	○	○	○	○	○
Indipendentemente da quello che faccio, ho sempre standard elevati per me.	○	○	○	○	○
Nelle mie scelte, non considero mai la seconda opzione.	○	○	○	○	○

<< Precedente | Successivo >>



SEZIONE 5

24. Luogo di Residenza:

seleziona

25. Titolo di studio:

- Scuola Elementare
- Scuola Media Inferiore
- Scuola Media Superiore
- Laurea
- Specializzazione post Laurea

26. Sesso:

- Maschio
- Femmina

27. Anno di nascita:

28. Quale categoria descrive meglio il tuo reddito familiare medio annuo al netto delle tasse (€)? Ricorda che il questionario è anonimo e i dati saranno utilizzati esclusivamente a fini scientifici.

- da 0 a 15000
- da 15001 a 20000
- da 20001 a 25000
- da 25001 a 30000
- da 30001 a 35000
- da 35001 a 40000
- da 40001 a 45000
- da 45001 a 50000
- da 50001 a 55000
- da 55001 a 60000
- oltre 60000
- preferisco non rispondere